June, 1998 (preliminary)

Credibility of Information Sources and the Formation of Individuals' Option Prices for Climate Change Mitigation

by

Trudy Ann Cameron*
Department of Economics, UCLA
Box 951477, Los Angeles, 90095-1477
tcameron@econ.ucla.edu

ABSTRACT

Ex ante willingness to pay to prevent adverse environmental change depends on people's perceptions about just how bad the situation will become if mitigation policies are not adopted. These perceptions are influenced by an array of external information sources that might be deemed more or less credible by different individuals. I use a survey wherein people's native subjective distributions on future environmental quality are elicited first. Respondents are then provided with "external" information attributed to different authorities. Respondents' revised subjective distributions then underlie their responses to a referendum question regarding support for a mitigation program at different levels of cost. It is assumed that individuals are expected utility maximizers and that option prices (the appropriate *ex ante* welfare measure in the face of uncertainty), are based on their subjective uncertainty. State-dependent preferences lead to an expected utility-difference function across the two alternatives in the referendum question that depends on the mean and variance of the revised subjective climate distribution. The estimated model allows counterfactual simulations regarding the effects on option prices of changes in (a.) factors that influence the updating of probabilities and/or (b.) factors that enter directly into the expected indirect utility-difference function. We find strong evidence of heterogeneity in the processing of external information about climate change and in the scope effects of expected future climate conditions.

*This paper has benefitted from comments received at presentations at the *CERE/NOAA Conference on Research Transformations in Environmental Economics: Policy Design in Response to Global Change* at Duke University (May 5-6, 1997) and at the *EML/NSF Symposium on Preference Elicitation* at UC Berkeley (July 29-August 1, 1997), and *the World Congress of Environmental and Resource Economists*, Venice, Italy (June 25-27, 1998). The data were collected from my graduate students, as well as the Spring 1997 undergraduate classes of Professors Kathleen McGarry and Fred Luk, the 1997 summer session classes of Professors Fred Luk, Michael Sproul, Ed McDevitt, and Pari Kasliwal, and my own Fall 1997 introductory microeconomics and regression analysis classes. Thanks are due to Anna Alberini, JR DeShazo, Barri Grossman, Jack Hirshleifer, Kathleen McGarry, and V. Kerry Smith for helpful comments, to Sara Wong Chang for careful data entry, and to Casey Williams for assistance in assembling the survey instruments. Any remaining errors are my own.

Credibility of Information Sources and the Formation of Individuals' Option Prices for Climate Change Mitigation

1. Introduction

In the upcoming US presidential election, especially if Albert Gore is the Democratic Party nominee, the vote will be (in part) a referendum on climate change mitigation. The willingness of the voting public to incur substantial costs in order to prevent climate change will be a key political "variable" that will be the target of manipulation by both parties. Consequently, it is important to gain some understanding of how individuals formulate their subjective conceptions of future climate prospects in the absence of mitigation. One relevant consideration is the possibility of systematically differing opinions across different subpopulations. Another is the manner in which people respond to climate predictions according to the source of the information. Third, it is crucial to know how these opinions translate into individuals' willingness to pay for climate change mitigation in terms of higher prices or taxes.

Global climate change does seem to have the potential to result in detectable shifts in the distributions of many environmental measures. Scientific controversy over the nature and magnitude of these changes, however, has made it very difficult for legislators to agree on optimal climate change policies. Different constituencies cannot even agree on the *necessity* for costly measures to mitigate climate change. In democratic jurisdictions like the US, support for legislation to manage the world's climate depends on the distribution in the population of individuals' *ex ante* willingness to pay to avoid the perceived consequences of failing to act. Citizens are asked to vote on policies (directly or indirectly) in advance of knowing the resolution of uncertainty about what will happen if nothing is done.[1]

[1] Some early research on the topic of how people make judgments in the presence of uncertainty is described in Tversky and Kahneman (1974).

What do people perceive to be the consequences of pursuing no policies to manage the world's climate? Individuals who have lived for some time in a particular location have become accustomed to the typical patterns of seasonal temperatures, rainfall, cloud cover, and humidity in their local area. Absent any appreciation of the forces that might produce systematic changes in these climate variables, individuals may assume that the current patterns will persist indefinitely. Other people have begun to recognize that without policies to prevent these changes, shifts in the distributions of their local climate variables may occur. In assessing willingness to pay to prevent climate change, we need to know how people combine alternative information about future climate prospects, based on evidence or conclusions that they pick up from different sources.[2]

It is generally acknowledged that most people update their own assessment of likely future conditions (which might start out being identical to current conditions) as they are exposed to external information. This external information may come from diverse sources, such as government scientists or environmental groups. Individuals will have different views about the credibility of these different sources.[3] In the face of new outside information, their updated personal assessments about the future state of the environment may be adjusted, and more-credible sources can be expected to have a greater influence.[4]

In this paper, we examine models intended to capture the nature of the opinion updating process as survey respondents are exposed to external information about the probable future state of the world's climate. This task is pursued in conjunction with the analysis of a survey of individuals concerning their willingness to pay to prevent climate change. This willingness to pay is elicited using a referendum-type contingent valuation survey (Arrow et al, 1993).

[2] In essence, the question of climate change mitigation falls into the class of policy problems involving the regulation of risk. The work of Slovic, Fischoff, and Lichtenstein (1985) is relevant.

[3] In the context of health risk assessment, Johnson and Slovic (1995) look at the problem of conveying uncertainties and the consequences for risk perception and trust.

[4] Adler and Pittle (1984) address the issue of information provision as a substitute for regulation.

The research reported in this paper is in the nature of a scoping exercise. The objective of the analysis is to set forth a simple illustration that captures the most important features of any model intended to measure the social benefits of climate change mitigation: individual subjective uncertainty, updating of native priors in response to external information, and estimation in terms of option prices formally derived from a common underlying indirect utility function that allows for heterogeneous preferences across individuals. The importance of incorporating these features is illustrated using a convenience sample, rather than a representative population sample, so further research is clearly warranted. Nevertheless, the present results confirm that there exists systematic heterogeneity in the manner in which different people respond to alternative sources of climate information. Individual support for climate change mitigation programs depends not only on the anticipated scope of climate change, but also on uncertainty about this scope. Furthermore, the scope and uncertainty effects are not constant across individuals, but vary systematically with a number of sociodemographic and circumstantial characteristics.

Section 2 reviews (in the general case) the modeling of option prices for environmental protection in the context of discrete-choice contingent valuation survey data with subjective uncertainty captured by a probability density function for one representative continuous dimension of future environmental quality. Section 3 gives an example in terms of a particular functional form for state-dependent individual indirect utility. This section also speculates upon how a revised distribution of the uncertain future environmental quality variable might to be formulated by individuals from (a.) their own native distribution as well as (b.) diverse external sources of information to which they have access. Section 4 outlines some obvious generalizations that can be pursued with richer data sets. Section 5 describes some available preliminary data that allow the basic model to be tested, and section 6 discusses the empirical results based on these data. Section 7 outlines some useful and interesting simulations that are possible using the estimated model. Section 8 takes a look at one particular generalization that may hold promise for future applications. Section 9 concludes, and outlines some of the future research agenda for the larger project for which this paper describes the preliminary research.

2. A Generic Model

Suppose we are interested in determining an *ex ante* measure of the social value of preventing a deterioration in environmental quality (in this case, climate). Suppose initially that environmental quality can be conveniently summarized (in just one dimension) as the level of a continuous variable, w. For example, in the context of climate change, one could think of w as annual average temperature.

Assume that if mitigation is undertaken (at known cost), environmental quality at the current level, w^1, is guaranteed. If society fails to mitigate, the level of environmental quality is likely to worsen, but individuals are subjectively uncertain as to the extent of this deterioration.[5] From the point of view of a single individual, let this uncertain future outcome--in the absence of intervention--be w^0. When called upon to make an evaluation about whether to undertake mitigation efforts, individuals decide whether or not to pay to prevent environmental degradation based on their current perceived distribution for w^0, which I will label $f^*(w^0)$.[6] The way in which individuals formulate their own subjective distributions for w^0 (partly in response to information from external sources) is one of the main issues in this paper, but discussion of this topic will be reserved until after the option price model has been introduced.

a.) ***General Discussion of Option Prices from Referendum CV Responses***

Under uncertainty, the appropriate measure of the social value of preventing environmental deterioration from w^1 to w^0 is the option price (OP) for this change. Option price is the common

[5] Arrow (1982) compares notions of risk perception in the disciplines of psychology and economics.

certain payment (regardless of which way the uncertainty is resolved) that yields the same *expected utility* as the set of (differing) payments that would be separately optimal under each possible state of the world under certainty.[7] The economic theory concerning option prices is very familiar in the case of uncertainty over only *two* possible states of the world. (See for example, Graham (1981), or an empirical adaptation in an environmental economics context by Cameron and Englin (1997).) Identical intuition can be brought to bear on a problem with a *continuum* of possible states of the world, where uncertainty is represented by a continuous probability density function, rather than simply the discrete probabilities of an event and its complement.

In order to estimate option price (OP) empirically, it is expedient to work with a class of indirect utility functions that is additively separable in some monotonic function of income, g(Y). Indirect utility is also affected by h(w,x), a function of the realized level of environmental quality, w, and other individual-specific factors x. Ex ante, individual subjective uncertainty exists across states of the world (environmental quality outcomes), represented by different values of w^0. However, for any one state, the individual can be modelled as having state-dependent[8] utility level V^1 if they elect to pay an offered amount t in order to preserve environmental quality at current level w^1. If they do not pay, environmental quality will deteriorate to the uncertain level w^0, distributed $f^*(w^0)$, which allows a utility level of only V^0. An additive normal error term facilitates econometric estimation.

$$\text{(1)} \qquad \begin{aligned} V^1(Y-t, w^1) &= g(Y-t) + h^1(w^1,x) + \varepsilon^1 \\ V^0(Y, w^0) &= g(Y) + h^0(w^0,x) + \varepsilon^0 \end{aligned}$$

---

[7] Of course, economists have noted that expected utility theory is not adequate to explain every economic decision under uncertainty. It is, however, a conventional theoretical starting point that appears well suited to the present application. See Machina (1987) for a simple overview of some competing theories.

[8] I use the term "state-dependent" in the same sense as it is used in Hirshleifer and Riley (1992). Preferences differ across the uncertain outcomes (states of the world), but only because the state of the world is an argument of a more-general specification of the individual's utility function.

The individual will prefer to pay amount t and thereby to preserve current environmental quality if $(V^1 - V^0)$ is positive, i.e. if

(2)
$$(V^1 - V^0) = g(Y-t) - g(Y) + [h^1(w^1,x) - h^0(w^0,x)] + (\varepsilon^1 - \varepsilon^0) > 0.$$

If one particular value of w^0 was to occur with certainty, the individual's maximum willingness to pay (WTP) for preventing environmental deterioration from w^1 to w^0 could be found by setting $(V^1 - V^0)$ to zero and solving for t*. Simplify by letting $\varepsilon = \varepsilon^0 - \varepsilon^1$ and solve for t^*_{w0} as follows:

(3)
$$g(Y-t^*_{w0}) = g(Y) - [h^1(w^1,x) - h^0(w^0,x)] + \varepsilon ;$$
$$Y-t^*_{w0} = g^{-1} \{ g(Y) - [h^1(w^1,x) - h^0(w^0,x)] + \varepsilon \};$$
$$t^*_{w0} = Y - g^{-1} \{ g(Y) - [h^1(w^1,x) - h^0(w^0,x)] + \varepsilon \}.$$

An *ex post* measure of consumer welfare, across all possible states of the world w^0-- usually called the "expected surplus"--could then be calculated by computing the probability-weighted average of these state-dependent WTP values, namely the expectation over w^0:

(4)
$$E_{w0}[t^*_{w0}] = E_{w0}[Y - g^{-1} \{ g(Y) - [h^1(w^1,x) - h^0(w^0,x)] + \varepsilon \}]$$
$$= \int [Y - g^{-1} \{ g(Y) - [h^1(w^1,x) - h^0(w^0,x)] + \varepsilon \}] f^*(w^0) \, dw^0.$$

When explicit functional forms have been selected for g, h^1 and h^0, this integral can typically be simplified.

