Preliminary and Incomplete: subject to revision
Please do not cite or quote without permission

Discounting versus risk aversion: their effects on individual demands for climate change mitigation

Trudy Ann Cameron
Department of Economics, University of Oregon
cameron@uoregon.edu

Geoffrey R. Gerdes
Federal Reserve Board of Governors

Acknowledgements: This research was supported in part by a grant from the NSF "Popular Support for Climate Change Policy: Regional, Intertemporal, and Sociodemographic Heterogeneity in Risk Perception, Receptiveness to 'Expert' Opinions, and Willingness to Incur Costs of Mitigation," (PI: Trudy Ann Cameron, SBR 9818875) and also by the resources of the Mikesell Chair in Environmental and Resource Economics at the University of Oregon. For comments and suggestions, we are grateful to W. Michael Hanemann and participants in the AERE session "Measuring Environmental Preferences and Performance" (ASSA meetings, Chicago, January 6, 2007) The opinions expressed in this paper are those of the authors and do not necessarily reflect the opinions of the Federal Reserve Board of Governors or its staff.

Discounting versus risk aversion: their effects on
individual demands for climate change mitigation

ABSTRACT: Risk aversion and time preferences are important sources of heterogeneity in preferences for public policies with near-term costs and uncertain future benefits. Using stated preference data, we first jointly estimate individual-specific risk aversion and discount rate parameters then use these as individual "characteristics" in a separate model to explain preferences for climate change mitigation policies. The more risk-averse the individual, and/or the lower their discount rate, the higher is their willingness to pay. We also simulate expected demand under counterfactual conditions—such as risk neutrality, or the lower social discount rates that would be used by a benevolent central planner.

JEL Classification: H43, D81

Keywords: climate change policy, risk aversion, discount rate, stated preference, information bias, construct validity

Discounting versus risk aversion: the effects of time and risk preferences on individual demands for climate change mitigation

I. Introduction

Policies to reduce carbon emissions in an effort to prevent climate change involve large near-term costs and uncertain long-term benefits (i.e. the avoided future adverse consequences of climate change). This uncertainty, along with the very different time profiles of costs and benefits, means that risk aversion and time preferences will be key features of any model that seeks to explain heterogeneity in consumer demand for climate change mitigation programs. Unfortunately, while most reduced-form empirical demand models for climate change mitigation can easily control for individual characteristics such as age, gender, and income, these two key structural determinants—risk preferences and time preferences—are typically unobservable. In this study, we have sufficient data to allow us to build explicit individual-specific measures of these two determinants and use them directly as sources of preference heterogeneity in an empirical random-utility model of climate policy choice.

Using a convenience sample of stated preference survey data concerning climate policy collected from roughly 100 colleges around the U.S. and Canada, we first use two specially tailored auxiliary questions about stated choices in other contexts to jointly estimate individual-specific measures of risk aversion and discount rates within a utility-theoretic choice framework. As functions of a wide range of observable individual characteristics, fitted individual risk parameters and fitted individual discount rates are positively related, but they exhibit a correlation of only 0.33. We then use these two fitted parameters as crude measures of these two key (but typically unmeasurable) individual characteristics in a separate random utility choice model, where they help explain heterogeneity in preferences for climate change mitigation policies.

We find that the more risk-averse the individual, the lower the marginal utility of net income implied by their climate policy preferences (which tends to increase their willingness to pay for climate change mitigation). The higher the individual's discount rate, however, the less they are willing to pay to prevent climate change. These intuitively plausible relationships between demand for climate change mitigation and individual-specific risk and time preferences are of course satisfying.

However, the most important reason to develop models of this type is their potential value for simulations. Previous demand models for climate policy do not include explicit individual-specific measures of risk and time preferences. Thus they do not permit us to straightforwardly simulate willingness to pay if people's risk and time preferences were different. For example, we may wish to know what people's choices would be if they were risk-neutral or if they used different discount rates. By specifically including measured risk and time preferences in our model, it is possible to simulate, counterfactually, what would be the demand for climate change mitigation under (a.) risk neutrality and (b.) the lower social discount rates that would be used by a benevolent central planner.

Our climate policy model also innovates in other ways by correcting for heterogeneity in objective and subjective informedness about climate change and subjects' perceptions of bias on the part of the research team, and includes a construct validity test based on a separate question concerning the subject's assessment of climate change as a policy priority.

We should, of course, acknowledge a number of related-but-distinct papers in the recent literature on climate change policy. Our approach to the problems of discounting and uncertainty in climate policy is very different from the perspectives in other work. Weitzman (2001) reports upon an email survey of more than 2000 economists concerning the real rate of discount to use in valuing environmental policies. In Weitzman's case, however, "uncertainty" is heterogeneity among economists (i.e. a lack of consensus) in opinions about what discount rate is appropriate. Newell and Pizer (2003) have also recently addressed discounting and uncertainty with respect to climate policy, but they focus on uncertainty about (and persistence in) future discount rates. Berrens, et al. (2004) also use stated preference data concerning climate change policy, but they focus on the relationships between information-seeking behavior and WTP.

A recent and very comprehensive survey of attitudes concerning climate change policy is described in Krosnick, et al. (2006). This study is non-economic, but reaches the strong conclusion that "[r]espondents' beliefs about the national seriousness of global warming predicted support for general ameliorative effort and for specific policies to reduce global warming. Those who believed global warming is likely to be a more serious problem were more likely to support government efforts and policies to reduce global warming." Other extensive non-economic survey results are described in Leiserowitz (2005) and Leiserowitz (2006) . For the general population of the U.S., Leiserowitz finds moderate climate change risk perceptions, strong support for a variety of national and international policies to mitigate climate change, but strong opposition to several carbon tax proposals. Like these other papers, our models include subjective perceptions about the potential impacts of climate change in the absence of mitigation, but we impose the structure of economic random utility specifications to model respondents' policy preferences.

Section II of this paper briefly describes our available data, including the three distinct types of stated choices that form the core of our analysis. Section III introduces the specific functional forms used in (a.) the jointly estimated structural random utility model that produces individual-specific estimates of discount rates and risk-preference parameters, and (b.) the more ad hoc and separately estimated random utility model to explain climate policy preferences. Section IV presents descriptive statistics, estimation results, and a discussion of our findings. Section V concludes.

II. Available Data: Climate Policy Survey

Our full dataset consists of approximately 2000 responses to a comprehensive survey of climate change policy preferences. The Global Policy Survey (http://globalpolicysurvey.ucla.edu) uses a remotely administered Web-based questionnaire which includes a variety of stated preference choice experiments designed to measure attitudes towards alternative climate change policies and willingness to incur the potential costs of climate change mitigation and adaptation. The design of the questionnaire also incorporates an unusually wide array of dynamically randomized formats that permit assessment of the sensitivity of choices to elicitation strategies. The sample used here consists primarily of college students—recruited by 114 different instructors from 92 different colleges and universities throughout the U.S. and Canada—who responded to the survey over the Internet. This sample is purely a convenience sample.[1]

[1] The data used here were collected primarily during the Fall of 2001. The survey instrument is still accessible for use as a pedagogical tool, but does not record choices. In other work with this same sample, Cameron and Gerdes (2005) make an exhaustive study of individual discount rates which takes full account of the effects of the different treatments embodied in the randomized elicitation formats. Burghart, et al. (2006) study responses to another auxiliary question

An analogous paper-and-pencil mail survey was administered to a general population sample from the U.S. population, analyzed separately in Lee and Cameron (2006). For this complementary mail survey, it is possible to construct enough variables to implement a selectivity correction model. The mail survey format, however, limits the opportunity to randomize treatments, compared to the online survey which produced the data used in this paper. Here, we exploit the richer data and the wider range of experimental treatments (randomizations) in the online survey to demonstrate the feasibility of (a.) actually measuring time preferences and risk preferences separately from climate policy preferences, and (b.) using these estimates as crude shifters on climate policy preference parameters and in simulations of likely preferences under counterfactual conditions such as risk neutrality and lower "social" discount rates.

A. Lottery winnings choices

To elicit individual time-preferences, we employ the device of a question about how the subject would prefer to take their payout, should they win a big lottery prize. In the Appendix to this paper, Figure A.1 shows one example of the lottery choice page entitled "Trade-offs involving money over time." Most lotteries allow winners to take their proceeds over time, or as a smaller immediate lump sum. Our survey software first randomizes the sizes of the annual payouts and the number of years over which they would accrue. This schedule of annual installments is conveyed as the status quo. Respondents were then presented with a number of different lump sums and asked if each lump sum would be preferable to the series of annual installments.

More subtle randomizations include the number of lump sums offered (either 3, 5, 7, or 13) and the number of answer options presented (2, 3, 4, or 5), as well as whether the lump sums

---

concerning willingness to give up a tax credit to support research for climate change adaptation (energy-efficient air conditioning technologies).

increase or decrease going down the page and whether the “yes” response option is presented on the left or the right side. In Table A-1 in the reviewer/online Appendix, we present a full accounting of respondents’ answers to the discounting questions. Each offered lump sum (before rounding) corresponds to an implicit discount rate. We report the distributions of responses to each implicit discount rate, for each of the four different response formats.[2]

We have analyzed just these lottery winnings choices in far more detail in a separate paper (Cameron and Gerdes, 2005). Here, we are more parsimonious. For tractability in this paper, we need to limit the size of the parameter space. We rely on the randomization process to limit any ordering biases in the average responses. We concentrate mostly on the sensitivity of choices to attributes of the respondent, rather than to the properties of the randomized design of the choice scenario.

B. Investment choices

The lottery-winnings choices described in the previous section provide our main insight into respondents’ time preferences, but we can exploit another type of choice by each respondent to identify risk preferences as distinct from time preferences. Our survey also asked each respondent about some hypothetical investment decisions. In the Appendix, Figure A.2 shows one example of the risky-investment choice page entitled “Investments with an element of risk.” Some respondents are asked to make three choices, as shown in the example. Others are asked to make only two, or just one. The survey software randomizes the amounts to be invested and the time horizon. The time horizon within each investment decision is the same for either a risky or a certain investment. The risky investment has a higher expected payoff, but has a 50-50

[2] Row totals in the reviewer/online Appendix Table A-1 are unequal because of the different numbers of lump sums presented to different respondents in our randomized design.

chance of a lower and a higher payoff. Respondents can also decide to make neither of these investments (i.e. to “invest elsewhere or just spend the money now”). Investment choices will reflect both the individual’s risk preference and their time preferences, given the long time horizons involved. The terms of the investments were varied among 10, 15, 20, 25, and 30 years. Amounts to be invested now were varied randomly among $100, $300, $600, $1200, and $2400.

Not obvious in the single illustrative example of these choice sets is the fact that we randomized the order of the risky and certain investments across respondents. Some saw the certain investment first and the risky investment second, while for others, this order was reversed. The status quo alternative, “Do not make either of these investments,” always appeared last.

Table A-2 in the reviewer/online Appendix gives descriptive statistics for the certain and risky investments, separately for each of the three Investment Decisions, and overall. The table also reports the proportions of respondents choosing each alternative, including the “neither investment” option.

We note that other researchers have also used surveys and hypothetical scenarios to measure individual risk preferences and have examined these risk preferences for systematic variation as a function of respondents’ observable characteristics. Donkers, et al. (2001) is one example, although their choices are contemporaneous and do not involve discounting over long time horizons.

C. Climate policy choices

Ideally, for a consistent, comprehensive, and fully utility-theoretic set of choice models, one would like to present respondents with the entire time profile of net costs and net benefits (relative to the status quo—"business-as-usual") for one or more proposed climate policy alternatives. However, pretesting of the survey instrument revealed significant design challenges for describing complete time profiles, as well as significant cognitive challenges for respondents in articulating subjective time profiles or responding to stated time profiles over a very long horizon. It was necessary to depart from the ideal choice scenario and to adopt one that focused on a "snapshot" of conditions at one benchmark point in the future. We treat the climate policy choice as separate from the discounting and risk aversion choices, passing the two key preference parameter estimates from the this preliminary joint model to the climate policy model as deterministic individual attributes.[3]

Prior to the policy choice scenario, we elicited individuals' expected climate change impacts: "Worldwide, how do you think climate change will affect each of the following, by 30 years from now, if a policy of "Business-as-Usual" is followed?" Respondents were then invited to rate climate change impacts as either single values or intervals on a nine-point scale (ranging from -4 for extremely negative impacts to +4 for extremely positive impacts). The categories of impacts were described as "Agriculture and water," "Ecosystems," "Human health," "Oceans and weather," and "Equity." We use the point values or interval midpoints for these ratings as an approximately continuous measure of anticipated climate change impacts on each dimension.

