Combining Revealed and Stated Preference Methods to Value the Presence and Quality of Environmental Amenities

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Proposed Running Head: Combining Revealed and Stated Methods

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ABSTRACT

This paper combines an established revealed preference method, discrete-choice hedonic analysis, and a relatively new stated preference method, choice-based conjoint analysis, in order to estimate more accurately the aesthetic benefits generated by the presence and quality of environmental amenities associated with residential locations. It applies the combined approach to the housing market of Fairfield, CT, which contains several environmental amenities and is experiencing an improvement in the quality of its coastal wetlands. This combined approach proves especially useful for measuring the aesthetic benefits of environmental amenities in an urban or suburban setting and assessing the increased aesthetic benefits from improved wetland quality.

KEY WORDS

Revealed preference, stated preference, hedonic analysis, conjoint analysis, valuation

1. Introduction

This paper employs a new methodology for valuing environmental benefits. It combines an established revealed preference method, discrete-choice hedonic analysis, and a relatively new stated preference method, choice-based conjoint analysis, in order to estimate more accurately the aesthetic benefits generated by the presence and quality of environmental amenities associated with residential locations. Although environmental amenities most likely generate both aesthetic and recreational benefits, this paper focuses on aesthetic benefits — the more prominent of the two. This paper applies the combined valuation approach to the housing market of Fairfield, CT, which contains several environmental amenities, including Long Island Sound, and, more importantly, is experiencing an improvement in the quality of one of its major environmental amenities: coastal wetlands. This combined approach proves especially useful for measuring the aesthetic benefits of environmental amenities in an urban or suburban setting and assessing the increased aesthetic benefits from improved wetland quality.

Several studies attempt to value some of the various benefits generated by wetlands — commercial fishing, recreation, water supply, water pollution control, storm protection, and habitat — but not the aesthetic value (Whitehead and Blomquist, 1991; Costanza et. al., 1989; Farber, 1987; Batie and Wilson, 1978; Hammack and Brown, 1974; Stevens et. al., 1995; Doss and Taff, 1996).[1] Only Doss and Taff (1996) assess the aesthetic benefits generated by wetlands. Yet, their analysis does not examine the increased benefits from improvements in wetland quality. On both counts, this

[1] Whitehead and Blomquist (1991) and Stevens et. al. (1995) use the contingent valuation method to estimate the total economic value of wetlands. Costanza et. al. (1989) examine commercial fishing, recreation, and storm protection. Hammack and Brown (1974) examine wetland habitat for ducks. Farber (1987) examines storm protection. Batie and Wilson (1978) examine oyster production.

paper contributes to our understanding of wetland benefits by combining two valuation methods.

Discrete-choice hedonic analysis and choice-based conjoint analysis can easily be combined to value environmental benefits. Hedonic analysis captures the willingness-to-pay for an environmental amenity by examining how individuals select the housing location that provides the best combination of attributes, including price and associated environmental amenity. Conjoint analysis attempts to mimic this selection by asking respondents to identify their choice from a hypothetical set of housing locations, generated by varying location attributes. Respondents' choices reveal their willingness-to-pay for the environmental amenity. As constructed, both models reflect the same decision process. Therefore, discrete choice random utility theory and multinomial logit estimation techniques can be applied to both models, generating comparable welfare measurements. By combining hedonic and conjoint analysis to value environmental amenities, the joint model generates two benefits: (1) an econometric model with more robust estimates and better identification of attributes and (2) welfare measurements less prone to the common types of bias — information, hypothetical, and strategic.

Few studies combine stated and revealed preference methods for valuing environmental benefits. Moreover, these studies focus almost exclusively on recreational benefits of environmental goods and use the travel cost method as the revealed preference method. Cameron (1992), Chapman et. al. (1996), and Huang et. al. (1997) combine the continuous choice-based travel cost and contingent behavior methods. Adamowicz et. al. (1994), Swait and Adamowicz (1996), and Adamowicz et. al. (1997) combine the discrete choice-based travel cost and conjoint methods. No previous study combines stated and revealed preference methods to value the aesthetic benefits of environmental goods, including wetlands. Moreover, no previous study combines stated and revealed methods to explore residential choices as a means to value environmental goods. In this regard, only Goodman (1989) employs an approach similar to the one reported in this paper; he links estimation results from factorial survey analysis, a stated preference method, with those from hedonic price analysis to value structural and neighborhood attributes of housing. Lastly, no previous study combines choice-based conjoint analysis and discrete-choice hedonic analysis to value any non-market good or applies either of these analytical methods to residential choices in order to value environmental benefits.

To examine the combination of revealed and stated methods, this research uses data on actual housing location choices made by individual households living in Fairfield, CT, and data on hypothetical housing location choices generated by distributing mail surveys to the same group of individuals. This approach is better than linking two different groups of homeowners and survey respondents as Goodman (1989) does.

This measurement technique will have numerous policy applications. Fortunately for the environment, several local conservation agencies along the Atlantic and Pacific seaboards are implementing or exploring the restoration of coastal wetlands, ecosystems that are considered threatened or endangered (Noss and Scott, 1997). Moreover, this research approach can produce useful measurements of aesthetic benefits generated by any policy designed to restore degraded ecosystems, especially those located in urban and suburban residential settings.

The remainder of the paper details these points. Section 2 describes the full rationale for combining these stated preference and revealed preference methods. Section 3 formulates the theoretical framework. Section 4 depicts the analytical approaches for data collection. Section 5 structures and interprets the econometric analysis. Section 6 summarizes.

2. Rationale for Combining Hedonic and Conjoint Analysis

Previous research utilizes the hedonic and conjoint analytical methods to measure environmental benefits. Numerous studies use hedonic analysis to measure the benefits of environmental amenities by examining housing markets. Some studies measure the benefits of air-based amenities (Harrison and Rubinfeld, 1978; Nelson, 1978; Graves et. al., 1988); other studies measure the benefits of water-based amenities (Brown and Pollakowski, 1977; Lansford and Jones, 1995; Epp and Al-Ani, 1979; Young, 1984; Milon, Gressel, and Mulkey, 1984; Wilman, 1981). (The author is aware of no previous study measuring land-based amenities.) All of these studies apply the hedonic price model, which assumes that a continuous function relates the price of a house to its attributes — the hedonic price function — and that people select a house by equating the marginal utility of each house attribute to its marginal price (Rosen, 1974). No previous study applies the discrete-choice hedonic model, which views the individual as choosing the house that gives him/her the highest utility from all the houses in its feasible choice set, with utility as a function of attributes (McFadden, 1978). [Cropper et. al. (1993) applies this model but only to synthetic data.] In order to combine the revealed and stated methods within a common theoretical framework, this paper employs the discrete choice hedonic model. Fortunately, Cropper et. al. (1993) find that the discrete choice model outperforms the hedonic price model in valuing non-marginal attribute changes, especially when data comes from a single housing market. My analysis faces exactly these conditions: valuation of two non-marginal changes —(1) from absence to presence of an environmental amenity and (2) from degraded to restored marsh — within the single housing market of Fairfield, CT.

In the valuation literature, conjoint analysis takes different forms. Rank-ordered conjoint analysis (also called factorial survey or vignette analysis) produces descriptions of various "goods" and asks respondents to rank or rate the goods. Only a few studies apply this form of conjoint analysis to non-market goods; Goodman (1989), Mackenzie (1992), and Roe et. al. (1996) examine choices involving houses, recreational hunting, and recreational fishing, respectively. This approach seems inappropriate for explaining housing purchases since it does not mimic the actual behavior of house buyers; although buyers may rank houses initially, the most relevant decision is the purchase of a single home (Freeman, 1991). Instead, choice-based conjoint analysis is more appropriate since it asks respondents to choose one housing location from a set of constructed housing alternatives. While numerous studies use this form of conjoint analysis to analyze the demand for common market goods (Bunch et. al., 1992; Louviere and Hensher, 1982; Louviere and Woodworth, 1983), few studies use it to examine non-market goods (Adamowicz et. al., 1994). No previous study applies this analysis to non-market goods associated with residential locations.[2]

Each of the chosen stated and revealed preference models — discrete-choice hedonic analysis and choice-based conjoint analysis — has its advantages and disadvantages. The common criticism of any stated preference method is the hypothetical nature of the questions and people's choices (Mitchell and Carson, 1989). The main strength of any revealed preference method is that it is based on observed behavior. However, the revealed method of hedonic analysis suffers from several weaknesses. First, hedonic analysis depends critically on the control of all important structural, neighborhood, and environmental factors behind location choices (Freeman, 1993). To cope with this dependence, previous studies incorporate numerous explanatory variables, yet may still omit important variables. Second, hedonic analysis suffers from collinearity between explanatory variables,

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[2] Timmermans and van Noortwijk (1995) and Timmermans et. al. (1992) apply choice-based conjoint analysis to housing decisions but do not consider environmental goods.

especially when many are included (Freeman, 1993); this aspect precludes the isolation of factors affecting housing choice, including the environmental attributes of interest. Moreover, collinearity generates coefficients with wrong signs or implausible magnitudes (Greene, 1993). Third, hedonic analysis of actual housing purchases is unable to capture effectively preferences for uncommon attributes or unusual levels of attributes, such as a restored coastal wetland. Fourth, given limited information on households' search strategies, any analysis of housing purchases requires the researcher to specify arbitrarily the feasible choice sets of alternative housing locations that were considered by individual households. Moreover, the size of the specified feasible choices set may be computationally intractable, forcing the analysis to reduce dimensionality through information-depleting means.