However, this *ex post* measure is not appropriate for *ex ante* policy decisions. Option price is the preferred measure. Option price is defined as the common certain payment, under *any* of the uncertain outcomes, which produces the same *expected utility* as the different maximum amounts willingly paid under each outcome with certainty. This latter expected utility is also identical to the expected utility gained from no payment and no mitigation, so that OP is defined by:

(5) $$\int V^1 (Y - OP, w^1)\, f^*(w^0)\, dw^0 = \int V^0(Y, w^0)\, f^*(w^0)\, dw^0,$$

or, identically,

(5') $$\int \{ V^1 (Y - OP, w^1) - V^0(Y, w^0) \} f^*(w^0)\, dw^0 = 0.$$

Substituting the generic expression for the indirect utility difference (from equation 2) into (5') yields:

(6) $$\int \{ g(Y - OP) - g(Y) + [h^1(w^1, x) - h^0(w^0, x)] + \varepsilon \} f^*(w^0)\, dw^0 = 0.$$

Solving this equation for OP yields the desired option price. One can simplify the notation by using $E_{w^0}[\ ]$ to denote an expectation over states of the world w^0.

(7) $$\int g(Y - OP)\, f^*(w^0)\, dw^0 = E_{w^0}[g(Y)] - E_{w^0}[h^1(w^1, x) - h^0(w^0, x)] + \varepsilon.$$

This analysis cannot be taken much further without committing to a specific functional form, especially for the function g(Y). Thus, I proceed in the next section to adopt one concrete assumption about an empirically tractable functional form.

3. Example: A Specific Functional Form

We require a simple functional form for the state-dependent indirect utility function that exhibits risk aversion and therefore allows *ex ante* option prices to differ from the *ex post* expected surplus measures. Such a model is one that is linear in the logarithm of income. Since w differs across the mitigate/don't-mitigate contingent valuation scenarios, indirect utility can be linear in w. However, we desire to allow the *dispersion* of the respondent's subjective distribution of future environmental quality also to affect option prices. It is therefore expedient to allow indirect utility to depend upon the squared deviation between realized w^0 and its ex ante expected value, $E[w^0]$. There will also be individual characteristics that do *not* vary across the two scenarios. If these are to remain in the indirect utility-*difference* function, they will have to enter V^1 and V^0 with different coefficients. A simple and tractable specific form for the model is therefore:

(8)
$$V^1(Y - t, w^1) = \beta_0 \log(Y - t) + \delta_0 w^1 + \delta_1 (w^1 - E[w^1])^2 + \varepsilon^1$$
$$V^0(Y, w^0) = \beta_0 \log(Y) + \delta_0 w^0 + \delta_1 (w^0 - E[w^0])^2 + \varepsilon^0$$

The utility-difference function, which also depends on the uncertain outcome with respect to w^0, is then:

(9)
$$(V^1 - V^0) = \beta_0 \log[(Y - t)/Y] + \delta_0 (w^1 - w^0) + \delta_1 \{(w^1 - E[w^1])^2 - (w^0 - E[w^0])^2\} + (\varepsilon^1 - \varepsilon^0).$$

In practice, each if the indirect utility parameters can be expressed as a systematic function of observable (exogenous) respondent attributes, in order to allow for heterogeneity in perferences. For example, we might let $\beta_0 = \beta_0'x$, $\delta_0 = \delta_0'x$, and $\delta_1 = \delta_1'x$, where the vector x may differ across these three systematic varying parameters. Also let $\varepsilon = \varepsilon^1 - \varepsilon^0$. Note that if w^1 is certain, the term $(w^1 - E[w^1])^2$ is zero.

a.) ***Option Prices from Referendum Contingent Valuation Responses***

As in the generic case, OP is the common certain payment that has the same *expected utility* as no payment and no mitigation (or the same *expected utility* as the set of each of the separately optimal payments under each possible outcome with certainty). The binary probit discrete choice model (that we will use to estimate OP) is based on the *expectation* of the utility difference across all possible outcomes for w^0. For the simple indirect utility difference specification illustrated above, this expectation takes the form:

(10) $$E_{w^0}[V^1 - V^0] = \beta_0 \ \lg[(Y - t)/Y] + \int \delta_0 (w^1 - w^0) f^*(w^0)\, dw^0 + \int \delta_1 ((w^1 - E[w^1])^2 - (w^0 - E[w^0])^2\} f^*(w^0)\, dw^0 + \varepsilon$$

If we assume that with mitigation, the current level of environmental quality can be sustained with certainty, this can be simplified as follows:[9]

(11) $$E_{w^0}[V^1 - V^0] = \beta_0 \ \lg[(Y - t)/Y] + \delta_0 \{ w^1 - E^*[w^0] \} + \delta_1 \int \{ - (w^0 - E[w^0])^2 \} f^*(w^0)\, dw^0 + \varepsilon.$$

Since the remaining expression involving an integral is simply the negative of the variance of w^0, the discrete choice probit "index" expression is thus a linear-in-parameters function of the indirect utility function parameters--scalars (or possibly vectors) β_0, δ_0, and δ_1:[10]

(12) $$E_{w^0}[V^1 - V^0] = \beta_0 \ \lg[(Y - t)/Y] + \delta_0 \{w^1 - E^*[w^0]\} + \delta_1 \{ - Var^*[w^0] \} + \varepsilon.$$

For a sample of survey respondents, we can now provide an inventory of the data required in order to estimate the model. The dependent variable is the discrete YES/NO response to the willingness to pay for mitigation question. Explanatory variables must be constructed from data on income, Y, the referendum offered value, t, the certain level of environmental quality with mitigation w^1, and individual characteristics x. Additional explanatory variables are constructed from the mean and the variance of the individual's revised distribution concerning future environmental quality in the absence of mitigation: $E^*[w^0]$ and $Var^*[w^0]$. One insight is that the precise shape of this revised

[9] We preserve the details of the derivation in this draft to facilitate verification.

environmental quality distribution can apparently be individual-specific and take any valid form. Only the mean and the variance of the distribution affect the expected utility difference.

The model, as specified above, is linear in parameters. If $E^*[w^0]$ and $Var^*[w^0]$ are treated as ordinary explanatory variables, a conventional packaged maximum likelihood probit algorithm can be used to estimate the unknown parameters. Note that the intercept should be suppressed. If it is not suppressed, it should be insignificantly different from zero.

To solve the estimated probit discrete choice model for option prices in this concrete example, recall that OP is the value of t that makes the expected utility difference exactly zero. Substituting OP for t (and simplifying the notation to highlight the essentials), the OP equation, for each individual, will take the following form:

$$E_{w^0}[V^1 - V^0] = B \log[(Y - OP)/Y] + A + \varepsilon = 0, \tag{13}$$

where we can make use of the simplifying notation of $B = \beta_0$ and $A = \delta_0\{w^1 - E^*[w^0]\} + \delta_1\{-Var^*[w^0]\}$. Solving for OP yields $OP = Y - Y \exp[-(A + \varepsilon)/B]$. Note that the error term ought to be carried through this process. Calculating a fitted value for an individual's OP involves taking the expectation of this formula over the implicit probit error term ε (which could be assumed to be distributed normally with mean zero and variance one). The expectation of OP for each individual is given by:

$$E\{OP\} = Y - Y \exp[-A/B] \exp[1/(2B^2)] \tag{14}$$

b.) ***Determinants of the Revised Subjective Distribution for w^0***

If the individual's revised distribution for w^0, $f^*(w^0)$, is taken as given, one could implement this model very easily by incorporating the observed values of $E^*[w^0]$ and $Var^*[w^0]$ directly into

---

[10] Note that in the current empirical application, w^1 is invariant.

equation (12). However, an important research question concerns the manner in which individuals update their native subjective distributions on w^0 in the face of new information from sources that may have different levels of credibility in the mind of the individual. I wish to be able to model explicitly the data-generating process that yields each individual's values of $E^*[w^0]$ and $Var^*[w^0]$ associated with their own revised distribution $f^*(w)$.

Since our survey instrument elicits native subjective distributions for environmental quality, provides all of the "outside" information, and then elicits revised subjective distributions, it can be a simple matter to model the updating process. Separate ad hoc specifications for the determinants of $E^*[w^0]$ and $Var^*[w^0]$ can be explored. More-formal Bayesian updating strategies can also be examined.

4. Possible Generalizations

Since this paper describes a stylized model and an empirical scoping exercise, it is important to note some obvious generalizations that have not been fully pursued here. All are potentially feasible, and each makes the scenario a little more realistic than it is for the basic model above. In what follows, I relax assumptions individually. It is unlikely to be empirically tractable to relax them all at once, but the exercises described below illustrate some of the different directions that could be explored.

Only three generalizations can been implemented (at least in part) with the currently available data. The others have not yet been addressed empirically, and have been relegated to an appendix in this paper.

a. *Generalizing the Distributional Updating Model*

Viscusi and Magat (1992) describe the possibility that individuals will respond too drastically to external information. Individuals may over-react to information they receive. For what they term an "alarmist learner," the relative informational weights on the two external sources of information would exceed one either individually or collectively. We can estimate our *ad hoc* specifications for E*[w^0] and Var*[w^0] with and without restrictions. Of particular interest is whether either of the effective weights on the opinions of government scientists and/or environmental groups are individually greater than one, or whether their sum exceeds unity.

b. ***Accounting for Ambiguity across External Information Sources***

Another extension suggested by the model in Viscusi and Magat (1992) is to allow respondents' revised density functions for w^0 to be affected by the extent of the disparity among the outside sources of information to which they are exposed.[11] This disparity might be crudely summarized as the difference between the highest and lowest expected values (range, R) among the density functions asserted by the various external information sources. If the range in these values is small, the individual may place relatively greater trust in all outside sources than in his or her own native subjective distributions. If the range is large, the respondent may retreat to place relatively greater weight on his or her own judgment.

In the survey envisioned for this analysis, range R is an attribute of the array of external information sources that can be designed into the survey instrument as an exogenous variable. Viscusi and Magat's (1992) scenario is different from the one envisioned here in that they do not observe the individual's prior probability. Therefore, they append a quadratic term in R to their empirical model for a discrete prior probability, and this term can pick up any systematic shift in the implied prior probability due to the extent of the ambiguity in the external information. Here, the native subjective density is elicited directly, so R must be incorporated differently, although one could retain the nonlinear generality of the quadratic form (as necessary). The obvious strategy is to let the coefficient

[11] See also Heath and Tversky (1991).

on native subjective expectation for future mean temperature be $(\kappa_0 + \kappa_1 R)$ or $(\kappa_0 + \kappa_1 R + \kappa_2 R^2)$. With ambiguity aversion, as R increases from zero, one would expect $(\kappa_1 R + \kappa_2 R^2)$ to increase.

