Environmental Valuation with Imperfect Information: The Case of the Random Utility Model

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WP 99-15

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December 1999

[1] I thank Nancy Bockstael, Ted McConnell, Ana Maria Ibáñez, Wei-Chun Tseng, and John Curtis for helpful comments. I also thank Victor Adamowicz for his extreme generosity in making his data available. All errors are my own responsibility.

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1 Introduction

Consumers rarely have perfect information about the quality of the goods that they purchase, and they are often forced to make consumption decisions in partial ignorance. With the classical experience good, for example, quality is at least partially unobservable at the time of purchase. After consuming the good, the individual observes its true quality, and his utility will be a function of this true quality. Thus, although purchase decisions are influenced by *perceptions* of quality, the consumer's *ex post* utility is determined by *true* quality. In this paper, I argue that environmental quality is often similar to the classical experience good, and efforts to value changes in environmental quality without taking this into consideration will result in welfare estimates that are incorrect.

The driving force behind the voluminous environmental valuation literature over the past three decades has been the desire to measure the welfare effects of changes in environmental quality (see Freeman, 1993; or Cropper and Oates, 1992). This literature has for the most part abstracted from information issues, and quite understandably.[2] After all, the obstacles to obtaining utility theoretic welfare measures have proven to be quite daunting (Bockstael and McConnell, 1999). However, with nonmarket environmental goods in particular, the assumption

[2] This is not to say that the problems associated with inaccurate perceptions have been ignored entirely. Several studies explore the role of perceptions within the context of environmental valuation (e.g., Taylor et al., 1999; Adamowicz et al., 1997; Bockstael et al., 1988; Bouwes and Schneider, 1979; Binkley and Hanemann, 1978). But the general approach has been to *compare* perceptions of quality to objective measures of quality or to *compare* welfare estimates using only perceptions of quality to welfare estimates using only objective measures. Although these comparisons provide a general feel for how far off we will be when we incorrectly assume that information is perfect, they ignore the fact that when perceptions of quality are wrong, the standard techniques for welfare measurement must be amended.

that perceptions of quality are correct is troubling, and it is arguably the rule rather than the exception for consumers to "purchase" environmental quality when information is imperfect. Swimmers will commit to a lengthy drive to the beach with only limited knowledge about water quality, hunters will drive several hours to a hunting site after hearing rumors of plentiful game, and home buyers will close on a house with no more than a rough idea about neighborhood air quality. In contrast, the quality of marketed goods is often easier to ascertain prior to purchase: tires are kicked, fruit is examined, and clothes are tried on.

Yet the standard practice for researchers using behavioral techniques to value changes in environmental quality is to assume that information is perfect and individuals' perceptions of quality are correct. Because these perceptions—rather than objective, scientific measurements of quality—are what ultimately determine choices, standard welfare estimates derived from these choices will be incorrect when perceptions are wrong. This paper will examine the implications for environmental valuation when perceptions of quality differ from true quality. I focus on the random utility model, a popular and utility theoretic approach to modeling choice, and a model often used in environmental valuation. With the exception of Foster and Just (1989), who confine their attention to the quality of a marketed good, previous attempts to apply welfare analysis to environmental quality changes under imperfect information have been incomplete.

A brief, intuitive discussion of the difficulties that arise when perceptions are incorrect will clarify the more formal results that follow. Consider the random utility model, where the consumer faces a choice from a set of mutually exclusive alternatives. Let the vector b represent the objective levels of quality associated with each alternative, and let the vector b^* represent the consumer's perception of those qualities prior to making his choice. In the choice of beaches, for example, b might represent water clarity as measured by natural scientists, while b^* might represent the consumer's perception of water clarity prior to the visit.

There are essentially two types of complications that arise when perceptions of quality are incorrect. The first complication involves estimation. When $b^* \neq b$, the parameters of the

preference function estimated by the researcher using data on b will be biased. In choosing from among the set of alternatives, the individual maximizes a utility function that depends on b^* rather than b. Although the utility received by the individual *ex post* may be a function of true quality, his *ex ante* decisions (which are used to estimate the preference function parameters) are a function of perceived quality.[3] The researcher will only be able to recover the parameters of the preference function in cases where $b^* = b$ or in cases where it is possible to actually measure b^*. The former may be true when environmental quality has been stable for a long period of time, so that individuals have had ample opportunity to revise incorrect perceptions through experience. The challenges associated with the latter approach are well known and discussed extensively in the contingent valuation literature (see Mitchell and Carson, 1989).

The second complication arises after these estimation difficulties have been overcome, and the researcher turns to the task of calculating welfare measures. Suppose that perceptions are perfectly in line with true environmental quality, so that the researcher is able to estimate the parameters of the individual's preference function. In assessing the benefits of a proposed environmental regulation, the next step is to use this function to calculate the compensating variation associated with a hypothetical change. The traditional approach is to assume that the individual will have perfect information after the change. But changes in environmental quality are far from transparent. When post-change perceptions of quality are incorrect, individuals' consumption choices will also be incorrect (in the sense that they will differ from choices made under perfect information). Although consumers may benefit from an improvement in quality, they will benefit less than they would if they were perfectly informed and could make optimal choices. As a result, the traditional welfare measure will be biased.

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[3] Of course, there are situations—especially those related to health rather than aesthetic impacts—where the consumer does not know quality even *ex post*. For example, a beachgoer may experience the negative health effects of bacterial contamination without recognizing the link to swimming in polluted waters (see Ibáñez, 1999). Furthermore, in many choice situations, quality will be stochastic and perhaps more appropriately characterized by a vector of distribution parameters (Foster and Just, 1989).