The benefits of climate change mitigation are framed as the prevention of these subjectively anticipated climate change impacts. One key insight from these data, drawn as they are from a large convenience sample from the college population, is that respondents have

[3] Had we been able to elicit net benefits profiles over time for the climate policy choice, there would have been a compelling argument for estimating climate policy choices jointly with the discounting and risk choices in one unified full-information maximum likelihood model.

varying familiarity and concern about the likely consequences of climate change, should it be allowed to occur.

See the Appendix, Figure A.3, for an example of one of the climate policy choice scenarios used in the online survey.[4] "Maximum Prevention" is cast as completely preventing the climate change impacts that the respondent has just described, but at a substantial cost per month (however with a range of uncertainty). We are also interested in knowing whether the initial distributional consequences of an aggressive climate change mitigation policy will affect support for these policies. Thus the choice scenario includes domestic cost shares (a "household costs" distribution) and international cost shares (a "global costs" distribution) associated with each policy. The individual is invited to "vote" for their most-preferred policy (or they are permitted to indicate that they decline to vote).

There are substantial less-obvious randomizations in the elicitation format for climate policy choices as well. A random subset of the sample saw a choice table that included an intermediate "Partial Prevention" option, where the business-as-usual impacts are scaled back, but not eliminated, and the cost of the policy is less than for Maximum Prevention. An independent random subset saw the costs displayed at the top of the table, and their previously stated climate change impacts (benefits of mitigation) reviewed at the bottom. The order of the individual impacts was varied randomly across respondents, although the equity impacts always appeared last.[5] The order of the domestic cost shares was randomized, as were the sizes of these

[4] In Lee and Cameron (2006), in our analysis of the general population mail survey, we capture individuals' ratings of likely future climate change impacts as aggregated sets of indicators. In the online data for the convenience sample from the college population, the pattern of expected impacts is rather different.

[5] An information "button" next to each impact label linked the subject to more detailed descriptions of what each rating option implies, and what types of impacts are included under that specific heading.

shares. For the global cost distribution, the share amounts were randomized, as was the order of the "US and Japan" or "India and China" shares, although the "US and Japan" share was always directly above "other industrialized" and "India and China" was always above "other developing" (to assist in comprehension while minimizing verbiage in the table).

III. Empirical Models

As outlined above, three distinct stated choices are employed in this analysis. The first two choices are the lottery winnings choice and the certain-versus-risky investment choice. These two choices must be estimated jointly because the risk aversion submodel unavoidably includes discounting. For consistency, we also explicitly include risk aversion in the discounting model, although this amounts only to allowing for indirect utility to be non-linear in net income (i.e. we assume that from the point of view of respondents, the certainty of the future lottery payouts is not in question—individuals completely trust the lottery commission to make the payments).

For both of these first two submodels, the objects of choice are denominated in money terms. In these choice scenarios, there is no difference across alternatives in the levels of any non-market environmental good, so we are not estimating any tradeoffs between money and the environmental good. In this pair of models, we are merely attempting to quantify systematic heterogeneity, across the sample, in time preferences and risk preferences.[6]

In designing our climate policy survey, we explicitly planned for the need to design separate elicitations for discounting, risk aversion, and climate policy choices. Chesson and

[6] The models used in this paper involve the maintained hypothesis that the risk aversion and discounting behavior evidenced in the answers to our two auxiliary survey questions are adequate approximations to the corresponding quantities that would apply in other contexts, such as the climate policy choice. Unlike many laboratory experiments designed to elicit either time preferences or risk preferences, the large money amounts and long time horizons involved in our stated choices are much more comparable to those which are relevant for climate policy questions.

Viscusi (2000) address discounting jointly with uncertainty, estimating implicit rates of time preference with respect to deferred gambles. They acknowledge that "the combined tasks of discounting and probability assessment exceed the cognitive capabilities of many survey subjects." We break into more manageable components the choice tasks to do with discounting, risk aversion, and climate policy—both from the respondent's and the researcher's perspective. This allows us to better identify both the risk aversion and the discounting parameters.

A. Discounting submodel

Each choice in the question about how the individual would prefer to take some hypothetical lottery winnings hinges upon whether their indirect utility from taking the lump sum, L_i, right now is greater than the present value of taking T_i annual payments, starting today, in the amount of x_i dollars per year. These discrete future payments are assumed to be discounted at an individual-specific rate of $r_i = r'Z_i$. To accommodate risk aversion, we allow utility to depend upon a Box-Cox transformation of discounted net income that involves the individual-specific transformation parameter $\lambda_i = \lambda' W_i$. (The Box-Cox transformation is an empirically convenient modification to a power transformation that provides for a smooth transition in the function as the exponent passes through zero, at which point the transformation is equivalent to a logarithmic transformation.) This parameter takes on a value of 1 if the individual is risk-neutral. Values less than 1 imply risk aversion, while values greater than 1 imply evidence of risk-loving behavior, at least among the risky investment choices the respondent has been asked to consider.

The net indirect utility from the lump sum option can be written as:

$$\Delta V_i = E\left[V_i^1 - V_i^0\right] = \beta_0 \left\{ \left[\frac{\left(y_i + L_i\right)^{\lambda' W_i} - 1}{\lambda' W_i} \right] - \left[\frac{\left(y_i + x_i \sum_{t=0}^{T_i - 1} \frac{1}{\left(1 + r' Z_i\right)^t} \right)^{\lambda' W_i} - 1}{\lambda' W_i} \right] \right\} + \varepsilon_i^w \qquad (1.1)$$

In estimation, the (systematically varying) implicit individual private discount rate, $r' Z_i$, is constrained to be non-negative by specifying it as $\exp(r' Z_i)$. We assume $\varepsilon_i^w \sim \text{logistic}(0, \kappa_D)$ where the dispersion parameter κ_D may be distinct from the error dispersion pertaining to other choices. We also allow different values of κ_D for each of the randomized numbers of response options (2-, 3-, 4-, or 5-alternative cases) used across different versions of the survey.

B. Risk aversion submodel

Each choice in the question about how the individual would choose to invest a small inheritance is a three-way choice between a certain investment, a risky investment, or just keeping the money and using it for something else. We again employ the individual-specific discount rate, $r_i' Z_i$ and allow for risk aversion by using the same Box-Cox transformation of the present value of net income with curvature parameter $\lambda' W_i$. The certain investment (alternative 1) involves a certain payout, CP_i, at time T_i. The risky investment (alternative 2) involves a 50-50 chance of the risky payout (low), RPL_i, or the risky payout (high), RPH_i, also at time T_i. If neither of these investment opportunities is appealing, the individual may simply choose to incorporate the inherited amount, IN_i, into their current-period income (alternative 3).

Indirect utility under each alternative can thus be written as follows.

(i.) Certain investment:

$$V_i^1 = \beta_0 \left\{ \frac{\left(y_i + \frac{CP_i}{\left(1+r'Z_i\right)^{T_i}} \right)^{\lambda' W_i} - 1}{\lambda' W_i} \right\} + \eta_i^r \tag{1.2}$$

(ii.) Risky investment:

$$V_i^2 = 0.5\beta_0 \left\{ \frac{\left(y_i + \frac{RPL_i}{\left(1+r'Z_i\right)^{T_i}} \right)^{\lambda' W_i} - 1}{\lambda' W_i} \right\} + 0.5\beta_0 \left\{ \frac{\left(y_i + \frac{RPH_i}{\left(1+r'Z_i\right)^{T_i}} \right)^{\lambda' W_i} - 1}{\lambda' W_i} \right\} + \eta_i^r \tag{1.3}$$

(iii.) No investment:

$$V_i^3 = \beta_0 \left\{ \frac{\left(y_i + IN_i \right)^{\lambda' W_i} - 1}{\lambda' W_i} \right\} + \eta_i^r \tag{1.4}$$

The error term η_i^r for the absolute utility level is distinct from the error terms for the utility-differences, ε_i, for the other submodels. The random utility conditional logit-type model for this three-way choice normalizes on the level of indirect utility for the "no investment" alternative and presumes that the individual chooses the alternative with the highest net utility relative to "no investment." We allow the logit-model error dispersion parameter for these indirect utility-differences, κ_R, to differ according to whether the choice is the first, second, or third investment choice considered by the individual.

C. Climate policy submodel

The ideal model would require that climate policies be described in terms of the separate time profiles of their costs and benefits, and that these future streams of net benefits be discounted back to the present based on the same discounting formulas used in the discounting and risk aversion models described above and that risk aversion be incorporated via the same Box-Cox transformation of net income. Regrettably, full time profiles of net benefits from alternative climate change policies were not tractable in the context of this survey. At this point, therefore, we will resort to more of a reduced-form analysis.

The first candidate functional form is a semi-structural specification that imposes the same transformation upon net income as is used in the lottery-winnings and risky investment choice submodels designed to measure individual discount rates and risk aversion.

$$\Delta V^c = \beta_0 \left\{ \left[\frac{\left(y_i - c_i\right)^{\hat{\lambda}' W_i} - 1}{\hat{\lambda}' W_i} \right] - \left[\frac{\left(y_i\right)^{\hat{\lambda}' W_i} - 1}{\hat{\lambda}' W_i} \right] \right\}$$

$$+ \sum_{i=1}^{3} \theta_j DC_{ji} + \sum_{i=1}^{3} \gamma_j IC_{ji} + \sum_{i=1}^{5} \beta_j E[M_{ji}] + \varepsilon_i^v \qquad (1.5)$$

However, this simple specification assumes that net income (equal to income y_i minus policy cost c_i) is certain. Each choice set, though, gave a low and a high cost, explicitly conveying uncertainty, in addition to a statement about the expected costs. We assume that the perceived range in costs can be approximated by a discrete distribution with five points of support. This distribution is assumed to have a probability mass of 1/12 at each of the lower and upper values mentioned in the choice scenario, a probability mass of 1/2 at the center, and masses of 1/6 at points half way between the center and each of the two endpoints. The first term in equation (1.5) is modified to be:

$$\beta_0 \left\{ \left(\sum_{k=1}^{5} P_k \left[\frac{\left(y_i - c_{ki}\right)^{\hat{\lambda}' W_i} - 1}{\hat{\lambda}' W_i} \right] \right) - \left[\frac{\left(y_i\right)^{\hat{\lambda}' W_i} - 1}{\hat{\lambda}' W_i} \right] \right\} \qquad (1.6)$$

where the five values of c_{ki} are the five points of support of the assumed distribution of policy costs. We will refer to the term in the outer braces in (1.6) as the expected transformed net income difference (or "expected transformed income").

An alternative functional form is more ad hoc. It assumes that indirect utility is approximately linear in net income (so that the level of income falls out of the model), and employs the fitted value of the risk aversion parameter $\hat{\lambda}_i = \hat{\lambda}'W_i$ as a systematic shifter of the marginal utility parameters in the climate policy choice model.

$$\Delta V^c = (\beta_{00} + \beta_{01}\hat{\lambda}'W_i)\left(-c_i\right) + \sum_{i=1}^{3}\theta_j DC_{ji} + \sum_{i=1}^{3}\gamma_j IC_{ji} + \sum_{i=1}^{5}\beta_j E[M_{ji}] + \varepsilon_i^v \qquad (1.7)$$

Since the climate policy choice is estimated alone, a unit error dispersion parameter, κ_P =1, will be assumed.

For the partial mitigation alternative, when it is offered to the respondent, there are analogous "structural" and "ad hoc" functional forms for the indirect utility difference, relative to the business-as-usual alternative.