Choice-based conjoint analysis avoids each of these weaknesses. First, the choice sets of conjoint analysis specify the attributes associated with each housing alternative; this specification clearly identifies the parameters to consider when choosing a house. Second, the statistical design of choice-based conjoint analysis avoids collinearity by generating orthogonal attribute data; i.e., the level of one attribute is held fixed, while the level of another attribute changes. Third, the survey design of conjoint analysis generates an adequate number of observations for all attributes and attribute values, including the uncommon ones. Fourth, conjoint analysis prespecifies the alternatives within each choice set faced by households.

By combining the stated and revealed preference methods, the joint model enhances the strengths and diminishes the drawbacks of each individual method. This combined approach yields three benefits. First, the addition of stated preference data, which is orthogonal in attribute levels, reduces the collinearity that most likely exists in the revealed preference data on housing choices.

Consequently, estimation is able to identify attribute effects that would be obscured by collinearity. Second, the stated preference questions generate additional observations for attributes or attribute values that are uncommon within the revealed data. Third, inclusion of revealed preference data ensures that estimation is based on observed behavior to some degree. Each benefit increases the accuracy of welfare measures for environmental amenities.

Fortunately, these two models can appropriately be combined since they reflect the same process of selecting a housing location based on attributes. As constructed, both models are discrete choice models. Therefore, discrete choice random utility theory and multinomial logit estimation techniques apply to both models and generate comparable welfare estimates (Cropper et. al., 1993).

3. Theoretical Framework

This paper employs random utility theory to model individuals' choice among housing location alternatives for both the hedonic analysis — observed choice from an actual choice set — and the conjoint analysis — induced choice from a hypothetical choice set. In both analyses, the individual (indexed by *n*) chooses the housing location that yields the highest utility of all locations in the feasible set K_n.

In the random utility framework, overall utility, U_{in}, is the sum of a deterministic component, V_{in}, and a random component, e_{in}:

$$U_{in} = V_{in} + e_{in},$$

where *i* identifies the location. I model the deterministic component as an indirect utility function conditional on the following arguments:

Z_i = vector of observed housing location attributes,

C_n = vector of observed individual characteristics,

y_n = income of individual *n*,

P_i = price of location *i*, and

β = parameter vector to be estimated.

In other words, $V_{in} = V_{in}\,(y_n - P_i , Z_i , C_n ; \beta)$. The random component (or error term) may reflect (1) unobserved attributes of the individual or housing location or (2) deviations in individual *n*'s preference vector β_n from the mean preference vector β; i.e., unobserved heterogeneity in preferences (Cropper et. al., 1993). If the error terms are identically and independently distributed (IID) Type I Extreme value with scale parameter μ,

μ = scale parameter,

the probability that individual *n* chooses location *i* rather than location *j* is of the logit form:

$$\begin{aligned} \pi_n(i) &= \text{probability that individual } n \text{ chooses location } i \text{ rather than location } j, \\ &= P\,(V_{in} + e_{in} \geq V_{jn} + e_{jn} : \forall\, j \in K_n), \\ &= \exp(\mu V_{in}) \,/\, \textstyle\sum_{j \in K} \exp(\mu V_{jn})\,. \end{aligned}$$

This equation represents a well-behaved probability bounded between zero and one (Quigley, 1985). If the deterministic utility component of the utility function is linear in its parameters,

$$V_{in} = \beta_0 + \beta_Z Z_i + \beta_C C_n + \beta_y (y_n - P_i),$$

where $\beta = \{\beta_0, \beta_Z, \beta_C, \beta_y\}$, then estimated parameters are unique up to the scale factor μ (McFadden, 1978).

This structure assumes that the odds of choosing housing unit *i* relative to unit *j* are independent of the attributes of all other housing alternatives — independence of irrelevance alternatives (IIA). While this assumption may be inappropriate in many situations involving the choice of housing locations (Quigley, 1985), models that include many socioeconomic attributes in an appropriate fashion may generate reasonable estimates since the deterministic component of the utility function should account for population heterogeneities (Ben-Akiva and Lerman, 1985).

A further complication involves selection of the feasible set of housing alternatives. In the conjoint analysis, the feasible set consists of the three constructed housing alternatives. However, in the hedonic analysis of actual housing choices, consumers select one specific housing location from a large number of alternative locations actually available on the market, K_n. In order to keep the analysis tractable, one must reduce the size of the choice sets. By selecting a subset of alternatives, noted *d*, and observing each household's selection among locations within this subset, regression analysis obtains consistent estimates of the correct choice model (Quigley, 1985). Let $f(d|i)$ represent the sampling rule for obtaining subset *d*, conditional upon the observed selection of housing unit *i*. McFadden (1978) shows that if the sampling rule has the "uniform conditioning property," maximization of the likelihood function based on a sample of observations on choice *i* from the subset *d* yields the <u>same</u> consistent parameter estimates obtained by maximizing the likelihood function based on observations of choice *i* from the set of <u>all</u> possible alternatives, K_n. The following sampling rule has this helpful property: choose *d* by including the chosen alternative and selecting at random ω rejected alternatives in the feasible set (Quigley, 1985); put differently,

$$f(d|i) = \omega / (N_n - 1),$$

where N_n indicates the number of elements in the feasible set K_n.

For the empirical analysis of the Fairfield housing market, the feasible set consists of all locations sold in the town during the same month and year. It seems reasonable to assume that any household could feasibly live anywhere in the study area given its small size (Nechyba and Strauss, 1998). Also, the number of randomly drawn alternatives, ω, equals three in the empirical analysis.

Parsons and Kealy (1992) show that even a limited number of alternatives, as small as three, is appropriate for randomly drawn opportunity sets in a random utility model.

4. Analytical Approach

Given this theoretical framework, the following section depicts two separate approaches to measuring the aesthetic benefits generated by environmental amenities associated with residential locations: discrete-choice hedonic analysis of revealed data and choice-based conjoint analysis of stated data. Section 5 further develops these two approaches and depicts a third analytical approach: joint analysis of combined data.

4.1. Discrete-Choice Hedonic Analysis

4.1.1. Research Framework

Hedonic models value environmental attributes associated with housing locations by estimating consumer preferences for these attributes. In the discrete choice hedonic model, utility is viewed as a direct function of the housing location attributes, including environmental attributes and the housing location price. By linking the revealed tradeoffs between environmental attributes and housing price, hedonic analysis estimates consumer preferences.

This paper focuses on the environmental amenity (or natural feature) associated with (or immediately adjacent to) a given housing location.[3] In the chosen research area, this amenity takes

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[3] This approach assumes that each housing location enjoys the benefits of an environmental amenity only when the site is immediately adjacent to the amenity. Such an approach facilitates this study's purpose of exploring various types of environmental amenities. Shabman and Bertelson (1979) employ this approach when examining the value of a waterfront amenity. Other hedonic price studies of water-based amenities measure the distance between each housing location and the shoreline of particular water bodies, then link distance to shoreline and housing price, generating a price gradient in distance (Brown and Pollakowski, 1977; Lansford and Jones, 1995; Milon, Gressel, and Mulkey, 1984). This more complete approach captures the beneficial effects of a water-based amenity on houses adjacent and <u>near</u> the amenity. The hedonic price framework easily accommodates the link between distance and price since both

one of the following seven values:

Water-Based Features:

(1) Long Island Sound,

(2) marsh,

(3) river or stream,

(4) lake or pond,

Land-Based Features:

(5) forest or woods,

(6) open field or park,

No Feature:

(7) backyard lawn.

The category of backyard lawn establishes the absence of a natural feature. Relative to this benchmark, the remaining features generate environmental or natural benefits, which this research attempts to estimate.

In addition, this paper estimates the benefits generated by restoration of a coastal wetland — the Pine Creek Marsh located in Fairfield, CT. Prior to the late 1950s, this wetland was relatively undisturbed. In the late 1950s and into the 1960s, the town of Fairfield diked a large portion of the wetland. This diking prevented tidal flushing of the marsh, causing the marsh to degrade from a marsh dominated by spartina grass, the natural flora, to a marsh dominated by phragmites grass, an

are treated as continuous variables. However, the discrete-choice hedonic model does not as easily accommodate distance. Incorporating distance into the chosen framework would substantially expand the analysis, especially the conjoint component, because distance would need to be interacted with each type of amenity. Future research should explore this interaction.

invasive plant species not native to the local habitat. In 1980, the town of Fairfield began restoring the Pine Creek Marsh back to a spartina-dominated marsh. To identify the relative value of a restored marsh, I divide category (2) into two sub-categories of marsh:

(2a) restored marsh (i.e., spartina-dominated marsh), and

(2b) disturbed marsh (i.e., phragmites-dominated marsh).[4]

In order to establish the tradeoffs between the environmental amenity and housing price, control of other relevant variables becomes critical (Freeman, 1993). The previous literature on hedonic analysis includes several control factors (Cropper et. al., 1988; Palmquist, 1992), which divide into three main categories: structural, neighborhood, and environmental. This analysis includes the most prominent structural features: (1) style, (2) number of bedrooms, (3) number of bathrooms, (4) interior space, (5) lot size, and (6) age of structure. This analysis includes two neighborhood features: (1) indicator variables for prominent neighborhoods in Fairfield, including the "beach", designated by census tract boundaries, and (2) flooding frequency, which is quite relevant for Fairfield given that much of the town is built on former coastal wetland (Steadman, 1996). Otherwise, this analysis ignores most neighborhood features because the study site involves only a single small town (population approximately 40,000) that is relatively homogenous in terms of the neighborhood features employed in previous research: percent professional, median income of census tract, percent of houses owner-occupied, percent white, and median age of census tract. This analysis excludes other environmental attributes, besides the adjacent environmental amenity, because the small study area generates only minimal variation in environmental attributes employed in previous research (e.g.,

[4] In the conjoint analysis survey, I use the terms —freshwater marsh and saltwater marsh — to improve respondents' understanding. Technically speaking, however, the distinction between freshwater and saltwater marshes does not accurately capture the distinction between disturbed and restored marshes.

air quality).