If perceptions of environmental quality are indeed wrong, then there will be value to providing information about environmental quality *even if true quality is held constant*. It would be useful to be able to measure an individual's willingness-to-pay to move from a situation where $b^* \neq b$ to a situation where $b^* = b$, holding true quality constant. For example, the United States Environmental Protection Agency maintains an internet site that provides information about the environmental quality at beaches across the country.[4] Such public information campaigns are not without cost, and estimates of the benefits associated with the provision of such information would be informative.

After briefly reviewing the literature, I derive a measure of the benefits of a change in environmental quality within the random utility model framework when perceptions of quality are allowed to be incorrect both before and after the change. This welfare measure is a generalization of the measure developed by Small and Rosen (1981) and Hanemann (1982); it reduces to the traditional measure when perceptions of quality are correct. An illustrative application to moose hunting is then presented, and welfare estimates are obtained for hypothetical changes in quality and information.

2 Literature Review

Data on perceptions of environmental quality are difficult (and expensive) to obtain, and the paucity of studies addressing the issue reflects this difficulty. It is much easier, for example, to obtain data on water clarity from a government agency than it is to *ask* swimmers about their perceptions of water clarity. Even if they could successfully state their true perceptions (which is questionable), different individuals will have different subjective scales of measurement. So although few economists would deny that perceptions are the basis of choices by individuals,

[4] www.yosemite.epa.gov/water/beach/nsf

only a handful of studies devote significant effort to exploring the issues that arise in valuing environmental quality changes when perceptions are incorrect.

Swartz and Strand (1981) examine the welfare losses caused by a contamination "scare" when consumers have imperfect information about quality. They provide estimates for the losses incurred when consumers shift consumption away from a good that is wrongly believed to be contaminated. In this case, the true quality of the good remains constant, but perceptions of quality decline, and consumers suffer welfare losses when they alter consumption choices to avoid the good. Swartz and Strand use changes in Marshallian consumer surplus to measure welfare losses. This approach overestimates welfare losses, since consumers do not actually experience the adverse health effects implied by the lower demand curve during the contamination "scare."

Foster and Just (1989) suggest an alternative approach—an approach that allows perceptions to influence purchase decisions while allowing true quality to influence *ex post* utility. Although they focus on the quality of a marketed good (the empirical application is to a milk contamination event in Hawaii), the conceptual approach that they develop is directly applicable to non-market valuation methods. Among other things, they are able to successfully measure the value of information about quality, which in their case is equal to the losses that consumers incur when a public agency withholds information about a contamination event. Prior to the event, consumers are assumed to have correct perceptions of quality, b^0.[5] After the event, perceptions of quality remain constant at b^0 and consumers continue to purchase the good, but true quality has declined to b^1. The authors suggest the following measure of the welfare effect of the change in quality:

$$cv = \tilde{e}\left(p,u,b^0;x^0\right) - \tilde{e}\left(p,u,b^1;x^0\right) = e(p,u,b^0) - \tilde{e}\left(p,u,b^1;x^0\right) \tag{1}$$

[5] Foster and Just assume that quality is random and can be represented by a vector of distribution parameters. In order to simplify the explanation, I allow quality to be deterministic. In addition, Foster and

Here, p is the price of x, the price of the numeraire, y, is unity, and $\tilde{e}(.)$ is a restricted expenditure function defined by

$$\tilde{e}\left(p,u,b,x^0\right)=\min_{x,y}\left\{px+y: x=x^0,\ u(y,x,b)\geq u\right\}, \tag{2}$$

and x^0 solves the unrestricted expenditure minimization problem,

$$e\left(p,u,b^0\right)=\min_{x,y}\left\{px+y:\ u(y,x,b^0)\geq u\right\}.$$

Thus, utility is allowed to depend on the true quality of the good (the second restriction within the brackets in expression (2)), but the quantity chosen is restricted to x^0, the quantity that would be selected under perceived quality (the first restriction within the brackets).

In what is perhaps the first extension of the Foster and Just methodology to the non-market arena, Ibáñez (1999) estimates the value of information about water quality to beach users in Colombia. She separates water quality into an aesthetic component, which is observable during the beach visit, and a health component, which is unobservable during the visit. Individuals are classified as "informed" or "uninformed" with respect to the health component of quality according to their responses to survey questions. She estimates a random utility model of beach choice, and she calculates the value of providing information to the uninformed individuals about the potential health effects of water contamination.

Although not necessarily concerned with environmental valuation, the risk perceptions literature has devoted great effort to understanding how perceptions of quality (or risk) are formed and updated (Viscusi, 1997; Smith et al., 1990; Smith and Johnson, 1988; Viscusi and O'Connor, 1984). The approach in this literature is to assume that a Bayesian learning process is operative: an individual holds prior beliefs about risk, and the individual's experiences provide new information that allow him to update this prior. Survey techniques are used in controlled experiments where respondents are questioned about their prior risk beliefs, given new

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Just's notation implies that compensating variation for a decline in quality would be positive. I reverse

information, then questioned about their posterior risk beliefs. Empirical implementation has typically involved a linear regression of posterior risk perception on prior risk perception and on some measure of the magnitude of risk implied by the new information. Again, despite providing considerable insight into how perceptions form and evolve, the focus in these studies is on the *process* of perception formation rather than on the implications for valuation when perceptions are incorrect.

In a recent paper, McCluskey and Rausser (1999) provide a link between the risk perception literature and the environmental valuation literature by embedding a model of perception formation within a hedonic property value model. They specify a hedonic price function that has perceived risk (from a nearby hazardous waste site) as one of the arguments. Risk perceptions are assumed to evolve in a Bayesian manner, with current perceived risk a function of prior risk perception and recent media information. Generalized maximum entropy techniques are applied to a panel data set to recover the parameters and the unknown state variable (perceived risk) in the model. Because McCluskey and Rausser lack data on objective risks from the hazardous waste site, they are unable to explore the welfare implications when housing *choices* are determined by risk perceptions but health *outcomes* are determined by actual risk.