We note that an increasingly popular alternative strategy for accommodating heterogeneity in preferences across a sample is to employed mixed logit (i.e. random parameters) models, where each element of the individual's vector of utility parameters is drawn from a pre-specified family of distributions. The researcher's goal is typically to estimate the central tendency and dispersion of that distribution. In the context of this study, falling back upon distributions for each parameter could provide a very good fit to the data. However, we wish to retain fitted individual-specific time- and risk-preferences as explicit variables in our models (to allow counterfactual simulations with respect to these factors). While a mixed logit framework could certainly be layered on top of fitted individual-specific time- and risk-preferences as systematic shifters of the preference parameters, the present paper does not pursue this additional generality.

IV. Results and Discussion

A. Time- and risk-preferences model

Table 1 gives descriptive statistics for the sample of 1971 individuals from the survey who have sufficiently complete data to permit their responses to the lottery winnings and investment choice questions to be used to jointly estimate individual discount rates and risk aversion parameters.[7] Both of these systematic varying parameters are allowed to vary with sets of dummy variables that capture age, gender, political ideology, income, educational attainment, and college major. We use the individual's actual lottery-playing behavior to help explain risk aversion and information about their subjective life expectancy to help explain their discounting behavior.

In Table 2, we present maximum likelihood estimates of the joint model for discounting and risk aversion.[8] To permit comparisons for the set of explanatory variables shared by both the discounting and risk aversion parameters, the results are split into two columns, even though this is just one single model. For the Box-Cox transformation, lower values of the risk parameter λ_i are associated with greater risk aversion. Our primary goal in this joint model is to capture as much heterogeneity as possible, across individuals, in both time preferences and risk preferences.

---

[7] Details about the randomized design of each of the two types of choice scenarios, and respondents' choices in each context, are relegated to a reviewer/online Appendix, Tables A-1 and A-2.

[8] Estimation was achieved via a general nonlinear function optimizing algorithm, implemented using Matlab. Details concerning the specification of choice probabilities for different elicitation formats, and the form of the likelihood function, are relegated to a reviewer/online Appendix.

The 21- to 25-year-old subgroup is less risk-averse than the 17- to 20-year-old group, but the differentials for the two higher age groups are not strongly significant. However, discount rates appear to increase monotonically with age, at least within this particular college sample. Women in the sample are more risk averse and have lower discount rates. In terms of political ideology, relative to those who identify themselves as being "moderate," both liberals and conservatives are more risk-averse. Liberals have statistically significantly lower discount rates than moderates, but conservatives do not differ significantly from the omitted moderate category.

There are seven discrete household income brackets, and we use the $30,000 - $50,000 income bracket as the omitted category. Compared to this group, the evidence loosely suggests that risk aversion may be U-shaped in income levels, with the middle income categories containing the most risk-averse individuals. We must keep in mind that effective "household" income, from the perspective of a student population, is somewhat difficult to capture. Individuals with very low reported incomes may simply be financially independent individuals at the beginnings of their careers, rather than dependants reporting incomes for their parents' households. Discount rates appear to decline through the $75,000 to $100,000 income bracket, and then to increase.

Given that education attainment is reported, we identify the omitted category as freshmen who have not yet completed one full year of college. The evidence in this sample suggests that risk aversion increases with the number of years of college completed. This will undoubtedly reflect, to a certain extent, self-selection into the college population with increasing age. Those with college education exceeding four years will include graduate students and faculty members, who can be expected to have preferences that differ from the undergraduate population. Discount rates after the freshman year appear to be higher, but to decline steadily with additional years of educational attainment. To the extent that impatient individuals self-select to leave college early, this may be a selection effect.

We include information on each individual's college major to explore whether apparent risk aversion and discounting behaviors are correlated with career choices. The omitted category is "arts and humanities." There is some evidence that life science majors are statistically significantly more risk-averse. Both physical-science and life-science majors appear to have lower discount rates. The other majors show little sign of systematic differences (although it may be comforting to see that engineering majors are, if anything, more risk-averse and have lower discount rates, though these differences are not statistically significant).

We sought to include at least one class of variable in each submodel that might separately identify the risk aversion and discounting parameters. For the risk-aversion parameter, we employ information about the individual's actual lottery-playing habits. The results are somewhat perplexing. There is plenty of systematic heterogeneity, but compared to the group that buys no lottery tickets (given that there is a lottery and they are eligible to play), those who purchase positive numbers of tickets per year tend to be more, rather than less, risk-averse. Risk aversion may also be increasing with the typical number of tickets purchased, rather than decreasing. This heterogeneity is statistically significant, so we retain these variables in the model. However, it is an open question what lottery participation behavior actually reflects. Perhaps lottery participation is a small-stakes form of "investment/entertainment" that more risk-averse individuals prefer to higher-stakes financial investments. We do not pursue the lottery behavior question here, but our broader data may offer an opportunity to delve further into this issue.

For the discount rate parameter, we include information on each individual's stated life expectancy. We ask each person whether they expect to be alive in each of several future decades. Different respondents saw differing numbers of future time periods. Questions concerning 10, 30 and 50 years hence were available for all respondents, so we use a dummy variable set equal to one if they said "yes" to each question. We control, albeit roughly, for the respondent's current age with our set of age-group variables. Life expectancy, therefore may partly capture current age and partly capture the individual's expected age at death. Obviously, one can only expect to be alive in 50 years if they also expect to be alive in 10 years and 30 years. People who say "yes" to the "50-years" question are also less likely to be members of the 31-50 year age group (i.e., they are less likely to be mature or graduate students, or faculty).

The remaining parameters at the foot of Table 2 are nuisance parameters. The fact that the lottery winnings question was presented with either 2, 3, 4, or 5 answer options necessitates that the random utility model used to estimate preferences must be an ordered logit model with different numbers of thresholds according to the number of answer categories. The error dispersion in error terms for the utility-differences is also allowed to vary by the complexity of the elicitation format. The baseline error dispersion parameter is normalized to one for the two-alternative discounting model (we estimate the logarithm of each dispersion parameter, which is therefore zero). The error dispersion for each alternative format is some multiple of this baseline dispersion. In this model, the error dispersions for the 3, 4, and 5-alternative discounting subsamples are not significantly different. However, the error dispersions for the first, second, and third risky-investment choices are statistically significantly smaller.

A graphical depiction of the joint variation in the fitted estimates for the individual-specific risk preference parameters and the individual-specific discount rates is given in Figure 1.

The individual risk parameters, on the horizontal axis, reveal that most individuals are estimated to be risk-averse (i.e. to have a fitted risk preference parameters less than one), but a number of people make choices which suggest that they are risk-loving. Discount rates are measured on the vertical axis, and lie between 2% and 10%, for the most part.[9]

B. Climate policy model

Our climate policy choice model is relatively parsimonious. We have explored a number of more elaborate specifications, but the results reported here are the most robust.[10] In particular, we note that despite the strong evidence that the domestic and international incidence of policy costs is important in our other sample of the general population—as determined by Lee and Cameron (2006)—concern about the distributional consequences of climate change is not so clear-cut in this college sample. It is possible, via the extensive use of interaction terms, to tease out statistically significant sensitivity to the distribution of costs for some subgroups in the sample. On average, however, there is no robustly significant effect (i.e. when the sets of domestic and international cost shares are entered in a simple linear and additively separable form, as in equation (1.5) or (1.7)). Thus we constrain the θ_j and γ_j coefficients in these two equations to be zero for the results shown here.[11]

---

[9] Separate histograms for the marginal distributions of fitted discount rates and fitted risk aversion parameters are provided as Figures A-1 and A-2 in the reviewer/online Appendix.

[10] Estimation for the climate policy model is accomplished using the "clogit" algorithm in Stata 9 SE.

[11] Baron (2006) finds that evidence of systematic differences in opinions about the liability of one's own country to bear the costs of climate change mitigation as a function of who is causing the problem and who is a victim (for a sample of 76 subjects ranged in age from 22 to 74, median 42.5). Li, et al. (2004) detect greater willingness to pay for climate change mitigation if developing countries also participate (i.e. share in the costs of mitigation).

A second insight concerning the college sample used in this analysis concerns perceived climate impacts, should nothing be done to prevent climate change. The relevance of individuals' risk perceptions concerning climate change, as a potent determinant of their willingness to vote for climate change mitigation policies, is documented by O'Connor, et al. (1999). Zahran, et al. (2006) also find that the extent to which citizens regard climate change as threatening to their material well-being drives support for costly climate change policies. Recall that in our survey, five categories of anticipated climate-change impacts are elicited from each respondent. These are impact ratings for the likely effects of climate change in terms of agriculture/water, ecosystems, human health, oceans/weather, and equity. In this college sample, there is considerable independent variation in two of these ratings—for ecosystem impacts and equity impacts. However, the ratings for agriculture/water impacts are highly collinear with those for equity impacts and especially with the ratings for ecosystem impacts. Additionally, there is little variability in the ratings for human health and oceans/weather—the vast majority of respondents rated the human health and oceans/ weather impacts as very negative.[12] Our parsimonious specification therefore preserves only the individual impacts on ecosystems and equity.[13] Thus, in equations (1.5) and (1.7), only two of the β_j parameters are non-zero.

[12] Figure A-3 in the reviewer/online Appendix depicts the amount of variation, across the five types of climate-change impacts, in respondents' ratings of the likely severity of these impacts. The figure shows the average of the five rating midpoints on the horizontal axis, and the variance across impacts in these rating midpoints. To precisely identify the independent effects of each impact, it is necessary that there be sufficient independent variation, across respondents, in these impacts. The mass of relatively low-variance sets of ratings implies that many people do not differentiate very much among the relative severities of the different impacts.

[13] There is other evidence that individuals may have preferences, more generally, over equity, e.g. Carlsson, et al. (2005) .

In adopting this parsimonious specification, we emphasize that the estimated coefficients on individuals' subjective ecosystems and equity impacts will include much of the influence of their subjective impacts on agriculture/water. We capture the (essentially non-varying) subjective impacts of climate change on human health and oceans/weather via two alternative-specific dummy variables in our choice models. We estimate a systematic shift in net indirect utility due to "complete mitigation" that is common to all respondents. This variable takes on a value of one for the complete mitigation alternative and is zero for the other two alternatives. This term picks up all the other subjective impacts (including, perhaps, the average effects of the six omitted cost distribution variables). For those individuals who saw a third (partial mitigation) option, we include an additional alternative-specific dummy variable that captures the average beneficial effects of all other improvements (besides the reductions in ecosystem and equity impacts) associated with the partial mitigation option. Each of these alternative-specific dummy variables will have its own "marginal utility" coefficient.

Since this is a convenience sample collected via an online survey, it is unsurprising that perhaps the salience of climate change problems would produce a sample that is biased towards a perception of substantial climate change threats. It is important to exercise considerable caution in extrapolating our results, even to the college population as a whole, let alone to the general population. We emphasize that the goal in this paper is to demonstrate the relevance of risk preferences and time preferences as determinants of the demand for climate change mitigation policies, rather than to measure a reliable national average willingness to pay for such policies.[14]

---

[14] In the context of comparing their survey results from different types of online and random-digit-dialed samples, Berrens, et al. (2003) provide a very thorough discussion of the legitimate uses of survey data from different types of subpopulations.

Table 3 gives descriptive statistics for the variables employed in our simple climate policy choice model. Our goal in this parsimonious specification is to start from a model with homogeneous preferences, and then to generalize to demonstrate heterogeneity with respect to individual risk attitudes and discount rates. However, it also appears to be important to control for a number of undesired and unintended biases. To this end, our survey collected several distinct attitudinal variables. We asked individuals to rate their subjective degree of informedness about environmental issues. We use this information to net out the systematic influence on our estimates that would otherwise be brought to bear by people who acknowledge that they are relatively uninformed about environmental issues, as well as those who acknowledge that they are more informed than average about environmental issues.[15]

In addition to this subjective assessment of informedness, we pose each subject a set of nine true-false questions about basic climate science. We use the number of incorrect answers on this "climate quiz" as a more objective measure of the subject's informedness about climate change, specifically.[16]

A major concern in all survey-based research about policy is the researchers' ability to convey the policy choices in a neutral manner. Unfortunately, the very fact that the policy in question is the subject of the survey often produces a perception that the research team is biased in favor of doing something about the problem in question. We elicited from each respondent

[15] O'Connor, et al. (1999) find that "knowledge and general environmental beliefs" are relevant predictors of behavioral intentions with respect to voting for climate change policies, in addition to perceptions about the risks of climate change.