In addition to control factors associated with structural and neighborhood attributes, this study also incorporates information on the characteristics of the home buyer: marital status, presence of dependent children living at home, size of household, and annual household income. This information helps to explain housing choices since it captures potential heterogeneity in individuals' housing demands and abilities to pay.

Since these factors may not sufficiently control for variation in housing locations, this analysis attempts to incorporate the "un-measured quality" associated with each housing location using hedonic price analysis (Ellickson, 1977). Using the same data examined for the discrete-choice hedonic analysis, this approach regresses the price of each housing location on the same set of structural, neighborhood, and environmental attributes included in the discrete-choice hedonic analysis.[5] The price residual calculated for each housing location captures "un-measured quality;" i.e., it represents an index of those aspects of housing quality not captured by the vector of attributes.

4.1.2. Data Collection Methods

Data on actual housing choices, their associated attributes, and characteristics of buyers are taken from several sources. The Town of Fairfield Tax Assessor records all housing purchases transacted in the town of Fairfield. A computer database supplied by this office provides all the necessary information on housing purchases: (1) prominent structural features, (2) purchase price, (3) date most recently sold, (4) location (i.e., street address), and (5) name of new owner. The database contains numerous types of houses: single-family residences, multi-family residences,

[5] This hedonic price approach technically regresses the log value of house price on the explanatory variables. In this way, the residual is not a linear combination of the explanatory variables included in the discrete-choice hedonic analysis.

condominiums, etc. To avoid the need of differentiating housing markets among these different types, this paper examines only privately-owned residential single-family dwellings.

Given the street address, I was able to collect data on the natural feature associated with each housing location. The Natural Resources Center of the Connecticut Department of Environmental Protection provides data on land use and land cover for the entire town of Fairfield. By overlaying these data with data on street addresses, examining topographical maps, and personally inspecting each and every site, I identified the natural feature associated with each housing location.

Information on street address also allowed the identification of flooding frequency for each particular housing location. The Town of Fairfield Planning and Zoning Commission provides information on flooding classifications for the entire town of Fairfield. By overlaying these data with data on street addresses, I classified each housing location according to three categories:

(1) subject to 100-year flood,

(2) subject to 500-year flood, and

(3) subject to minimal flooding.

Information on individual homeowners' characteristics is elicited through mail surveys. This collection method is described in Section 4.2.2.

4.2. Choice-Based Conjoint Analysis

4.2.1. Research Framework

Choice-based conjoint analysis attempts to mimic the discrete choice hedonic analysis. Rather than observing people's choice from an actual set of housing alternatives, choice-based conjoint analysis asks people to choose from a hypothetical set of housing alternatives, which vary according to the associated attributes. The attributes used to describe each alternative reflect the actual characteristics of housing locations in the study area; Table 1 displays these attributes. (Conjoint analysis excludes the "neighborhood" attribute because it is difficult to present within a survey context.) Moreover, the analysis bases the values for each attribute on the actual ranges of values for housing locations in the study area. The statistical design process used to generate the choice sets requires discrete attribute levels. For some attributes, the variables are inherently discrete (e.g., house style). In these cases, I selected the most frequent categories found in the revealed preference data in order to span a reasonable portion of the market. For other attributes, the variables are inherently continuous (e.g., lot size). In these cases, I selected "rounded" values near the first-quartile, median, and third-quartile levels of the revealed preference data, as appropriate. For example, the first-quartile value for purchase price is $ 182,000; the value included in the choice set design process is $ 200,000. Table 1 displays the values included for each attribute.

In the conjoint survey, each choice set includes three housing alternatives. These alternatives are based on the natural feature associated with the housing location: water-based feature, land-based feature, and no natural feature. (Backyard lawns are viewed as a feature that is not truly "natural.") Figure 1 shows an example taken from this portion of the conjoint survey.[6] The survey need not divide the choice set into categories; alternatively, the survey could identify the alternatives merely by number (e.g., House # 1, House # 2, etc.). The chosen design serves two purposes: (1) focuses respondents' attention on the natural feature of each housing alternative and (2) reduces the number

[6] Timmermans and van Noortwijk (1995) include two housing alternatives and a third "no purchase" option in their conjoint survey. Without this third option, the construction of housing alternatives assumes the conditional logit model applies, that is, one of the choices is acceptable to each respondent. The inclusion of a "no purchase" option is not appropriate for matching the stated data with the available revealed data on housing purchases since a household is always observed buying a home. Moreover, the greater is the number of alternatives, the more realistic is the choice set.

of choice sets sufficient to estimate consumer preferences (as explained in the next paragraph).

The set of attributes and levels displayed in Table 1 can be seen as establishing the space to be spanned in the choice experiment (Adamowicz et. al., 1994). Given that one views each attribute as discrete, there exist (2^2 x 3^3 x 4^2 x 5^2) possible water-based alternatives, (2^3 x 3^3 x 4^2 x 5) possible land-based alternatives, and (2^2 x 3^3 x 4^2 x 5) possible no-feature alternatives. Consequently, one can view the issue of choice set construction as sampling from the space of possible triplets of water-based, land-based, and no-feature alternatives (Adamowicz et. al., 1994). In this design strategy, I first treat the attributes of water-based, land-based, and no-feature alternatives as a collective factorial — (2^2 x 3^3 x 4^2 x 5^2) x (2^3 x 3^3 x 4^2 x 5) x (2^2 x 3^3 x 4^2 x 5). Then I use an orthogonal main effects design that varies simultaneously all the attribute levels; i.e., the attributes of the choice alternatives are orthogonal within and between alternatives.[7] Assuming that the choice process can be depicted by McFadden's (1975) "Mother" logit model, the design strategy described here is consistent with a subset form of the more general Mother logit form (Adamowicz et. al., 1994; Louviere and Woodworth, 1983; Louviere and Hensher, 1983). This design permits the consistent estimation of the strictly additive variance components of the Mother logit model, given that all interactions are zero; however, the design does not generate optimally efficient parameter estimates (Adamowicz et. al., 1994). Still, it produces relatively efficient estimates (Bunch et. al., 1992).

4.2.2. Data Collection Methods

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[7] Adamowicz et. al. (1994) notes logit models are "difference-in-utility" models, that is, parameters are defined by differences in attribute levels. The statistical design employed in this study orthogonalizes the absolute attribute levels but not the differences. (Nevertheless, the logit model applies.) Inclusion of a constant reference alternative to each choice set preserves the orthogonality, even in differences, by providing a constant point for calculation. However, no constant reference is appropriate for matching the stated data with the revealed data on actual purchases since no one alternative was available to all buyers.

The main effects design demands 81 choice sets, derived from the (2^7 x 3^9 x 4^6 x 5^4) full factorial of potential attribute level combinations. Few individuals would be willing to respond to all 81 choice sets in a mail survey. Two focus groups found nine choice sets to be reasonable. Accordingly, I randomly divided the 81 choice sets into 9 groups of 9 choice sets each.[8] I placed each group of nine choice sets into a similar survey format. In other words, I generated nine versions of the same survey format, each containing nine choice sets.

The complete survey consists of four parts.[9] Part one introduces and briefly explains the research project. Part two visually depicts the eight natural features using digitally scanned black-and-white photographs. (See Figure 2.) By visually depicting rather than verbally describing the natural features, this study reduces the perceptional variation across respondents. In other words, all respondents have the same visual image for a given natural feature. Part three collects information on contingent behavior by asking the respondents to imagine that they must leave their current home and choose among three possible new housing locations. (See Figure 1.) Part four requests information on the respondents' characteristics.

This research project mailed 499 mail surveys (evenly distributed across the nine survey versions) to homeowners in the town of Fairfield, CT, in late 1996. The names and addresses of potential respondents were taken from the house purchase database provided by the Town of Fairfield Tax Assessor. The database includes all sales contracted between January 1994 and August 1996,

[8] Rather than randomly dividing the 81 choice sets, I could have blocked them into 9 groups by using an additional four-level column as a factor in the main effects design. This blocking procedure guarantees that every level of every attribute is represented in each group. Computer limitations at a critical juncture unfortunately precluded this better procedure.

[9] A copy of the survey is available from the author upon request.

inclusively. For this period, the sample of privately-owned residential single-family dwellings includes 1,501 houses. Then I applied a stratified random sample selection process, within which I oversampled houses located close to Fairfield's coastal marshes — Pine Creek Marsh and Ash Creek Marsh — by including all such houses (130 houses) in the final mailing sample.[10] This oversampling attempts to increase the hedonic model's capacity to differentiate the benefits of restored and disturbed coastal marshes. Then I randomly selected 369 houses not located adjacent to a coastal marsh from the possible 1,371 non-marsh-adjacent houses. Of the 499 people contacted, 105 returned completed surveys, for a response rate of 21 %.

4.3. Improvement upon Previous Valuation Approaches

Having described the preference valuation methods of discrete-choice hedonic analysis and choice-based conjoint analysis, the rest of this section details how combining these preference methods improves the means for valuing environmental benefits. The combined approach produces numerous improvements over previous hedonic studies. First, hedonic analysis depends critically on the control of all important factors, some of which may be omitted, yet conjoint analysis overcomes this weakness by observing choice from a prespecified choice set, as shown in Figure 1. Second, hedonic analysis suffers from collinearity between explanatory variables, which conjoint analysis eliminates with a survey design that generates orthogonal attribute levels. Third, hedonic analysis does not effectively capture preferences for uncommon attributes or attribute values, while conjoint analysis captures preferences over any attribute level, including those that are uncommon or lie beyond the range of actual data. Fourth, combining the two methods increases the data used to explore the distinction between disturbed and restored coastal wetlands (or other ecosystems).

