PRELIMINARY DRAFT
Not for citation

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

by

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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 individuals. I describe an empirical game plan wherein people's native prior distributions on future environmental quality are elicited first. Respondents are then provided with "external" information from different sources. I assume Bayesian updating as a consequence of this additional information. Respondents' subjective posterior distributions then underlie their responses to a referendum contingent valuation question regarding a mitigation program. 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 subjective posterior distribution. The referendum discrete choice option price equation can be estimated simultaneously with the Bayesian updating equations for the mean and variance of climate variables absent mitigation. The model will allow the researcher to simulate counterfactually the effects on option prices of changes in factors that influence the Bayesian updating of probabilities and/or factors that enter directly into the expected indirect utility-difference function.

* Thanks are due to Jack Hirshleifer and to Barri Grossman for helpful comments, and to my Economics 204G class and to Kathleen McGarry's Spring 1997 Economics 11 class for their participation in survey trials.

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1. Introduction

Over the coming decades, global climate change has the potential to result in detectable shifts in the distributions of many environmental measures. Controversy over the nature and magnitude of these changes has made it very difficult for legislators to agree on optimal climate change policies. Different constituencies cannot agree on the necessity for costly measures to mitigate climate change. In democratic jurisdictions, 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. We are asked to vote (directly or indirectly) on policies in advance of knowing the resolution of uncertainty about what will happen if nothing is done.

What are the consequences of pursuing no policies to manage the climate? People 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.[1]

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

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 such diverse sources as government scientists or environmental groups. Individuals will have different views about the credibility of these different sources.[2] 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.[3]

This paper develops a model intended to capture the nature of the Bayesian updating process as survey respondents are exposed to external stimuli regarding the probable future state of the environment. I also outline carefully the types of questions that would be required on a survey instrument designed to implement this model. The context in which this model is developed is a proposed survey of individuals concerning their willingness to pay to prevent climate change. This willingness to pay is assumed to be elicited using a referendum format contingent valuation survey (Arrow et al., 1993).

Section 2 reviews in general the modeling of option prices for environmental protection in the context of discrete-choice contingent valuation survey data and some unspecified continuous posterior distribution concerning a limited form of subjective uncertainty about future environmental quality. Section 3 gives an example in terms of a particular functional form for state-dependent individual indirect utility. This section also outlines the process by which a posterior distribution of uncertainty is assumed to be formulated by individuals from their own priors as well as diverse external sources of information to which they have access. Section 4 lays out the key features of a survey

[2] 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.

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

instrument that would allow the basic model to be implemented. Section 5 describes some useful and interesting simulations that would be possible using the estimated model. Section 6 introduces an assortment of generalizations and their implications for the empirical specifications, and section 7 concludes.

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. Suppose initially that environmental quality can be conveniently summarized in just one dimension as the level of a variable, w. For example, in the context of climate change, one could think of w as mean summer temperature.

Assume that if mitigation is undertaken (at known costs), 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 what extent.[4] From the point of view of a single individual, let this uncertain 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 $f^*(w^0)$. 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.

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

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 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.[5] 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 states of the world and the associated continuous probability density function.

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 the level of environmental quality and by other individual-specific factors x. Individual subjective uncertainty exists across states of the world, represented by different values of w^0, but for any one state, the individual can be modelled as having state-dependent[6] utility level $V^1_{w^0}$ 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 $f^*(w^0)$. An additive normal error term facilitates econometric estimation.

[5] 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.

[6] 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.

(1)
$$V^1_{w^0}(Y - t, w^1) = g_{w^0}(Y - t) + h^1_{w^0}(w^1,x) + \epsilon^1_{w^0}$$
$$V^0_{w^0}(Y, w^0) = g_{w^0}(Y) + h^0_{w^0}(w^0,x) + \epsilon^0_{w^0}$$

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

(2)
$$(V^1 - V^0)_{w^0} = g_{w^0}(Y-t) - g_{w^0}(Y) + [h^1_{w^0}(w^1,x) - h^0_{w^0}(w^0,x)] + (\epsilon^1_{w^0} - \epsilon^0_{w^0}) > 0.$$

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 $(V^1 - V^0)_{w^0}$ to zero and solving for $t^*_{w^0}$. Simplify by letting $\epsilon = \epsilon^0 - \epsilon^1$ and solve for t* as follows:

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

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:

$$(4) \quad E_{w^0}[t^*_{w^0}] = E_{w^0}[\, Y - g_{w^0}^{-1}\{\, g_{w^0}(Y) - [h^1_{w^0}(w^1,x) - h^0_{w^0}(w^0,x)] + \epsilon \,\}\,]$$

$$= \int [\, Y - g_{w^0}^{-1}\{\, g_{w^0}(Y) - [h^1_{w^0}(w^1,x) - h^0_{w^0}(w^0,x)] + \epsilon \,\}]\, f^*(w^0)\, dw^0.$$

When functional forms have been selected for g_{w^0}, $h^1_{w^0}$ and $h^0_{w^0}$, this integral has the potential to 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:

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

or, identically,

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

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

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

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

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

This analysis cannot be taken much further without committing to a specific functional form for the indirect utility function. Thus, I proceed in the next section to make some concrete suggestions about empirically tractable functional forms.