3 Welfare Analysis with the Random Utility Model Under Imperfect Information

The purpose of this section is to derive a welfare measure for a change in environmental quality within the random utility model framework when perceptions of quality are incorrect. For the present, I abstract from problems of estimation. That is, I assume that the researcher is able to estimate the utility function successfully either by obtaining data in a period when individuals are correctly informed about quality (for example, after site qualities have been constant for a

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their notation to maintain consistency with the convention in Just, Hueth, and Schmitz (1982).

considerable length of time), or by obtaining data on perceptions of quality. I also assume that environmental quality is an experience good. That is, although choices are based on perceptions of quality, the objective level of quality is perfectly observable after the good is consumed, and the consumer's utility is a function of this objective quality.

3.1 The Random Utility Model Under Perfect Information

Suppose for the moment that perceptions of quality are correct. As in the traditional random utility model (McFadden, 1974), assume that individual i chooses a single unit from among N mutually exclusive alternatives in his choice set, S_i. Upon selecting alternative j, indirect utility is given by

$$v_j(y - c_j, x_j, b_j) + \varepsilon_j = v_j + \varepsilon_j, \tag{3}$$

where y is the income available for the choice occasion, c_j is the cost of alternative j, x_j is a vector of observable characteristics associated with alternative j, b_j is the objective level of quality associated with alternative j, and ε_j represents the effect of characteristics of alternative j that are observable to the individual but unobservable from the researcher's perspecive (subscripts associated with the individual are omitted for simplicity). The consumer will choose alternative j when

$$v_j + \varepsilon_j \geq v_r + \varepsilon_r \qquad \forall r \in S.$$

If the ε are independently and identically distributed as type I extreme value (or Weibull), then the probability that site j maximizes utility is given by

$$\pi_j = \frac{\exp(v_j)}{\sum_{r \in S} \exp(v_r)},$$

and a likelihood approach can be used to estimate the parameters of v_j. Let d_{ij} be a dummy variable equal to one if individual i chooses alternative j and zero otherwise. If Q individuals are observed making independent choices, the likelihood function can be written as

(4) $$L = \prod_{i=1}^{Q} \prod_{j \in S_i} \pi_{ij}^{d_{ij}}.$$

McFadden (1974) shows that under relatively weak conditions, this likelihood function is globally concave.

In environmental applications, c_j is usually interpreted as the (money and time) cost of traveling to a recreational site. The consumer weighs travel costs against environmental quality in selecting an alternative, and by observing these tradeoffs, the analyst is able to make inferences about the value of environmental quality. Consider a hypothetical improvement in environmental quality from b^0 to b^1. Compensating variation (cv) for this improvement can be expressed implicitly as

(5) $$V(y - c - cv, x, b^1, \varepsilon) = V(y - c, x, b^0, \varepsilon),$$

where y, c, x, b, and ε are vectors and V is the unconditional indirect utility function defined as

$$V(y - c, x, b, \varepsilon) = \max\{v_1 + \varepsilon_1, \ldots, v_N + \varepsilon_N\}.$$

Because ε is stochastic from the researcher's perspective, cv will be a random variable. Hanemann (1982) demonstrates that if marginal utility of income is constant across alternatives, one can take the expectation of both sides of equation (5) and solve for the following explicit expression for cv:

(6) $$cv = \frac{1}{\gamma}\left[\ln \sum_{j \in S} \exp(v_j^1) - \ln \sum_{j \in S} \exp(v_j^0)\right],$$

where γ is the implicit coefficient on income.

3.2 *Allowing Information to be Imperfect*

The expression in (6) has been used to value improvements in environmental quality in a variety of settings. However, if individuals are poorly informed with respect to the distribution of environmental quality across sites, then they will make choices that are different from the choices

they would make under perfect information, and the above measure of compensating variation will be biased. Let b_j^{s*} denote the individual's perception of quality at site j under quality level s ($s = 0$ or 1). The goal is to obtain a welfare measure for a change from b^0 to b^1 when *perceptions* of quality determine site selection probabilities, but *actual* quality determines utility after a particular site has been selected.

First, define the unconditional indirect utility function as

$$V(y-c,x,b^s,b^{s*},\varepsilon) = \max{*}\left\{v_1(y-c_1,x_1,b_1^{s*})+\varepsilon_1,\ldots,v_N(y-c_N,x_N,b_N^{s*})+\varepsilon_N;b_1^s,\ldots,b_N^s\right\},$$

where max* is a function that chooses the maximum of the N expressions prior to the semicolon (the kth expression), but then returns the value of the kth expression when b_k^s is substituted for b_k^{s*}. Defined in this way, the unconditional indirect utility function appropriately reflects what is happening to the consumer when perceptions are incorrect. Upon choosing site k, the consumer expects to visit site k and experience utility $v_k(y-c_k,x_k,b_k^{s*})+\varepsilon_k$, which is a function of his perception of quality. However, he will actually experience utility $v_k(y-c_k,x_k,b_k^s)+\varepsilon_k$, which is a function of the true quality at the site.