[10] The town government of Fairfield has also partially restored Ash Creek Marsh.

Within the chosen combination of revealed and stated preference methods, the use of choice-based conjoint analysis greatly improves the methods for valuing environmental benefits, especially in comparison to the contingent valuation method. First, choice-based conjoint analysis mimics the actual choice of housing locations. Consequently, this approach is less prone to hypothetical bias. The home buyers have very recently faced a similar format in real life and have chosen to spend money on a housing location. (Note that this study surveyed homeowners within months of their house purchases.) Second, this approach does not suffer information bias; the respondents have a solid understanding of the good (and the associated attributes) being valued. Third, this approach reduces the possibilities for strategic bias. In the contingent valuation format, the policy option being evaluated is generally apparent. In the conjoint analysis format, the variety of choice sets obscures the policy options being evaluated, in this case, restoration of coastal wetlands. Fourth, this approach gives respondents focused tasks, while emphasizing the tradeoffs between housing location attributes (Adamowicz et. al., 1994).

5. Econometric Analysis

This section analyzes the collected data on actual and hypothetical housing choices. It attempts to estimate the benefits generated by environmental amenities by addressing the following two questions. First, what is the value of a natural feature associated with a housing location, using broad categories, relative to nature's absence? Moreover, what is the value of each individual natural feature within its own broad category of nature (e.g., the value of rivers/streams within the broad category of water-based natural features)? Second, what is the value of a restored marsh relative to a disturbed marsh? In other words, what is the value of marsh restoration?

5.1. Structure

Given the assumptions of the random utility framework structured in Section 3, this paper applies the multinomial logit model and estimates the parameter vector β associated with deterministic utility using full-information maximum likelihood techniques (Cropper et. al., 1993). Due to the stratified random sampling design, I weight the observations according to their different likelihoods of entering the estimation.[11] When estimating the stated data, the replications of choices from individual respondents are assumed independent, a common practice when examining stated choice data (Adamowicz et. al., 1994; Adamowicz et. al., 1997; Swait and Adamowicz, 1996).

Estimation demands a few further details. First, I employ 1,0 dummies for two of the three broad natural feature categories: water-based and land-based (no-feature is the benchmark category). These dummy variables represent alternative-specific constants in the conjoint model but not the hedonic model, which involves no specific alternatives across the choice sets considered by individual households. Second, I employ effect codes rather than 1,0 dummies to distinguish all other attributes with multiple levels (e.g., house style), as is conventional in conjoint analysis.[12] This specification improves the interpretation of coefficients involving interactions and does not confound the estimation of the alternative-specific constants. [See Adamowicz et. al. (1994, pg. 280-281) for the full rationale behind this specification.] Third, I interact the explanatory parameters regarding household characteristics with a selected housing attribute; otherwise, these explanatory parameters do not vary within each household's choice set. For the hedonic model, I interact household

[11] Estimation of this weighted exogenous sample maximum likelihood function generates consistent estimates; however, they are not asymptotically efficient (Ben-Akiva and Lerman, 1985).

[12] Each level of the attribute except the base level is represented by a column. Each column contains a "1" for the level represented by the column and a "-1" for the base level. The interpretation of these parameters is that the base level takes the utility level of the negative of the sum of the estimated coefficients and each other level takes the utility associated with the coefficient (Adamowicz et. al., 1994).

characteristics with housing price.[13] For the conjoint model, I use two specifications. In one specification, I interact household characteristics with the two alternative-specific constants (water-based features and land-based features), as is conventional in conjoint analysis and discrete-choice analysis (Ben-Akiva and Lerman, 1985; Louviere, 1988). In the other specification, I interact household characteristics with housing price for comparability with the hedonic model. Fourth, in the conjoint model, I interact another type of household characteristic — natural feature associated with the household's current location — with the broad natural feature categories offered within the survey. In this way, I can test whether respondents simply confirm (or rationalize) their actual choices with their responses to the survey. Fifth, effects codes capturing different years prove to be statistically insignificant for the hedonic model and do not apply to the conjoint model.

5.2. Estimation

To estimate the parameter vector of deterministic utility and measure the benefits generated by environmental amenities, I employ three separate sets of data: only revealed preference data, only stated preference data, and combined data.

5.2.1. Separate Estimation of Revealed and Stated Preference Data

This sub-section estimates household utility using each type of data separately. First, it estimates household utility using only revealed data on actual house purchases. Estimation results are shown in Table 2 and reveal the following. Water-based natural features generate higher utility than no natural feature, while land-based features do not differ in their ability to generate utility

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[13] This interaction allows the effect of price to vary across households with presumably differing abilities to pay. Other types of interaction serve the purposes of incorporating household characteristics and addressing interesting aspects of housing choice. For example, the effect of interior space may depend on household size or the presence of children. However, these specifications of interactions generate less satisfying results, which are available from the author upon request.

relative to no natural feature. Within the broad category of water-based features,[14] rivers/streams and restored marshes generate relatively higher utility, while disturbed marshes generate relatively lower utility. Thus, restored marshes generate higher utility than disturbed marshes.

As expected, collinearity between the explanatory variables may be confounding the coefficients' significance and magnitudes. With respect to significance, land-based features do not generate significantly greater utility than no natural feature and Long Island Sound does not differ in its utility-generating ability relative to water features as a group. With respect to magnitudes, Long Island Sound generates lower utility than either rivers/streams or restored marshes do.

Second, this sub-section estimates household utility using <u>only</u> stated data on hypothetical house purchases. Estimation results for the two specifications of household interactions — broad natural feature and housing price — are shown in Tables 3 and 4, respectively; they reveal the following. Water-based and land-based features generate higher utility than no natural feature. (The latter effect on utility becomes insignificant when land-based features are interacted with household characteristics.) Within the broad category of land-based features, forests generate higher utility than open fields. Within the broad category of water-based features, Long Island Sound, rivers/streams, and lakes/ponds each generate relatively higher utility, while both disturbed and restored marshes generate relatively lower utility. (The effect of restored marshes is insignificant.) Since disturbed marshes cause a greater negative effect, restored marshes generate higher utility than disturbed marshes. Thus, marsh restoration generates higher utility in both sets of data, even though the relative effect of restored marshes is positive in the revealed data, yet negative (albeit insignificantly

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[14] Unfortunately, no respondent chose sites associated with lakes/ponds. Consequently, inclusion of observations involving these features confounds estimation of the broad category of water-based features. Therefore, analysis ignores these observations, precluding estimation of this individual category.

so) in the stated data.

The results based on stated data show an improvement upon those based on revealed data. First, they better identify the effect of land-based features as a group, the distinction between forests and open fields, and the effect of Long Island Sound relative to all water-based features. Also, they reveal relative coefficient magnitudes that are more appropriate: Long Island Sound generates higher utility than restored marshes, rivers/streams, and lakes/ponds.

Lastly, households' hypothetical choices of natural features seem to depend on their current, actual feature choices. Households currently living at locations associated with water-based features are more likely to select a hypothetical water feature than no feature and more likely to select a hypothetical land feature than no feature. When land-based features are not interacted with household characteristics, results indicate that households currently living at locations associated with land-based features are less likely to select a hypothetical water feature than no feature. These results show that households living at locations associated with water-based features seem to appreciate nature more so than households living at locations associated with either land-based features or no feature. Moreover, these results do not indicate that households simply confirm or "rationalize" their actual feature choices with their survey responses.

5.2.2. Joint Estimation of Revealed and Stated Data

Application of the multinomial logit / maximum likelihood techniques to the first two sets of revealed and stated data is straightforward. Application to the combined data demands further comment since it involves a joint estimation procedure. Swait and Louviere (1993) describe the appropriate steps to joint estimation. First, separately estimate the revealed model and the stated model. The log-likelihood values for these models are L_r and L_s , respectively. For comparability to the revealed model, the stated model is estimated using interactions between household characteristics and housing price. Second, concatenate the two data sets and estimate the joint model. Revealed and stated data are assumed independent, a common practice when combining these types of data (Adamowicz et. al., 1994; Adamowicz et. al., 1997; Swait and Adamowicz, 1996). The log-likelihood value for this model is L_n. Third, concatenate the two data sets but rescale the stated data relative to the revealed data (or vice versa) by conducting a grid search:

(a) multiply the stated data matrix by a constant, beginning at one end of the search range;

(b) estimate the joint model and its log likelihood, denoted L_c;

(c) repeat by incrementing the constant; and

(d) stop at the constant value that maximizes the likelihood value.

This procedure generates the optimal rescaling constant that maximizes the fit of the stated and revealed parameters given the conditional logit model (Adamowicz et. al., 1994). Fourth, use these log-likelihood values to examine whether the preference structures are similar between the two data sets by testing the hypothesis of equal parameters, after adjusting for the relative scale effect. In other words, use the following likelihood ratio test of the difference between parameters: $\lambda = -2[L_c - (L_r+L_s)]$. Failure to reject this χ^2 test would provide sufficient evidence that the stated and revealed data contain similar preference structures. In this analysis, the calculated χ^2 test statistic, λ, for housing location choices equals 91.446. Given 31 degrees of freedom,[15] this test statistic significantly rejects the hypothesis of equal parameters at the 1 % confidence level. In other words, the full set of parameters for the revealed and stated data are not compatible.