3. Example: Specific Functional Forms

Probably the simplest 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 is a model that is linear in the logarithm of income. Furthermore, in order to have state-dependent utility levels, the functions $g(Y)$, $h^1(w^1,x)$ and $h^0(w^0,x)$ need to vary across states of the world. The simplest way to achieve this is to let the parameters of these functions vary systematically with the level of the uncertain future environmental quality. The simplest systematic varying parameter formulation specifies the parameters as linear in the level of w^0, the uncertain laissez-faire environmental quality variable.[7]

Since w differs across the mitigate / don't-mitigate contingent valuation scenarios, indirect utility can be linear in w. However, there will be individual characteristics that do *not* vary across the two scenarios. If these are to remain in the indirect utility-*difference*

[7] The parameters could easily be made quadratic or otherwise non-linear in the level of the uncertain laissez-faire environmental quality for greater generality.

function, they will have to enter V^1 and V^0 with different coefficients. A tractable specific form for the model is therefore:

$$(8) \qquad V^1_{w^0}(Y - t, w^1) = (\beta_0 + \beta_1 w^0)\log(Y - t) + (\delta_0 + \delta_1 w^0)w^1 + (\alpha + \alpha w^0)'x + \epsilon^1_{w^0}$$

$$V^0_{w^0}(Y, w^0) = (\beta_0 + \beta_1 w^0)\log(Y) + (\delta_0 + \delta_1 w^0)w^0 + (\alpha + \alpha w^0)'x + \epsilon^0_{w^0}$$

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

$$(9) \qquad (V^1 - V^0)_{w^0} = (\beta_0 + \beta_1 w^0)\log[(Y - t)/Y]$$
$$+ (\delta_0 + \delta_1 w^0)(w^1 - w^0)$$
$$+ [(\alpha + \alpha w^0) - (\alpha + \alpha w^0)]'x + (\epsilon^1_{w^0} - \epsilon^0_{w^0}).$$

Simplify by letting $\alpha_0 = \alpha - \alpha$ and $\alpha_1 = \alpha - \alpha$, so that the term in x can be written as $[\alpha_0 + \alpha_1 w^0]'x$. Also let $\epsilon = \epsilon^1_{w^0} - \epsilon^0_{w^0}$.

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

As in the generic case, OP is the common sure payment that has the same *expected utility* as no payment and no mitigation (or as the set of each of the optimal payments under each possible outcome with certainty). The binary probit discrete choice model that would allow us to estimate OP is based on the expectation of the utility difference across all possible outcomes for w^0.

(10) $$E_{w^0}[V^1 - V^0] = \int (\beta_0 + \beta_1 w^0)\, f^*(w^0)\, dw^0 \quad \log[(Y - t)/Y]$$

$$+ \int (\delta_0 + \delta_1 w^0)(w^1 - w^0)\, f^*(w^0)\, dw^0$$

$$+ [\int (\alpha_0 + \alpha_1 w^0)\, f^*(w^0)\, dw^0\,]'x + \epsilon$$

This can be simplified as follows:[8]

(11) $$E_{w^0}[V^1 - V^0] = \{\beta_0 + \beta_1\, E_*[w^0]\} \log[(Y - t)/Y]$$

$$+ \{\delta_0 + \delta_1\, E_*[w^0]\}\, w^1 - \int (\delta_0 + \delta_1 w^0)\, w^0\, f^*(w^0)\, dw^0$$

$$+ \{\alpha_0 + \alpha_1\, E_*[w^0]\}'x + \epsilon.$$

The integral that remains in the above equation can be rewritten as follows:

(12) $$\int \delta_0\, w^0\, f^*(w^0)\, dw^0 + \int \delta_1\, (w^0)^2\, f^*(w^0)\, dw^0$$

$$= \delta_0\, E_*[w^0] + \delta_1\, E_*[\, (w^0)2\,]$$

$$= \delta_0\, E_*[w^0] + \delta_1\, \{\, Var_*[w^0] - E_*[w^0]^2\, \}.$$

Making this substitution, the discrete choice probit "index" expression is thus a linear-in-parameters function of scalar parameters β_0, β_1, δ_0, δ_1, and parameter vectors α_0 and α_1:

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

$$E_{w^0}[V^1 - V^0] = \beta_0 \log[(Y - t)/Y] + \beta_1 E_*[w^0] \log[(Y - t)/Y] + \delta_0 \{w^1 - E_*[w^0]\} + \delta_1 \{w^1 E_*[w^0] + E_*[w^0]^2 - Var_*[w^0]\} + \alpha_0'x + \alpha_1 E_*[w^0]'x + \epsilon. \tag{13}$$

For a sample of survey respondents, we can now inventory the data required for 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 posterior distribution concerning future environmental quality in the absence of mitigation: $E_*[w^0]$ and $Var_*[w^0]$. A key insight is that the precise shape of this posterior 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 could be used to estimate the unknown parameters.[9]

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:

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[9] A later section acknowledges that the necessary moments of w^0 are estimated regressors.

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

where we can make use of the simplifying notation of $A = \beta_0 + \beta_1 E_*[w^0]$ and $B = \delta_0\{w^1 - E_*[w^0]\} + \delta_1\{w^1 E_*[w^0] + E_*[w^0]^2 - Var_*[w^0]\} + \{\alpha_0 + \alpha_1 E_*[w^0]\}'x$. Solving this for OP yields $OP = Y - Y \exp[-(A + \epsilon)/B]$. Note that the error term must 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:

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

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

NOTE: This section will be modified. The "mixture"-type model described here proves not to be compatible with the empirical data. There are several alternatives.

If $f^*(w^0)$, the individual's posterior distribution for w^0, was observed and 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 the constructed explanatory variables employed in equation (13). However, an important research question concerns the manner in which individuals update their native prior distributions on w^0 in the face of new information from sources that may have differing 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 posterior distribution $f^*(w)$. Viscusi and Magat

(1992), and Heath and Tversky (1991) provide valuable insights for this task. I also draw upon some of the ideas in Smith and Desvousges (1987, 1988) and Smith and Johnson (1988). Other sources include Viscusi (1985a, 1985b), Viscusi and Magat (1987), Viscusi and O'Connor (1984) and Viscusi, Magat and Huber (1986).