To determine whether the degree of ambiguity in the available external information has any systematic effect on the updating process, one would test the hypothesis that the coefficient(s) κ_1 (and κ_2) is (are jointly) equal to zero. In a more elaborate model, where there might be a much larger number of outside information sources, the standard error of means across all outside sources might be a more useful measure of the degree of ambiguity. Whatever measure is used, it is associated only with the normalized weight on the individual's own native subjective distribution on environmental quality. Whether a linear, quadratic, or other form is used for the ambiguity, it plays the same role: to shift the weight on the individual's native subjective distribution, as opposed to the remaining weight on the outside sources collectively.

c. *Demands for Environmental Quality as Derived Demands*

In the basic model, it has been assumed that environmental quality is a direct argument of individuals' utility functions. It is more likely, however, that environmental quality affects the levels of different environmental services, and it is the levels of these services that confer utility for individuals. Individuals may care little about the environment *per se*, but care greatly about how the environment affects their lives.

In the context of valuing climate change mitigation, it is important to recognize that at least two layers of uncertainty are involved. First, individuals may be uncertain as to the extent of global change, as assumed in the basic model. But second, they may be uncertain about how this change, even if it is known with certainty, maps into changes in the levels of utility-conferring environmental services to which they are accustomed.

Suppose it is not **w** itself, but s(w) that enters directly into each respondent's utility function. Here, s(w) is a vector of environmental services, the quantity (or quality) of each depending upon the level of **w** that materializes. Each individual has, potentially, a different perception about the functions $s_j(w)$ whereby **w** is translated into j different environmental service commodities that matter to the individual's utility level.

In order to illustrate a modelling strategy under these circumstances, assume that the vector s(w) has only one element, and that this element is linear in the level of **w**: $s(w) = \zeta'_0 + \zeta'_1 w$. Individuals are familiar with their current levels of environmental services, $s^1 = s(w^1)$, produced by the current level of environmental quality w^1. Assume again that if mitigation is undertaken, the current level of w^1, and hence of $s(w^1)$, will be preserved with certainty. However, if society does not mitigate, there will be a deterioration of environmental quality to uncertain level w^0, but now the manner in which this quality maps into a change in available environmental services is also uncertain. However, for any particular level of w^0 and given the assumption of linearity for the s(w) function, s^0 is given by $s^1 + \zeta(w^1 - w^0)$, where we simplify by letting $\zeta'_1 = \zeta$.

In this extension, then, both ζ and w^0 are uncertain in the minds of respondents. The indirect utility-difference function in equation (9) must therefore be modified. First, it is **s**, not **w**, that enters directly into the indirect utility function. The relevant "states of the world" now consist of a spectrum of possible states of environmental quality compounded by a spectrum of possibilities for the transformation between **w** and **s** (since the relevant slope parameter ζ is uncertain). Consistent with the form of the indirect utility function employed earlier in this paper, the revised specification becomes:

$$(15) \qquad (V^1 - V^0)_{W0} = \beta_0 \log[(Y - t)/Y] + \delta_0 (s^1 - [s^1 + \zeta(w^1 - w^0)]) + \delta_1 ((s^1 + \zeta(w^1 - w^0)) - E[s^1 + \zeta(w^1 - w^0)])^2 + \varepsilon.$$

In the face of this additional source of uncertainty, the expected utility difference that reveals a respondent's option price (equation 13) will also have to be modified. The expectation must now be taken across both w^0 and ζ. The expectation of this expression will involve terms in the individual's revised expectations about the individual quantities w^0 and ζ, as well as the covariance (or correlation) between these two random quantities. The "variance" term in this model is particularly unwieldy. These problems may render empirically intractable any model without an assumption of independence between ζ and w^0.

Simplification may improve tractability. Perhaps s^0 should be elicited directly from respondents, so that the model can be made analogous to the original specification, with s^1 and s^0 in place of w^1 and w^0. As necessary, a point estimate for each individual's value of the parameter ζ could be inferred from the relationship between s^0 and w^0. This parameter could be used in ex post exercises to infer the likely consequences, for option prices, of changes in w^0.

If both ζ and w^0 are retained in the model, despite the more complicated moments that this specification would require, and if the elicitation problem was not prohibitively daunting, however, it is easy to anticipate how one would proceed. The updating submodel for the revised subjective distribution of w^0 would be extended to cover the joint distribution of w^0 and ζ. A system of equations could be employed to produce fitted values of each of the required fitted moments.[12]

5. A Small Sample of Data

In a first round of sampling, approximately 500 pretest surveys were distributed, mostly to 1997 Spring Quarter and Summer Session undergraduate economics classes at UCLA. Students received a five-minute introduction to the survey during the lecture period and were requested to

[12] Different weighting parameters may apply for the updating of the environmental quality distribution and the "translation into environmental services parameter" distribution. Respondents may place relatively more trust in government scientists' assessments of the effects a given change in climate will have on environmental services, but relatively less trust in these scientists' judgments about just how severe the climate change will be.

return the completed survey by the next lecture.[13] We collected approximately 144 fully usable responses from this distribution.[14] A second round of sampling was conducted in two classes in Fall 1997, with the sampling period coming on the heels of a heatwave. Nominal extra credit was offered for participation in the larger class and we garnered about 250 additional responses. Table 1 gives descriptive statistics for the estimating sample.

a. ***Data on Respondents' Opinions about Future Environmental Conditions***

If the model described in Section 3 is estimated in two stages, the first estimation task involves establishing the determinants of the moments of the individual's revised distribution for future environmental quality: E*[w] and Var*[w].[15] There has been substantial policy interest in recent years in the topic of risk communication (e.g. Davies et al, 1987). This literature focuses on the best way to convey to individuals the true objective magnitudes of risks.[16] There has been less attention devoted to the problem of eliciting subjective probabilities. Reliable elicitation of (at least) the means and variances of the native subjective and revised probability distributions is crucial to this analysis.[17]

In economics, the topics of (i.) individuals' risk perceptions, (ii.) how these risk perceptions respond to information, and (iii.) the value of risk changes, have been fertile areas for research. Some representative studies include Smith and Desvousges (1987, 1988), Smith and Johnson (1988), Viscusi (1985a, 1985b), Viscusi and Magat (1987, 1992), Viscusi et al. (1986), and Viscusi and

[13] The chair of the Department of Economics would not approve the dedication of lecture time for the students to complete the questionnaires in the classes of other faculty members, so our response rate was much lower than it might have been.

[14] Given the exploratory nature of the sample, we have not pursued non-respondents aggressively.

[15] Except where it may lead to confusion, we now drop the 0 superscript on E*[w^0], Var*[w^0] and the corresponding quantities for the native subjective distribution of future annual average temperatures, as well as the distributions attributed to government scientists and environmental groups.

[16] The issue of long-term environmental risks is addressed in Fischoff (1990).

[17] Benson, Curley and Smith (1995) address the role of belief assessment in the process of eliciting

O'Connor (1984). In almost all cases, however, the risks under consideration are physical health or workplace risks. But "risk" can be defined more broadly to include preferences over uncertain outcomes more generally.

For climate change, the variable that I designate to illustrate the uncertainty is annual average temperature during a decade twenty years into the future. At the beginning of the survey, we elicit from the respondent their initial assumptions about the future distribution of the **w** variable. Historical data are provided for the weather station nearest the respondent. Provision of this information insures that the respondent is making his or her forecast for the expected value and dispersion of *future* mean temperatures (for the decade of 2011-2020) based on valid *current* data.

After establishing the true local annual average temperature, we first elicit information on the mean and variance of the individual's *native subjective distribution* for future environmental quality. Expected values seem relatively easy to elicit. It is more difficult to ask respondents to convey information on variances. For dispersion measures, we have elected to ask for "plus" and "minus" amounts relative to their expected value (and described as a 95% range), and then to interpret this as four standard deviations, squaring 0.25 times this amount to yield a variance approximation.

Once these prior distributions have been established, the respondent is presented with information describing the distributions of future average temperatures (purportedly) forecasted by government scientists and by environmental groups.[18] One objective of the analysis is to discriminate among the effects of different external information sources on the respondent's distributional updating process. The design of the different survey versions ensures that there is orthogonal variation across respondents in these purported external forecasts.

---

probabilities.

[18] This information is part of the experimental design of the survey. All stylized forecasts fall within the range of assorted actual forecasts. Concerning survey research ethics, there is the delicate matter of not lying to respondents. Since we are purposefully vague about the precisely *which* "government scientists" and "environmental groups" have made these forecasts, there may be some natural attenuation of the credibility assigned by respondents to these opinions.

After the external information on future climate has been provided, respondents are invited to update their priors on the distribution of future annual average temperatures, giving both a new expected value and a new 95% range (which we convert to a variance, again invoking strong distributional assumptions).

b.) ***Data on Willingness to Pay to Prevent Climate Change***

No established markets exist for the mitigation of climate change. Furthermore, there are few opportunities to invoke weak complementarity and to rely on indirect market information to infer implicit demands for climate change mitigation. Despite the acknowledged shortcomings of contingent valuation methods, direct elicitation of people's stated willingness to trade off money for environmental protection is likely to be the best source of information about the social value of climate change mitigation activity.

Prior to the valuation question, the survey respondent has been asked about their opinion of climate change prospects. We also invite respondents to consider the implications for a variety of climate services of an arbitrary 4 degree Fahrenheit average temperature increase. Demand for climate services give rise to derived demand for climate change mitigation. These effects on climate services are captured by questions concerning the following:

- heating costs
- air-conditioning costs
- personal comfort
- food prices
- severity of storms
- frequency of storms
- frequency of droughts
- water consumption [prices]
- housing prices in your region
- sea levels
- tropical diseases
- welfare of the poorest 50% of US residents
- welfare of the poorest 50% of the world's population

Having explored with the respondent the anticipated consequences of failing to prevent a 4 degree Fahrenheit temperature increase, we then review the respondent's probable budget constraint over the relevant future period. We elicit expected annual income categories (in 1997 dollars) for the year 2005 and the year 2020. The proposed policy is described as follows:

> Suppose that policy-makers have identified a set of domestic and international environmental **regulations and incentives.** *If put into place, these policies will prevent any detectible change in your regional climate so that average temperatures will continue, indefinitely, to be much as they were during 1987-1996.* In other words, putting these policies in place would allow society to avoid any of the consequences (bad or good) to be expected if we do nothing.

The monthly costs of the policy are assigned randomly, in ten different amounts from $5 to $150, presented in the following form:

> Suppose that these policies will mean higher prices and/or higher taxes so that by the year 2000, your monthly household costs will be higher by $______ (in 1997 dollars) for as long as these policies are followed.

Respondents are then asked if they would vote in favor of this package of policies, given their expected income and these costs. They are then probed to detect "protest bids." The last part of the survey collects sociodemographic and attitudinal variables, including the respondent's perceptions of bias (for or against the policy) on the part of the research team.

The basic option price model can be estimated using data on: the YES/NO response to this question, the exogenously assigned value of monthly costs, t, imposed for this respondent, information on other sociodemographic characteristics, s, current environmental quality w^1, and the values of $E^*[w]$ and $Var^*[w]$ (which can be explained by the pair of equations in the revised subjective distribution submodel).