[15] The degrees of freedom equal the number of parameters in the revealed data model plus the number of parameters in the stated data model minus the number of parameters in the joint model plus one additional degree for the relative scale factor (Swait and Louviere, 1993).

Nevertheless, the effects of certain parameters are comparable between the two data sets, while the effects of other parameters are different. In order to separate compatible and incompatible variables, I allow certain subsets of the coefficients to vary between the two data sets when estimating the joint model. In other words, the two data sets are pooled, yet certain coefficients are not restricted to be equal across the two data sets. The strategy is to identify the largest subset of variables constrained to be equal across the two data sets which does not reject the hypothesis of equal parameter estimates. This method finds that 12 particular variables represent the largest collection of compatible variables, including water-based features, land-based features, Long Island Sound, rivers/streams, and forests. Eight other variables, including restored marshes and housing price remain unrestricted in their effects between the two data sets. Six variables are not common to both sets, yet they are regarded as being compatible.

Estimation of this specification for combining revealed and stated data generates the results shown in Table 5. Water-based and land-based features generate higher utility than no natural feature. Within the broad category of land-based features, forests generate higher utility than open fields. Within the broad category of water-based features, Long Island Sound, rivers/streams, and lakes/ponds generate relatively higher utility, while disturbed marshes generate relatively lower utility. Restored marshes generate relatively higher utility within the revealed data, yet relatively (and insignificantly) lower utility within the stated data. Regardless of the data set, restored marshes generate higher utility than disturbed marshes, indicating that marsh restoration increases utility.

5.3. Welfare Measures of Natural Features

From each set of parameter estimates reported in Section 5.2, I calculate welfare measures of the environmental benefits generated by broad and individual categories of natural features, including welfare measures for coastal wetland restoration. The standard welfare measure is the compensating variation (CV) associated with the change from one type of natural feature to another, in particular, the change from no natural feature to some type of natural feature and the change from disturbed marsh to restored marsh. In the discrete-choice framework, economic studies generally base the level of welfare benefits (CV) on a change in expected utility. In terms of residential choice, this analysis assumes that an individual household is not certain which house it will choose, except up to a probability distribution (Hau, 1985). Given this perspective, economic studies commonly use the following CV measure:

$$CV = (1/\alpha)\,[\ln(\Sigma_{i\in K} \exp(V_{in1})) - \ln(\Sigma_{i\in K} \exp(V_{in0}))]\ ,$$

where α represents the coefficient on the housing purchase price term in absolute terms (interpreted as the marginal utility of income), V_{in0} represents the level of utility in the initial state, and V_{in1} represents the level of utility in the subsequent state (McConnell, 1995). The initial state is either the absence of a natural feature (i.e., backyard) or a disturbed marsh; the subsequent state is either the presence of a natural feature or a restored marsh. In order to compare welfare measures among the various natural features, the analysis adjusts the CV measures according to the number of houses affected by each particular change from initial to subsequent state. In this way, each CV level measures environmental value per housing location.

CV measures based on expected utility are unfortunately sensitive to the contents of each choice set, including the attributes of any affected housing site and the attributes of unaffected housing sites (Kaoru and Smith, 1990; Freeman, 1993). Since each household very likely faces a distinctively different choice set, this sensitivity may substantially affect the CV calculations. Consequently, this measure of CV may not retain the relative magnitudes or even rankings of the coefficient estimates associated with natural features. This problem generally does not arise (or is at least muted) in other discrete-choice contexts examined by environmental economics, such as recreational choice, since the associated analyses treat individuals as sharing identical (or at least similar) choice sets.[16]

CV measures for stated data alone are based on the specification with interactions between household characteristics and broad natural features for two reasons. First, the chosen specification permits complete interaction across each choice set, unlike the other specification, which depends on the variation of housing price within each choice set. Second, the chosen specification generates a significant and reasonable estimate of the coefficient on housing price. Since this coefficient proves critical for calculating CV measures, this specification generates more reasonable CV values.

CV measures for the combined data can be calculated in four different ways according to the set of coefficients used to calculate deterministic utility and the price coefficient used to represent marginal utility of income. The set of coefficients for calculating utility may include incompatible coefficients specific to <u>either</u> the revealed data <u>or</u> the stated data, in addition to the compatible coefficients. Similarly, the price coefficient may be specific to <u>either</u> the revealed data <u>or</u> the stated

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[16] An alternative welfare measure derives compensating variation from the change in actual utility rather than expected utility. From this perspective, CV is the amount of money required to compensate an individual for the attribute change, <u>given</u> that the individual chooses to consume the affected housing location (Small and Rosen, 1981; Hanemann, 1984). Let β_b indicate the coefficient on natural feature *b* and β_{bf} indicate the coefficient on natural feature *f* within broad category *b*. Then the welfare measure for each broad category and individual category of natural feature is respectively:

$CV_b = \beta_b / \alpha$, and

$CV_{bf} = (\beta_b + \beta_{bf}) / \alpha$.

This CV measure obviously retains the relative magnitudes and rankings of the coefficient estimates for the natural features. (Calculations of this CV measure are available from the author upon request.)

Both types of welfare measure are valid. However, the measure based on expected utility is more consistent with the choice framework in that it captures the gain in value enjoyed by a household facing a residential decision. On the other hand, the CV measure based on actual utility is essentially tied to a particular house rather than a particular household.

data. Table 6 reports three of the four possible combinations for calculating CV; the table omits the combination of utility based on revealed-data-specific coefficients and marginal utility of income based on the stated-data-specific price coefficient because it lacks usefulness.

Table 6 reports the welfare measures for each broad and individual category of natural feature generated by each estimation model: only revealed data, only stated data, and combined revealed and stated data (rescaled optimally). CV measures based on revealed data seem too small in general. Given a median house price of approximately $ 245,000 in the Fairfield market, one would expect water-based features to generate more than $ 8,990 in benefits, rivers/streams to generate more than $ 6,137, and Long Island Sound to generate much more than a paltry $ 7,924. Relative to these values, other welfare measures seem too large. Restored marshes generate $ 40,578 in benefits — five times the value of Long Island Sound — and disturbed marshes generate negative benefits of $ 32,412. Collinearity between explanatory variables in the revealed data appear to confound the calculation of CV measures, stemming from collinearity's effect on the individual coefficients associated with environmental amenities.

CV measures based on stated data seem too large in general. The environmental benefits range from $ 64,000 for an open field to $ 164,048 for lakes/ponds. The only reasonable CV measure is $ 123,145 for Long Island Sound. The rather small coefficient on housing price most likely drives these unreasonably high values.

Relative to these CV measures based on each individual data set, combining the revealed and stated data substantially improves benefit valuation. Consider first the case where utility is calculated using the set of coefficients specific to the revealed data, plus the compatible coefficients, and the marginal utility of income is based on the price coefficient specific to revealed data. Estimates of benefits generated by water-based features, land-based features, Long Island Sound, disturbed marshes, forests, and open fields are more reasonable than those based on either revealed or stated data. However, estimates of benefits generated by rivers/streams and lakes/ponds shrink to practically nothing — $ 906 and $ 369, respectively.

Next, consider the case where utility is calculated using the set of coefficients specific to the stated data, plus the compatible coefficients, and the marginal utility of income is based on the price coefficient specific to the stated data. These CV measures are much too large. They span from $ 230,765 for an open field to a whopping $ 612,196 for a lake/pond. The very small price coefficient specific to stated data drives these unreasonable results.

However, calculating utility based on coefficients specific to stated data, plus compatible coefficients, seems to produce good results. If this measure of utility is divided by the price coefficient specific to revealed data, the CV measures become quite reasonable. Water-based and land-based features generate benefits of $ 14,135 and $ 17,520, respectively. Individual water features generate benefits between $ 11,073 and $ 21,308. Individual land features generate benefits between $ 8,032 and $ 18,652. In addition, the relative magnitudes seem more in line with expectations. Long Island, rivers/streams, and lakes/ponds generate greater benefits than restored or degraded marshes. [In absolute terms, Long Island Sound unfortunately generates an unreasonably low level of benefits at $ 14,785.]

Based on these results, combining revealed and stated data improves the calculation of welfare measures. In particular, inclusion of stated data seems to avoid problems with collinearity and generates more accurate coefficients in general. Analysis should use these coefficients to calculate deterministic utility. On the other hand, estimation of stated data generates a price coefficient that is too small. Possibly, the context of the conjoint survey does not adequately capture the tradeoff between housing price and other attributes; i.e., respondent choices are insufficiently sensitive to price changes. In contrast, the real-life context of actual housing purchases seems to capture more effectively this tradeoff. In other words, estimation of revealed data generates a price coefficient more in touch with reality. Analysis should use this price coefficient to represent marginal utility of income.

Combining revealed and stated data similarly improves the welfare measures for marsh restoration. Welfare measures based on revealed data alone and stated data alone are comparable at $ 50,124 and $ 40,632, respectively. Yet, these measures seem too large relative to a median house price of $ 245,000. Combining the two data sets, while basing utility and marginal utility of income on the set of coefficients specific to the same data set — both specific to revealed data or both specific to stated data, actually increases the CV measure. As with welfare measures for individual natural features, the very small price coefficient specific to stated data drives the latter CV measure to an unreasonably high level ($ 192,036). Fortunately, when deterministic utility is based on coefficients specific to stated data, plus the compatible coefficients, and marginal utility of income is based on the revealed-data-specific price coefficient, combining revealed and stated data generates a small but quite reasonable welfare measure for marsh restoration of $ 6,684.