I will assume that each individual has his or her own native prior concerning the likely future value of w^0, captured by a probability density function $f^a(w^0)$. Each individual may also be exposed to predictions about the likely future value of w^0 from other sources. Suppose government scientists predict a distribution $f^b(w^0)$ for environmental quality, and environmental groups predict a distribution $f^c(w^0)$. If individuals are informed about these other opinions regarding future environmental quality, they may engage in Bayesian updating of their native prior, leading to a posterior distribution for w^0 that they employ in answering the environmental valuation question.[10]

I adapt (to the continuous outcome case) a form of Bayesian updating suggested in the context of discrete binary outcomes by Viscusi and Magat (1992). Individuals who are not informed about other opinions will use a posterior distribution identical to their prior: $f^*(w^0)= f^a(w^0)$. Individuals who are informed about one or the other of the two additional sources of information about the distribution of w^0 will update their priors using distributional information from other sources (e.g. $f_b(w^0)$ for government scientists, $f_c(w^0)$ for environmental groups) as follows:

(16) $$f^*(w^0) = [\, \gamma_a f^a(w^0) + \gamma_b f^b(w^0) \,] \;/ (\gamma_a + \gamma_b), \text{ or}$$

$$f^*(w^0) = [\, \gamma_a f^a(w^0) + \gamma_c f^c(w^0) \,] \;/ (\gamma_a + \gamma_c)$$

[10] The number of outside information sources could readily be expanded.

If a respondent is exposed to *both* other sources of information about the likely distribution of w^0, they will update their priors according to a more general formula.[11]

(17) $$f^*(w^0) = [\, \gamma_a f^a(w^0) + \gamma_b f^b(w^0) + \gamma_c f^c(w^0) \,] \,/\, (\gamma_a + \gamma_b + \gamma_c).$$

As noted above, the option price model requires only the mean and the variance of the individual's posterior distribution for w^0, not the density function itself. Therefore, instead of making some explicit assumption about these distributional shapes, it is sufficient to model just the mean and the variance. One can begin with the generic underlying density functions, $f_a(w^0)$, $f_b(w^0)$ and $f_c(w^0)$ suggested above. If individuals engage in Bayesian updating of their native prior density, $f_a(w^0)$, in the face of additional information from outside sources according to the parameters γ_a, γ_b, and γ_c as given in equation (17), then their posterior expected value for w^0 will be:

(18) $$\begin{aligned} E_*[w^0] &= \int w^0 f^*(w^0)\, dw^0 \\ &= \int w^0 (\gamma_a + \gamma_b + \gamma_c)^{-1} \{\gamma_a f_a(w^0) + \gamma_b f_b(w^0) + \gamma_c f_c(w^0)\}\, dw^0 \\ &= (\gamma_a + \gamma_b + \gamma_c)^{-1} \{\gamma_a E_a[w^0] + \gamma_b E_b[w^0] + \gamma_c E_c[w^0]\} \end{aligned}$$

Normalizing by $(\gamma_a + \gamma_b + \gamma_c)^{-1}$ ensures that the effective weights on each of the constituent densities sum to unity. Since the ratios $\gamma_k / (\gamma_a + \gamma_b + \gamma_c)^{-1}$ are invariant to the scale of the individual γ_k parameters, we normalize by setting $\gamma_a = 1$.

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[11] It is possible that the γ coefficients that determine the relative weights each individual assigns to their priors and each of the other sources of information about the distribution may differ according to how many sources of information are available to the individual, but we will constrain them to be identical for now.

Derivation of the posterior variance for w^0 relies on repeated applications of the rule that $Var(X) = E[X^2] - E[X]^2$.

$$(19) \quad Var_*[w^0] = \int [w^0]^2 \; f^*(w^0)\, dw^0 \; - E_*[w^0]^2$$

$$= \int [w^0]^2 \, (1+\gamma_b+\gamma_c)^{-1} \{f_a(w^0)+\gamma_b \, f_b(w^0)+\gamma_c \, f_c(w^0)\} dw^0 - E_*[w^0]^2$$

The sum of terms in braces allows the integral in equation (19) to be factored into three separate integrals, each in the form of

$$(20) \quad \gamma_k \, (1+\gamma_b+\gamma_c)^{-1} \int [w^0]^2 \; f_k \,(w^0)\, dw^0, \qquad k = a, b, c,$$

and each of these can be expressed in terms of the mean and the variance of one of the underlying distributions $f_k(w^0)$:

$$(21) \quad \gamma_k \, (1+\gamma_b+\gamma_c)^{-1} \{ \, Var_k(w^0) + [E_k(w^0)]^2 \, \}, \qquad k = a, b, c.$$

Simplifying the notation by writing $\gamma_k \, (1+\gamma_b+\gamma_c)^{-1}$ as γ^*_k, one can write the posterior expected value simply as:

$$(22) \quad E_*[w^0] = \; \gamma^*_a \, E_a[w^0] + \gamma^*_b \, E_b[w^0] + \gamma^*_c \, E_c[w^0],$$

The model for the posterior variance can then be expressed as:

(23) $$\mathrm{Var}_*[w^0] = \left\{ \Sigma_k \, \gamma^*_k \, (\mathrm{Var}_k[w^0] + (E_k[w^0])^2) \right\} - \left\{ \Sigma_k \, \gamma^*_k \, E_k[w^0] \right\}^2.$$

The mean and the variance are thus nonlinear functions of the same scalar parameters, γ_k, that form the weights in the posterior density formula. Note that the terms in $E_k[w^0]$ do not cancel because the final term is the square of the weighted sum of the expectations, rather than the sum of the weighted squared expectations.