6. Empirical Findings

Given the exploratory nature of the empirical work in this study, we have not pursued state-of-the-art simultaneous full information maximum likelihood (FIML) estimates of the three equations involved in this specification. In future work, when a more-representative data set can be collected, more sophisticated estimation techniques will be warranted. These would involve a cumulative trivariate normal joint density function for the three error terms.

a. *Models for the Revised Subjective Moments of Future Average Temperatures*

How do survey respondents process the information attributed to government scientists and environmental groups when they are given the opportunity to update their own opinions in the light of this additional information? One possibility is that they may be Bayesians. In the presence of two additional sources of information about mean and variance (precision) of a distribution, the usual Bayesian formulas appear to generalize straightforwardly. The posterior mean should be a precision-weighted average of the component means. The posterior precision should be the sum of the component precisions.[19]

In order to simplify the notation, define the sum of precisions:

$$D = (Var[w]_{own})^{-1} + (Var[w]_{gov})^{-1} + (Var[w]_{env})^{-1}. \tag{16}$$

It seems appropriate to test whether the updating process could be Bayesian (or whether it is more general) by specifying the following two regression models, one for the posterior expected value, and one for the posterior precision:

---

[19] Some research on the issue of whether individuals are Bayesian decision-makers includes Viscusi (1985b), Viscusi and Magat (1992), Viscusi and O'Connor (1984), and Fischoff and Beyth-Marom (1983).

$$(17)\quad E^*[w] = \alpha_0 + \alpha_1 E[w]_{own}/(D^*Var[w]_{own}) + \alpha_2 E[w]_{gov}/(D^*Var[w]_{gov}) + \alpha_3 E[w]_{env}/(D^*Var[w]_{env}) + \varepsilon_E$$

$$(18)\quad (Var^*[w])^{-1} = \beta_0 + \beta_1 (Var[w]_{own})^{-1} + \beta_2 (Var[w]_{gov})^{-1} + \beta_3 (Var[w]_{env})^{-1} + \varepsilon_P.$$

Estimating these two models, and testing the joint hypothesis that $\alpha_0 = 0$ and $\alpha_1 = \alpha_2 = \alpha_3 = 1$ for the expected value model and the joint hypothesis that $\beta_0 = 0$ and $\beta_1 = \beta_2 = \beta_3 = 1$ for the precision model (either separately, or jointly) would constitute a rough test of whether the updating process could indeed be strictly Bayesian.

Table 2 shows the results for unrestricted estimation of the models in equations (17) and (18), as well as estimates when the intercepts are constrained to zero. While the point estimates of the slope parameters appear close to unity in the case of the expected value equation (17), F-tests of the restriction that all slopes be simultaneously unity soundly reject that hypothesis. (The P-values for these F-tests are essentially zero for the expected value equation. For the precision equation (18), the point estimates of the slopes are markedly different from one, and the null hypothesis of jointly unitary slopes is again rejected conclusively. These individuals are not behaving like Bayesians.

A competing model might be that respondents' updated expected values and updated variances are determined more simply. Consider the hypothesis that $E^*[w]$ is simply a linear function of $E[w]_{own}$, $E[w]_{gov}$, and $E[w]_{env}$, instead of a more-elaborate linear function of the precision-weighted expectations as implied for testing Bayesian updating. This competing model (which we will call H1) is:

$$(19)\quad E^*[w] = \alpha_0 + \alpha_1 E[w]_{own} + \alpha_2 E[w]_{gov} + \alpha_3 E[w]_{env} + \varepsilon_E.$$

The model in Equation (17) above (which we will call hypothesis H2) subsumes the Bayesian updating model as a special case where $\alpha_0 = 0$ and $\alpha_1 = \alpha_2 = \alpha_3 = 1$.

These non-nested hypotheses can be tested. We perform a Cox test and a Davidson-

MacKinnon J-test for these competing models, for specifications with and without intercepts. For specifications including an intercept term, the Cox test rejects both H1 and H2. The J-test procedure fails to reject H1 (the simple linear relationship) at the 5% level but can reject at the 10% level. The J-test procedure, however, does soundly reject H2 (the generalized Bayesian relationship), since the fitted value from the simple linear model, when included in the Bayesian model, bears a t-test statistic greater than 6. The results for specifications that suppress the intercept term are qualitatively the same.

For the variances, analogous Cox and J-tests are not appropriate. Again, the competing model (versus Bayesian behavior) should probably consist of a simple linear relationship between $Var^*[w]$ and the constituent variances, $Var[w]_{own}$, $Var[w]_{gov}$, and $Var[w]_{env}$. The dependent variable in the Bayesian specification, however, is the posterior *precision*, not the posterior *variance* (unless nonlinear-in-parameters models are broached) so the competing variance specifications are not as amenable to Cox or J-tests.

This preliminary evidence seems to suggest quite clearly, however, that the strict Bayesian formulation is probably not appropriate in this context, particularly for the variance. The simple linear model appears to dominate even the *generalization* of the Bayesian specification with nonzero intercept and non-unitary slopes. So it is reasonable to consider possible ad hoc specifications more carefully. We will focus first on models to explain $E^*[w]$.

In Table 3, Model 1, we specify $E^*[w]$, the respondent's revised subjective average annual temperature, as a simple unrestricted linear function of $E[w]_{own}$, $E[w]_{gov}$, and $E[w]_{env}$. Model 2 imposes the restriction that the intercept be zero, which cannot be rejected at the 5% level according to the t-test statistic on the intercept in Model 1. With this restriction, the individual slopes are all strongly statistically significant. Model 2 is offered in order to test for the presence of Viscusi/Magat "alarmist learning." With a zero intercept imposed, but the slope parameters free to take on whatever values are dictated by the data, the absolute value of the F-test statistic for the null hypothesis that the sum of the slopes on $E[w]_{gov}$ and $E[w]_{env}$ is one achieves a value in excess of 12[revise]. The point estimate of the sum is on the order of 0.60[revise], so there is no evidence of alarmist learning in this sample.

Model 3 restricts $E^*[w]$ to be a simple weighted average of the component expectations (i.e. zero intercept, slopes summing to unity). An F-test of these restrictions (compared to the unrestricted specification in Model 1) fails to reject these three restrictions.

Model 4 explores the hypothesis that the extent of the disparity between the two outside sources of information about the E[w] will affect the weight applied to $E[w]_{own}$. In an otherwise unrestricted specification, Model 3 shows that greater disparity between $E[w]_{gov}$ and $E[w]_{env}$ does indeed increase the weight on the own-expectation by a statistically very significant amount. Based on this finding, and the fact that the intercept coefficient in Model 4 is insignificantly different from zero, we will be generalizing Model 4 to incorporate systematic varying parameters in our subsequent modelling efforts for $E^*[w]$.

Model 5 is the last experimental specification for $E^*[w]$. Here, we allow $E^*[w]$ to depend (in an ad hoc fashion) upon not only the three component expectations, but also upon the three component variances, with the weight on the own-expectation and own-variance allowed to differ according to the disparity between the corresponding "external information" moments. None of the three variance terms is a statistically significant factor in determining $E^*[w]$, and neither is the variance-disparity interaction term.

Table 4 explores some simple linear specifications for the relationship between posterior variance and the three component variances. The unrestricted linear specification in Model 1 shows the intercept to be insignificantly different from zero. Model 2, in contrast, restricts the intercept to zero and forces the slopes to sum to unity. This set of three restrictions cannot be rejected. For these preliminary data, then, both expected values and variances seem to be reasonably well approximated by simple weighted averages of the three components. These models will be the basis for the generalizations to be described next.

In Table 5, we show the results of employing the available variables capturing respondent characteristics as factors that may shift an individual's relative weights on the different sources of information about future climate conditions (for both the mean and the variance). The estimates stem from a two-equation simultaneous non-linear least squares model that is specified in a manner that ensures that the models display zero intercepts and non-negative weights that sum to unity, for both the expectation equation and the variance equation. In order to minimize the notation, the subscripts "gov" and "env" have been abbreviated to "g" and "e". The basic form of the model is as follows:

$$(20)\quad E^*[w] = (1+ \kappa_E\,|E[w]_g - E[w]_e|)\,[(1+\kappa_E\,|E[w]_g-E[w]_e|) + \exp(\gamma_g) + \exp(\gamma_e)]^{-1}\,E[w]_{own}$$
$$+ \exp(\gamma_g)\,[(1+\kappa_E\,|E[w]_g-E[w]_e|) + \exp(\gamma_g) + \exp(\gamma_e)]^{-1}\,E[w]_g$$
$$+ \exp(\gamma_e)\,[(1+\kappa_E\,|E[w]_g-E[w]_e|) + \exp(\gamma_g) + \exp(\gamma_e)]^{-1}\,E[w]_e + \varepsilon_E$$

$$(21)\quad V^*[w] = (1+ \kappa_V\,|V[w]_g - V[w]_e|)\,[(1+\kappa_V\,|V[w]_g-V[w]_e|) + \exp(\delta_g) + \exp(\delta_e)]^{-1}\,V[w]_{own}$$
$$+ \exp(\delta_g)\,[(1+\kappa_V\,|V[w]_g-V[w]_e|) + \exp(\delta_g) + \exp(\delta_e)]^{-1}\,V[w]_g$$
$$+ \exp(\delta_e)\,[(1+\kappa_V\,|V[w]_g-V[w]_e|) + \exp(\delta_g) + \exp(\delta_e)]^{-1}\,V[w]_e + \varepsilon_V$$

Each of the six parameters, κ_E, κ_V, γ_{gov}, γ_{env}, δ_{gov}, and δ_{env} could be estimated as a true but unknown constant parameter, analogous to the independently estimated specifications in Table 3 (Model 4) and Table 4 (Model 3). Instead, we have rendered each of the γs and δs a systematic varying parameter. We employ as shifters for all of these four parameters (i.) a set of available sociodemographic variables (AGE, gender), as well as (ii.) attitudinal variables (informedness about environmental issues, degree of conservatism, likelihood of living in the same area in the future, and perceptions of researcher bias), and (iii.) a dummy variable to identify observations collected in the Fall of 1997. Not all of these variables are statistically significant shifters of the systematic varying parameters in this specification. Persistently insignificant terms have therefore been dropped.

The model in Table 5 allows for Viscusi/Magat ambiguity effects. Each of the E*[w] and Var*[w] equations in the joint model is augmented with a single ambiguity parameter, κ_E and κ_V, respectively, that allows the weight placed on the individual's own priors to vary systematically with the absolute difference between the two external opinions.

The implications of the estimated model in Table 5 seem plausible. While it is not possible to distinguish an age effect from a cohort effect in a cross-sectional sample such as this, it nevertheless appears that older college students place less weight on government opinions and on environmental group opinions in deciding upon Var*[w].

Gender has a statistically significant effect on all four weighting parameters. In formulating E*[w], female students place relatively more weight on government and more on environmental groups than do male students. For Var*[w], they also put more weight on the opinions of both external groups than do male students. Subjective degree of informedness about environmental issues does not have a significant effect upon any of the weights.

Students who identify themselves as being more conservative appear to place systematically less weight on environmental groups' opinions about E*[w] than do more-liberal students. More-conservative students also place significantly less weight on government scientists' opinions about temperature uncertainty. The more likely the student is to remain in the same region in the future, the more weight they tend to place on government scientists opinions in formulating their assessments of E*[w] and Var*[w]. (Alternately, the more likely it is that they will move to another region before the future time period stipulated in the survey, the less attention they pay to government opinion about E*[w] and Var*[w].)

