Combining Revealed and Stated Preference Methods to Value Environmental Amenities at Residential Locations

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ABSTRACT. *This paper combines an established revealed-preference method, discrete-choice hedonic analysis, and a relatively new stated-reference 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, Connecticut, which contains several environmental amenities and is experiencing an improvement in the quality of its coastal wetlands due to active restoration efforts.* (JEL Q26)

I. INTRODUCTION

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 aesthetic benefits generated by the presence and quality of environmental amenities associated with residential locations.[1] Discrete-choice 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. Choice-based 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. Combined analysis generates three benefits: (1) an econometric model with more robust estimates and better identification of attributes; (2) welfare measurements less prone to common types of bias—information, hypothetical, and strategic; and (3) measures of price responsiveness drawn from actual financial settings. This approach represents the new application of a recently introduced valuation approach that combines discrete-choice revealed and stated preference methods (Adamowicz, Louviere, and Williams 1994).

Moreover, this paper empirically applies the combined-valuation approach to the housing market of Fairfield, Conn., which contains several environmental amenities. More important, Fairfield is experiencing an improvement in the quality of one of its major environmental amenities—coastal wetlands—due to active restoration by the local government. Several studies measure benefits generated by wetlands—commercial fishing, recreation, water supply, pollution control, storm protection, and habitat—but not aesthetic benefits (Costanza, Farber, and Maxwell 1989; Batie and Wilson 1978; Stevens, Benin, and Larson 1995; Hammack and Brown 1974; Farber 1987. Only Doss and Taff (1996) assess aesthetic benefits but do not examine the increased benefits from improvements in wetland quality. On both counts, this paper contributes to our understanding of wetland benefits by combining two valuation methods.

The remainder of the paper details these points. Section 2 describes the full rationale

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[1] Although environmental amenities most likely generate both aesthetic and recreational benefits, this paper focuses on aesthetic benefits—the more prominent of the two.

for combining the valuation methods. Section 3 formulates the theoretical framework. Section 4 depicts the analytical approaches for data collection. Section 5 structures and interprets the econometric analysis, and Section 6 summarizes.

II. 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 of housing markets to measure the benefits of various environmental amenities: air-based amenities (Graves et al. 1988); water-based amenities (Brown and Pollakowski 1977; Lansford and Jones 1995; Shabman and Bertelson 1979; Milon, Gressel, and Mulkey 1984); and land-based amenities (Vaughn 1981; Mahan, Polasky, and Adams 1998). (No previous study examines land-based amenities other than parks.) All of these studies apply the hedonic-price model, which assumes that a continuous function relates the price of a house to its attributes and that people select a house by equating the marginal utility of each house attribute to its marginal price. No previous study of environmental benefits applies the discrete-choice hedonic model, which views the individual as choosing the house that provides the highest utility from all the houses in its feasible choice set, with utility as a function of attributes (McFadden 1978). In order to combine the revealed and stated methods within a common 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 come from a single housing market. My analysis faces exactly these conditions.

In the valuation literature, conjoint analysis takes different forms. Rank-ordered conjoint analysis produces descriptions of various "goods" and asks respondents to rank or rate the goods (Goodman 1989). This approach seems inappropriate for explaining housing purchases since it does not mimic the actual behavior of buyers, whose 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. Few studies use it to examine non-market goods (Adamowicz, Louviere, and Williams 1994). No previous study applies this analysis to non-market goods associated with residential locations.[2]

Both 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 choices. 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, it depends critically on the control of all important factors behind location choices (Freeman 1993). To cope with this dependence, hedonic studies incorporate numerous explanatory variables, yet may still omit important variables. Second, hedonic analysis suffers from collinearity between explanatory variables, especially when many are included (Freeman 1993); this aspect precludes the isolation of factors, including environmental factors, and generates coefficients with wrong signs or implausible magnitudes (Greene 1997). Third, hedonic analysis does not capture effectively preferences for uncommon attributes, such as restored wetlands. Fourth, given limited information on households' search strategies, analysis of housing purchases requires the researcher to specify arbitrarily the feasible choice sets of housing locations that were considered by households. Moreover, the size of the specified feasible choice 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

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

sets clearly identify the parameters to consider when choosing a house. Second, the statistical design avoids collinearity by generating orthogonal attribute data. Third, the survey design generates an adequate number of observations for all attributes, including the uncommon ones. Fourth, conjoint analysis prespecifies the alternatives within each choice set.