[16] Bord, et al. (1998) determine that "[e]rrors in assessing the causes of global warming are global in nature." Bord, et al. (2000) report that "[k]nowing what causes **climate** change, and what does not, is the most powerful predictor of both stated intentions to take voluntary actions and to vote on hypothetical referenda to enact new government policies to reduce greenhouse gas emissions."

their perception of the extent to which the research team was biased in favor of climate change mitigation policies, and we use controls for cases where individuals perceived this bias to be either high (for) or low (against). The desired preference estimates would be associated with the impression that the research team was neutral on the subject.

A final category of controls is one we employ in order to assess the so-called "construct validity" of our preference estimates. Early in the survey, respondents were asked to prioritize a list of policy problems, including climate change along with health, crime, education, poverty, and war, among others (in randomized order). Relative to an omitted category for a moderate priority rating, we control for systematically different policy preferences according to whether the individual rated the prevention of climate change as a low priority or a high priority. We do not "simulate out" this variation, since it is not an unintended or undesired distortion of preferences. However, statistically significant and intuitively plausible effects of these sentiments on climate policy preferences reinforces the notion that our model is measuring what it is intended to measure.

In Table 4, we display results for five different variations on our basic parsimonious model. Model 1 shows results for a specification that does not take advantage of individual-specific information about risk aversion and discount rates. This specification is merely linear in net income. Purged of basic distortions due to either low or high subjective informedness, or poor objective informedness, the marginal utilities from avoided ecosystem and equity impacts are strongly significant and positive, as expected. Perceived researcher bias has a strongly significant effect only on the utility associated with the partial mitigation option (i.e. when it is available). However, utility from this option is greater both when the researchers are perceived to be biased against the policy, as well as when the researchers are perceived to be biased for the policy. Individuals who were also offered the partial mitigation option conveyed a higher utility from the complete mitigation option than those who did not see the partial option. As expected, for the vast majority of respondents who answer the question about the priority they accord to preventing climate change, people placing either low or high priority convey policy preferences that are consistent with these opinions.[17]

Model 2 in Table 4 shows the consequences of using the same Box-Cox transformation of net income estimated in the discounting and risk-aversion submodels—along with a discrete approximation to a normal distribution (with five symmetric points of support) for the uncertain costs of the policy—to compute the expected value of the transformed net income under each alternative. This "expected transformed income" enters with a positive coefficient, significant at the 10% level, but much of the improvement in the log-likelihood function between Model 1 and Model 2 is due to the simultaneous introduction of the individual-specific discount rate as a shifter on demand for complete mitigation. While this structural model is appealing, it is essentially a second-best solution. The data do not permit a fully formal structural model because we could not convey full time profiles of climate policies to respondents in assessing their demand for mitigation. As a consequence, we fall back on more ad hoc models, seeking merely to identify systematic effects of risk preferences and time preferences on the basic parameters of our linear parsimonious model.

Models 3, 4, and 5 in Table 4 demonstrate the progression of estimates as we add first the individual-specific risk aversion parameter estimates and then the individual-specific discounting parameter estimates as shifters on the preference parameters of the climate policy choice

[17] The fact that many people perceive that the prevention of climate change is a lower priority than other personal and social issues is noted by Lorenzoni and Pidgeon (2006): for many people, climate change remains a "psychologically, temporally, and spatially distant risk."

specification in Model 1. Again, this parsimonious specification reflects the most robust effects identified during a broad investigation of many different ways in which these two additional variables might enter the model. Alone, or jointly, these two key variables enter in a strongly statistically significant manner. We will discuss only Model 5. Despite is cruder linear-in-net-income form and ad hoc incorporation of risk- and time-preference parameters, Model 5 achieves a maximized log-likelihood value almost 10 points higher than the more structural specification in Model 2.

Model 5 reveals that the marginal utility of net income is statistically significantly greater, the larger is the estimated risk preference parameter for the individual in question. A larger risk preference parameter corresponds to less risk aversion (where risk neutrality is associated with a parameter value of 1). The marginal utility of net income is the denominator of the marginal rate of substitution between climate change mitigation and "money," and a higher marginal utility of income therefore implies a lower willingness to pay for climate change mitigation. If one is less risk averse, they are less concerned about the consequences of climate change and thus less willing to pay to prevent it.

Model 5 also shows that the higher the individual's fitted discount rate, the lower their marginal utility from complete mitigation of climate change. This conforms with intuition because the net benefits of climate change mitigation are skewed toward the future, so that for someone with a higher discount rate, the present discounted net benefits of the mitigation program will be smaller. This effect is also strongly statistically significant.

Our results with respect to both risk aversion and discount rates are consistent with the theoretical predictions and numerical simulations of Ha-Duong and Treich (2004). Our results are also consistent with the results concerning discount rates obtained by Hersch and Viscusi

(2006). They detect "a steady decline with age in whether respondents are willing to incur higher gasoline prices to protect the environment." Our models show that discount rates increase with age, and that support for climate change mitigation policies declines as discount rates rise.

C. Simulations

Despite the likely non-representativeness of our convenience sample, relative to the general population, it is important to assess the implications of Model 5 for willingness to pay for complete mitigation of climate change (i.e. to preserve conditions as they were at the time of the survey). Table 5 displays results for selected simulations. These simulations involve a set of 1000 random draws from the asymptotically jointly normal distribution of the maximum likelihood parameter estimates for Model 5. Each randomly drawn vector of model parameters is used to calculate the implied WTP for complete mitigation under the specified conditions. A sampling distribution is built up from these random draws, and we display selected percentiles of this distribution.[18]

Simulation A in Table 5 calculates WTP for complete mitigation for someone who saw only the "complete mitigation" and "business-as-usual" alternatives, and uses observed sample averages for all of the relevant variables in the model. Median predicted WTP is $327 per month, with the dispersion in the estimated parameters producing a 90% interval between $270 and $419. Simulation B imposes moderate subjective informedness, no wrong answers on the climate change science quiz, no partial mitigation option (and thus no perceived researcher bias), and the availability of a subjective prioritization for preventing climate change, but assignment

[18] The mean of the sampling distribution is technically undefined, since it involves the ratio of normally distributed variables. Since zero is a possible value of the denominator, infinity is a possible value for WTP.

of only moderate priority to this problem. For mean risk aversion and discount rates, and mean ecosystem and equity impact ratings, the median simulated WTP is only $329.

While these monthly willingness-to-pay estimates may seem high, they are not out of line with the results obtained by Viscusi and Zeckhauser (2006). These authors report that when willingness to pay is elicited as a percentage of income, their student sample conveys a median willingness to give up roughly $4,500 per year (equal to $375 per month).[19] These WTP amounts are also consistent with the types of WTP estimates obtained for the general population mail-survey sample in Lee and Cameron (2006). In that study, willingness to pay depends significantly on the domestic and international distribution of cost shares for the program. Point estimates of WTP, across several different cost distributions, range from about $125 to $335 per month. As with all stated preference research, however, one must be wary of a tendency for subjects to overstate their willingness to participate in the provision of desirable public goods.[20]

The pair of simulations C and D impose risk neutrality and employ the sample means of the ecosystem and equity impact ratings, but demonstrate the difference between a 5% discount rate (close to the mean fitted value) and a 2% discount rate, sometimes advocated for long-term policies.[21] The 5% rate yields a WTP of $284, whereas the 2% discount rate yields $501.

---

[19] When willingness-to-pay is elicited in terms of an acceptable gasoline tax, however, the implied value is only about 1/3 as large, suggesting that the initial incidence of the costs of any policy may be a relevant determinant, as was found in Lee and Cameron (2006), although this effect is nowhere near as evident in the online student sample used in this paper.

[20] Jamieson (2006) cites a wide variety of survey data demonstrating the paradox contained in disparities between Americans' stated concerns about climate change and their stated support for specific policies that might help to combat the problem.

[21] Newell and Pizer (2004), for example, identify 2% as their lower bound on the consumer rate of interest. Davidson (2006), however, makes an argument for a social discount rate around 1% or even lower, from a legal perspective. Howarth (2003) explains the logic for a using the annual return on risk-free financial assess, which would be somewhere between 0% and 2.6%.

The set of five simulations E through I continue with risk neutrality and a 2% discount rate, but show the effects of reducing the severity of the ratings for ecosystem and equity impacts of climate change. Recall that activating the alternative-specific dummy for complete mitigation captures all other subjective impacts of climate change. WTP for complete mitigation falls from \$890 if ecosystem and equity impacts are perceived as most severe (rated at -4) to only \$250 if no change along these two dimensions is perceived. \$250 is thus the average perceived WTP to avoid the other likely impacts of climate change.

The pair of simulations J and K show a predicted WTP of \$141 solely to avoid the average expected ecosystems impacts (which will pick up some of the expected effects on agriculture and water, as noted above), and a predicted WTP of \$107 solely to avoid the average expected equity impact. WTP to avoid other impacts of climate change have been netted out by simulating no alternative-specific effect for complete mitigation.

We reiterate that the specific estimates of willingness to pay, based on this sample, reflect systematic selection into the sample. Given the anonymity of the survey, there is no way to correct for sample selection biases, so there is little to be done to correct for the possibly greater salience of climate change problems (and possibly inferior estimates of effective income for a college population). These qualifications, however, do not lessen the insight that individual-specific risk preferences and time preferences do figure significantly in explaining heterogeneity in the degree of support for climate change policies. A priori, one would of course expect this to be the case. The contribution of this research has been to separately measure each individual's risk preferences and time preferences and to include these individual characteristics specifically in a separate model of climate policy preferences.

We note in passing that it is of course possible to allow all or all of the main utility parameters in Model 1 to shift systematically with both the fitted risk parameter and discount rate. In particular, we considered a model that uses both the fitted risk parameter and the fitted discount rate to shift the marginal utility of net income, instead of allowing the fitted discount rate to shift the coefficient on the alternative-specific dummy for complete mitigation, as in Model 5. The maximized log-likelihood is -1225.065, just slightly better than Model 5. This model also produces very similar values for Simulation A: the 5^{th}, 50^{th} and 90^{th} percentiles are \$263, \$321, and \$400. However, we wish to simulate conditions using a counterfactual discount rate of 0.02, which lies just outside of the range of observed fitted values in the data (which lie between 0.0246 and 0.1162). In part because this alternative specification produces a considerably less-precise estimate of the coefficient on the interaction term between net income and the fitted risk parameter, many simulated values of the resulting marginal utility of income are near zero (and a substantial number are tiny and negative). This estimated marginal utility forms the denominator of the willingness-to-pay function, so there are many instances of very large positive and negative simulated values for WTP. We thus reject this alternative specification because it appears to be unsuitable for the type of out-of-sample forecasting we need to undertake.[22]

V. Caveats and Conclusions

The main point of this research is to draw attention to the potential value of being able to measure and control explicitly for individual variations in time and risk preferences when modeling policy choices that will allow calculation of willingness-to-pay for public programs

[22] In future revisions of this paper, we may make a transition to non-linear-in-parameters specifications which will allow us to constrain the marginal utility of income to be strictly positive (by estimating its logarithm, rather than its level, as a systematically varying parameter). In our current estimation framework, however, this is not feasible.

with distant and uncertain benefits. Our available data pertain to public opinions about climate change impacts and climate change mitigation policies. If we ask stated choice questions only about climate policy preferences, we can certainly use various measures of individual heterogeneity (age, gender, ideology, income, educational attainment, training, etc.) directly as ad hoc shifters on the utility parameters for the climate policy choice. However, risk preferences and time preferences are then only implicit in the model. We cannot straightforwardly simulate predicted WTP under risk neutrality and a lower (social) discount rate if we do not control specifically for individual heterogeneity in risk-aversion and discounting during estimation of policy preferences. It may occasionally be possible, with a rich enough set of data concerning policy choices alone, to tease out distinct estimates of discount rates and risk aversion parameters. To do this, however, it is essential to ask respondents to choose among policies with a sufficient variety in time horizons and risk.