The more the research team is perceived to be biased in favor of climate change mitigation programs, the less is the weight assigned to the ostensible external information sources in formulating an opinion about E*[w]. However, perceptions of researcher bias have no statistically discernible effects on the weights assigned to different information sources in formulating a revised subjective variance for w.

Respondents in the Fall 1997 subsample appear to be very strongly statistically significantly less attentive to the degree of uncertainty about future climate conveyed by both government scientist opinions and environmental group opinions. This apparent effect may be an artifact of the greater representativeness of the Fall 1997 sample. (No extra-credit incentives were provided in the earlier sample, so self-selection in responses is a greater problem there.)

b. ***Models to Explain Option Prices (Willingness to Pay)***

How willing are respondents to vote in favor of the climate change mitigation policies at different levels of cost? Given the microeconomic theory behind our estimating specification, the discrete choice probit model explaining stated voting behavior can be used to produce fitted estimates of individuals' option prices for climate change mitigation. Table 6 displays the results from some preliminary models using our exploratory sample.

Keep in mind that our basic estimating specification is based on a utility difference function with three parameters (the coefficients on log[(Y-t)/Y], E*[w], and Var*[w]).[20] Introducing respondent heterogeneity (potentially) generalizes each of these three parameters to a linear function of individual attributes. This is how we accommodate preferences that differ according to the observable characteristics of different groups of respondents.

Model 1 is the most rudimentary specification, since it assumes homogeneous preferences and even excludes Var*[w]. The initial term, log[(Y-t)/Y], ought always to be important, since it captures both the effect of income and that of policy costs. It is solidly significant in all the specifications shown in Table 6. If E*[w] is the only regressor capturing the character of the expected change in

---

[20] For ease of estimation with packaged maximum likelihood algorithms, we allow for an intercept term in the specifications to be described here. In none of our models is the point estimate for this intercept terms statistically significantly different from zero. Thus the qualitative results are unlikely to be very sensitive to whether this intercept is suppressed.

climate to be avoided by incurring the stated costs, its coefficient is positive, but statistically insignificant. This implies "insensitivity to scope," acknowledged to be an undesirable property in a stated preference valuation exercise (Arrow et al., 1993).

If we still assume homogeneous preferences and include both E*[w] and Var*[w], as implied by equation (12) in the theoretical section, the coefficient on E*[w] becomes marginally significant at the 10% level. These results, under an assumption of homogenous preferences throughout the sample, may seem somewhat disappointing. Models 3 through 6, however, reveal the possibility of some important heterogeneities in preferences across the sample.

Under some conditions, gender is an important factor in determining willingness to pay for climate change mitigation (where climate change is interpreted by most people as "global warming"). Unfortunately, the overall effect of any specific individual attribute, such as gender, on fitted option prices for climate change mitigation is a rather complex function of all the parameters and all the data. The overall effects of gender on option prices will be illustrated via simulation exercises in the next section.

Model 6 will be our working specification for the upcoming simulations. One interesting feature of this model is the distinction between gender effects and sample-time effects (FALL97), and their interaction. In the Winter/Spring 1997 subsample, women were much less willing to pay to prevent climate change. One could speculate that women, as a group, are more inclined to feel the cold than are men (there is some anecdotal evidence to this effect). However, the very strong gender effect that existed in the initial Winter/Spring 1997 sample failed to persist when these data were pooled with observations from the Fall 1997 sample. There are a number of possible reasons for this outcome. First, the weather was much hotter at the time the Fall 1997 sample was collected, and women and men may respond differently to current weather conditions in conveying their willingness to pay for climate change mitigation. Alternately, the different gender effects in the two subsamples may be a consequence of the fact that participation was less self-selected in the Fall 1997 sample due to the extra credit associated with submitting a completed questionnaire. Also, the Fall 1997 classes were all students of the researcher (as opposed to other faculty). Larger and more diverse samples, collected in in a number of different seasons, would be necessary to distinguish these effects.

From Models 3 through 6, where the scope effect (the coefficient on E*[w]) is allowed to vary with respondent characteristics, we learn that the scope effect differs systematically across our sample. Age appears to increase the scope effect, and informedness about environmental issues also increases it. However, greater conservatism lessens the scope effect. The effect of gender is difficult to discern, since it is confounded with sample timing.

A key feature of this paper is the question of whether uncertainty about future climate conditions influences respondents' willingness to support climate change mitigation programs at any given cost. Models 5 and 6, which control for the greatest amount of heterogeneity across respondents, display a statistically significant negative effect of Var*[w]. The more likely it is that the respondent expects to be living in the same region, however, the less negative the effect of greater climate uncertainty. (Or, alternately, plans to live in a different geographic region exacerbate the negative effects of uncertainty on willingness to vote for mitigation policies.)

7. Simulations

If models like the ones in this paper could be estimated with richer data, they will permit counterfactual simulations that are potentially very relevant to policy-making. With the limited data currently available, we pursue simulations with caveats. The sample size and representativeness are insufficient to allow general conclusions to be drawn. Some straightforward simulations will nevertheless illustrate the potential of the model.

Simulations are necessary because the point estimates of option price are non-linear functions of the data and the estimated model parameters. Equation (14) can be used to produce point estimates of the expected value of OP for each individual in the sample. We can then report descriptive statistics for these point estimates (mean, standard deviation, median) calculated across all individuals in the sample.

For the simulations that follow, we employ the non-Bayesian simultaneous nonlinear equations specifications and parameter estimates of the E*[w] and Var*[w] equations in Table 5, and the option price equation of Model 6 in Table 6. The first two lines in the body of Table 7 display descriptive statistics for fitted expected option prices (with monthly expected future income statistics for comparison). Option price point estimates range widely in the sample, with all of this variation attributable to differences in expected income and other individual attributes.[21] One class of simulations concerns what would happen if everyone had instead placed zero weight on the opinions of one (or the other) of the external authorities. In our counterfactual simulations, we scale the weights on the remaining information sources so they continue to sum to one. If everyone placed zero weight on the opinions of environmental groups, the average OP would increase from $268 to $272--probably not a significant change. If people ignored the opinions of government scientists, the average OP would increase to $270, which does not represent an appreciable difference either.

A second class of simulations concerns changes in the sociodemographic or attitudinal variables that influence the weights placed on different information sources by individuals as they arrive at E*[w] and Var*[w]. We use E*[w] and Var*[w] directly in the option price probit model, not their fitted values. Counterfactual simulations concerning sociodemographics or attitudes are assumed to change the fitted portion of these variables; we retain the estimated error term, however.

We make modest changes in some of the variables that affect the weights, and the simulations reveal the overall effects of these changes on predicted OP values. Making everyone in the sample 4 years older, without changing any of their other characteristics, would reduce option prices from the

---

[21] As individual expected option prices are calculated, estimates less than zero are counted as zero, and occasional fitted values in excess of income are counted as equal to income (there are only about a dozen cases where this occurs).

current average of 268 to only 162. Age (or perhaps it is a cohort effect) has a pronounced effect on perceived benefits of climate change mitigation. If everyone was made one unit subjectively more-informed about environmental issues (to a maximum of the sample upper bound of 7 units), mean expected option prices would increase from 268 to 291. If everyone was made one unit more conservative, option prices would drop from 268 to 229. If *mobility* increased by one unit, the overall effect on mean expected option prices would be negligible (from 268 to 271).

Eliminating everyone's uncertainty about future climate (but leaving their individual $E^*[w]$ unchanged would increase option prices from 268 to 300. Eliminating all uncertainty and convincing everyone that there would be a temperature increase of one degree Celsius would increase WTP from 268 only to 271. However, a certain temperature increase of two degrees Celsius would boost expected option prices to 303 on average.

The size of the gender effect on option prices for climate change mitigation can also be assessed. It is not sufficient merely to divide the sample by gender and to calculate the average fitted option price for each subsample. Systematic differences in other attributes, by gender, could obscure the gender effect. Instead, we illustrate the size of the gender effect, ceteris paribus, by counterfactual simulations. First, we make all respondents females (while retaining all of their other attributes, namely age and the attitudinal variables). This will affect the weights on different information sources in the calculation of $E^*[w]$ and $Var^*[w]$, as well as the gender dummy variable in the option price probit equation. Due to the complex interaction of gender with the FALL97 survey-timing variable, the mean option price if all respondents had been female is predicted to be $268. In contrast, if we make all respondents males (again retaining all of their other attributes), the sample average option price would increase to $283. The difference in mean expected option prices between the genders appears to be about $15 per month, with men willing to pay more for climate change mitigation.

8. <u>A Generalization: Demand for Climate Services</u>

One of the generalizations proposed in the theory section can be examined in a crude fashion with these limited data. In lieu of E*[w] and Var*[w], the moments of the anticipated distribution of future annual average temperatures, we consider substituting each respondent's assessment of the future levels and variances of an array of climate services. Table 7 displays four different specifications of models for deriving option prices in terms of climate services.

In the survey instrument, we asked each respondent to speculate on the likely effects of one particular increase in average temperatures, namely a 4 degree Fahrenheit increase. Assuming linearity, we then apply their best guess about this effect to their reported E*[w]. The range of climate services addressed included: heating costs (HEAT), air-conditioning costs (AIR), personal comfort, food prices, severity of storms (SEVR), frequency of storms, frequency of droughts, water consumption (WATR), regional housing prices, sea levels, tropical diseases, the welfare of the poorest 50% of US residents, and the welfare of the poorest 50% of the world's population (EQWL). We attempted to elicit enough information to construct no only expected values, but also anticipated "variances" in the future levels of these services.[22]

Despite the variability in E*[w] across respondents, individuals' assessments of the effects on different climate services of a 4 degree Fahrenheit increase in temperatures are rather collinear. Nevertheless, a number of significant effects are revealed in Table 7.

Since the sample was collected in Los Angeles, air-conditioning expenses are probably a more salient consideration than heating costs, although most modern homes are heated during the winter season, at least at night. The scope effect in terms of expected heating cost increases avoided by mitigation is larger for females than for males.

[22] Table 7 includes a dummy variable for "Non-zero Var?" which takes on a value of 1 if the respondent offered a range of values for the future level of at least one climate service. This confirms that they understood the opportunity to express uncertainty. We do not wish to confound failure to understand the survey instructions with perfect certainty about climate services. This means that the coefficients on any variance terms are *conditional* on

The scope effect with respect to higher air conditioning costs is positive, but this scope effect varies directly with the respondents' subjective informedness about environmental issues. The more severe the storms that are expected to be avoided by mitigation, the more willing is the respondent, on average, to support mitigation policies.

If some variance in the increase in anticipated heating costs (without mitigation) was expressed by the respondent, greater variance (uncertainty) increases support for climate change mitigation policies. In contrast, greater variance (uncertainty) about air conditioning costs reduces support for climate change mitigation. These effects are more strongly revealed in the Fall 1997 subsample, which was collected at the end of a heat wave.

Uncertainty about the effects of climate change on water consumption appears to have a significant negative effect on support for mitigation policies for females. In contrast, uncertainty about the effects of climate change on world distributional equity appears to have a positive effect on support for climate change mitigation measures among females.

The models in Tables 6 and 8 are not nested, so no formal hypothesis testing can be performed. But it is interesting to note that the maximized values of the log-likelihood functions in Table 8 seems to be higher than the models of roughly corresponding complexity in Table 6. Non-nested tests will certainly be indicated with richer data sets.