$E_*[w^0]$ and $\mathrm{Var}_*[w^0]$ are random variables, and a pair of values for these variables is elicited from each individual. Thus, it is appropriate to allow for cross-equation error correlations in modelling these variables. The correct econometric model, under the assumption of correlated additive normal errors, would be a system of two nonlinear seemingly unrelated regressions corresponding to equations (22) and (23).

4. Empirical Implementation of the Basic Model

If the model described above is estimated in two stages, the first estimation task will involve establishing the determinants of the moments of the individual's posterior distribution for future environmental quality: $E_*[w^0]$ and $\mathrm{Var}_*[w^0]$. The second task will be estimation of the discrete choice contingent valuation model that yields the formula for individual option prices.

a.) *Modelling the Posterior Distribution of w^0*

There has been substantial policy interest in recent years in the topic of risk communication (Davies et al., 1987). This literature focusses on the best way to convey to individuals the true objective magnitudes of risks.[12] There has been less attention devoted to

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

the problem of eliciting subjective probabilities. Reliable elicitation of (at least) the means and variances of subjective prior and posterior probability distributions is crucial to this analysis.[13]

For climate change, the variable that I suggested to illustrate the uncertainty was average summer temperature. At the beginning of the survey, the interviewer might attempt to elicit from the respondent their assumptions about the current distribution of the w variable. Historical data (perhaps over the previous two decades) could be assembled for this variable, based on measurements from the weather station nearest the respondent. A coarse histogram showing the actual distribution over these twenty observations could be presented to the respondent. This distribution would help the respondent calibrate his or her forecast for the expected value and dispersion in these mean temperatures at some reference point in the future (e.g. 15 years hence).

After establishing the "true" distribution of average summer temperatures, the respondent would be presented with the analogous distributions (purportedly) forecasted by government scientists and by environmental groups. One objective of the analysis is to discriminate between the effects of different external information sources on the respondent's Bayesian updating process. The statistical design of the contingent valuation survey would have to ensure that, within plausible ranges, there is sufficient orthogonal variation across survey instruments in these purported external forecasts.

Empirically, one must first elicit information on the individual's *native prior* mean and variance for future environmental quality. This might be done both before and after the respondent is informed about the true historical data. Expected values would be the easiest to elicit. It is more difficult to ask respondents to convey information on variances. For

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

dispersion measures, one could at best ask them for a "plus or minus" amount associated with their expected value, and then interpret this as two standard deviations, squaring half the amount to yield a variance. Alternately, one could elicit a 95% range, invoke some strong distributional assumptions, and "back out" a corresponding variance estimate.

The process of eliciting priors, conveying additional information, and then eliciting posterior distributions could happen entirely during the same interview. Alternatively, posteriors could be elicited in a follow-up interview, with the external information being conveyed in the interim and with time being allowed for respondents to digest it. Sample attrition would then need to be addressed.

If the objective of estimation was simply to ascertain the values of the three weighting parameters γ^*_k for the different types of information, an additive normal error term could be appended to each of the two equations and they could be estimated simultaneously, by non-linear methods, with the corresponding γ^*_k parameters in the $E_*[w^0]$ and $Var_*[w^0]$ equations constrained to be identical. This approach would yield the average weights that survey respondents assign to their own opinions about future environmental quality versus the opinions of government scientists or environmental groups. Note that, if necessary, these weights could be forced to be non-negative by substituting $\exp(\gamma'_k)$ for γ_k, and estimating values for γ'_k (for k = b,c) instead.

A richer model, however, would allow the weights on different types of information to be individual-specific. This could be accommodated within the model by converting the γ_k (k = b, c) to systematic varying parameters. Plausible individual attributes to include among factors that might shift the value of each γ_k include gender, age, education, membership in environmental organizations, or explicit subjective assessments of the relative credibility of the external information sources. Thus, one could replace the scalar γ_k, with

γ_k'**s**, where **s** is a vector of sociodemographic or stated attitude variables. Alternately, to restrict the sign on each systematically varying weighting parameter to be non-negative, one could use exp(γ_k^{+}'**s**), and estimate the model in terms of γ_k^{+} instead of γ_k.

Systematically varying γ_k parameters will greatly increase the goodness of fit of the two-equation sub-model for the moments of respondents distributions on w^0, and thereby to provide more accurate fitted values for inclusion in the probit model for estimating the parameters of the option price formula.

b.) ***A Model for Option Price for Mitigation of Environmental Damages***

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. I will frame the discussion in terms of a discrete choice (referendum) contingent valuation question.

Prior to the valuation question, the survey respondent must be asked about their native understanding about climate change prospects. Then, they must be briefed about the (possibly divergent) opinions of a selection of experts or advocacy groups. Then their updated understanding must be assessed. These tasks are relevant to establishing the Bayesian updating of their probability distributions. Following this comes the key valuation question. It might take the following form:

> "Consider what you believe is likely to happen to [environmental quality] by [15 years hence] if nothing is done. Policies that could successfully maintain [environmental quality] the way it is right now are estimated to cost the equivalent of $__t__ per household per year, indefinitely, either in higher prices or higher taxes. Would you vote in favor of implementing these policies?" YES / NO

Certainly, the expertise of cognitive psychologists and veteran survey designers would be required to optimize the wording of this question. The survey would of course substitute a more tangible measure of climate than the place-holding [environmental quality] variable.