6. Summary

In sum, this paper combines the revealed method of discrete-choice hedonic analysis and the stated method of choice-based conjoint analysis to estimate the benefits of environmental amenities and coastal marsh restoration in an urban/suburban setting of southwestern Connecticut. Estimation is based on three different data sets — only revealed data on actual house purchases, only stated data on hypothetical house locations, and combined revealed and stated data. Combining the revealed and stated data substantially improves the welfare measurement of each environmental amenity and marsh restoration. In particular, inclusion of the stated data improves estimation of overall utility associated with housing locations, including the utility stemming from the environmental amenity, while inclusion of the revealed data improves estimation of the marginal utility of income, as captured by the coefficient on housing price.

The town of Fairfield will find these calculations of environmental benefits valuable for examining the scope and relevance of its restoration efforts. Based on these results, restoration of the Pine Creek Marsh wetland complex should increase aesthetic benefits. Other cities considering ecosystem restoration in urban and suburban settings will also find this valuation technique useful.

Figure 1

Example of Conjoint Survey

Choice Set 1

Suppose you needed to leave your current home and were considering 3 houses to buy in Fairfield. The columns below describe these 3 housing options. The first house includes a water-based natural feature denoted by reference to the preceding photographs. The second house includes a land-based natural feature denoted by reference to the preceding photographs. (Each feature will remain natural for your entire time in the given house.) The third house includes neither feature.

Which house would you buy given your current financial situation?

House 1 __ House 2 __ House 3 __

	House 1	House 2	House 3
Natural Feature	Photo A	Photo G	Photo H
Number of Bedrooms	4	3	3
Number of Bathrooms	1	1	1
Internal Space (ft^2)	1500	1500	1500
Style	Colonial	Colonial	Ranch
Age (years)	new	70	new
Lot Size (acres)	0.2	0.6	0.6
Frequency of Flooding	never	never	never
Price	$ 250,000	$ 200,000	$ 600,000

Table 1

Attributes and Levels Included in Conjoint Analysis

Attribute	Levels	Attribute	Levels
Natural Feature	Long Island Sound	Age of House	0 years (new)
	Saltwater Marsh		40 years
	Freshwater Marsh		70 years
	River/Stream	Lot Size	0.2 acres
	Lake/Pond		0.6 acres
	Forest/Woods	Flooding	never
	Open Field/Park		every 100 years
	Backyard Lawns	Price	$ 200,000
Bedrooms	3		$ 250,000
	4		$ 350,000
Bathrooms	1		$ 600,000
	2	Style	Cape Cod
Interior Space	1,500 square feet		Colonial
	2,500 square feet		Ranch

Table 2

Multinomial Logit Regression of Revealed Data

Variable [a]	Description	Coefficient Estimate	
Attributes			
Broad Natural Feature [b]	None (=0) versus	0	
	Water (=1)	2.977	***
		(1.175)	
	Land (=1)	0.524	
		(0.546)	
Water Feature	Disturbed Marsh (= -1) versus	- 4.966	
	Restored Marsh (=1)	2.184	***
		(0.821)	
	Long Island Sound (=1)	1.329	
		(0.866)	
	River/Stream (=1)	1.453	*
		(0.868)	
	Lake/Pond (=1) [c]	--	
Land Feature	Forest (=1) versus Field (= -1)	0.368	
		(0.529)	
Bedrooms	Number	- 0.148	
		(0.277)	
Bathrooms	Number	0.056	
		(0.315)	
Interior Space	1,000 ft^2	0.989	*
		(0.528)	

Style	Cape Cod (= -1) versus Colonial (=1)	- 2.226 0.981	 ***
		(0.257)	
	Ranch (=1)	0.313	
		(0.260)	
	Other (=1)	0.932	***
		(0.261)	
Age	Years	- 0.008	
		(0.006)	
Lot Size	Acres	- 0.034	
		(0.142)	

Flooding	Minimal (= -1) versus	0.072	
	500-year Flood (=1)	- 0.672	
		(0.425)	
	100-year Flood (=1)	0.600	
		(0.425)	
Price	$ 1,000	- 0.019	**
		(0.010)	
Census Tract	Other (= -1) versus	- 0.591	
	Beach area (= 1)	- 0.319	
		(0.402)	
	Greenfield Hills (= 1)	0.910	**
		(0.401)	
Residual Quality [d]	$ 1	5.348	***
		(1.694)	
Household Characteristics Interacted with House Price			
Marital Status	Married (=1) versus Single (= -1)	0.003	
	[per $ 1,000]	(0.004)	
Children	Yes (=1) versus No (= -1)	- 0.0001	
	[per $ 1,000]	(0.002)	
Household Size	Number	0.003	
	[per $ 1,000]	(0.002)	
Income [e]	Low (= -1) versus	- 0.002	
	Medium (=1)	0.008	***
	[per $ 1,000]	(0.003)	
	High (=1)	0.010	***
	[per $ 1,000]	(0.004)	
Number of Observations	404		
Log-Likelihood	- 94.935		

Likelihood ratio statistic (χ^2)	95.41
McFadden's ρ^2	0.33

[a] Attributes with multiple levels are coded using effects codes, except as noted. Each level except the base level is represented by a column. Each column contains a "1" for the level represented by the column and a "-1" for the base level. The interpretation of these parameters is that the base level takes the utility level of the negative of the sum of the estimated coefficients and each other level takes the utility associated with the coefficient.

[b] Broad natural features are coded as 1,0 dummy variables.

[c] Observations involving lakes/ponds were deleted since no respondent chose these sites.

[d] Residuals from regression of the log values of house price on set of explanatory variables identical to discrete-choice hedonic analysis; residuals converted into dollar values.

[e] Low: < $ 100,000; Medium: $ 100,000 - $ 200,000; High: > $ 200,000.

Standard errors in parentheses. *,**,*** indicate statistical significance at levels of 10%, 5%, 1%, respectively.

Table 3

Multinomial Logit Regression of Stated Data:

Interactions between Household Characteristics and Broad Natural Features

Variable [a]	Description	Coefficient Estimate	
Attributes			
Broad Natural Feature [b]	None (=0) versus	0	
	Water (=1)	2.519	***
		(0.600)	
	Land (=1)	0.817	
		(0.552)	
Water Feature	Disturbed Marsh (= -1) versus	- 0.871	
	Restored Marsh (=1)	- 0.130	
		(0.114)	
	Long Island Sound (=1)	0.412	***
		(0.114)	
	River/Stream (=1)	0.234	**
		(0.118)	
	Lake/Pond (=1)	0.355	***
		(0.142)	
Land Feature	Forest (=1) versus Field (= -1)	0.161	**
		(0.084)	
Bedrooms	Number	0.067	
		(0.096)	
Bathrooms	Number	0.348	***
		(0.097)	
Internal Space	1,000 ft^2	0.692	***
		(0.099)	
Style	Cape Cod (= -1) versus	- 0.018	

	Colonial (=1)	0.146	***
		(0.057)	
	Ranch (=1)	- 0.128	**
		(0.062)	
	Other (=1)	N/A	
Age	Years	- 0.003	**
		(0.002)	
Lot Size	Acres	0.930	***
		(0.241)	
Flooding	Minimal (= -1) versus	0.062	
	100-year Flood (=1)	- 0.062	
		(0.051)	
Price	$ 1,000	- 0.0039	***
		(0.0004)	
Household Characteristics Interacted with Broad Natural Features			
Interactions with Water-Based Feature			
Marital Status	Married (=1) versus Single (= -1)	- 0.109	
		(0.186)	
Children	Yes (=1) versus No (= -1)	0.138	
		(0.175)	
Household Size	Number	- 0.201	
		(0.164)	
Income [c]	Low (= -1) versus	- 0.171	
	Medium (=1)	0.105	
		(0.121)	
	High (=1)	0.066	
		(0.184)	
Current Natural Feature	None (= -1) versus	- 0.614	
	Water (=1)	0.763	***
		(0.226)	
	Land (=1)	- 0.149	
		(0.156)	

Interactions with Land-Based Feature			
Marital Status	Married (=1) versus Single (= -1)	0.414	**
		(0.200)	
Children	Yes (=1) versus No (= -1)	- 0.064	
		(0.180)	
Household Size	Number	- 0.030	
		(0.165)	
Income [c]	Low (= -1) versus	0.169	
	Medium (=1)	- 0.132	
		(0.119)	
	High (=1)	- 0.037	
		(0.181)	
Current Natural Feature	None (= -1) versus	- 0.769	
	Water (=1)	0.822	***
		(0.226)	
	Land (=1)	- 0.053	
		(0.146)	
Number of Observations	2,727		
Log-Likelihood	- 811.055		
Likelihood Ratio Statistic (χ^2)	367.229		
McFadden's ρ^2	0.18		

[a] Attributes with multiple levels are coded using effects codes, except as noted. Each level except the base level is represented by a column. Each column contains a “1" for the level represented by the column and a “-1" for the base level. The interpretation of these parameters is that the base level takes the utility level of the negative of the sum of the estimated coefficients and each other level takes the utility associated with the coefficient.

[b] Broad natural features are coded as 1,0 dummy alternative-specific constants.

[c] Low: < $ 100,000; Medium: $ 100,000 - $ 200,000; High: > $ 200,000.

Standard errors in parentheses. *,**,*** indicate statistical significance at levels of 10%, 5%, 1%, respectively.