9. Conclusions and Directions for Future Research

Due to the small convenience sample used for the empirical exercise in this study, the findings from the analysis of this survey are not conclusive. They are, however, very thought-provoking. The issue of how individuals process the disparate information they receive concerning climate change has not been addressed before, and it will be a key political issue over the next few years. People do not

---

the respondent having expressed nonzero variance in at least one case.

appear to be Bayesian in this matter. The jointly estimated systematically varying parameters models for the mean and variance of future average temperatures reveals behavior patterns that seem intuitively plausible. With a sample that is representative of the broader population, richer models could undoubtedly be supported.

The derivation of a simple but rigorous model of the theoretic underpinnings of a referendum discrete choice model for climate change mitigation is also important. Option prices have been argued to be the correct theoretical construct for cost-benefit analysis of public policies under uncertainty. A simple state-preference model with a well-defined indirect utility function is shown in this paper to lead to a convenient empirical specification for use with respondent's subjective assessments of the expected value and variance of future climate conditions. This degree of rigor allows the estimated model to be solved for the theoretically appropriate valuation construct. The specifications that can be supported with the current data are admittedly rudimentary. Richer data will allow more elaborate (and realistic) models in the same spirit.

Wherever the estimated parameters of our option price models are statistically significant (or might approach significance in larger samples), many of their signs are plausible. Knowledge of the nature of heterogeneity in preferences with respect to climate change mitigation will be a very important consideration in the politics of "selling" (or derailing) climate change mitigation policies.

We have found persuasive evidence, even in this small sample, that the scope of climate change in the absence of mitigation makes a statistically significant difference in individuals' willingness to pay for mitigation. This is an expected and satisfying result. Greater climate uncertainty also seems to reduce people's willingness to incur the costs of climate change mitigation. Resolving the role of uncertainty about future climate in determining the strength of support for climate change policies should be an important item on the research agenda. The results in this paper suggest that, for any group that is trying to limit support for climate change mitigation, a campaign to amplify uncertainty about future climate conditions will lead to reduced support for mitigation policies.

This paper has also reported on an alternative view of what drives WTP for climate change mitigation. If climate services, rather than climate itself, enter into the utility function, different empirical specifications are appropriate. We have demonstrated that models in terms of climate services are potentially viable.

The next phase of this research program consists of an on-line (World Wide Web) enhanced version of the classroom surveys used to generate the data analyzed in this paper. (A prototype version of the survey, which is still under development, can be found at the URL http://www.sscnet.ucla.edu/ssc/labs/cameron/ClimateSurvey.html. The software has been developed with the valuable assistance of Geoffrey Gerdes.) By surveying "classroom samples" at other universities in North America and possibly around the world, we can get a better sense of how WTP for climate change mitigation varies with regional climate, with variation in survey-date weather conditions, with differences in fields of study among these students, and across universities and countries. We are working on a survey instrument that will eventually be offered in different languages (initially just English, French, and Spanish), and with links to local historical climate data and currency conversion software. Samples will be collected in collaboration with faculty correspondents at other universities, so that information can be gleaned from these faculty about the nature of each student population from which respondents are recruited. This information will be critical to the process of modelling sample selectivity.[23]

Online surveys are very promising for the intermediate phases of survey development. World Wide Web access is not yet sufficiently universal to allow for representative samples, but a great deal

---

[23] Anyone interested in having students at their institution participate in this survey is invited to contact the author at tcameron@econ.ucla.edu. We are most interested in large classes of students in courses that do *not* have environmental economics specifically as their main subject matter (to avoid having samples biased in favor of environmental causes). Corresponding faculty will have access to the full data set collected as part of the study. We plan to have the online survey remain open for several years. At intervals, different modules of questions may be appended to the main survey instrument to allow for a variety of studies. It is hoped that this online survey will become a data resource for many researchers.

can be learned about the variety of preferences in some well-defined subpopulations. Telephone surveys were unreliable in the 1930s due to insufficient market penetration, but they are now widely employed to good effect. It may be a decade or more before Web access is sufficiently universal to make it a useful medium for survey research. In the meantime, there is much to be learned about the special capabilities of Web-based surveys that make them very attractive for research.

REFERENCES

Adler, Robert S. and R. David Pittle (1984) "Cajolery or Command: Are Education Campaigns an Adequate Substitute for Regulation?" *Yale Journal of Regulation* 1(2) 159-194.

Arrow, Kenneth (1982) "Risk Perception in Psychology and Economics," *Economic Inquiry* 20, 1-9.

Arrow, Kenneth J., Robert Solow, Edward E. Leamer, Paul Portney, Roy Radner, and Howard Schuman (1993), "Report of the NOAA Panel on Contingent Valuation," *Federal Register* 58, 4601-4614.

Benson, P.G., Curley, S.P. and Smith, G.F. (1995) "Belief Assessment - An Underdeveloped Phase of Probability Elicitation," *Management Science* 41(10) 1639-1653.

Cameron, Trudy Ann, and Jeffrey Englin (1997) "Welfare Effects of Changes in Environmental Quality Under Individual Uncertainty about Use," *RAND Journal of Economics*, **28**(0) Special Issue in honor of Richard E. Quandt, S45-S70.

Davies, J. Clarence, Vincent T. Covello, and Frederick W. Allen, eds (1987) *Risk Communication: Proceedings of the Conference on Risk Communication*. Washington, D.C: The Conservation Foundation.

Fischoff, Baruch (1990) "Understanding Long-Term Environmental Risks," *Journal of Risk and Uncertainty* 3, pp. 315-30.

Graham, Daniel A. (1981) "Cost-Benefit Analysis under Uncertainty," *American Economic Review* 71 (715-725).

Heath, Chip, and Amos Tversky (1991) "Preference and Belief: Ambiguity and Competence in Choice Under Uncertainty," *Journal of Risk and Uncertainty* 4(1), 5-28.

Hirshleifer, Jack, and John G. Riley (1992) *The Analytics of Uncertainty and Information*, New York: Cambridge University Press.

Johnson, B.B. and P. Slovic (1995) "Presenting Uncertainty in Health Risk Assessment - Initial Studies of Its Effects on Risk Perception and Trust," *Risk Analysis* 15(4) 485-494.

Machina, Mark (1987) "Choice under Uncertainty: Problems Solved and Unsolved." *Journal of Economic Perspectives* 1, pp. 121-54.

Slovic, Paul, Baruch Fischoff, and Sarah Lichtenstein (1985) "Regulation of Risk: A Psychological Perspective," in Roger Noll (ed.) *Regulatory Policy and the Social Sciences*, Berkeley, CA: University of California Press.

Smith, V. Kerry, and William Desvousges (1987) "An Empirical Analysis of the Economic Value of Risk Changes," *Journal of Political Economy* 95, pp. 89-114.

Smith, V. Kerry, and William Desvousges (1988) "Risk Perception, Learning and Individual Behavior," *American Journal of Agricultural Economics* 70, pp. 1113-17.

Smith, V. Kerry, and F. Reed Johnson (1988) "How Do Risk Perceptions Respond to Information? The Case of Radon," *Review of Economics and Statistics* 70(1) 1-8.

Viscusi, W. Kip (1985a) "A Bayesian Perspective on Biases in Risk Perception," *Economics Letters* 17, 59-62.

Viscusi, W. Kip (1985b) "Are Individuals Bayesian Decision Makers?' *AEA Papers and Proceedings*, pp. 381-385.

Viscusi, W. Kip, and Wesley A Magat (1987) *Learning about Risk: Consumer and Worker Responses to Hazard Information*. Cambridge: Harvard University Press.

Viscusi, W. Kip, and Wesley A. Magat (1992) "Bayesian Decisions with Ambiguous Belief Aversion," *Journal of Risk and Uncertainty* 5, 371-387.

Viscusi, W. Kip, Wesley A. Magat, and Joel Huber (1986) "Informational Regulation of Consumer Health Risks: An Empirical Evaluation of Hazard Warnings," *Rand Journal of Economics* 17, 351-365.

Viscusi, W. Kip, and Charles J. O'Connor (1984) "Adaptive Responses to Chemical Labeling: Are Workers Bayesian Decision Makers?' *American Economic Review*, 942-956.

Fischoff, Baruch, and Ruth Beyth-Marom (1983) "Hypothesis Evaluation from a Bayesian Perspective," *Psychological Review* 90, pp. 239-60.

Pratt, John, Howard Raiffa, and Robert Schlaifer (1975) *Introduction to Statistical Decision Theory*, New York: McGraw-Hill.

Tversky, Amos and Kahneman, Daniel (1974) "Judgment under Uncertainty: Heuristics and Biases," *Science* 185, 1124-31.

APPENDIX

Other Generalizations to Consider

a. ***Uncertainty About w^1 As Well As w^0***

The basic model described above assumes that all of the uncertainty about the future state of the environment, if mitigation is not pursued, can be reduced to a distribution on a single variable, w^0--future environmental quality in the absence of mitigation efforts. The first logical extension is to admit that individuals may *also* be uncertain about future environmental quality if protection policies are in fact implemented. It is likely that w^1 is also uncertain. How does the model change if one allows for subjective uncertainty about the level of w^1 as well as w^0? The uncertainty can now be characterized as the individual's joint revised distribution $f^*(w^1,w^0)$.

The analogous formula for the expected utility-difference in equation (13) now involves additional data for $E^*[w^1]$ and $Var^*[w^1]$--the other marginal moments of the individual's revised subjective *joint* distribution for w^1 and w^0. To allow for state-dependent preferences, the indirect utility function again varies systematically with the realizations of the uncertainty (now for both w^1 and w^0). The estimating specification now takes the form:

(A1) $$E_{w^0}[V^1 - V^0] = \beta_0 \log[(Y - t)/Y] + \delta_0 \{E^*[w^1] - E^*[w^0]\} + \delta_1 \{Var^*[w^1] - Var^*[w^0]\} + \varepsilon.$$

Analogous to the simpler case, parameters to be estimated are again the scalars (or vectors) β_0, δ_0, and δ_1. More-elaborate formulations of the basic indirect utility function can necessitate using $Cov[w^1,w^0]$, but this simple specification in equation (8) avoids this requirement. Of course, if w^1 and w^0 are assumed independent in the mind of the respondent, $Cov^*[w^1,w^0] = 0$ can be assumed.

To implement many of the richer models, it will be necessary to elicit from each respondent the extent to which the two future outcomes, w^1 and w^0, are correlated. Since some measure of correlation is probably easier to elicit that the concept of covariance, one could replace $Cov^*(w^1,w^0)$ with the product of the individual's correlation and the two relevant standard deviations.

To elicit correlations, it would be necessary to craft very carefully an introduction to the idea of joint variability. One might then show the respondent a number of representative scatters of points in (w^1,w^0)-space with degrees of correlation varying between -1 and + 1 (although negative correlations may not be relevant). These scattergrams could be arrayed along a line indexed from -1 to + 1, and respondents could then be asked to mark a point on the line that indicates which degree of correlation looks most plausible to them.