Here, we demonstrate that there may be distinct advantages from designing the questions in a stated preference survey so that the researcher has the ability to derive these individual-specific time- and risk-preference parameters more-or-less independently, based on responses to entirely separate questions from the main policy choice. We do not pretend that time- and risk-preferences derived from the separate choices we use in this study are guaranteed to be exactly the same time- and risk-preferences that will apply to climate change policy. However, we are confident that there should be considerable correlation between the available measures and the desired time- and risk-preference measures—so we employ the available measures as proxies.

We are also well aware that expected utility is only one way to model risk preferences and exponential discount rates are only one way to model time-preferences. Our data are probably rich enough to allow us to pursue, in subsequent work, alternatives to expected utility as well as other forms of discounting (perhaps hyperbolic, which we explore in Cameron and Gerdes (2005) in research that focuses solely on the time-preferences part of the story). We use the simpler and more-standard assumptions here merely to demonstrate the tractability and potential value of this approach.

In this example, our data are rich enough to permit simultaneous estimation of the time- and risk-preference parameters within a framework of conforming random utility models. However, we found no feasible way to render our climate policy choice scenario rich enough—in terms of the time profiles of avoided future climate change impacts—to permit a conforming utility-theoretic policy choice in terms of present discounted expected utility. Thus our ultimate policy-choice model is more ad hoc. Still, it is a useful illustration.

In the more conventional approach, climate policy preferences might be modeled as shifting systematically with a variety of observable respondent attributes, and the researcher might speculate that respondents with different characteristics have different demands for climate change mitigation because they probably have higher discount rates, or are more risk-averse. Our approach first identifies the sources of systematic variation in discount rates and risk aversion, and then uses these fitted individual characteristics directly in the policy choice model. This strategy is also illuminating in that it reveals that greater risk aversion appears to act most directly on willingness to pay for mitigation policies via its effect of decreasing the marginal utility of income. A larger discount rate acts most directly via decreasing the utility from avoided "generic" adverse impacts of climate change (corresponding, in our data, to impacts on human health and oceans/weather). These two findings have a certain intuitive appeal.

Based on preferences expressed in just this sample, we again urge caution with respect to the quantitative estimates of willingness to pay for a program to completely prevent climate change. Recall that we draw respondents from 92 different colleges and universities, but participation was still voluntary and the 114 different instructors who directed potential participants to the survey all had in common their interest in environmental economics (although many classes participating in the survey were general-education courses in introductory economics, or economics courses with no particular emphasis on environmental problems). However, it is unavoidable that this sample will likely contain more than a representative subset of individuals with a strong interest in environmental problems. We also could not fully control the strategies used by our faculty collaborators to encourage their students to participate. A script was provided for use in recruitment, but we have no way of knowing whether the survey was introduced, for example, as a supplement to a course module designed to heighten students' awareness of the problem of climate change.

We may not be able to control for unobserved heterogeneity related to self-selection into the sample. However, we are careful, in our climate policy model, to control for a number of observed dimensions of heterogeneity, including both subjective and objective measures of informedness, and for any distortions that might be introduced by the subject's perceptions of bias on the part of the research term. We also measure the extent to which self-stated assignments of priority to the problem of preventing climate change and use this to assess the construct validity of our model of policy preferences. By controlling for these potential distortions and biases, we can also net out their effects to get a better sense of the tradeoffs willingly made by the average respondent under more-or-less optimal conditions.

In spite of these caveats concerning sample representativeness, it is noteworthy that the magnitudes of willingness to pay for climate change mitigation derived from our models appear to be consistent with at least some of the estimates contained in the existing literature.

Table 1 – Descriptive statistics for sociodemographic variables capturing systematic variation in risk aversion and discounting parameters (n = 1971 individuals)

Age (omitted category = age is between 17 and 20 years)		
age 21-25	= 1 if age is 21 to 25	0.458
age 26-30	= 1 if age is 26 to 30 years	0.076
age 31-50	= 1 if age is 31 to 50 years	0.054
Gender		
female	= 1 if female	0.503
Self-reported ideology		
liberal	= 1 if "liberal" or "moderately liberal"	0.433
conserv	= 1 if "conservative" or "moderately conservative"	0.254
Annual income bracket for family (omitted category = $30,000 to $50,000)		
inc <10K	= 1 if "less than $10,000"	0.049
inc 10-20K	= 1 if "$10,000 to $20,000"	0.076
inc 20-30K	= 1 if "$20,000 to $30,000"	0.095
inc 50-75K	= 1 if "$50,000 to $75,000"	0.197
inc 75-100K	= 1 if "$75,000 to $100,000"	0.183
inc >100K	= 1 if "more than $100,000"	0.223
Years of college completed (omitted category = less than 1 year)		
have college	= 1 if college years reported	0.968
college=1 yr	= 1 if "1 year"	0.143
college=2 yrs	= 1 if "2 years"	0.174
college=3 yrs	= 1 if "3 years"	0.245
college=4 yrs	= 1 if "4 years"	0.130
college>4 yrs	= 1 if "more than 4 years"	0.153
Major if attended any college (omitted category = arts and humanities)		
maj phys-sci	=1 if "physical sciences"	0.105
maj life-sci	= 1 if "life sciences"	0.141
maj soc-sci	= 1 if "social sciences"	0.300
maj engin.	= 1 if "engineering"	0.081
maj business	= 1 if "business"	0.349
maj other	= 1 if "other"	0.189
Lottery-playing behavior (omitted category = zero lottery tickets per year)		
can lotto	=1 if lottery exists and can legally play	0.836
tickets 1-6	= 1 if purchase 1-6 lottery tickets per year	0.326
tickets 7-12	= 1 if purchase 7-12 lottery tickets per year	0.079
tickets >12	= 1 if purchase more than 12 lottery tickets per year	0.063
Life expectancy		
alive 10 yrs	= 1 if expects to be alive in 10 years	0.971
alive 30 yrs	= 1 if expects to be alive in 30 years	0.953
alive 50 yrs	= 1 if expects to be alive in 50 years	0.817

Table 2 – MLE parameter estimates for joint model to estimate individual-specific discount rates and risk aversion parameters (n = 1971)

	$\log(\beta_0)$	1.502 (18.4)**	
		λ	$\log(r)$
baseline parameter	constant	-0.9967 (-2.57)**	-3.067 (-21.1)**
age	*1(age 21-25)	0.5098 (4.19)**	0.2346 (4.13)**
	*1(age 26-30)	0.2863 (1.63)	0.3135 (4.06)**
	*1(age 31-50)	0.3891 (2)**	0.4668 (5.73)**
gender	*1(female)	-0.2467 (-3.48)**	-0.1007 (-2.93)**
ideology	*1(liberal)	-0.2558 (-3.26)**	-0.1676 (-4.37)**
	*1(conserv)	-0.1834 (-2.14)**	-0.00398 (-0.0952)
income	*1(inc <10K)	1.511 (4.84)**	0.2027 (2.63)**
	*1(inc 10-20K)	1.093 (3.56)**	0.1657 (2.23)**
	*1(inc 20-30K)	1.225 (3.8)**	0.04918 (0.669)
	*1(inc 50-75K)	1.176 (3.33)**	-0.1788 (-1.76)*
	*1(inc 75-100K)	1.763 (5.51)**	0.06097 (0.874)
	*1(inc >100K)	2.057 (6.57)**	0.08461 (1.29)
education	*1(have college)	0.2802 (1.32)	-0.1017 (-0.943)
	*1(college=1 yr)	-0.04372 (-0.323)	0.02147 (0.298)
	*1(college=2 yrs)	-0.2353 (-1.96)*	0.2322 (3.27)**
	*1(college=3 yrs)	-0.2036 (-1.33)	0.1372 (1.75)*
	*1(college=4 yrs)	-0.4906 (-2.78)**	0.1057 (1.23)
	*1(college>4 yrs)	-0.3422 (-1.96)**	0.01256 (0.151)
discipline	*1(maj phys-sci)	0.001446 (0.0138)	-0.1327 (-2.27)**
	*1(maj life-sci)	-0.2295 (-2.1)**	-0.1403 (-2.55)**

	*1(maj soc-sci)	0.1298	0.06243
		(1.46)	(1.51)
	*1(maj engin.)	-0.0895	-0.09913
		(-0.628)	(-1.45)
	*1(maj business)	0.05841	0.02013
		(0.674)	(0.511)
	*1(maj other)	0.1283	-0.009648
		(1.41)	(-0.209)
lottery habits	*1(can lotto)	-0.1068	
		(-1.09)	
	*1(tickets 1-6)	-0.3122	
		(-4.26)**	
	*1(tickets 7-12)	-0.1869	
		(-1.57)	
	*1(tickets >12)	-0.4946	
		(-2.19)**	
life expectancy	*1(alive 10 yrs)		0.2165
			(1.76)*
	*1(alive 30 yrs)		-0.2968
			(-2.91)**
	*1(alive 50 yrs)		0.1777
			(3.83)**

Ordered logit threshold parameters		Dispersion parameter differentials	
α_{30}	-0.6328	$\log(\kappa_{D2})$	0
	(-9.68)**		
α_{31}	-0.03829	$\log(\kappa_{D3})$	-0.1562
	(-0.828)		(-1.63)
α_{40}	-1.451	$\log(\kappa_{D4})$	0.152
	(-10.7)**		(1.63)
α_{42}	1.1	$\log(\kappa_{D5})$	-0.05129
	(10.1)**		(-0.569)
α_{50}	-1.62	$\log(\kappa_{R0})$	-1.192
	(-11.6)**		(-11.7)**
α_{51}	-0.7123	$\log(\kappa_{R1})$	-1.079
	(-10.1)**		(-8.7)**
α_{52}	-0.1043	$\log(\kappa_{R3})$	-0.8945
	(-2.18)**		(-4.84)**
α_{53}	0.7459		
	(8.24)**		
Max Log L	18704.47		

Table 3: Descriptive statistics for variable used in climate policy model
(n = 1697 choices; 0,1 indicator variables unless std. dev. is shown)

Variable	Sample means	Std. dev.
fitted risk parameter (from discount/risk model)	0.152	0.777
fitted discount rate (from discount/risk model)	0.0533	0.0128
household income ($ ‘000, midpoint of bracket)	68.25	38.35
policy cost ($‘000/year)		
- complete mitigation	3.14	1.64
- partial mitigation	1.59	0.98
- business-as-usual	0	0
ecosystem impacts (avoided adverse rating points)		
- complete mitigation	2.02	1.43
- partial mitigation	0.0706	0.719
- business-as-usual	0	0
equity impacts (avoided adverse rating points)		
- complete mitigation	1.17	1.42
- partial mitigation	0.0400	0.801
- business-as-usual	0	0
other individual-specific variables		
low informed (subjective informedness)	0.164	
high informed (subjective informedness)	0.324	
# wrong on climate quiz (objective informedness)	2.77	1.54
perceived researcher bias against policy	0.124	
perceived researcher bias for policy	0.784	
saw a partial mitigation alternative	0.346	
gave a “preventing climate change” priority	0.959	
climate priority low	0.319	
climate priority high	0.447	

Table 4: Conditional logit parameter estimates (n = 1697 respondents)