The proposed model can be estimated using data on the YES / NO response to this question, the exogenously assigned value of t imposed for this respondent, information on other sociodemographic characteristics, s, current environmental quality w_1, and the fitted values of $E_*[w^0]$ and $Var_*[w^0]$ from the pair of equations in the posterior probability submodel.

c.) ***A Jointly Estimated Model***

The two-stage estimation procedure described in sections (a.) and (b.) would allow the parameters of the model to be estimated using packaged econometric software. But the second-stage inferences in the option price model will be clouded by reliance on estimated regressors in the form of fitted values for $E_*[w^0]$ and $Var_*[w^0]$. A more sophisticated approach would be to estimate both parts of the full model simultaneously.

It would be difficult to allow for correlation between the probit response and the errors in the equations for $E_*[w^0]$ and $Var_*[w^0]$, so one would probably begin by assuming that the errors in $E_*[w^0]$ and $Var_*[w^0]$ are correlated between themselves, but not with the ϵ in the probit model for option price. An appropriate log-likelihood function would then involve the sum of the probit log-likelihood function and the explicit log-likelihood for the system of nonlinear seemingly unrelated regressions that explains $E_*[w^0]$ and $Var_*[w^0]$. Within the probit portion of the likelihood, however, one would substitute for $E_*[w^0]$ and $Var_*[w^0]$ the systematic portions of the fitted model in terms of the unknown parameters γ_k, $E_k[w^0]$ and $Var_k[w^0]$ (or the systematically varying inner products $\gamma_k'\mathbf{s}$).

Generalized function optimization software would have to be used to estimate this joint model (e.g. GAUSS, GQOPT), but such a model would allow the researcher to estimate simultaneously the complete set of unknown parameters in all sub-equations: the βs, the δs, the αs, as well as the γ_b and γ_c parameters (or parameter vectors) and the usual error covariance parameter matrix Σ for the nonlinear SUR portion of the model. In this FIML model, the standard errors on the estimated parameters of the option price equation will be much more appropriate.

5. Possible Simulations using the Basic Model

The last section proposed a fairly general form for the pair of equations that describes the Bayesian updating process that leads to the individual-specific fitted values of $E^*[w^0]$ and $Var^*[w^0]$. These fitted values can be employed in place of the "observed" values of these moments of the individual's posterior distribution for w^0 in the model used to explain respondent's answers to the contingent scenario concerning willingness to pay to prevent environmental degradation. Once the model has been estimated, it can be used not only to calculate fitted option prices for environmental protection under actual conditions, but also to simulate what each individual's option price *would be* for this type of environmental protection under counterfactual conditions. For example:

a.) What would option prices be if everyone placed zero weight on their own priors and zero weight on the advice of environmental groups, basing their posterior distribution entirely on the opinions of the government scientists (i.e. set $\gamma_a = \gamma_c = 0$)?

b.) What would option prices be if government scientists lost credibility so that posterior distributions on w^0 were based entirely on each individual's priors and the opinions of environmental groups (i.e. set $\gamma_b = 0$).

c.) What would option prices be if all existing sources of information were overridden by new information on the probable distribution of w^0 (i.e. replace the fitted values of $E^*[w^0]$ and $Var^*[w^0]$ with arbitrarily specified moments, μ and σ^2.

d.) What would be the social value of reducing uncertainty about future environmental quality in the absence of mitigation? The derivative of the formula for option price with respect to $Var^*[w^0]$ reveals the sensitivity of option prices for environmental protection to variations in the magnitude of uncertainty.

e.) What would option prices be if an older population or a higher average education level has a systematic effect on the updating weights (i.e. replace the true data on AGE and EDUC with different values and recompute fitted values of the mean and variance of the posterior distribution)?

If the two portions of the model are estimated simultaneously by FIML methods, it will be possible to test fairly rigorously hypotheses about the effects on fitted option prices of changes in any of the postulated determinants, s, of the Bayesian updating parameters. To preserve readability, we will approach the derivation of $\partial E\{OP\} / \partial s$ via applications of the chain rule for partial differentiation:

$$(24) \qquad \partial E\{OP\} / \partial E_*[w^0] =$$

$$Y\,(B / A^3) \exp[-B / A]\ \{ B\, \partial A / \partial E_*[w^0] - A\, \partial B / \partial E_*[w^0] \}\ \exp[1 / (2A^2)]$$

$$-\ Y / (2A^2) \exp[\, 1 / (2A^2) - B / A]\ \{ \partial A / \partial E_*[w^0] / (A^3) \}$$

The expression for $\partial E\{OP\} / \partial E_*[w^0]$ is identical except that it substitutes $\partial A / \partial Var_*[w^0]$ and $\partial B / \partial Var_*[w^0]$ for $\partial A / \partial E_*[w^0]$ and $\partial B / \partial E_*[w^0]$.

The derivatives of A and B can now be expanded as:

$$(25) \qquad \partial A / \partial E_*[w^0] = \beta_1 \log [(Y - t) / Y],$$

$$\partial B / \partial E_*[w^0] = -\delta_0 + \delta_1 (w^1 + 2\, E_*[w^0]) + \alpha_1,$$

$$\partial A / \partial Var_*[w^0] = 0, \text{ and}$$

$$\partial B / \partial Var_*[w^0] = -\delta_1.$$

The derivatives of $E_*[w^0]$ and $Var_*[w^0]$ with respect to the normalized parameters γ^*_k are now required. These are:

(26) $$\partial E_*[w^0]/\partial\gamma^*_k = (\partial\gamma^*_k/\partial s)\, E_a[w^0] + (\partial\gamma^*_k/\partial s)\, E_b[w^0] + (\partial\gamma^*_k/\partial s)\, E_c[w^0]$$

$$\partial Var_*[w^0]/\partial\gamma^*_k = \sum_k (\partial\gamma^*_k/\partial s)\, Var_k[w^0] + \sum_k (\partial\gamma^*_k/\partial s)\, (E_k[w^0]^2)$$

$$- 2\, (\sum_k \gamma^*_k\, E_k[w^0])\, \{\sum_k (\partial\gamma^*_k/\partial s)\, E_k[w^0]\}.$$

Finally, the derivatives of the γ^*_k with respect to **s** are needed:

(27) $$(\partial\gamma^*_a/\partial s_j) = -(\gamma + \gamma)[1+\gamma^{b\prime}s+\gamma^{c\prime}s]\, \exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s]/\{\exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s])^2$$

$$(\partial\gamma^*_b/\partial s_j) = \left\{ \gamma\, \exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s] - (\gamma^{b\prime}s)(\gamma + \gamma)[1+\gamma^{b\prime}s+\gamma^{c\prime}s]\, \exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s]\right\} / \{\exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s])^2$$

$$(\partial\gamma^*_b/\partial s_j) = \left\{ \gamma\, \exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s] - (\gamma^{c\prime}s)(\gamma + \gamma)[1+\gamma^{b\prime}s+\gamma^{c\prime}s]\, \exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s]\right\} / \{\exp[1+\gamma^{b\prime}s+\gamma^{c\prime}s])^2$$

If no variables are shared between the **s** vector that determines the Bayesian updating weights and the **x** vector in the option price portion of the model, the derivative of option price with respect to any single variable s_j can be found by successive substitutions of the appropriate terms.

It should be clear that obtaining point estimates for each individual of the m derivatives of E{OP} with respect to individual variables s_j will be tedious but straightforward. As a practical matter, calculating standard errors for these individual derivatives will be prohibitively complex, although they could in principle be computed via the delta method.

The distribution of the point estimates of these derivatives across the estimating sample of respondents will be informative. For example, suppose that as individuals age, their opinions become less susceptible to manipulation by outside sources. If age is variable

s_j, the coefficients γ and γ would be expected to be negative (or likewise, the corresponding γ and γ if the method for a non-negativity constraint $\exp(\gamma_k'\mathbf{s})$ is employed). But the effect of advancing age on option price, acting via the credibility of outside information sources in the formulation of posterior probabilities, will depend upon all of the estimated parameters and all of the individual's data.

If some element of the **s** vector, s_j, is shared with **x** (which appears in the B term of the option price portion of the model), the derivatives of option price with respect to s_j are only slightly more complicated. One must additionally use the derivative:

$$(28) \quad \partial B/\partial s_j = \delta_0\, \partial E_*[w^0]/\partial s_j + \delta_1 \{\, w_1\, \partial E_*[w^0]/\partial s_j + 2E_*[w^0](\partial E_*[w^0]/\partial s_j) - \partial Var_*[w^0]/\partial s_j \,\}$$
$$+ \alpha_{0j} + \alpha_{1j}\, E[w^0] + (\alpha_1'x)(\partial E_*[w^0]/\partial s_j).$$

6. Generalizations

A number of important generalizations are feasible, all of which (separately) make 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 below illustrate some of the different directions that could be explored.

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 posterior distribution $f^*(w^1,w^0)$.

The analogous formula for the expected utility-difference in equation (13) above now involves additional data for $E_*[w^1]$, $Var_*[w^1]$, and $Cov_*[w^1,w^0]$--the other moments of the individuals subjective posterior *joint* distribution for w^1 and w^0. To allow for state-dependent preferences, I can again let the parameters of the utility function vary systematically with the realizations of the uncertainty (now for both w^1 and w^0). Let the form of this systematic variation remain linear for illustration. The estimating specification now takes the form:

$$
\begin{aligned}
(29) \qquad E_{w^0}[V^1 - V^0] = {} & \beta_0 \log[(Y - t)/Y] \\
& + \beta_1 E_*[w^0] \log[(Y - t)/Y] \\
& + \beta_2 E_*[w^1] \log[(Y - t)/Y] \\
& + \delta_0 \{E_*[w^1] - E_*[w^0]\} \\
& + \delta_1 \{Cov^*[w^1,w^0] + E_*[w^1]E_*[w^0] - Var_*[w^0] - E_*[w^0]^2 \} \\
& + \delta_2 \{Var_*[w^1] + E_*[w^1]^2 - Cov^*[w^1,w^0] - E_*[w^1]E_*[w^0] \} \\
& + \alpha_0'x + \alpha_1 E[w^0]'x + \alpha_2 E[w^1]'x + \epsilon.
\end{aligned}
$$

Analogous to the simpler case, parameters to be estimated now include scalars β_0, β_1, β_2, δ_0, δ_1 and δ_2, as well as vectors α_0, α_1 and α_2. If w^1 and w^0 are independent in the mind of the respondent, the formula in equation (29) will have $Cov_*[w^1,w^0] = 0$.

To implement this richer model, 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).

The model for Bayesian updating of individuals' native priors would also have to be modified. I would retain the assumption that the posterior distribution is a weighted average of the native prior, the distribution attributed to government scientists, and the distribution attributed to environmental groups. Assume that the parameter associated with the native prior, γ_a, is again normalized to one. Now, instead of just two equations for this part of the model, there should be five: two marginal expectations, two marginal variances, and a covariance.