If the concept of correlation cannot be conveyed, this factor could be assess qualitatively. For example, it might only be established that correlation is positive or negative, and then high, medium, or low. It would be necessary to describe in words the interpretation of correlation. Respondents could be asked whether they would expect underlying factors to drive both temperatures higher or lower, regardless of whether mitigation is pursued (leading to positive correlation). Or, they might be informed that mitigation could be more or less effective than anticipated, and at the same time, the consequences of no mitigation could be better or worse than anticipated (so that a zero correlation could be plausible).

b. ***<u>Uncertainty About Costs (and Other Variables)</u>***

The simple model we have used in this paper makes use only of the uncertainty in the future climate variable. The real decision context for individuals also involves uncertainty about future income, the prices of substitutes and complements in the future, and about the true opportunity costs of the climate change mitigation programs that are being proposed. These additional sources of uncertainty could be incorporated into the model.

c. ***<u>Multiple Dimensions of "Climate"</u>***

In reality, climate is characterized by many correlated variables. Global climate change may *simultaneously* affect the levels of such typically recorded variables as winter and summer temperatures, humidity, wind speed and direction, heating and cooling degree days, percent sunshine, precipitation (rain and snow), expected frost dates, and so on. It is probably not feasible with current technologies to convey to respondents (or to elicit from them) a forecasted joint distribution for more than two variables if these variables are correlated.

One can easily generalize the basic model, which has uncertainty only in the absence off mitigation, to the case with two potentially correlated measures of environmental quality. Suppose the second quality variable is z, which takes on the value z^1 with certainty if there is mitigation, and the uncertain level z^0 in the absence of mitigation. The individual relevant joint distribution will be $f^*(w^0, z^0)$, and the survey would need to elicit expected values, variances, and (possibly) correlations for both w^0 and z^0. The estimating specification for the binary probit model that allows option price to be calculated would then be:

(A2)
$$E_{w^0}[V^1 - V^0] = \beta_0 \log[(Y - t)/Y]$$
$$+ \delta_0 \{w^1 - E^*[w^0]\} + \delta_1 \{-Var^*[w^0]\}$$
$$+ \theta_0 \{z^1 - E^*[z^0]\} + \theta_1 \{-Var^*[z^0]\} + \varepsilon.$$

Richer specifications of the basic underlying indirect utility function may require covariances between w^0 and z^0. Once again, correlations, rather than covariances, should probably be elicited. In the distributional updating portion of the model, the four (or five) moments of the joint distribution of w^0 and z^0 would need to be modelled.

d. ***Uncertainty about Trajectories of Environmental Quality***

The models described in this paper have been developed on the assumption that it is likely to be easiest to elicit from individuals a description about their uncertainty about climate characteristics at some point in the future (I have used "2011-2020" as an example). People are probably assuming that if climate variables change, they are unlikely to do so precipitously, either in the near or distant future. Instead, climate characteristics are likely to change fairly smoothly in many cases, much as some of them appear to have been doing in recent years.

It is likely, therefore, that individuals harbor uncertainty not about climate characteristics at specific points in the future, but about rates of change of climate characteristics. However, if the researcher is willing to impose strong assumptions about the functional form of the trajectory of some key climate variable, uncertainty about the value of the variable at a single future point in time would readily map into uncertainty about the rate of change of that variable. Suppose we are considering an anticipated warming trend--increases in mean summer temperature. Subject to the assumption of a smooth trajectory, a respondent's answer to the question about conditions in "2011-2020" would translate into a corresponding distribution on growth rates for this mean temperature. The scenario with mitigation would correspond to a certain zero growth rate in mean temperatures.

e. Other Contingent Valuationn Formats

Referendum contingent valuation surveys are generally thought to provoke the fewest strategic distortions and to mimic most closely a type of policy choice with which many individuals will be familiar.[24] However, they are a statistically inefficient way of gathering non-market value information. In implementing a survey like the one described here, the research might contemplate supplementing a core sample of referendum-based survey respondents with other samples that are "treated" with open-ended valuation questions or payment-card value-elicitation devices. It is possible to make the responses to such alternative treatments conformable with the data generated from a referendum survey.

The point values from an open-ended question, or the interval values from a payment-card question, could be explained using the (very nonlinear) formula for OP appearing in equation (15).

Alternately, since income Y is considered exogenous, the "dependent" variable could be specified as:

$$\log[(Y - OP)/Y] = -A/B + \varepsilon/B \qquad \text{(A3)}$$

where, again, $B = \beta_0$ and $A = \delta_0\{w^1 - E^*[w^0]\} + \delta_1\{-Var^*[w^0]\}$. The error term ε should be the same error that enters into the probit formula in the basic model (in standardized form). It will be important to accommodate during estimation the fact that the effective error in equation (A3), ε/B, will be intrinsically heteroscedastic if B is a systematic varying parameter (i.e. a function of the respondent's data, rather than simply β_0).

The referendum contingent valuation data could be pooled with valuation data elicited using alternative formats. Common parameters can be constrained to be identical and estimated in the context of a single encompassing specification.

f. ***Other Functional Forms for the Indirect Utility Function***

The functional form used to illustrate this model is still very restrictive. It has the advantage that the expectation of option price E{OP} is easy to calculate when the log of income is used. The linearity in parameters of the function h also allows the option price portion of the model to be estimated using conventional packaged maximum likelihood binary probit algorithms if the two-stage estimation method is employed. If the researcher is prepared to program non-linear index functions for a probit model, the possibilities for the functions g and h are diverse.

---

[24] Carson, Machina and Groves…

Table 1

Descriptive Statistics for Complete Estimating Sample (n = 392)

VARIABLE	DESCRIPTION	MEAN	STD. DEV
Distributions of future annual mean temperature: (degrees Fahrenheit)			
$E[w]_{own}$	Native subjective mean temp.	66.35	3.10
$E[w]_{gov}$	"Government Scientists" mean temp.	66.01	0.50
$E[w]_{env}$	"Environmental Groups" mean temp.	67.99	1.50
$\mathbf{E^*[w]}$	Revised subjective mean temp.	66.53	1.75
$Var[w]_{own}$	Native subjective temp. variance	2.46	3.55
$Var[w]_{gov}$	"Government Scientists" temp. variance	1.04	0.79
$Var[w]_{env}$	"Environmental Groups" temp. variance	3.62	3.28
$\mathbf{Var^*[w]}$	Revised subjective temp. variance	2.17	2.37
Incomes, Cost, and Vote:			
Y_{2005}	Expected income in 2005	62895.	31722.
Y_{2020}	Expected income in 2020	102030.	38424.
t	Monthly cost of policies	59.40	48.96
WTP?	Vote for policies? (1=yes, 0=no)	0.74	0.44
Respondent Attributes:			
AGE	Age of respondent	19.98	2.397
FEM	Gender (1=female, 0=male)	0.4821	
INFORM	Informedness about env. (1-7 scale)	4.207	1.331
CONSRV	Conservativism (1-7 scale)	4.018	1.180
IMMOBILE	Likelihood of living in same region (1-7 scale)	4.202	1.740
RES. BIAS	Perceived bias of survey *for* policy (1-7 scale)	5.287	1.133
FALL97	Membership in Fall1997 subsample	0.6327	
Expected change in climate services for 4 degree Fahrenheit temp increase:			
HEAT4	Heating expenses	-0.6252	0.8887
AIR4	Air-conditioning expenses	1.084	1.072
COMF4	Personal comfort	-0.3019	0.9617
FOOD4	Food prices	0.5233	0.9073
SEVR4	Severity of storms	0.4140	0.9543
FREQ4	Frequency of storms	0.3262	0.9495
WATR4	Water consumption	1.178	1.088
HOUS4	Housing prices	0.2416	0.8067
SEA4	Sea levels	0.1586	1.244
TROP4	Tropical diseases	0.5858	0.8411
*DROU4	Frequency of droughts	0.9262	1.096
*EQUS4	Welfare of poorest 50% of US residents	-0.1992	0.8777
*EQWL4	Welfare of poorest 50% of world's population	-0.3539	1.149

* Present only for Version 4 of the Survey Trials.

Table 2
Test of Bayesian Updating in Formulation of
Revised Sujective Distribution of Future Annual Average Temperatures
(n = 392)

VARIABLE	$E^*[w]$		$(Var^*[w])^{-1}$	
own-term	1.138 (14.65)**	1.002 (299.7)	0.7740 (36.31)**	0.7664 (36.65)**
gov-term	1.151 (14.98)**	1.016 (394.3)	0.04635 (0.80)	-0.02054 (-0.48)
env-term	1.122 (14.81)**	0.9891 (200.6)	0.1033 (0.80)	-0.02052 (-0.19)
constant	-8.948 (-1.760)	-	-0.2857 (-1.72)	-
H_0: Bayesian? (F-test P-value)	0.00000	0.00000	0.00000	0.00000

NOTE: Let $D = (Var[w]_{own})^{-1} + (Var[w]_{gov})^{-1} + (Var[w]_{env})^{-1}$. Then the estimated equations are:

$$E^*[w] = \alpha_0 + \alpha_1 E[w]_{own}/(D * Var[w]_{own}) + \alpha_2 E[w]_{gov}/(D * Var[w]_{gov}) + \alpha_3 E[w]_{env}/(D * Var[w]_{env}) + \varepsilon_E$$

$$(Var^*[w])^{-1} = \beta_0 + \beta_1 (Var[w]_{own})^{-1} + \beta_2 (Var[w]_{gov})^{-1} + \beta_3 (Var[w]_{env})^{-1} + \varepsilon_P.$$

Table 3
Non-Bayesian Models to Explain
Revised Subjective Average Annual Temperature ($E^*[W]$)
(n = 392)

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
$E[W]_{own}$	0.3291 (14.67)**	0.3291 (14.90)**	0.3291 (14.91)**	0.1252 (3.62)	0.1207 (3.45)**
$E[W]_{gov}$	0.4577 (3.29)**	0.4577 (9.45)**	0.4673 (14.20)**	7.658 (7.83)	7.772 (7.81)**
$E[W]_{env}$	0.2128 (4.59)**	0.2128 (4.88)**	0.2036 (7.41)**	-7.000 (-7.20)	-7.018 (-7.15)**
$E[W]_{own} * \lvert E[W]_{gov} - E[W]_{env} \rvert$	-	-	-	0.1087 (7.43)	0.1085 (7.32)**
$Var[W]_{own}$	-	-	-	-	0.03022 (1.19)
$Var[W]_{gov}$	-	-	-	-	-0.1418 (-1.42)
$Var[W]_{env}$	-	-	-	-	0.02960 (0.99)
$Var[W]_{own} * \lvert Var[W]_{gov} - Var[W]_{env} \rvert$	-	-	-	-	-0.003645 (-0.66)
CONSTANT	-0.002910 (-0.0002)	-	-	14.33 (1.51)	8.357 (0.74)
R-Squared	0.3887	0.3887	0.4648	0.4703	0.55
P-value (F-test of Restr.)	-	0.9998	0.9642	-	-

[a] H_0: Slopes in Model 1a sum to unity.
[b] H_0: Model 2 (zero intercept, slopes sum to unity) is true model (versus Model 1).

Table 4

Non-Bayesian Models to Explain Revised Subjective Variance in Annual Temperature (Var*[w])
(n = 392)

VARIABLE	MODEL 1	MODEL 2	MODEL 3
$Var[w]_{own}$	0.4043 (16.78)**	0.4079 (17.82)**	0.4056 (16.75)**
$Var[w]_{gov}$	0.1848 (1.71)	0.2190 (2.67)	0.1456 (1.20)
$Var[w]_{env}$	0.2451 (9.38)**	0.2521 (11.55)**	0.3169 (3.06)**
$Var[w]_{own} * \lvert Var[w]_{gov} - Var[w]_{env} \rvert$	-	-	-0.07829 (-0.72)
CONSTANT	0.08919 (0.49)	-	0.09335 (0.51)
R-Squared	0.4943	0.4940	0.4947
P-value for F-test of Restrictions *	0.1956	0.0817	-

*Restriction that intercept to zero and coefficients to sum to unity cannot be rejected.