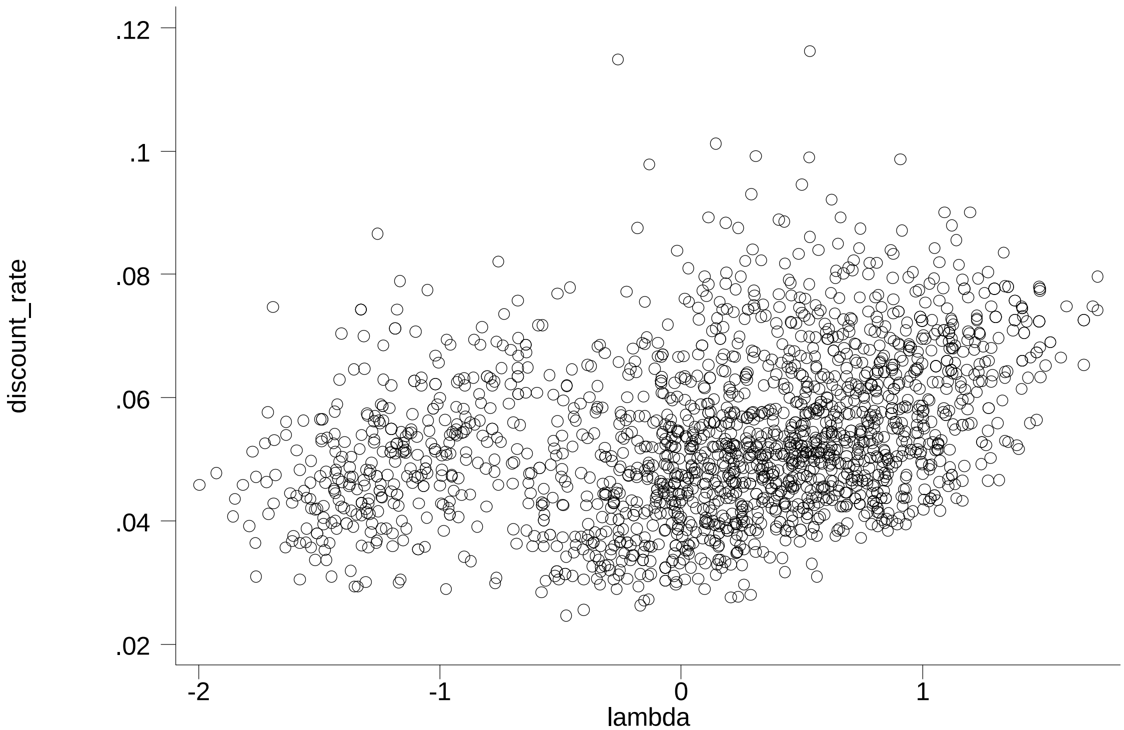
	Model 1	Model 2	Model 3	Model 4	Model 5
	no-risk no-disc.	structural	risk only	disc. only	risk and disc.
expected transf. income	-	.0142 (1.75)*	-	-	-
net income (= -cost)	.144 (4.15)***	-	.134 (3.83)***	.153 (4.38)***	.145 (4.11)***
…*fitted risk parameter	-	-	.0717 (3.36)***	-	.0483 (2.17)**
ecosystem impacts	.161 (3.42)***	.158 (3.34)***	.166 (3.51)***	.157 (3.31)***	.161 (3.39)***
…*1(low informed)	-.104 (1.62)	-.118 (1.84)*	-.119 (1.84)*	-.109 (1.69)*	-.119 (1.84)*
…*1(high informed)	.188 (3.83)***	.179 (3.63)***	.188 (3.82)***	.184 (3.72)***	.185 (3.74)***
equity impacts	.213 (3.23)***	.199 (3.01)***	.212 (3.20)***	.206 (3.10)***	.207 (3.11)***
…* #wrong on climate quiz	-.0431 (2.34)**	-.0393 (2.13)**	-.0425 (2.30)**	-.0425 (2.30)**	-.0422 (2.28)**
1(partial mitigation)	.861 (2.60)***	.599 (1.84)*	.877 (2.65)***	.845 (2.55)**	.858 (2.59)***
*1(pcvd bias againset policy)	.850 (2.12)**	.933 (2.32)**	.844 (2.11)**	.908 (2.26)**	.896 (2.23)**
*1(pcvd bias for policy)	.827 (2.54)**	.869 (2.66)***	.821 (2.52)**	.861 (2.64)***	.852 (2.61)***
…*1(low informed)	-.517 (2.10)**	-.525 (2.13)**	-.535 (2.17)**	-.527 (2.14)**	-.539 (2.19)**
1(complete mitigation)	-.308 (1.01)	.118 (0.33)	-.303 (0.99)	.749 (1.95)*	.602 (1.54)
…*1(saw partial mitigation)	.467 (3.12)***	.46 (3.07)***	.467 (3.11)***	.465 (3.09)***	.464 (3.08)***
…*fitted discount rate	-	-16.3 (3.73)***	-	-19.3 (4.50)***	-16.5 (3.70)***
…*1(gave climate priority)	.295 (1.00)	.324 (1.10)	.296 (1.00)	.304 (1.02)	.305 (1.03)
…*1(climate priority low)	-.435 (2.83)***	-.43 (2.79)***	-.454 (2.94)***	-.447 (2.89)***	-.458 (2.95)***
…*1(climate priority high)	.432 (3.00)***	.454 (3.14)***	.42 (2.91)***	.45 (3.10)***	.441 (3.03)***
Total alternatives	3982	3982	3982	3982	3982
Log L	-1238.727	-1236.495	-1233.008	-1228.393	-1226.028

*asymptotic t-test statistics in parentheses; parsimonious specification retaining only those variables with robustly significant coefficients

Table 5: Simulated distributions of fitted WTP under different specific conditions
(Sampling distribution across 1000 random draws from asymptotically joint normal MLE coefficient vector)

	Mean vs. neutral controls (complete mitigation only)		For r = 0.05, 0.02 (risk neutral, complete mitigation only)		As anticipated impacts are less severe (risk neutral, r = 0.02, complete mitigation only) (e.g. 4 = policy prevents impact of -4 on rating scale)					For individual impacts (risk neutral, r = 0.02, complete mitigation)	
Specific conditions:	A	B	C	D	E	F	G	H	I	J	K
fitted risk parameter	0.152	0.152	1	1	1	1	1	1	1	1	1
ecosystem impacts	2.021	2.021	2.021	2.021	4	3	2	1	0	2.021	0
…*1(low informed)	0.299	0	0	0	0	0	0	0	0	0	0
…*1(high informed)	0.726	0	0	0	0	0	0	0	0	0	0
equity impacts	1.167	1.167	1.167	1.167	4	3	2	1	0	0	1.167
…* #wrong on climate quiz	3.189	0	0	0	0	0	0	0	0	0	0
1(partial mitigation)	0	0	0	0	0	0	0	0	0	0	0
…*1(pcvd bias against policy)	0	0	0	0	0	0	0	0	0	0	0
…*1(pcvd bias for policy)	0	0	0	0	0	0	0	0	0	0	0
…*1(low informed)	0	0	0	0	0	0	0	0	0	0	0
1(complete mitigation)	1	1	1	1	1	1	1	1	1	0	0
…*1(saw partial mitigation)	0	0	0	0	0	0	0	0	0	0	0
…* fitted discount rate	0.053	0.053	0.05	0.02	0.02	0.02	0.02	0.02	0.02	0	0
…*1(gave climate priority)	0.959	1	1	1	1	1	1	1	1	0	0
…*1(climate priority low)	0.319	0	0	0	0	0	0	0	0	0	0
…*1(climate priority high)	0.447	0	0	0	0	0	0	0	0	0	0
Percentiles of fitted WTP distribution (dollars per month for complete mitigation of climate change)											
5^{th}	270	200	176	336	623	508	394	255	79	71	47
25^{th}	304	274	238	424	770	636	494	342	183	109	82
50^{th}	**327**	**329**	**284**	**501**	**890**	**733**	**571**	**411**	**250**	**141**	**107**
75^{th}	354	386	330	584	1047	855	670	486	324	178	135
95^{th}	419	485	406	730	1338	1086	829	618	431	246	184

Figure 1 – Joint distribution of fitted discount rate and risk aversion parameters



Appendix: Choice scenarios

Figure A.1 – Lottery Winnings (Discount Rate) Choice

PROGRESS METER

Climate Policy Survey

Trade-offs involving money over time

Imagine that you have won a lottery. FAQ

The lottery commission gives you two ways of taking your winnings:

1. **$2,400 each year** for **20 years** (for a total of **$48,000**), with the first payment today, OR
2. A smaller **lump sum** payment today (which you could put into a savings account or invest, or just use it to pay for something you really want or need right now).

For *each* row in the table below, please click *one answer button*.

If your lump sum payment would be:	**Would you prefer this lump sum payment, rather than the annual installments?**		
	yes	**not sure**	**no**
$44,000	☐	☐	☐
$34,000	☐	☐	☐
$27,000	☐	☐	☐
$22,000	☐	☐	☐
$14,000	☐	☐	☐
	yes	**not sure**	**no**

OK

Figure A.2 – Risky Investment (Risk Preferences) Choice

PROGRESS METER

Climate Policy Survey

Investments with an element of risk

FAQ

For **each** of the "Investment Decisions" summarized in the table below, please assume you have just inherited a small amount of money (labeled as "Amount invested this year" in the first two rows of the decision profile). You can use it to make

- a risky investment,
- a "no-risk" investment, or
- neither of these investments (invest elsewhere or just spend the money now).

For **each** of the "Investment Decisions" below, please pick your most-preferred option by clicking on one of the three buttons at the right.

Amount invested this year	Time to payoff	Pay-off amount in constant $ (today's purchasing power)	Most-preferred?
Investment Decision #1			
$300	30 yrs	$2,600 with certainty	
$300	30 yrs	50% chance of $1,900 and 50% chance of $4,100	
$0		Do not make either of these investments	
Investment Decision #2			
$1,200	10 yrs	$2,500 with certainty	
$1,200	10 yrs	50% chance of $2,100 and 50% chance of $4,100	
$0		Do not make either of these investments	
Investment Decision #3			
$100	25 yrs	$380 with certainty	
$100	25 yrs	50% chance of $180 and 50% chance of $680	
$0		Do not make either of these investments	

OK

Figure A.3 – Climate Policy Choice

Climate Policy Survey

If these were the ONLY policy alternatives, what would be your choice?

This is the most important page in the survey. Please take a little extra time to read it carefully. A lot of information about potential climate policies is being presented in the most compact form possible. (Vote for ONE policy by clicking ONE button at the bottom. Choose carefully. After you move to the next page, no changes will be allowed.)

FAQ

NOTE: Each column in the table summarizes one possible policy. The checked boxes in the **"Business-as-Usual"** column display the levels and ranges of uncertainty that you chose earlier in the survey.

	POLICY: **Maximum Prevention** To *completely* prevent your anticipated changes	POLICY: **Business-as-Usual** Just leave the effects at the level you anticipate
Consequences for:	-4 -3 -2 -1 0 +1 +2 +3 +4	-4 -3 -2 -1 0 +1 +2 +3 +4
Oceans, Weather ?	☐ ☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐	☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐ ☐
Human health ?	☐ ☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐	☐ ☐ ☑ ☐ ☐ ☐ ☐ ☐ ☐
Ecosystems ?	☐ ☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐	☐ ☑ ☐ ☑ ☐ ☐ ☐ ☐ ☐
Agriculture, Water ?	☐ ☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐	☐ ☐ ☑ ☐ ☑ ☐ ☐ ☐ ☐
Equity, Fairness ?	☐ ☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐	☐ ☐ ☐ ☑ ☐ ☐ ☐ ☐ ☐
Household cost/month:	**about $ 500/mo ($ 250 to $ 750)**	**about $ 0/mo ($ 0 to $ 0)**
How these higher household costs will be experienced:	**20%** via ↑energy taxes **10%** via ↑income taxes **60%** via ↑prices **10%** via ↓invest. returns	
How global costs will be shared across countries:	**25%** US and Japan **10%** other industrialized **15%** India and China **50%** other developing	
I would vote for:	**Maximum Prevention** ○	**Business-as-Usual** ○
	○ **I would not vote**	

After you click OK, you will not be able to change your voting decision.

OK

References

Baron, J. (2006). "Thinking about global warming", *Climatic Change* 77, 137-150.

Berrens, R.P., Bohara, A.K., Jenkins-Smith, H., Silva, C., Weimer, D.L. (2003). "The advent of internet surveys for political research: A comparison of telephone and internet samples", *Political Analysis* 11, 1-22.

Berrens, R.P., Bohara, A.K., Jenkins-Smith, H.C., Silva, C.L., Weimer, D.L. (2004). "Information and effort in contingent valuation surveys: Application to global climate change using national internet samples", *Journal of Environmental Economics and Management* 47, 331-363.

Bord, R.J., Fisher, A., O'Connor, R.E. (1998). "Public perceptions of global warming: United States and international perspectives", *Climate Research* 11, 75-84.

Bord, R.J., O'Connor, R.E., Fisher, A. (2000). "In what sense does the public need to understand global climate change?" *Public Understanding of Science* 9, 205-218.