Compensating variation for a change in site qualities from b^0 to b^1 is defined implicitly as

$$V(y-c-cv,x,b^1,b^{1*},\varepsilon) = V(y-c,x,b^0,b^{0*},\varepsilon). \tag{7}$$

Note that cv is an implicit function of both true site qualities *and* perceived site qualities. Once again, ε is not known to the researcher, so that cv is random from the researcher's perspective. Following the approach taken by Hanemann (1982), I define compensating variation as the value of cv that equates the expected value of both sides of (7), or

$$E\left[V(y-c-cv,x,b^1,b^{1*},\varepsilon)\right] = E\left[V(y-c,x,b^0,b^{0*},\varepsilon)\right]. \tag{8}$$

I then evaluate these expectations and solve for an explicit expression for cv. In order to simplify notation, let

$$\bar{v}_j^s = v_j(y-c_j-cv,x_j,b_j^s)$$

and let $$\bar{v}_j^{s*} = v_j(y - c_j - cv, x_j, b_j^{s*}).$$

It can be shown that (see, for example, Morey, 1999) the probability the individual will choose site j under quality level s is given by

$$\pi_j^{s*} = \int_{-\infty}^{\infty} F_j\left(\bar{v}_j^{s*} - \bar{v}_1^{s*} + \varepsilon_j, \ldots, \bar{v}_j^{s*} - \bar{v}_N^{s*} + \varepsilon_j\right) d\varepsilon_j,$$

where $F_j(.)$ is the derivative of the cumulative density function of $(\varepsilon_1, \ldots, \varepsilon_N)$ with respect to its jth argument, and π_j^{s*} is written with an asterisk to emphasize the fact that this probability depends on *perceived* quality. Since the realized utility after choosing site j is given by $\bar{v}_j^s + \varepsilon_j$, the contribution of site j to $E\left[V(y - c - cv, x, b^1, b^{1*}, \varepsilon)\right]$ is given by

$$\int_{-\infty}^{\infty} \left(\bar{v}_j^1 + \varepsilon_j\right) F_j\left(\bar{v}_j^{1*} - \bar{v}_1^{1*} + \varepsilon_j, \ldots, \bar{v}_j^{1*} - \bar{v}_N^{1*} + \varepsilon_j\right) d\varepsilon_j,$$

and summing over all sites,

(9) $$E\left[V(y - c - cv, x, b^1, b^{1*}, \varepsilon)\right] = \sum_{j \in S} \int_{-\infty}^{\infty} \left(\bar{v}_j^1 + \varepsilon_j\right) F_j\left(\bar{v}_j^{1*} - \bar{v}_1^{1*} + \varepsilon_j, \ldots, \bar{v}_j^{1*} - \bar{v}_N^{1*} + \varepsilon_j\right) d\varepsilon_j.$$

This expression is identical to the expression used in the derivation of (6), except that in equation (9), *perceptions* affect the site choice probabilities through $F_j(.)$, while *true* quality determines the realized utility through $(\bar{v}_j^1 + \varepsilon_j)$. In what follows, I simplify equation (9), set it equal to a similar simplified version of the right hand side of (8), and solve for cv.

As a first step towards simplifying (9), recall that if a set of random variables, $\delta_0, \ldots, \delta_N$, are independently and identically distributed as extreme value with scale parameter equal to one and a mode equal to zero, then their multivariate cumulative distribution is given by

$$F(\delta_0, \ldots, \delta_N) = \exp\left[\sum_{i=1}^{N} \exp(-\delta_i)\right],$$

and the derivative of this cumulative distribution with respect to its jth argument is given by

$$F_j(\delta_0,\ldots,\delta_N) = -\exp\left[\sum_{i=1}^{N}\exp(-\delta_i)\right]\exp(-\delta_j).$$

Thus, if $(\varepsilon_1,\ldots,\varepsilon_N)$ are also distributed as extreme value with scale parameter equal to one and mode equal to zero, (9) will simplify to

$$E\left[V(y-c-cv,x,b^1,b^{1*},\varepsilon)\right] = \sum_{j\in S}\int_{-\infty}^{\infty}\left(\bar{v}_j^1+\varepsilon_j\right)\exp\left[-\sum_{i\in S}\exp(\bar{v}_i^{1*}-\bar{v}_j^{1*}-\varepsilon_j)\right]\exp(-\varepsilon_j)d\varepsilon_j.$$

Next, using a change of variables where $w=\bar{v}_j^{1*}+\varepsilon_j$ and substituting $D=\sum_{i\in S}\exp(\bar{v}_i^*)$, the following expression results

$$\begin{aligned} E\left[V(y-c-cv,x,b^1,b^{1*},\varepsilon)\right] &= \int_{-\infty}^{\infty} wD\exp[-D\exp(-w)]\exp(-w)dw \\ &\quad + \sum_{j\in S}\left[\exp(\bar{v}_j^{1*})(\bar{v}_j^1-\bar{v}_j^{1*})(1/D)\right]\int_{-\infty}^{\infty} D\exp[-D\exp(-w)]\exp(-w)dw. \end{aligned} \tag{10}$$

Fortunately, the properties of the extreme value distribution make this expression fairly easy to simplify. It can be shown that the probability density function of an extreme value distribution with a scale parameter equal to one and mode equal to ln$D$ is

$$f(w) = D\exp[-D\exp(-w)]\exp(-w).$$

Thus, the first integral in (10) is simply the expected value of a random variable distributed as extreme value with scale parameter of one and mode of ln$D$. The expected value of such a random variable is known to equal ln$D$ + A, where A is Euler's constant. Furthermore, the integral in the second term of equation (10) is over a probability density function, so it is equal to one. If the marginal utility of environmental quality (α) is assumed to be constant, then one may substitute back in for D and simplify to obtain

$$E\left[V(y-c-cv,x,b^1,b^{1*},\varepsilon)\right] = -\gamma(cv)+\ln\sum_{j\in S}\exp(v_j^{1*})+\alpha\sum_{j\in S}\pi_j^{1*}(b_j^1-b_j^{1*})+A,$$

where π_j^{1*} is the probability of choosing site j after the change in quality (according to *perceptions* after the change), or

$$\pi_j^{1*} = \frac{\exp(v_j^{1*})}{\sum_{i \in S} \exp(v_i^{1*})}.$$

Similarly,

$$E\left[V(y-c,x,b^0,b^{0*},\varepsilon)\right] = \ln \sum_{j \in S} \exp(v_j^{0*}) + \alpha \sum_{j \in S} \pi_j^{0*}(b_j^0 - b_j^{0*}) + A.$$