By combining the stated and revealed preference methods, the joint model enhances the strengths and diminishes the drawbacks of each individual method, which yields three benefits. First, the addition of orthogonal stated data reduces the collinearity that most likely exists in the revealed data. Thus, estimation is able to identify attribute effects otherwise obscured by collinearity. Second, the stated preference questions generate additional observations for uncommon attributes in 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. No previous study combines stated and revealed methods to explore residential choices as means for valuing environmental goods, especially their aesthetic benefits.[3]

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

III. THEORETICAL FRAMEWORK

This paper employs random-utility theory to model individuals' choice among housing location alternatives for both the hedonic and conjoint analysis. 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. 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. The deterministic component is modeled as an indirect-utility function conditional on the following arguments: $\mathbf{Z_i}$ = vector of observed housing location attributes, $\mathbf{C_n}$ = vector of observed individual characteristics, y_n = income of individual n, P_i = price of location i, and β = parameter vector. If the random components are identically and independently distributed (IID) Type I Extreme value with scale parameter μ, then the probability that individual n chooses location i rather than location j, $\pi_n(i)$, is of the logit form:

$$\begin{aligned}\pi_n(i) &= \text{Prob}\,(V_{in} + e_{in} \geq V_{jn} + e_{jn} : \forall\, j \in K_n)\\ &= \exp(\mu\, V_{in}) \,/\, \textstyle\sum_{j\in K} \exp(\mu\, V_{jn})\,. \end{aligned} \qquad [1]$$

The estimated parameters in vector β 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).[4]

A further complication involves selection of the feasible set of housing alternatives. In the conjoint analysis, the feasible set is the three constructed-housing alternatives. In the hedonic analysis, consumers select one specific housing location from a large number of locations available on the market. For tractability, one must reduce the size of the choice sets. One useful approach selects a subset consisting of the chosen location and a fixed number of rejected locations randomly

[3] Previous studies that combine stated and revealed preference methods focus almost exclusively on recreational benefits of environmental goods (Cameron 1992; Adamowicz, Louviere, and Williams 1994).

[4] This analysis could explore the appropriateness of the IIA assumption by estimating a nested logit specification and examining the existence of residual correlations.

drawn from the feasible set. By observing households' selection among locations within this subset, regression analysis obtains consistent estimates of the correct choice model (McFadden 1978).

For the empirical analysis, the feasible set consists of all locations sold in the town of Fairfield during the same month and year. It seems reasonable to assume that any household could feasiblely live anywhere in the study area given its small size (Nechyba and Strauss 1998). Also, the number of randomly drawn alternatives 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.[5]

The final complication involves the effect of an income constraint on residential choice. An income constraint obviously affects actual house purchases. The survey for conjoint analysis explicitly instructs respondents to select a housing location "*given their current financial situation*." In both the actual and hypothetical housing markets, the feasible choice set, K_n, may include housing locations unaffordable to a given household. As constructed, the feasible choice subset in the hedonic analysis includes at least one affordable housing location (chosen location). The feasible choice set in the conjoint analysis may consist partially or completely of unaffordable houses. If at least one house in the choice set is affordable, then the discrete choice framework applies. Price, as a parameter of utility, prompts the household to reject the unaffordable houses. However, the effect of price is nonlinear since the price of an unaffordable house affects residential choice much more than the price of an affordable house. One way to handle this nonlinearity is to allow price to affect household utility nonlinearly. However, this nonlinearity does not apply to sufficiently wealthy households. The better approach is to interact price with household income, which allows the price effect to increase as income decreases. All the regression results strongly confirm this expectation.

The case remains where no house in K_n is affordable, which is possible only for conjoint analysis. Then the hypothetical choices are presumably disconnected from price and based exclusively on other attributes. This situation downwardly biases the estimated price effect. However, respondents may retain some loose ranking of locations with respect to price. If true, the price effect remains relevant, though probably downwardly biased.

IV. ANALYTICAL APPROACH

Given this theoretical framework, this section depicts two separate analytical approaches: discrete-choice hedonic analysis of revealed data and choice-based conjoint analysis of stated data.

Discrete-Choice Hedonic Analysis

Research framework. Hedonic models value environmental attributes associated with housing locations by estimating consumer preferences for these attributes, that is, linking tradeoffs between environmental attributes and housing price. This paper focuses on the environmental amenity (or natural feature) associated with (or immediately adjacent) to a given housing location.[6]

Water-Based Amenities: Long Island Sound, marsh, river/stream, lake/pond
Land-Based Amenities: forest/woods, open field/park
No Amenity: backyard lawn

[5] As noted in Section 4, to collect the hedonic data, I needed to visit each housing site in the sample, which was very time consuming. As a reasonable compromise, I chose to visit three alternative sites in addition to the purchased site.

[6] Some hedonic price studies of water-based amenities link the distance between a housing location and the shoreline of particular water bodies to housing price (Brown and Pollakowski 1977; Lansford and Jones 1995; Milon, Gressel, and Mulkey 1984). The hedonic price framework easily accommodates this link since both variables are treated as continuous. Incorporating distance into the discrete-choice 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.

The category of backyard lawn establishes the benchmark for measuring environmental benefits.