Burghart, D.R., Cameron, T.A., Gerdes, G.R. (2006). Questioning some maintained hypotheses in stated preference estimation: Allowing for failure, substitutes, adjustments, and inattention. Department of Economics, University of Oregon. Eugene, OR. 41 pp.

.

Cameron, T.A., Gerdes, G.R. (2005). Individual subjective discounting: Form, context, format, and noise. Department of Economics, University of Oregon. Eugene, OR. 65 pp.

.

Carlsson, F., Daruvala, D., Johansson-Stenman, O. (2005). "Are people inequality-averse, or just risk-averse?" *Economica* 72, 375-396.

Chesson, H., Viscusi, W.K. (2000). "The heterogeneity of time-risk tradeoffs", *Journal of Behavioral Decision Making* 13, 251-258.

Davidson, M.D. (2006). "A social discount rate for climate damage to future generations based on regulatory law", *Climatic Change* 76, 55-72.

Donkers, B., Melenberg, B., Van Soest, A. (2001). "Estimating risk attitudes using lotteries: A large sample approach", *Journal of Risk and Uncertainty* 22, 165-195.

Ha-Duong, M., Treich, N. (2004). "Risk aversion, intergenerational equity and climate change", *Environmental & Resource Economics* 28, 195-207.

Hersch, J., Viscusi, W.K. (2006). "The generational divide in support for environmental policies: European evidence", *Climatic Change* 77, 121-136.

Howarth, R.B. (2003). "Discounting and uncertainty in climate change policy analysis", *Land Economics* 79, 369-381.

Jamieson, D. (2006). "An american paradox", *Climatic Change* 77, 97-102.

Krosnick, J.A., Holbrook, A.L., Lowe, L., Visser, P.S. (2006). "The origins and consequences of democratic citizens' policy agendas: A study of popular concern about global warming", *Climatic Change* 77, 7-43.

Lee, J., Cameron, T.A. (2006). Thorough non-response modeling as an alternative to minimum survey response rate requirements: Popular support for climate change mitigation. Department of Economics, University of Oregon. Eugene, OR. 50 pp.
.

Leiserowitz, A. (2006). "Climate change risk perception and policy preferences: The role of affect, imagery, and values", *Climatic Change* 77, 45-72.

Leiserowitz, A.A. (2005). "American risk perceptions: Is climate change dangerous?" *Risk Analysis* 25, 1433-1442.

Li, H., Berrens, R.P., Bohara, A.K., Jenkins-Smith, H.C., Silva, C.L., Weimer, D.L. (2004). "Would developing country commitments affect US households' support for a modified Kyoto protocol?" *Ecological Economics* 48, 329-343.

Lorenzoni, I., Pidgeon, N.F. (2006). "Public views on climate change: European and USA perspectives", *Climatic Change* 77, 73-95.

Newell, R.G., Pizer, W.A. (2003). "Discounting the distant future: How much do uncertain rates increase valuations?" *Journal of Environmental Economics and Management* 46, 52-71.

Newell, R.G., Pizer, W.A. (2004). "Uncertain discount rates in climate policy analysis", *Energy Policy* 32, 519-529.

O'Connor, R.E., Bord, R.J., Fisher, A. (1999). "Risk perceptions, general environmental beliefs, and willingness to address climate change", *Risk Analysis* 19, 461-471.

Viscusi, W.K., Zeckhauser, R.J. (2006). "The perception and valuation of the risks of climate change: A rational and behavioral blend", *Climatic Change* 77, 151-177.

Weitzman, M.L. (2001). "Gamma discounting", *American Economic Review* 91, 260-271.

Zahran, S., Brody, S.D., Grover, H., Vedlitz, A. (2006). "Climate change vulnerability and policy support", *Society & Natural Resources* 19, 771-789.

Table A-1: Descriptive statistics for discounting choices; responses to discount rates implicit in offered lump sum payment (n = 1971)

Two response category formats:

Implicit r		Yes		No		Total
0.01	-	330	-	34	-	364
0.02	-	94	-	14	-	108
0.03	-	290	-	65	-	355
0.04	-	191	-	51	-	242
0.05	-	162	-	68	-	230
0.06	-	134	-	99	-	233
0.07	-	155	-	147	-	302
0.08	-	80	-	72	-	152
0.09	-	120	-	177	-	297
0.10	-	76	-	140	-	216
0.12	-	89	-	163	-	252
0.15	-	41	-	93	-	134
0.20	-	82	-	256	-	338
0.30	-	4	-	14	-	18
0.50	-	11	-	51	-	62

Three response category formats:

Implicit r		Yes	Not Sure	No		
0.01	-	308	28	27	-	363
0.02	-	99	6	21	-	126
0.03	-	272	55	57	-	384
0.04	-	154	36	42	-	232
0.05	-	139	38	80	-	257
0.06	-	125	40	88	-	253
0.07	-	116	62	125	-	303
0.08	-	57	35	71	-	163
0.09	-	96	49	166	-	311
0.10	-	57	30	128	-	215
0.12	-	66	36	185	-	287
0.15	-	31	10	102	-	143
0.20	-	64	28	254	-	346
0.30	-	5	2	16	-	23
0.50	-	9	1	50	-	60

continued…

Four response category formats:

Implicit r	Def. Yes	Prob. Yes		Prob. No	Def. No	
0.01	256	53	-	24	11	344
0.02	77	25	-	10	5	117
0.03	195	103	-	34	21	353
0.04	98	73	-	36	24	231
0.05	88	72	-	41	29	230
0.06	61	76	-	63	40	240
0.07	75	85	-	75	55	290
0.08	32	42	-	42	39	155
0.09	52	59	-	94	92	297
0.10	36	37	-	58	81	212
0.12	41	37	-	66	107	251
0.15	19	17	-	38	62	136
0.20	43	38	-	64	180	325
0.30	3	1	-	2	10	16
0.50	7	5	-	9	33	54

Five response category formats:

Implicit r	Def. Yes	Prob. Yes	Not Sure	Prob. No	Def. No	
0.01	278	60	24	13	10	385
0.02	84	30	4	9	7	134
0.03	212	107	35	32	22	408
0.04	90	84	37	22	18	251
0.05	95	78	33	31	31	268
0.06	78	53	51	49	43	274
0.07	75	60	78	61	58	332
0.08	40	30	28	31	42	171
0.09	66	45	59	84	95	349
0.10	36	30	23	64	80	233
0.12	45	23	37	80	107	292
0.15	17	11	14	28	82	152
0.20	45	19	31	73	199	367
0.30	1	0	0	2	13	16
0.50	6	1	0	5	41	53

Table A-2 – Descriptive statistics for investment choices (n = 1971)

Variable	Mean (s.d.)	Mean (s.d.)	Mean (s.d.)	Mean (s.d.)	Min	Max
Investment Decision #	1	2	3	all		
Number of observations	1971	1320	666	3957		
Amount invested this year ($'000)	0.939 (0.838)	0.918 (0.827	0.899 (0.818	0.925 (0.831)	0.1	2.4
Time to payoff (years)	20.05 (7.23)	20.24 (7.10)	19.64 (6.94)	20.04 (7.14)	10	30
Payoff for certain investment ($'000)	5.112 (9.557)	5.023 (9.888)	4.784 (10.38)	5.027 (9.808)	0.1	116
Low payoff for risky investment ($'000, with 50% chance)	2.754 (4.849)	2.679 (4.797	2.611 (4.593	2.705 (4.789)	0.1	58
High payoff for risky investment ($'000, with 50% chance)	12.10 (24.47)	12.19 (25.84)	11.42 (26.64)	12.01 (25.30)	0.12	239
Choices:						
Certain investment %	651 0.330	421 0.319	205 0.308	1277 0.323		
Risky investment %	1045 0.530	671 0.508	332 0.498	2048 0.518		
Neither investment %	275 0.140	228 0.173	129 0.194	632 0.160		

Figure A-1 – Marginal distribution of fitted discount rate parameters

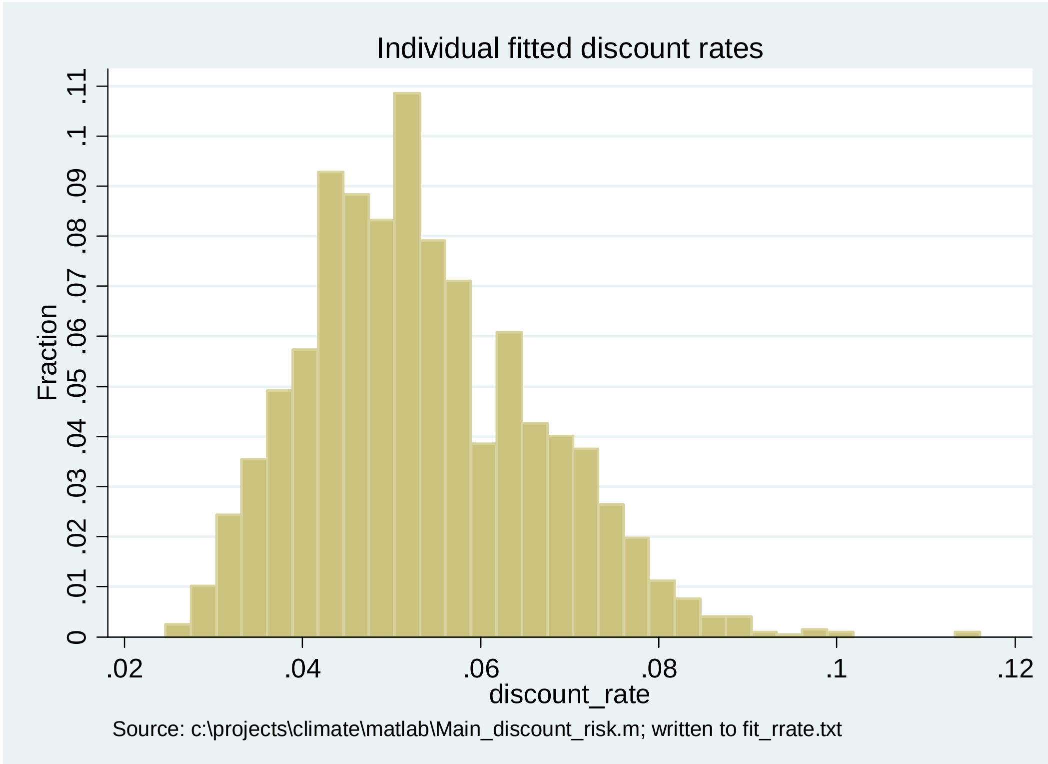


Figure A-2 – Marginal distribution of fitted individual risk preference parameters