Setting these two expressions equal to one another and solving for cv yields the following expression for compensating variation:

$$cv = \frac{1}{\gamma}\left[\ln \sum_{j \in S} \exp(v_j^{1*}) - \ln \sum_{j \in S} \exp(v_j^{0*}) + \alpha \sum_{j \in S} \left(\pi_j^{1*}(b_j^1 - b_j^{1*}) - \pi_j^{0*}(b_j^0 - b_j^{0*})\right)\right]. \tag{11}$$

In the next section, this expression is interpreted and compared to the welfare measure proposed by Foster and Just (1989).

3.3 Interpretation

Expression (11), which measures the welfare impact of a change in environmental quality when perceptions of quality are incorrect, has a very intuitive interpretation. First, note that if $b_j^{1*} = b_j^1$ and $b_j^{0*} = b_j^0$ for all j (i.e., perceptions are correct), then the final summation in (11) is equal to zero and (11) reduces to (6), the welfare effect of a change in quality under perfect information.

On the other hand, when perceptions of quality differ from true quality, the first two terms within the brackets in (11) can be interpreted as the individual's "anticipated" benefits from the change. That is, these two terms capture the benefits that the individual expects to receive from the change, based on his perceptions of quality.[6] But these anticipated benefits are of course

[6] In truth, the terms represent *the researchers view of* the individual's anticipated benefits, a view that results from particular assumptions about the distribution of ε. For the sake of clarity, I omit references to the researcher.

based on inaccurate perceptions and will therefore be wrong; when the individual visits the site, his utility will be a function of the true quality at the site rather than his pre-visit perception of quality.

As a result, the anticipated benefits are corrected in order to obtain the true benefits from the change. The final summation in (11) accomplishes this correction. First, the individual's perceived value of a site visit after the change in quality, $(1/\gamma)\ln\sum\exp(v_j^{1*})$, is adjusted by adding the expected cost of misinformation (where site selection probabilities are based on post-change *perceptions*), $(\alpha/\gamma)\sum\pi_j^{1*}(b_j^1 - b_j^{1*})$. This expression will be negative (positive) when the individual is optimistic (pessimistic) about the post-change quality, so that the "anticipated" benefits would be adjusted downwards (upwards). Next, the individual's perception of the value of a site visit before the change in quality, $(1/\gamma)\ln\sum\exp(v_j^{0*})$, is adjusted in a similar manner. The result is an expression for the true benefits of a change in quality when perceptions are incorrect.

The welfare measure in (11) is the discrete choice analog of (1), which measures the welfare effect of contamination under imperfect information for the continuous case, and which is similar to the measure presented in Foster and Just (1989). In order to make this analogy clear, generalize the continuous case welfare result in (1) by allowing perceptions of quality to be incorrect both before *and* after the contamination event. In addition, assume that x solves the consumer's unrestricted expenditure minimization problem based on perceptions of quality. That is, x solves

$$\min_{x,y}\left\{px + y:\ u(y,x,b^{s*}) \geq u\right\},$$

so that x can be written as a function of perceptions, or $x(b^{s*})$. With this generalization, the continuous case welfare measure in (1) becomes

$$cv = \tilde{e}\left(p,u,b^0;x(b^{0*})\right) - \tilde{e}\left(p,u,b^1;x(b^{1*})\right).$$

Again, the utility realized will be a function of true quality, but the quantity chosen is constrained to depend on the individual's perception of quality. This expression may be expanded as follows:

$$\begin{aligned} cv &= \tilde{e}\left(p,u,b^0;x(b^{0*})\right)-\tilde{e}\left(p,u,b^1;x(b^{1*})\right) \\ &= \tilde{e}\left(p,u,b^0;x(b^{0*})\right)+\left[\tilde{e}\left(p,u,b^{1*};x(b^{1*})\right)-e(p,u,b^{1*})\right] \\ &\quad -\tilde{e}\left(p,u,b^1;x(b^{1*})\right)+\left[e(p,u,b^{0*})-\tilde{e}\left(p,u,b^{0*};x(b^{0*})\right)\right] \end{aligned}$$

because the expenditure functions within each set of brackets sum to zero. This expansion can then be rearranged to obtain an expression that has an interpretation similar to that of the discrete case welfare measure in (11):

$$\begin{aligned} cv = \left[e(p,u,b^{0*})-e(p,u,b^{1*})\right]&+\left[\tilde{e}(p,u,b^{1*},x(b^{1*}))-\tilde{e}(p,u,b^1,x(b^{1*}))\right] \\ &-\left[\tilde{e}(p,u,b^{0*},x(b^{0*}))-\tilde{e}(p,u,b^0,x(b^{0*}))\right] \end{aligned}$$

The two terms within the first set of brackets represent the consumer's "anticipated" benefits from the change (negative in this case, because we are considering a contamination event), based on *perceptions* of quality. Because these perceptions of quality are incorrect, the anticipated benefits will differ from the true benefits. To obtain the true benefits, the anticipated benefits are adjusted using the second and third bracketed expressions, which play a role similar to the final summation in expression (11). The terms within the second set of brackets correct the consumer's perception of his expenditure function after the event, $e(p,u,b^{1*})$, by adding the difference between the expenditure necessary to achieve u under the perceived and the actual quality, restricting the consumption of x to $x(b^{1*})$. The terms within the third set of brackets correct the initial perceived expenditure function in the same manner.