Using logic similar to that developed above, the five equations to be estimated by non-linear least squares will be:

(30)
$$E_*[w^0] = \{E_a[w^0] + \gamma_b\, E_b[w^0] + \gamma_c\, E_c[w^0]\} + \nu_1$$
$$E_*[w^1] = \{E_a[w^1] + \gamma_b\, E_b[w^1] + \gamma_c\, E_c[w^1]\} + \nu_2$$
$$Var_*[w^0] = \left\{ \Sigma_k\, \gamma^*_k\, (Var_k[w^0] + (E_k[w^0])^2) \right\} - \left\{ \Sigma_k\, \gamma^*_k\, E_k[w^0]\right\}^2 + \nu_3$$
$$Var_*[w^1] = \left\{ \Sigma_k\, \gamma^*_k\, (Var_k[w^1] + (E_k[w^1])^2) \right\} - \left\{ \Sigma_k\, \gamma^*_k\, E_k[w^1]\right\}^2 + \nu_4$$
$$Cov_*[w^0,w^1] = \left\{ \Sigma_k\, \gamma^*_k\, (Cov_k[w^0,w^1] + E_k[w^0]E_k[w^1]) \right\}$$
$$- \left\{ \Sigma_k\, \gamma^*_k\, E_k[w^0]\right\} \left\{ \Sigma_k\, \gamma^*_k\, E_k[w^1]\right\} + \nu_5.$$

In the above equations, the notation $\gamma^*_a = 1 / (1 + \gamma_b + \gamma_c)$, $\gamma^*_b = \gamma_b / (1 + \gamma_b + \gamma_c)$, and $\gamma^*_c = \gamma_c / (1 + \gamma_b + \gamma_c)$ is used for simplicity. These five nonlinear equations would be jointly estimated in terms of the underlying parameters γ_b and γ_c.

Since all of the variables in these five equations are again elicited from the same individual, it would still be appropriate to allow for correlated errors. The correct procedure would be to use a system of five non-linear seemingly unrelated regression. Note that the system with scalar values of γ_b and γ_c involves only two unknown parameters.

As recommended above, however, the model is much more interesting and useful for simulations if the underlying parameters γ_b and γ_c are generalized to systematic varying parameters. Exponentiation could again be used to restrict the individual effective weights γ^*_a, γ^*_b, and γ^*_c to be positive, as well as to lie between zero and one. The dimensionality of the parameter space for this Bayesian updating model will be 2(m+1), where m is the number of regressors used to explain variations across individuals in their degree of reliance on different sources of data.

b. ***Multiple Dimensions of "Climate"***

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 event of no 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 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:

(31)
$$\begin{aligned} E_{w^0}[V^1 - V^0] = {} & \beta_0 \log[(Y - t)/Y] \\ & + \beta_1 E_*[w^0] \log[(Y - t)/Y] \\ & + \beta_2 E_*[z^0] \log[(Y - t)/Y] \\ & + \delta_0 \{w^1 - E_*[w^0]\} \\ & + \delta_1 \{w^1 E_*[w^0] - Var_*[w^0] - (E_*[w^0])^2\} \end{aligned}$$

$$+ \delta_2 \{w^1 E_*[z^0] - Cov_*[w^0,z^0] - E_*[w^0]E_*[z^0] \}$$

$$+ \theta_0 \{z^1 - E_*[z^0]\}$$

$$+ \theta_1 \{z^1 E_*[w^0] - Cov_*[w^0,z^0] - E_*[w^0]E_*[z^0]\}$$

$$+ \theta_2 \{z^1 E_*[z^0] - Var_*[z^0] - (E_*[z^0])^2 \}$$

$$+ \alpha_0'x + \alpha_1 E[w^0]'x + \alpha_2 E[w^1]'x + \epsilon.$$

Once again, correlations, rather than covariances, should probably be elicited. In the Bayesian updating portion of the model, five moments of the joint distribution of w^0 and z^0 would be modelled, each with the cross-equation restrictions implied by the assumption that respondents employ a weighted average of the joint probability distributions involved: their native prior, and the purported joint distributions of government scientists and environmental groups. The five-equation estimating specification would be completely analogous to that proposed in the previous section wherein the joint density $f^*(w^0,w^1)$ was considered.

Incidentally, it is important to note that **w** and **z** could both refer to different aspects of the same basic climate variable. For example, **w** could be mean summer temperature and **z** could be the standard deviation of summer temperatures. Certainly, climate change in some areas will contribute to higher variability in temperatures, not just changes in mean temperatures.

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 level of different environmental services, and it is the levels of these services that confer utility for individuals. Individual 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 body of this paper. 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, where 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, $s^1 = s(w^1)$, that are produced by the current level of environmental quality w^1. Assume, as before, 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, as before, but now the manner in which this quality maps into a change in available environmental services is also uncertain. For any given level of w^0 and given the assumption of linearity for the s(w) function, however, $s^0 = s^1 + \zeta(w^1 - w^0)$, where we simplify by letting $\zeta'_1 = \zeta$.

In this extension, then, ζ and w^0, are uncertain in the mind of the respondent. The indirect utility-difference function in equation (9) thus needs to be modified differently yet again. 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** (namely, the relevant slope parameter ζ is uncertain). The revised specification becomes:

$$(V^1 - V^0)_{w^0} = (\beta_0 + \beta_1 [s^1 + \zeta(w^1 - w^0)])\log[(Y - t)/Y] \tag{32}$$
$$+ (\delta_0 + \delta_1 [s^1 + \zeta(w^1 - w^0)])(s^1 - [s^1 + \zeta(w^1 - w^0)])$$
$$+ (\alpha_0 + \alpha_1 [s^1 + \zeta(w^1 - w^0)])'x$$
$$+ (\epsilon^1_{w^0} - \epsilon^0_{w^0}).$$

In the face of this additional source of uncertainty, the expected utility difference assumed to reveal 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. Analogous to previous examples, the expectation of this expression will involve terms in the individual's posterior expectations about the individual quantities w^0 and ζ, as well as the covariance (or correlation) between these two random quantities. But it will also involve the terms $E_*[\zeta^2 w^0]$ and $E_*[\zeta^2 (w^0)^2]$, among others. This may make a model without independence between ζ and w^0 empirically intractable. It is likely to be difficult enough to elicit a covariance between two uncertain quantities, let alone any more complicated moments.