Table 4

Multinomial Logit Regression of Stated Data:

Interactions between Household Characteristics and Housing Price

Variable [a]	Description	Coefficient Estimate	
Attributes			
Broad Natural Feature [b]	None (=0) versus	0	
	Water (=1)	1.838	***
		(0.348)	
	Land (=1)	1.189	***
		(0.244)	
Water Feature	Disturbed Marsh (= -1) versus	- 0.951	
	Restored Marsh (=1)	- 0.119	
		(0.115)	
	Long Island Sound (=1)	0.449	***
		(0.115)	
	River/Stream (=1)	0.244	**
		(0.120)	
	Lake/Pond (=1)	0.377	***
		(0.144)	
Land Feature	Forest (=1) versus Field (= -1)	0.172	**
		(0.084)	
Bedrooms	Number	0.077	
		(0.097)	
Bathrooms	Number	0.395	***
		(0.098)	

Internal Space	1,000 ft^2	0.668	***
		(0.100)	
Style	Cape Cod (= -1) versus	- 0.029	
	Colonial (=1)	0.149	***
		(0.058)	
	Ranch (=1)	- 0.120	**
		(0.062)	
	Other (=1)	N/A	
Age	Years	- 0.004	***
		(0.002)	
Lot Size	Acres	0.869	***
		(0.244)	
Flooding	Minimal (= -1) versus	0.065	
	100-year Flood (=1)	- 0.065	
		(0.051)	
Price	$ 1,000	- 0.0017	
		(0.0018)	
Household Characteristics Interacted with House Price			
Marital Status	Married (=1) versus Single (= -1)	- 0.001	*
	[per $ 1,000]	(0.0007)	
Children	Yes (=1) versus No (= -1)	- 0.0002	
	[per $ 1,000]	(0.0006)	
Household Size	Number	0.0004	
	[per $ 1,000]	(0.0006)	
Income [c]	Low (= -1) versus	- 0.005	
	Medium (=1)	0.001	***
	[per $ 1,000]	(0.0005)	

	High (=1)	0.004	***
	[per $ 1,000]	(0.0006)	
Current Natural Features Interacted with Broad Natural Features			
Interactions with Water-Based Feature			
Current Natural Feature	None (= -1) versus	- 0.526	
	Water (=1)	0.792	***
		(0.225)	
	Land (=1)	- 0.266	**
		(0.128)	
Interactions with Land-Based Feature			
Current Natural Feature	None (= -1) versus	- 0.869	
	Water (=1)	0.834	***
		(0.224)	
	Land (=1)	0.035	
		(0.120)	
Number of Observations	2,727		
Log-Likelihood	- 791.043		
Likelihood Ratio Statistic (χ^2)	407.253		
McFadden's ρ^2	0.20		

[a] Attributes with multiple levels are coded using effects codes, except as noted. Each level except the base level is represented by a column. Each column contains a "1" for the level represented by the column and a "-1" for the base level. The interpretation of these parameters is that the base level takes the utility level of the negative of the sum of the estimated coefficients and each other level takes the utility associated with the coefficient.

[b] Broad natural features are coded as 1,0 dummy variables.

[c] Low: < $ 100,000; Medium: $ 100,000 - $ 200,000; High: > $ 200,000.

Standard errors in parentheses. *,**,*** indicate statistical significance at levels of 10%, 5%, 1%, respectively.

Table 5

Multinomial Logit Regression of Combined Revealed and Stated Data

Variable [a,b]	Description	Coefficient Estimate [c]	
		Revealed Data	Stated Data
Attributes			
Broad Natural			
Feature [d]	None (=0) versus		0
	Water (=1)	1.714 ***	
		(0.311)	
	Land (=1)	1.014 ***	
		(0.198)	
Water Feature	Disturbed Marsh (= -1) versus	- 2.429	- 0.969
	Restored Marsh (=1)	1.333 ***	- 0.127
		(0.521)	(0.117)
	Long Island Sound (=1)	0.455 ***	
		(0.117)	
	River/Stream (=1)	0.260 **	
		(0.123)	
	Lake/Pond (=1)	0.381 ***	
		(0.145)	
Land Feature	Forest (=1) versus Field (= -1)	0.179 **	
		(0.086)	
Bedrooms	Number	0.022	
		(0.092)	

Bathrooms	Number			0.332	***		
				(0.095)			
Interior Space	1,000 ft^2			0.681	***		
				(0.101)			
Style	Cape Cod (= -1) versus	- 1.668				- 0.094	
	Colonial (=1)	0.718	***			0.156	***
		(0.217)				(0.060)	
	Ranch (=1)	0.737	***			- 0.119	*
		(0.238)				(0.064)	
	Other (=1)			0.213			
				(0.243)			
Age	Years			- 0.004	***		
				(0.002)			
Lot Size	Acres	- 0.084				0.890	***
		(0.135)				(0.254)	
Flooding	Minimal (= -1) versus	- 0.211				0.525	
	500-Year Flood (=1)			- 0.454			
				(0.332)			
	100-year Flood (=1)	0.665	*			- 0.071	
		(0.400)				(0.535)	
Price	$ 1,000	- 0.026	***			- 0.001	
		(0.005)				(0.002)	
	Household Characteristics Interacted with House Price						
Marital Status	Married (=1) versus Single (= -1)	0.007	**			- 0.002	**
	[per $ 1,000]	(0.003)				(0.001)	
Children	Yes (=1) versus No (= -1)			- 0.0003			
	[per $ 1,000]			(0.0006)			

Household Size	Number	0.0033	***			0.0002
	[per $ 1,000]	(0.001)				(0.001)
Income [e]	Low (= -1) versus			- 0.0066		
	Medium (=1)			0.0019	***	
	[per $ 1,000]			(0.001)		
	High (=1)			0.0047	***	
	[per $ 1,000]			(0.001)		
Number of Observations	3,131					
Log-Likelihood	- 931.702					
Likelihood Ratio Statistic (χ^2)	481.549					
McFadden's ρ^2	0.21					

[a] Attributes with multiple levels are coded using effects codes, except as noted. Each level except the base level is represented by a column. Each column contains a "1" for the level represented by the column and a "-1" for the base level. The interpretation of these parameters is that the base level takes the utility level of the negative of the sum of the estimated coefficients and each other level takes the utility associated with the coefficient.

[b] Table shows only variables common to both the stated and revealed data. The regression additionally includes the uncommon variables.

[c] Parameters with only one reported coefficient are constrained to be equal across the two data sets.

[d] Broad natural features are coded as 1,0 dummy variables.

[e] Low: < $ 100,000; Medium: $ 100,000 - $ 200,000; High: > $ 200,000.

Standard errors in parentheses.

*,**,*** indicate statistical significance at levels of 10%, 5%, 1%, respectively.

Stated data are re-scaled by a factor of 0.85.

Table 6

Welfare Measures of Natural Features and Marsh Restoration

6.a. Natural Features

Feature Categories	Type of Data used for Estimation				
	Revealed ($)	Stated [a] ($)	Combined ($) [b,c]		
			Revealed Utility Revealed MU	Stated Utility Revealed MU	Stated Utility Stated MU
Broad Categories					
Water	8,990	142,535	12,557	14,135	406,107
Land	9,804	100,472	15,034	17,520	503,355
Individual Categories					
Water-Based					
Disturbed Marsh	- 32,412	141,001	- 5,754	11,073	318,134
Restored Marsh	40,578	141,101	45,871	11,905	342,048
Sound	7,924	123,145	8,565	14,785	424,776
River/Stream	6,137	147,191	906	15,889	456,500
Lake/Pond	N/A	164,048	369	21,308	612,196
Land-Based					
Forest	10,967	104,372	15,080	18,652	535,892
Open Field	2,208	64,008	12,894	8,032	230,765

6.b. Marsh Restoration

	Type of Data used for Estimation				
	Revealed	Stated	Combined		
			Revealed Utility Revealed MU	Stated Utility Revealed MU	Stated Utility Stated MU
CV Measure ($)	50,124	40,632	53,424	6,684	192,036

[a] Estimation of stated data uses interactions between household characteristics and broad natural features.

[b] Estimation of combined data uses interactions between household characteristics and housing price.

[c] Utility is based on a set of coefficients specific to either revealed or stated data, in addition to coefficients compatible between the two data sets. Marginal utility of income (MU) is equal to the price coefficient specific to either revealed or stated data.

REFERENCES

Adamowicz, Wiktor, J. Louviere, and M. Williams (1994), "Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities," *Journal of Environmental Economics and Management*, v. 26, n. 3, pg. 271-292.

Adamowicz, Wiktor, J. Swait, P. Boxall, J. Louviere, and M. Williams (1997), “Perceptions versus Objective Measures of Environmental Quality in Combined Revealed and Stated Preference Models of Environmental Valuation,” *Journal of Environmental Economics and Management*, v. 32, pg. 65-84.

Batie, S.S. and J.R. Wilson (1978), “Economic Values Attributable to Virginia’s Coastal Wetlands as Inputs in Oyster Production,” *Souther Journal of Agricultural Economics*, v. 10, pg. 111-117.

Ben-Akiva, Mosha and Steve Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press: Cambridge, MA.

Brown, Gardner M. Jr., and Henry Pollakowski (1977), “Economic Valuation of Shoreline,” *Review of Economics and Statistics*, v. 59, n. 3, pg. 272-278.

Bunch, D.S., J.J. Louviere, and D.A. Anderson (1992), “A Comparison of Experimental Design

Strategies for Multinomial Logit Models: The Case of Generic Attributes," unpublished working paper, Graduate School of Management, University of California, Davis.

Cameron, Trudy (1992), "Combining Contingent Valuation and Travel Cost for the Valuation of Nonmarket Goods," *Land Economics*, v. 68, pg. 302-317.

Chapman, David, W. Michael Hanemann, and Barbara Kanninen (1996), "Non-Market Valuation Using Contingent Behavior: Model Specification and Consistency Tests," presented at 1996 Association of Environmental and Resource Economists Summer Workshop, Lake Tahoe, CA, June 2-4, 1996.