In order to make the result in (11) more concrete, consider the following two special cases. First, consider a case where consumers' perceptions of quality are correct *ex ante*. Assume that environmental quality improves, but perceptions of quality remain constant. This situation is likely to arise if the improvement involves an aspect of environmental quality that is difficult to perceive with the human senses. Suppose, for example, that mercury contamination in beach

sediments were cleaned up. If the cleanup received no media attention, then perceptions of quality would not change. In this case, $v^{1*} = v^{0*}$ for all j (because $b^{1*} = b^{0*}$ for all j), so that the first two terms in (11) cancel. In addition, because perceptions haven't changed, $\pi_j^{1*} = \pi_j^{0*}$, and the remaining terms will simplify to

$$cv = \frac{-\alpha}{\gamma} \sum_{j \in S} \pi_j^{1*} (b_j^1 - b_j^0). \tag{12}$$

In this case, because perceptions do not change, the change in quality will *not* affect decisions among sites; it will only affect utility after a site has been chosen. As a result, the expression for compensating variation is rather simplistic: the expected benefits are equal to the change in true quality at each site times the probability that the site will be selected, summed over all sites and converted into dollars by $-\alpha/\gamma$.

Second, consider a case where information improves, but true quality is held constant at all sites. In other words, what is the value of informing the public about the true distribution of environmental quality across sites? Holding true environmental quality constant so that $b^0 = b^1$ and assuming that information is perfect after the change so that $b^{1*} = b^1 = b^0$, expression (11) reduces to

$$cv = \frac{1}{\gamma}\left[\ln \sum_{j \in S} \exp(v_j^{1*}) - \ln \sum_{j \in S} \exp(v_j^{0*}) - \alpha \sum_{j \in S} \pi_j^{0*} (b_j^0 - b_j^{0*}) \right]. \tag{13}$$

The expression in (13) measures the value of information about the distribution of environmental quality. This may be important in conducting cost-benefit analyses of public information campaigns.

4 An Application to Moose Hunting in Alberta, Canada

In this section, the welfare measure in (11) is applied to a data set that includes both perceptions of quality and objective measurements of quality at moose hunting sites in Alberta,

Canada. These data have been analyzed elsewhere (Adamowicz et al., 1997; McLeod et al., 1995), and the purpose of this section is neither to replicate the results of these studies nor to obtain reliable welfare estimates that will guide policy decisions. Rather, the intent is simply to demonstrate several approaches to applying the welfare measure in (11) and to discuss some practical difficulties that arise.

4.1 The Data

At the conclusion of the 1992 hunting season, Alberta moose hunters were surveyed in an effort to learn about the effect of site characteristics on hunting choices (McLeod et al., 1995). A sample of 422 moose hunting license holders was drawn. The selected hunters were telephoned and asked to fill out a survey in a group setting regarding their perceptions and experiences at 14 wildlife management units (WMUs) in west-central Alberta. 271 of the contacted hunters attended the meetings, and after omitting incomplete responses, 187 useable surveys remain. For each of the 14 sites, hunters were asked to categorize their current perceptions of moose populations, hunter congestion levels, and trail quality.[7] These categories are summarized in Table 1 and described in detail below.

Moose populations were expected to be one of the most important determinants of site choice. Respondents were asked to select a category that they felt most appropriately described the moose population at each site. After defining "evidence of moose" as "seeing or hearing moose or seeing fresh sign such as tracks, browse or droppings by you or members of your party," the survey asked the respondent to categorize moose populations at each site as either "Evidence of less than 1 moose per day" (MOOSE1), "Evidence of 1 or 2 moose per day" (MOOSE2), "Evidence of 3 moose per day" (omitted), or "Evidence of more than 4 moose per

[7] The hunters were also asked about road quality en route the site and the intensity of forestry activities at the site. Adamowicz et al. (1997) found that the parameters associated with these variables were not

day" (MOOSE3). Higher levels of moose sightings are expected to increase the value of a site visit, *ceteris paribus*. Even if the hunter does not successfully "bag" a moose, the value of a site visit is likely to be enhanced by moose sightings alone.

Hunter sightings are another story. During a focus group meeting, hunters expressed a distaste for on-site encounters with other hunters, especially when the other hunters were using all-terrain vehicles (ATVs) or trucks. This is not at all surprising, given the dangers associated with hunter congestion and given the free access nature of hunting. Respondents were asked to indicate which of the following levels of hunter congestion best characterized the typical hunting day at each site: "No hunters, other than my hunting party, are encountered" (CONGESTION1), "Other hunters, hunting on foot, are encountered" (CONGESTION2), "Other hunters, on ATV's, are encountered" (omitted), and "Other hunters, in trucks, are encountered" (CONGESTION3). Encounters with other hunters is expected to negatively affect the value of a site visit relative to seeing no hunters at all, and encounters with other hunters using vehicles (such as ATVs and trucks) is expected to detract more from the experience than encounters with other hunters on foot.

Finally, respondents were asked to categorize the quality of the trails within each WMU. The four trail quality categories were "No trails, cutlines or seismic lines" (ACCESS1), "Old trails, cutlines or seismic lines, not passable without ATV" (ACCESS2), "Newer trails, cutlines, or seismic lines, passable with a 4WD" (omitted), and "Newer trails, cutlines, or seismic lines, passable with 2WD" (ACCESS3). The expected impact of trail quality on the value of a hunting experience is unclear *a priori*. Hunters may prefer the primitive hunting experience that the absence of trails or that old trails provide. On the other hand, newer trails offer fast, convenient access to remote areas of the site.

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significantly different from zero when they estimated a random utility model using this data set. For the sake of simplicity, these two variables are omitted from the analysis.