In addition, this paper estimates the benefits generated by restoration of a coastal wetland—the Pine Creek Marsh located in Fairfield, Conn. 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, causing the marsh to degrade from a marsh dominated by spartina grass, the natural flora, to a marsh dominated by phragmites grass, a nonnative invasive species. 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 the marsh category into restored marsh and disturbed marsh.

To isolate the effects of environmental amenities, the analysis controls for other factors: structural, neighborhood, and environmental. The analysis includes the following structural features: (1) style; (2) number of bedrooms; (3) number of bathrooms; (4) interior space; (5) lot size; and (6) age of structure. It includes two neighborhood features: (1) indicator variables for prominent neighborhoods designated by census tract boundaries; and (2) flooding frequency (much of Fairfield is built on former coastal wetland). 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. The analysis excludes other environmental attributes employed in previous research (e.g., air quality) because the small study area generates only minimal variation.

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 (Ellickson 1977). This approach regresses the log value of housing price on the same set of structural, neighborhood, and environmental attributes included in the discrete-choice hedonic analysis; the regression residual captures "un-measured quality." By using the log value of price, the residual is not a linear combination of the explanatory variables.

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 provides data on structural features, price, date of sale, and location for housing purchases. To avoid the need of differentiating various housing markets, this paper examines only residential single-family dwellings. The Natural Resources Center of the Connecticut Department of Environmental Protection provides data on land use and land cover for Fairfield. By overlaying these data with data on house locations, examining topographical maps, and personally inspecting *each and every* site, I identified the environmental amenity for each location.[7] Similarly, I identified flooding frequency using data provided by the Town of Fairfield Planning and Zoning Commission 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, as described in the next sub-section.

[7] The need to visit each site, which is very time consuming, severely limits the number of alternatives included in the feasible set for the discrete-choice hedonic analysis of revealed data. As a reasonable compromise, I chose to visit three alternative sites in addition to the purchased site.

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

Choice-Based Conjoint Analysis

Research framework. Choice-based conjoint analysis attempts to mimic the discrete-choice hedonic analysis by asking people to choose from a hypothetical set of housing alternatives. 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 discrete *values* for each attribute on the actual ranges of *values* for housing locations in the study area, as shown in Table 1. For inherently discrete attributes, such as house style, I selected the most frequent categories in the Fairfield housing market. For inherently continuous attributes, such as price, I selected ''rounded'' values near the first-quartile, median, third-quartile, and 90-percentile levels, as appropriate. For example, the price level of $ 600,000 is ''rounded'' from the 90-percentile value. (This top price is needed for consistency with the housing market along Long Island Sound.)

In the conjoint survey, each choice set includes three housing alternatives, each based on the associated environmental amenity: water-based amenity, land-based amenity, and no amenity.[8] (Figure 1 shows an example from the conjoint survey.) Rather than exploring all possible combinations of attribute levels within and among the alternatives, I use an orthogonal main effects design to vary simultaneously all the attribute levels. This design permits the consistent estimation of the strictly additive components of the relevant logit model and generates relatively, but not optimally, efficient estimates (Adamowicz, Louviere, and Williams 1994).

Data collection methods. The main effects design demands 81 choice sets, too many for one individual to complete. Based on the feedback of two focus groups, nine choice sets were deemed reasonable. Accordingly, I randomly divided the 81 choice sets into 9 groups of 9 choice sets each and placed each group into a similar survey format. To reduce

[8] Although the survey could identify the alternatives merely by number (e.g., House #1, House #2). The chosen design serves two purposes: (1) focuses respondents' attention on the environmental amenity; and (2) reduces the number of choice sets sufficient to estimate consumer preferences.

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.

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

FIGURE 1
EXAMPLE OF CONJOINT SURVEY

the perceptional variation across respondents, the survey visually rather than verbally depicts the eight environmental amenities using digitally scanned photographs. It also requests information on the respondents' characteristics.

This research project mailed 464 mail surveys (evenly distributed across the nine survey versions) to Fairfield homeowners in late 1996. Potential respondents were drawn from the aforementioned housing purchase database, which includes all sales contracted between January 1994 and August 1996, inclusively, consisting of 1,466 residential single-family dwellings. 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 (120 houses). This oversampling attempts to increase the hedonic model's capacity to differentiate the benefits of restored and disturbed coastal marshes. Then I randomly selected 344 houses not located adjacent to a coastal marsh from the possible 1,371 non-marsh-adjacent houses. Of the 464 people contacted, 105 returned completed surveys, for a response rate of 22.6%. Probit analysis of the choice to respond reveals no evidence of a non-response bias based on house and location characteristics.[9]

[9] Lack of demographic information on non-respondents obviously precludes inclusion of these factors. The included set of coefficients is not statistically significant. The associated likelihood ratio chi-square statistic is 48.091 and significant at a level greater than 10%.