Costanza, Robert, Stephen Farber, and Judith Maxwell (1989), "Valuation and Management of Wetland Ecosystems," *Ecological Economics*, v. 1, pg. 335-361.

Cropper, Maureen L., Leland B. Deck, and Kenneth E. McConnell (1988), "On the Choice of Functional Form for Hedonic Price Functions," *Review of Economics and Statistics*, v. 70, n. 4, pg. 668-675.

Cropper, Maureen L., Leland B. Deck, Nalin Kishor, and Kenneth E. McConnell (1993), "Valuing Product Attributes Using Single Market Data: A Comparison of Hedonic and Discrete Choice Approaches," *Review of Economics and Statistics*, v. 75, pg. 225-232.

Doss, Cheryl and Steven Taff (1996), "The Influence of Wetland Type and Wetland Proximity on Residential Property Values," *Journal of Agricultural and Resource Economics*, v. 21, n. 1, pg. 120-129.

Ellickson, Bryan (1977), "Economic Analysis of Urban Housing Markets: A New Approach," R-2024 NSF (Rand Corporation, Santa Monica, CA).

Epp, Donald and K.S. Al-Ani (1979), "The Effect of Water Quality on Rural Nonfarm Residential Property Values," *American Journal of Agricultural Economics*, (August), pg. 529-533.

Farber, Stephen (1987), "The Value of Coastal Wetlands for Protection of Property against Hurricane Wind Damage, *Journal of Environmental Economics and Management*, v. 14, pg. 143-151.

Freeman, A. Myrick (1991), "Factorial Survey Methods and Willingness to Pay for Housing Characteristics: Comment," *Journal of Environmental Economics and Management*, v. 20, pg. 92-96.

Freeman, A. Myrick (1993), *The Measurement of Environmental and Resource Values: Theory and Methods*, Resources for the Future: Washington, DC.

Goodman, Allen (1989), "Identifying Willingness-to-Pay for Heterogeneous Goods with Factorial

Survey Methods," *Journal of Environmental Economics and Management*, v. 16, pg. 58-79.

Graves, Phil, James Murdoch, Mark Thayer, and Don Waldman (1988), "The Robustness of Hedonic Price Estimation: Urban Air Quality," *Land Economics*, v. 64, pg. 220-33.

Greene, William (1993), *Econometric Analysis*, Prentice-Hall: Englewood Cliffs, NJ.

Hammack, Judd and Gardner Brown, Jr. (1974), *Waterfowl and Wetlands: Toward Bioeconomic Analysis,* Resources for the Future: Washington, DC.

Hanemann, Michael (1984), "Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses," *American Journal of Agricultural Economics*, v. 66, pg. 332-341.

Harrison, David, Jr., and Daniel L. Rubinfeld (1978), "Hedonic Housing Prices and the Demand for Clean Air," *Journal of Environmental Economics and Management*, v. 5, n. 2, pg. 81-102.

Hau, Timothy Doe-Kwong (1985), "A Hicksian Approach to Cost-Benefit Analysis with Discrete Choice Models," *Economica*, v. 52, pg. 479-490.

Huang, Ju-Chin, and Timothy Haab, and John Whitehead (1997), "Willingness to Pay for Quality Improvements: Should Revealed and Stated Preference Data be Combined?" *Journal of Environmental Economics and Management*, v. 34, pg. 240-255.

Kaoru, Yoshiaki, and V. Kerry Smith (1990), "'Black Mayonnaise' and Marine Recreation: Methodological Issues in Valuing a Cleanup," Resources for the Future discussion paper QE91-02, Resources for the Future: Washington, DC.

Lansford, Notie H., Jr., and Lonnie L. Jones (1995), "Marginal Price of Lake Recreation and Aesthetics: An Hedonic Approach," *Journal of Agricultural and Applied Economics*, v. 27, n. 1, pg. 212-223.

Louviere, Jordan (1988), *Analyzing Decision Making: Metric Conjoint Analysis*, Sage University Paper series on Quantitative Applications in the Social Sciences, series no. 67-001, Sage Publications: Beverly Hills, CA.

Louviere, Jordan and D.A. Hensher (1982), "On the Design and Analysis of Simulated Travel Choice or Allocation Experiments in Travel Choice Modeling," *Transportation Research Record*, v. 890, pg. 11-17.

Louviere, Jordan and D.A. Hensher (1983), "Using Discrete Choice Models with Experimental Design Data to Forecast Consumer Demand for a Unique Cultural Event," *Journal of Consumer Research*, v. 10, pg. 348-361.

Louviere, Jordan and G.G. Woodworth (1983), "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data," *Journal of Marketing*

Research, v. 20, pg. 350-367.

Mackenzie, J. (1992), "Evaluating Recreation Trip Attributes and Travel Time via Conjoint Analysis," *Journal of Leisure Science*, v. 24, pg. 171-184.

McConnell, K.E. (1995), "Consumer Surplus from Discrete Choice Models," *Journal of Environmental Economics and Management*, v. 29, pg. 263-270.

McFadden, D. (1975), "On Independence, Structure and Simultaneity in Transportation Demand Analysis," Working Paper 7511, Urban Travel Demand Forecasting Project, Institute of Transportation Studies, University of California, Berkeley.

McFadden, D. (1978), "Modeling the Choice of Residential Location," in *Spatial Interaction Theory and Planning Models*, eds., Anders Karlqvist et. al., North-Holland: Amsterdam, pg. 75-96.

Milon, J. Walter, Jonathan Gressel, and David Mulkey (1984), "Hedonic Amenity Valuation and Functional Form Specification," *Land Economics*, v. 60, n. 4, pg. 378-387.

Mitchell, Robert Cameron and Richard T. Carson (1989), *Using Surveys to Value Public Goods: The Contingent Valuation Methods*, Resources for the Future: Wash, DC.

Nechbya, Thomas and Robert Strauss (1988), "Community Choice and Local Public Services: A

Discrete Choice Approach," *Regional Science and Urban Economics*, v. 28, pg. 51-73.

Nelson, Jon P. (1978), "Residential Choice, Hedonic Prices, and the Demand for Urban Air Quality," *Journal of Urban Economics*, v. 5, n. 3, pg. 357-369.

Noss, Reed and J. Michael Scott (1997), "Ecosystem Protection and Restoration: The Core of Ecosystem Management" in *Ecosystem Management: Applications for Sustainable Forest and Wildlife Resources,* Yale University Press: New Haven, CT.

Palmquist, Raymond (1992), "Valuing Localized Externalities," *Journal of Urban Economics*, v. 31, n. 1, pg. 59-68.

Parsons, George and Mary Jo Kealy (1992), "Randomly Drawn Opportunity Sets in a Random Utility Model of Lake Recreation," *Land Economics*, v. 68, pg. 93-106.

Quigley, John (1985), "Consumer Choice of Dwelling, Neighborhood, and Public Services," *Regional Science and Urban Economics,* v. 15, pg. 41-63.

Roe, Brian, Kevin Boyle, and Mario Teisl (1996), "Using Conjoint Analysis to Derive Estimates of Compensating Variation," *Journal of Environmental Economics and Management*, v. 31, pg. 145-159.

Rosen, Sherwin (1974), "Hedonic Prices and Implicit Markets: Product Differentiation in Perfect Competition," *Journal of Political Economy*, v. 82, n. 1, pg. 34-55.

Shabman, Leonard and Michael K. Bertelson (1979), "The Use of Development Value Estimates for Coastal Wetland Permit Decisions," *Land Economics*, v. 55, n. 2, pg. 213-222.

Small, K.A. and Sherwin Rosen (1981), "Applied Welfare Economics with Discrete Choice Models," *Econometrica*, v. 49, pg. 105-130.

Steadman, Geoffrey (1996), "Multiple Use Management Plan for Coastal Open Space: Volume II," prepared for Fairfield Conservation Commission, April.

Stevens, Thomas, Samuel Benin, and Joseph Larson (1995), "Public Attitudes and Economic Values for Wetland Preservation in New England," *Wetlands*, v. 15, n. 3, pg. 226-231.

Swait, Joffre and Wiktor Adamowicz (1996), "The Effect of Choice Complexity on Random Utility Models: An Application to Combined Stated and Revealed Preference Models or Tough Choices: Contribution or Confusion?" presented at 1996 Association of Environmental and Resource Economists Summer Workshop, Lake Tahoe, CA, June 2-4, 1996.

Swait, Joffre and J. Louviere (1993), "The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models," *Journal of Marketing Research*, v. 30, pg. 305-

314.

Timmermans, H., A. Borgers, and J. van Dijk, and H. Oppewal (1992), “Residential Choice Behavior of Dual-Earner Households: A Decompositional Joint Choice Model,” *Environment and Planning A*, v. 24, pg. 517-533.

Timmermans, H. and L. van Noortwijk (1995), “Context Dependencies in Housing Choice Behavior,” *Environment and Planning A*, v. 27, pg. 181-192.

Whitehead, John and Glenn Blomquist (1991), “Measuring Contingent Values for Wetlands: Effects of Information About Related Environmental Goods,” *Water Resources Research*, v. 27, n. 10, pg. 2523-2531.

Wilman, Elizabeth (1981), “Hedonic Prices and Beach Recreational Values,” in *Advances in Applied Microeconomics*, ed. V. Kerry Smith, JAI Press, Inc: Greenwich, CT, pg. 77-103.

Young, C. Edwin (1984), “Perceived Water Quality and the Value of Seasonal Homes,” *Water Resources Bulletin*, v. 20, pg. 163-166.