Travel costs were obtained by measuring the distance along the road network between each hunter's home and the center of each WMU. This distance was converted into round trip travel cost by assuming a constant out-of-pocket cost of $0.22[8] per km and then adding the full value of foregone wages for all individuals who indicated that they could have been working during their hunting trips.

Objective measures of site quality were obtained from Alberta Fish and Wildlife managers who were familiar with the study area. These officials were interviewed and asked to categorize moose populations, hunter congestion, and trail quality at each of the sites using categories identical to the categories used in the hunter survey. These consultations resulted in a *single* "objective" description of each site.

4.2 Estimation

Before proceeding with the estimation, further discussion is warranted regarding the relationship between this particular data set and the argument advanced at the beginning of this paper. The earlier discussion centered around the observation that environmental quality might best be characterized as an experience good. If this characterization holds for moose hunting, then the present survey, which was conducted at the end of the season, should provide *accurate* perceptions for all sites that were visited.

But the data reveal that even for visited sites, individuals' perceptions of quality differ from managers' objective characterizations of quality. Certainly, some of this discrepancy can be explained by the stochastic nature of hunting: each site visit is essentially a draw from an urn, and the hunter will only gradually learn about the true contents of the urn. Still, the hunter does learn *something* from each site visit, and his perceptions of quality at the end of the season will differ from his perceptions of quality at the time the site choices were made. Without data on

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[8] All figures are in 1992 U.S. dollars (exchange rate of 0.83 U.S. Dollars per Canadian Dollar was used).

perceptions of quality each time a site choice is made, the analyst is forced to make bold assumptions about these perceptions in order to estimate a random utility model.[9]

The approach taken here is to view each hunter as choosing a single, "favorite" hunting site. The favorite site is defined as the site that the hunter visited most often during the 1992 season, and the random utility model is used to explain the choice of this favorite hunting site. (Approximately 75% of all 1992 site visits were to these "favorite" sites.) The hunter's perception of quality at this site is assumed to be accurate and constant through the course of the season. Perceptions of "non-favorite" sites are allowed to be incorrect (because hunters have little or no experience at these sites), and these perceptions are also assumed to remain constant through the course of the season.

The observed differences between hunters' perceptions of quality and the managers' "objective" assessments of quality at the favorite sites are assumed to result from hunter-specific differences in skill. The manager reports the number of moose sightings per day that the average moose hunter might experience, while the individual reports the number of moose sightings per day that he can expect based on his unique level of skill, which may be higher or lower than average. Objective quality at the favorite site is individual-specific and assumed to be given by

$$b_{ij} = b_{ij}^{*} = b_j + a_i, \tag{14}$$

where b_j is the average level of quality at site j as reported by the manager, and a_i is a term that captures the individual's hunting skill. Knowing b_j and b_{ij}^{*} for the favorite site, one can calculate a_i for each individual. The a_i are then used to adjust the managers' "objective" quality at the non-favorite sites, so that objective qualities at these sites are also individual-specific and skill dependent.

[9] An alternative tact is to assume a Bayesian learning process and *estimate* pre-visit perceptions of quality. This approach is complicated by the categorical nature of the data.

In estimating the parameters of the random utility model, only perceptions of quality are needed, since perceptions are what determine choices. The deterministic component of the individual's conditional indirect utility function is given by

$$
\begin{aligned}
v_j = {} & \alpha_1 TRAVELCOST \\
& + \alpha_2 MOOSE1 + \alpha_3 MOOSE2 + \alpha_4 MOOSE3 \\
& + \alpha_5 CONGESTION1 + \alpha_6 CONGESTION2 + \alpha_7 CONGESTION3 \\
& + \alpha_8 ACCESS1 + \alpha_9 ACCESS2 + \alpha_{10} ACCESS3.
\end{aligned}
$$

Parameter estimates were obtained by maximizing the logarithm of (4) with the GAUSS MAXLIK routine. Table 2 presents the estimated coefficients and the likelihood ratio test statistic for the model. The travel cost coefficient is negative and highly significant as anticipated. The results with respect to the moose population variable are encouraging. The parameter estimate corresponding to the lowest moose population (MOOSE1) is negative and highly significant, the estimate corresponding to the highest moose population (MOOSE3) is positive and highly significant, and the estimate corresponding to the intermediate moose population category (MOOSE2) is not significantly different from zero (this is not unexpected, since the true parameter associated with an intermediate category is expected to be near zero). Although the congestion parameters are not significant, the estimates decline steadily as the amount of congestion increases, as one would expect. Finally, none of the access variables is significantly different from zero.

4.3 Welfare Analysis

First, consider the benefits associated with an improvement in *perceptions* of quality, holding true quality constant. This will be a measure of the value of information about the distribution of environmental quality across sites. Although actual quality does not change in this case, individuals will benefit from the ability to make correct choices among sites. Assume that true quality, perceptions of congestion, and perceptions of access remain constant, but post-

change perceptions of moose populations are perfect. Expression (13) measures the value of information about quality, but the general measure in (11) is required here, because perceptions of congestion and access remain imperfect. Applying this measure, average compensating variation (per trip) for an improvement in information about moose populations is $24.86.

Next, consider the benefits associated with an improvement in the objective level of quality. The analysis of such an improvement requires assumptions about post-change perceptions of moose populations. Consider two possibilities. First, assume that perceptions of moose populations would remain constant if actual moose populations were to increase. This is a reasonable assumption if there is a sudden increase in moose populations that does not receive significant media attention. Certainly, after repeated trips and conversations with others, hunters will become aware of the improvements. In the meantime, welfare measurements should reflect perceptions of quality that remain constant. This first case of constant perceptions is analyzed by allowing objective moose populations to increase by two levels for all sites where the manager's assessment of the population is at the lowest level (3 of the 14 sites). With perceptions held constant, site selection decisions do not change. As a result, individuals only receive benefits if they decide to choose the improved site based on the pre-change perceptions. The appropriate welfare measure is given in (12). The average compensating variation for this change is $7.95.