Table 5
Simultaneous Nonlinear Least Squares Model with Ambiguity Effects
$E^*[w]$ and $Var^*[w]$ Each a Weighted Average of Own, Government,
and Environmental Group Moments (n = 392)

VARIABLE	γ_{gov}	γ_{env}	δ_{gov}	δ_{env}
"ambiguity"	κ_E = 0.006383 (2.57)**		κ_V = 0.02566 (1.73)*	
constant	1.854 (2.95)**	2.254 (2.38)**	19.18 (6.02)**	12.91 (4.43)**
AGE	-	-	-0.8237 (-5.93)**	-0.6043 (-4.62)**
FEMALE	0.4264 (1.71)*	0.8944 (2.76)**	0.8169 (3.41)**	0.9981 (4.23)**
INFORM	-	-	-	-
CONSRV	-	-0.3091 (-2.50)**	-0.2920 (-3.47)**	-
IMMOBILE	0.2340 (2.70)**	-	0.1149 (1.89)*	-
RES.BIAS	-0.4237 (-4.08)**	-0.2741 (-1.90)*	-	-
FALL'97	-	-	-3.408 (-6.57)**	-2.562 (-4.66)**

$$E^*[w] = (1 + \kappa_E\,|E[w]_{gov} - E[w]_{env}|)\,[(1 + \kappa_E\,|E[w]_{gov} - E[w]_{env}|) + \exp(\gamma_{gov}) + \exp(\gamma_{env})]^{-1}\,E[w]_{own}$$
$$+ \exp(\gamma_{gov})\,[(1 + \kappa_E\,|E[w]_{gov} - E[w]_{env}|) + \exp(\gamma_{gov}) + \exp(\gamma_{env})]^{-1}\,E[w]_{gov}$$
$$+ \exp(\gamma_{env})\,[(1 + \kappa_E\,|E[w]_{gov} - E[w]_{env}|) + \exp(\gamma_{gov}) + \exp(\gamma_{env})]^{-1}\,E[w]_{env} + e_E$$

$$V^*[w] = (1 + \kappa_V\,|V[w]_{gov} - V[w]_{env}|)\,[(1 + \kappa_V\,|V[w]_{gov} - V[w]_{env}|) + \exp(\delta_{gov}) + \exp(\delta_{env})]^{-1}\,V[w]_{own}$$
$$+ \exp(\delta_{gov})\,[(1 + \kappa_V\,|V[w]_{gov} - V[w]_{env}|) + \exp(\delta_{gov}) + \exp(\delta_{env})]^{-1}\,V[w]_{gov}$$
$$+ \exp(\delta_{env})\,[(1 + \kappa_V\,|V[w]_{gov} - V[w]_{env}|) + \exp(\delta_{gov}) + \exp(\delta_{env})]^{-1}\,V[w]_{env} + e_V$$

Each of the four parameters, γ_{gov}, γ_{env}, δ_{gov}, and δ_{env} are systematically varying. The parameters κ_E and κ_V capture the "ambiguity" effect. If the κ parameter is positive in a particular equation, greater disparities between the opinions of the two outside sources will increase the weight on the individual's own prior opinion.

Table 6

Constant Parameter and Systematic Varying Parameter Specifications
for the Indirect Utility-Difference Function:
(n = 392 ;n(1)=291, n(0)=101)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CONSTANT	-2.722 (-1.05)	-3.524 (-1.30)	-3.545 (-1.28)	-4.300 (-1.53)	-1.910 (-0.67)	-2.68 (-0.92)
log[(Y-t)/Y]	20.71 (4.32)**	20.98 (4.36)**	27.40 (3.96)**	26.40 (3.76)**	-142.2 (-2.33)**	-139.7 (-2.31)**
log[(Y-t)/Y]*AGE	-	-	-	-	7.318 (2.43)**	7.118 (2.39)**
log[(Y-t)/Y]*FEMALE	-	-	-12.57 (-1.31)	-11.79 (-1.22)	-	-
log[(Y-t)/Y]*IMMOBILE	-	-	-	-	4.73 (1.90)*	4.90 (1.96)**
E*[w]	0.05550 (1.42)	0.06873 (1.68)*	0.07189 (1.71)*	0.08983 (2.09)**	0.004644 (0.10)	0.02731 (0.57)
E*[w]*AGE	-	-	-	-	0.002066 (2.27)**	0.001918 (2.06)**
E*[w]*FEMALE	-	-	-0.006259 (-1.66)*	-0.01384 (-2.85)**	-	-0.009770 (-2.42)**
E*[w]*FALL97	-	-	-	-0.009731 (-2.76)**	-	-0.009105 (-2.47)**
E*[w]*FEMALE*FALL97	-	-	-	0.01173 (2.49)**	-	0.01237 (2.58)**
E*[w]*INFORM	-	-	-	-	0.001473 (1.76)*	0.001271 (1.49)
E*[w]*CONSERV	-	-	-	-	-0.001817 (-1.91)*	-0.001900 (-1.96)**
Var*[w]	-	-0.03366 (-1.12)	-0.05551 (-1.47)	-0.05233 (-1.37)	-0.1565 (-2.14)**	-0.1726 (-2.30)**
Var*[w]*FEMALE	-	-	0.05938 (0.94)	0.04654 (0.73)	-	-
Var*[w]*IMMOBILE	-	-	-	-	0.03680 (1.91)*	0.04025 (2.06)**
Max Log L	-213.25	-212.61	-211.16	-206.88	-202.77	-198.75

Table 7

Counterfactual Simulations
Descriptive Statistics Across Sample for Fitted Individual Option Prices

SIMULATION	Sample Mean	Sample Std.dev.	Median Value
Benchmark Information:			
Fitted Expected OP	268	334	194
Monthly Expected Income	\$5241	\$2644	\$5208
Simulations regarding DGP for E[w]:*			
Zero weight on ENV opinion	272	357	189
Zero weight on GOV opinion	270	350	203
Different sociodemographics or attitudes:			
All 4 years older	162	98	138
One unit more informed	291	351	209
One unit more conservative	229	302	170
One unit more mobile	271	272	196
Different opinions about future climate:			
Certainty about future climate (Var*[w]=0)	300	452	201
All believe exactly + 1°C	271	362	188
All believe exactly + 2°C	303	418	208
Gender effects:			
All female (same other characteristics)	268	327	193
All male (same other characteristics)	283	357	207
Timing of Survey:			
All Winter/Spring 1997 (same otherwise)	328	427	225
All Fall 1997 (same otherwise)	236	206	186

NOTES: Simulations are of three basic varieties: (i.) alter the weights on external information exogenously; (ii.) alter the weights on the external information via changes in the variables that systematically affect the magnitudes of the weights; and (iii.) alter the demographics that enter directly into the Option Price model. When the same variables enter both the updating model for E*[w] and Var*[w] and the Option Price model, the simulations must capture both effects.

Table 8

Constant Parameter and Systematic Varying Parameter Specifications
for the Indirect Utility-Difference Function; Model in terms of *climate services*
(n = 392; n(1) = 291, n(0) = 101)

	Model 1	Model 2	Model 3	Model 4
CONSTANT	0.4539 (0.89)	0.3238 (0.5996)	0.3080 (0.57)	0.1528 (0.27)
log[(Y-t)/Y]	20.97 (4.24)**	19.62 (3.86)**	19.23 (3.75)**	18.96 (3.66)**
Version 4	0.05875 (0.28)	0.05697 (0.23)	0.1038 (0.38)	0.02660 (0.11)
E[HEAT]	0.3150 (2.30)**	0.03116 (0.17)	-0.3250 (-0.98)	0.07480 (0.40)
E[HEAT]*FEMALE	-	0.4835 (2.82)**	0.9975 (2.17)**	0.3636 (1.85)*
E[HEAT]*FALL97	-	-	0.4934 (1.14)	-
E[HEAT]*FEMALE *FALL97	-	-	-0.7041 (-1.24)	-
E[AIR]	0.4322 (3.47)**	0.3164 (0.95)	0.2878 (0.65)	-0.003300 (-0.01)
E[AIR]*FEMALE	-	-	0.1161 (0.27)	-
E[AIR]*FALL97	-	-	-0.04471 (-0.12)	-
E[AIR]*FEMALE *FALL97	-	-	-0.08636 (-0.172)	-
E[AIR]*INFORM	-	0.1292 (2.60)**	0.1362 (2.67)**	0.1044 (2.02)**
E[AIR]*CONSERV	-	-0.09566 (-1.60)*	-0.08960 (-1.49)	-
E[SEVR]	0.2462 (2.84)**	0.2353 (2.68)**	0.2435 (2.65)**	0.2789 (3.05)**

continued…

Table 8, continued

Non-zero Var ?	0.1838 (0.38)	0.2366 (0.48)	0.2088 (0.42)	0.3796 (0.72)
Var[HEAT]	0.8958 (2.52)**	-0.4886 (-0.62)	-0.5708 (-0.63)	-0.1508 (-0.19)
Var[HEAT]*FALL97	-	1.638 (1.88)*	1.740 (1.69)*	1.567 (1.72)*
Var[AIR]	-0.6199 (-2.71)**	1.005 (1.28)	0.7915 (0.87)	1.102 (1.36)
Var[AIR]*FALL97	-	-1.753 (-2.25)**	-1.562 (-1.62)*	-1.432 (-1.79)*
Var[WATR]	-	-	-	0.1195 (0.28)
Var[WATR]*FEMALE	-	-	-	-0.7510 (-1.66)*
Var[EQWL]	-	-	-	-0.5915 (-1.54)
Var[EQWL]*FEMALE	-	-	-	1.880 (2.62)**
Log _	-198.18	-186.89	-185.06	-182.22

There is some evidence of multicollinearity among perceived changes in climate services. If we were to specify a model that incorporated all expected service changes and all variances in services changes, it is constructive to assess multicollinearity by inspecting the R-squared values for regressions of each of the following variables on all of the others in this list. Specifically, these R-squared values are: log[(Y-t)/Y]: 0.0782 ; version 4 dummy: 0.2625 ; E[HEAT]: 0.4960 ; E[AIR]: 0.6665 ; E[COMF]: 0.1945 ; E[FOOD]: 0.5117 ; E[SEVR]: 0.8099 ; E[FREQ]: 0.7650 ; E[DROU]: 0.7501 ; E[WATR]: 0.7701 ; E[HOUS]: 0.2985 ; E[SEA]: 0.4056 ; E[TROP]: 0.6107 ; E[EQUS]: 0.6718 ; E[EQWL]: 0.6925 ; nonzero variance dummy: 0.0457 ; Var[HEAT]: 0.6148 ; Var[AIR]: 0.7963 ; Var[COMF]: 0.4845 ; Var[FOOD]: 0.6790 ; Var[SEVR]: 0.6675 ; Var[FREQ]: 0.5476 ; Var[DROU]: 0.8198 ; Var[WATR]: 0.8515 ; Var[HOUS]: 0.3363 ; Var[SEA] : 0.5802 ; Var[TROP]: 0.6482 ; Var[EQUS]: 0.7202 ; Var[EQWL]: 0.7554.