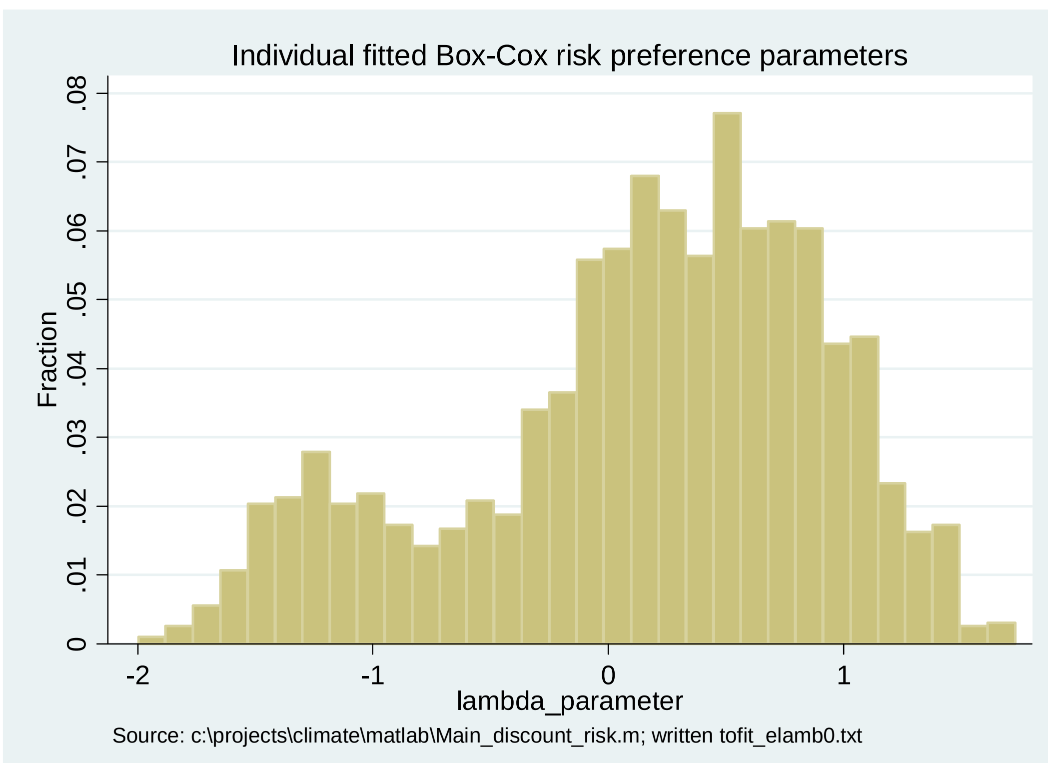
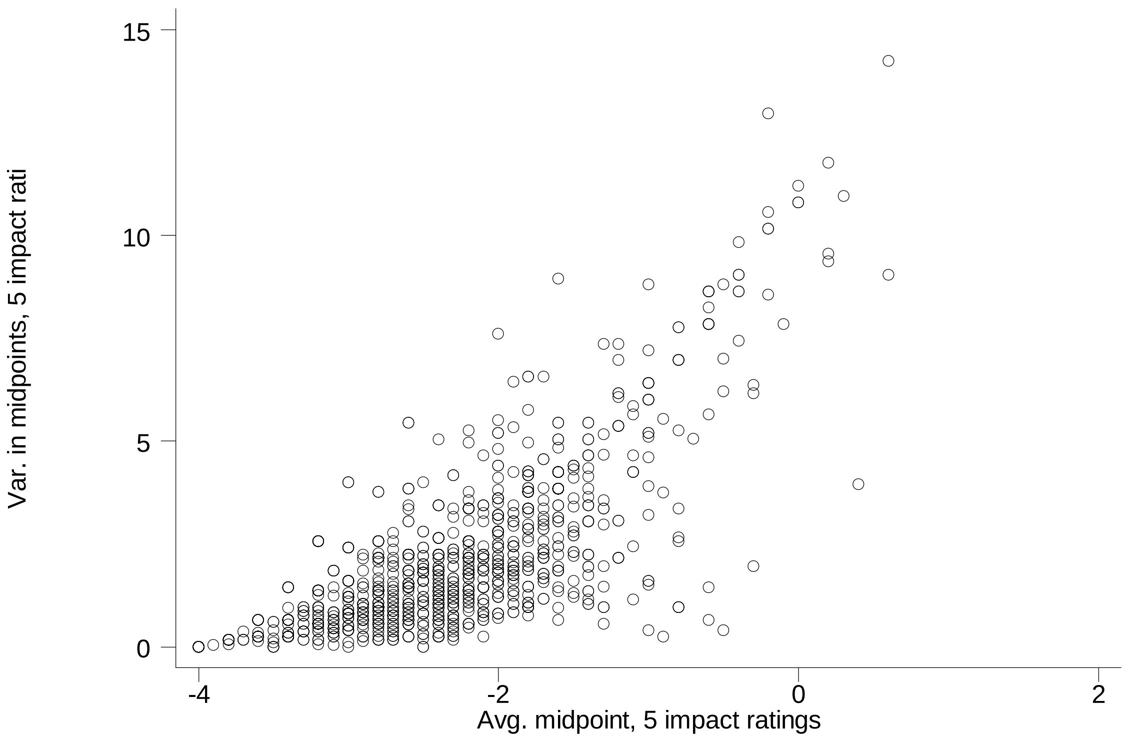


Figure A-3: Means and variances in anticipated impact midpoints, cross the five impacts



Log-likelihood functions

A. Lottery winning choices (discount rate parameter)

There are different probability formulas for each different number of answer options for the ordered logit models used in estimation. We assume logistic errors for the utility-differences that drive the choices about how to take lottery winnings. We allow a different error-dispersion parameter for each elicitation format (2, 3, 4, or 5) response alternatives, where the 3-alternative and 5-alternative formats allow for a “not sure” response. Thus the parameter κ_i, to appear below, will be estimated as $\exp\left(\kappa_i^*\right)$. The parameter κ_i^* is normalized to zero for the 2-alternative format, and we estimate factors by which the dispersion differs for other formats.

If each subsample with a different number of response options m were to be used independently, there would be $m-1$ unknown threshold parameters to be estimated for each format. (We label our thresholds as α_{jk}, where j denotes the number of answer categories and k denotes the threshold number, counting from the bottom, starting with zero.) However, with the pooled data from all four variants, the boundary between "YES" and "NO" will be normalized to zero, which means that α_{20}=0 and α_{41}=0 in the 2-level and 4-level cases, respectively. The locations of the remaining thresholds are freely estimated (without symmetry restrictions).

2-level:

$$P2DY_i = \frac{1}{1+\exp(\alpha_{20}/\kappa_i - \Delta V_i)} \qquad \text{YES}$$

$$P2DN_i = \frac{\exp(\alpha_{20}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{20}/\kappa_i - \Delta V_i)} \qquad \text{NO}$$

$$P3DY_i = \frac{1}{1+\exp(\alpha_{31}/\kappa_i - \Delta V_i)} \qquad \text{YES}$$

3-level: $$P3DM_i = \left(\frac{\exp(\alpha_{31}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{31}/\kappa_i - \Delta V_i)}\right) - \left(\frac{\exp(\alpha_{30}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{30}/\kappa_i - \Delta V_i)}\right) \qquad \text{NOT SURE}$$

$$P3DN_i = \frac{\exp(\alpha_{30}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{30}/\kappa_i - \Delta V_i)} \qquad \text{NO}$$

$$P4DDY_i = \frac{1}{1+\exp(\alpha_{42}/\kappa_i - \Delta V_i)} \qquad \text{Def. YES}$$

$$P4DPY_i = \left(\frac{\exp(\alpha_{42}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{42}/\kappa_i - \Delta V_i)}\right) - \left(\frac{\exp(\alpha_{41}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{41}/\kappa_i - \Delta V_i)}\right) \qquad \text{Prob. YES}$$

4-level:

$$P4DPN_i = \left(\frac{\exp(\alpha_{41}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{41}/\kappa_i - \Delta V_i)}\right) - \left(\frac{\exp(\alpha_{40}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{40}/\kappa_i - \Delta V_i)}\right) \qquad \text{Prob. NO}$$

$$P4DDN_i = \frac{\exp(\alpha_{40}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{40}/\kappa_i - \Delta V_i)} \qquad \text{Def. NO}$$

$$P5DDY_i = \frac{1}{1+\exp(\alpha_{53}/\kappa_i - \Delta V_i)} \qquad \text{Def. YES}$$

$$P5DPY_i = \left(\frac{\exp(\alpha_{53}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{53}/\kappa_i - \Delta V_i)}\right) - \left(\frac{\exp(\alpha_{52}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{52}/\kappa_i - \Delta V_i)}\right) \qquad \text{Prob. YES}$$

5-level: $$P5DM_i = \left(\frac{\exp(\alpha_{52}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{52}/\kappa_i - \Delta V_i)}\right) - \left(\frac{\exp(\alpha_{51}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{51}/\kappa_i - \Delta V_i)}\right) \qquad \text{NOT SURE}$$

$$P5PN_i = \left(\frac{\exp(\alpha_{51}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{51}/\kappa_i - \Delta V_i)}\right) - \left(\frac{\exp(\alpha_{50}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{50}/\kappa_i - \Delta V_i)}\right) \qquad \text{Prob. NO}$$

$$P5DN_i = \frac{\exp(\alpha_{50}/\kappa_i - \Delta V_i)}{1+\exp(\alpha_{50}/\kappa_i - \Delta V_i)} \qquad \text{Def. NO}$$

The last necessary ingredient for the development of the log-likelihood function for this model is a set of indicators for choices. Indicators have the general format DnX_i. The value of n indicates how many answer levels were offered to the respondent (n = 2, 3, 4, 5), and *X* includes *Y* and *N* for Yes and No, with *P* for the modifier "probably" and *D* for "definitely". *NS* is the abbreviation for the "not sure" category. All indicators take a value of 1 if the designated response is selected, and are 0 otherwise.

All respondents provide either 3, 5, 7 or 13 responses to discounting questions. The different orderings and different formats of the answer options were randomized across split samples, so the log-likelihood formulas appropriate for each number of response options can simply be summed.

B. Investment choices (risk aversion parameter)

The raw explanatory variables for these choices are available in the form of absolute levels, not just differences (as in the Climate Policy choice scenarios), so the investment choices submodel probabilities can be expressed in terms of the absolute levels of indirect utility.

$$PRC_i = \frac{\exp\left(V_i^c\right)}{\exp(V_i^c) + \exp(V_i^r) + \exp(V_i^n)} \qquad \text{certain}$$

$$PRR_i = \frac{\exp\left(V_i^r\right)}{\exp(V_i^c) + \exp(V_i^r) + \exp(V_i^n)} \qquad \text{risky}$$

$$PRN_i = \frac{\exp\left(V_i^n\right)}{\exp(V_i^c) + \exp(V_i^r) + \exp(V_i^n)} \qquad \text{neither}$$

C. Climate policy choices (marginal utility parameters)

$$PCM_i = \frac{\exp\left(V_i^c\right)}{\exp(V_i^c) + \exp(V_i^p) + 1} \qquad \text{complete mitigation}$$

$$PPM_i = \frac{\exp\left(V_i^p\right)}{\exp(V_i^c) + \exp(V_i^p) + 1} \qquad \text{partial mitigation}$$

$$PBAU_i = \frac{1}{\exp(V_i^c) + \exp(V_i^p) + 1} \qquad \text{business-as-usual}$$

Table A-3: Components of the two log likelihood functions

Joint model for Lottery Winnings and Investment Decisions choices	
$\sum_{i=1}^{ND2}\left[DY_i \ln(PDY_i) + DN_i \ln(PDN_i)\right]$	pairwise Lottery Winnings choices
$+\sum_{i=1}^{ND3}\left[DY_i \ln(PDY_i) + DM_i \ln(PDM_i) + DN_i \ln(PDN_i)\right]$	three-alternative Lottery Winnings choices
$+\sum_{i=1}^{ND4}\left[\begin{array}{l} DDY_i \ln(PDDY_i) + DPY_i \ln(PDPY_i) \\ +DPN_i \ln(PDPN_i) + DDN_i \ln(PDDN_i) \end{array}\right]$	four-alternative Lottery Winnings choices
$+\sum_{i=1}^{ND5}\left[\begin{array}{l} DDY_i \ln(PDDY_i) + DPY_i \ln(PDPY_i) + DM_i \ln(PDM_i) \\ +DPN_i \ln(PDPN_i) + DDN_i \ln(PDDN_i) \end{array}\right]$	five-alternative Lottery Winnings choices
$+\sum_{i=1}^{NR0}\left[RC_i \ln(PRC_i) + RR_i \ln(PRR_i) + RN_i \ln(PRN_i)\right]$	first Investment Decision choices
$+\sum_{i=1}^{NR1}\left[RC_i \ln(PRC_i) + RR_i \ln(PRR_i) + RN_i \ln(PRN_i)\right]$	second Investment Decision choices (if offered)
$+\sum_{i=1}^{NR2}\left[RC_i \ln(PRC_i) + RR_i \ln(PRR_i) + RN_i \ln(PRN_i)\right]$	third Investment Decision choices (if offered)
Separate model for Climate Policy choices:	
$\sum_{i=1}^{NP1}\left[CM_i \ln(PCM_i) + BAU_i \ln(PBAU_i)\right]$	sample with pairwise Climate Policy choices
$+\sum_{i=1}^{NP3}\left[CM_i \ln(PCM_i) + PM_i \ln(PPM_i) + BAU_i \ln(PBAU_i)\right]$	sample with three-way Climate Policy choices