Alternatively, assume that the same hypothetical increase in true quality occurs, but perceptions of these sites now increase by two levels after the change. For example, all individuals who perceived the moose population at an improved site to be MOOSE2 are assumed to update their perception by two levels, so that their post-change perception of the population is set at MOOSE3 (recall that the third level was omitted). (If an individual believed that the pre-change population was best described by the highest category, that individual's perception of quality is assumed to remain constant.) This approach may reflect what happens to perceptions when there is a media report about an improvement in quality. Often, a report will only qualitatively describe the improvement; individuals are left on their own to update perceptions,

and the only thing they are certain about is that quality has increased. In this case, the general measure in (11) is used to value the change, because changes in both perceptions and true quality occur. The average compensating variation for this change is $8.41.

It is tempting to compare these three welfare estimates and to conclude that the value of information outweighs the value of improvements in actual quality. Such comparisons are misguided. Information and actual quality will be measured on different scales, so it will be impossible to compare the benefits of a hypothetical improvement in true quality to the benefits of an "equivalent" hypothetical improvement in information. However, the cost of imperfect information does appear to be substantial in this application. This indicates that incorrect perceptions of quality are causing many individuals to make wrong decisions with respect to site visits; these individuals could acheive greater utility if they had more accurate information about the quality of alternative sites.

Notwithstanding the above caveat, the results indicate that it is *possible*—at least in some situations—for public information campaigns to provide benefits that are larger than the benefits from actual improvements in environmental quality. Of course, such a result will depend on the size of the improvement in actual quality and on the number of sites that are improved. In addition, as the number of sites in the individual's choice set declines and as the characteristics of these sites become more similar, the value of information will tend to decrease. When there are fewer sites, the probability that the individual will choose the wrong site decreases (in the limit, with one site, the individual always chooses correctly). When the sites are more similar, the cost of making an incorrect choice declines.

5 Conclusion

Environmental economists observe the tradeoffs that individuals make between environmental quality and travel costs in order to make inferences about the welfare effects of quality changes. This paper points out that when consumers' perceptions of environmental

quality are incorrect, the values revealed by such tradeoffs will be misleading. In the case of environmental goods in particular, perfect information assumptions are quite troubling, and the application of traditional welfare measures will result in estimates that are incorrect.

Foster and Just (1989) introduce a methodology for evaluating the welfare impact of environmental changes when information is imperfect. They confine their attention to a marketed good where continuous quantities may be purchased. Here, their approach is extended to the discrete choice case. An expression is derived for compensating variation within the random utility framework when consumers' perceptions of the characteristics of the alternatives are allowed to be incorrect. This expression is given an intuitively appealing interpretation, and an application to moose hunting in Alberta is presented. The application highlights some of the difficulties that arise once we relax the assumption of perfect information. In environmental applications, for example, it will often be quite difficult to measure post-change perceptions of quality.

Although the discussion has focused on the *ex ante* welfare analysis of hypothetical changes in environmental quality, the techniques developed may also be useful in situations where *ex post* analysis is required, such as in damage assessment cases. After an injured site has been cleaned up, there will often be an adjustment period during which the public slowly learns about the improvement and gradually resumes recreation activities at the site. Thus, even after the site has been remediated, the public will continue to suffer welfare losses due to imperfect information about quality. These are real losses, and they would not have occurred if the injury had not happened in the first place. It may therefore be argued that the polluter should be held liable for these information-related damages in addition to the damages incurred while the site was in a degraded state. The techniques developed here provide one approach to measuring such damages.

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Table 1: Site Characteristics

Attribute	Level	Variable Name
Moose population	Evidence of <1 moose per day	MOOSE1
	Evidence of 1 or 2 moose per day	MOOSE2
	Evidence of 3 or 4 moose per day	(omitted)
	Evidence of >4 moose per day	MOOSE3
Hunter congestion	Encounters with no other hunters	CONGESTION1
	Encounters with other hunters on foot	CONGESTION2
	Encounters with other hunters on ATVs	(omitted)
	Encounters with other hunters in trucks	CONGESTION3
Hunter access	No trails, cutlines, or seismic lines	ACCESS1
	Old trails, passable with ATV	ACCESS2
	Newer trails, passable with 4WD vehicle	(omitted)
	Newer trails, passable with 2WD vehicle	ACCESS3
Travel cost	Continuous (1992 U.S. Dollars)	TRAVEL COST

Table 2: Maximum Likelihood Estimates

Characteristic	Parameter Estimate[1]
MOOSE1	-0.9545
(< 1 moose per day)	(-2.607)
MOOSE2	-0.2154
(1 or 2 moose per day)	(0.3183)
MOOSE3	1.0801
(> 4 moose per day)	(2.765)
CONGESTION1	0.0446
(no other hunters)	(.1000)
CONGESTION2	-0.2057
(other hunters on foot)	(-.5620)
CONGESTION3	-0.2926
(other hunters on trucks)	(-1.009)
ACCESS1	-7.151
(no trails)	(-0.2350)
ACCESS2	-0.0054
(older ATV trails)	(-0.0180)
ACCESS3	0.0004
(newer 2WD trails)	(-0.001)
TRAVEL COST	-0.0045
	(-3.670)
Number of Individuals	187
Likelihood Ratio Statistic	72.292

Note:

[1]The number in parentheses is the ratio of the coefficient to its asymptotic standard error