If the elicitation problem was not prohibitively daunting, however, it is easy to anticipate how one would proceed. The Bayesian updating submodel for the posterior 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. In this case, however, it would be appropriate to allow for different weighting parameters for the updating of the environmental quality distribution and the environmental services distribution. For the climate change example, 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.

d. *Generalizing the Bayesian Updating Models*

Viscusi and Magat (1991) 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.

The way I have specified the estimating models in this paper precludes any weight lying outside the unit interval. By removing the restrictions imposed by functional form (i.e. not normalizing, and not using exponentiation), it would be possible to determine whether the Bayesian updating model is supported by the data. It is likely to be supported if one common pair of weighting parameters is estimated for all respondents. If the weights are generalized to be systematic varying parameters, depending upon individual characteristics, it is possible that some proportion of the sample might deviate from the Bayesian updating model.

e. *Accounting for Ambiguity across External Information Sources*

Another extension suggested by the model in Viscusi and Magat (1991) is to allow the posterior density function to be affected by the extent of the disparity among outside sources of information.[14] 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 priors. 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. Consider the simple case where the Bayesian updating parameters are modelled as scalars (γ_a, γ_b, and γ_c, with γ_a normalized to unity) so that the weights on the three densities are $\gamma_k(1+\gamma_b+\gamma_c)^{-1}$. Viscusi and Magat's (1991) 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 prior density is elicited directly, so R must be incorporated differently, although one would probably retain the nonlinear generality of the quadratic form (as necessary). The obvious strategy is to let $\gamma_a = 1 + \kappa_1 R + \kappa_2 R^2$, so that the effective weights become $\gamma_k[(1+\kappa_1 R+\kappa_2 R^2) + \gamma_b + \gamma_c]^{-1}$. 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 Bayesian updating process, one would test the hypothesis that the coefficients κ_1 and κ_2 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

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

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 prior 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 prior, as opposed to the remaining weight on the outside sources collectively.

f. ***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 specific point in the future (I have used "fifteen years hence" as an example). People are probably aware that if climate variables changes, 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 "fifteen years hence" 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.

g. ***Other Contingent Valuation Formats***

While 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, 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:

$$\log[(Y - OP) / Y] = -B / A + \epsilon / A \tag{33}$$

where, again, $A = \beta_0 + \beta_1 E_*[w^0]$ and $B = \delta_0\{w^1 - E_*[w^0]\} + \delta_1\{w^1 E_*[w^0] + E_*[w^0]^2 - Var_*[w^0]\} + \{\alpha_0 + \alpha_1 E_*[w^0]\}'x$. If ϵ is to 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 (33), ϵ / A, will be intrinsically heteroscedastic.

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.

h. ***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. And if the preferred joint estimation strategy is used, general function-optimizing software will be required anyway, so the additional effort necessary to incorporate more-complex indirect utility-function specifications will be minimal.

8. Conclusions

I have outlined a framework for analysis that is intended to guide future attempts to design surveys to gather data to address a complex problem.[15] First, how closely do individuals attend to the pronouncements by different information sources regarding future levels of environmental quality? What are the determinants of variations across individuals in this level of attention? Does the degree of ambiguity in external information affect this process? How does individual uncertainty about the consequences of failing to mitigate against adverse environmental change affect the amount people are willing to commit to pay, *ex ante*, to mitigate environmental change? If we consider government scientists (or any

[15] At the time of this writing, I am engaged in a series of small pre-test surveys of a possible survey instrument. These pre-tests use graduate and undergraduate students in economics. A copy of the current draft survey instrument is attached as an exhibit. It is proving difficult to elicit correlations between uncertain variables, so I have ceased to explore this avenue. However, participants appear to be responding very well to the other stimuli provided by the instrument. If subsequent trials perform well, I will consider pursuing funding to undertake a major empirical study along these lines.

other specific source) to be authoritative on climate change, how much would people be willing to pay if they actually believed these forecasts? What policy instruments might enhance the credibility of climate change information and thereby alter voter sympathies for climate change mitigation policies?

The greatest empirical challenge in addressing these issues is almost certainly the task of eliciting from individuals their subjective probability distributions for future climate variables. The means and variances of univariate distributions are likely to be difficult enough to elicit; the correlations between joint distributions even harder. The more complicated moments, such as those necessary if we view demand for climate change mitigation as *derived* from the demand for preservation of environmental services, will be even harder to elicit. Economists will have to tap the resources of other areas of the social sciences in order to develop suitable survey devices.

It is also hard to imagine how a survey meeting the data requirements of this model could be conducted by mail or over the telephone. The need to make "before" and "after" assessments of subjective distributions for future environmental quality precludes a single-contact mail survey, although if attrition could be minimized, a mail survey with two rounds might be effective. A telephone survey would require accompanying mailed information in order to guide the process of eliciting subjective probability distributions. In-person surveys would undoubtedly be best, but the cost of such a survey could be very high, especially because referendum contingent valuation data necessitate large sample sizes.

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.

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*, special issue in honor of Richard E. Quandt, forthcoming.

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

Viscusi, W. Kip (1985) "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) "Information al 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.

Wright, G. and P. Aytoun (199?) *Subjective Probability*