Improvement upon Previous Stated Preference Methods

The application of choice-based conjoint analysis avoids biases inherent in other stated preference methods. First, it is less prone to hypothetical bias since it mimics the actual choice of housing locations by home buyers who have very recently faced a similar format in real life; homeowners were surveyed within months of their house purchases. Second, this approach does not suffer information bias; the respondents have a solid understanding of the good being valued. Third, this approach reduces the possibilities for strategic bias because the variety of choice sets obscures the policy option being evaluated—wetland restoration.

IV. ECONOMETRIC ANALYSIS

This section analyzes the collected data on housing choices to estimate environmental benefits by addressing the following questions: What is the value of a natural feature associated with a housing location? What is the value of marsh restoration?

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.[10] When estimating the stated data, the replications of choices from individual respondents are assumed independent, a common practice when examining stated choice data (Adamowicz, Louviere, and Williams 1994; Adamowicz et al. 1997).[11]

Estimation demands a few further details. First, I employ 1, 0 dummies for two of the three broad natural categories: water-based and land-based (no-feature as benchmark). 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. Second, I employ effect codes rather than 1, 0 dummies to distinguish other attributes with multiple levels 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 (Adamowicz, Louviere, and Williams 1994). Third, I interact the explanatory parameters regarding household characteristics with a selected housing attribute, housing price in this case; otherwise, these explanatory parameters do not vary within each household's choice set. The chosen interaction allows the effect of price to vary across households with presumably differing abilities to pay. Fourth, in the conjoint model, I interact the natural feature associated with the household's current location and the broad natural feature categories offered within the survey. Then I can test whether respondents simply "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.

Estimation

To estimate household utility and measure environmental benefits, I employ three separate sets of data: only revealed preference data, only stated preference data, and combined data.

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

[11] Although common practice, this approach may bias the estimated standard errors, likely overstating the precision with which individual parameters are estimated.

[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, Louviere, and Williams 1994).

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. Estimation results shown in Table 2 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 relative to no natural feature. Within the broad category of water-based features, rivers/streams and restored marshes generate relatively higher utility, while disturbed marshes generate relatively lower utility.[13] Thus, marsh restoration increases utility.

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 *only* stated data. Estimation results shown in Table 2 reveal the following. 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 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, marsh restoration increases utility.

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; households currently living at locations associated with land-based features are *less* likely to select a hypothetical water feature than no feature. These results do *not* indicate that households ''rationalize'' their actual feature choices with their survey responses.

Joint estimation of revealed and stated data. Econometric analysis of the combined data demands comment since it involves a joint estimation procedure (Swait and Louviere 1993). First, separately estimate the revealed model and the stated model. The log-likelihood values for these models are L_r and L_s, respectively. Second, concatenate the two data sets and iteratively rescale the stated data relative to the revealed data until the log likelihood value, denoted L_c, is maximized. This procedure maximizes the fit of the stated and revealed parameters given the conditional logit model (Adamowicz, Louviere, and Williams 1994). The revealed and stated data are assumed independent (Adamowicz et al. 1997). Third, test the hypothesis of equal parameters, after adjusting for the relative scale effect, with a likelihood ratio test: $\lambda = -2[L_c - 2(L_r + L_s)]$. Failure to reject this χ^2 test would provide sufficient evidence that the stated and revealed data contain similar preference structures. The calculated χ^2 test statistic, λ, equals 91.446. Given 31 degrees of freedom, this test statistic significantly rejects the hypothesis of equal parameters (after rescaling) at the 1% confidence level.

This rejection undermines the notion that the stated and revealed data contain similar

[13] 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.

TABLE 2

MULTINOMIAL LOGIT REGRESSION OF REVEALED DATA AND STATED DATA SEPARATELY

Variable[a]	Description	Coefficient Estimate: Revealed Data	Coefficient Estimate: Stated Data
Attributes			
Broad Natural Feature[b]	None (= 0) vs.	0	0
	Water (= 1)	2.977***	1.838***
		(1.175)	(0.348)
	Land (= 1)	0.524	1.189
		(0.546)	(0.244)
Water Feature	Disturbed Marsh (= −1) vs.	−4.966	−0.951
	Restored Marsh (= 1)	2.184***	−0.119
		(0.821)	(0.115)
	Long Island Sound (= 1)	1.329	0.449***
		(0.866)	(0.115)
	River/Stream (= 1)	1.453*	0.244**
		(0.868)	(0.120)
	Lake/Pond (= 1)[c]	—	0.377***
			(0.144)
Land Feature	Forest (= 1) vs. Field (= −1)	0.368	0.172**
		(0.529)	(0.084)
Bedrooms	Number	−0.148	0.077
		(0.277)	(0.097)
Bathrooms	Number	0.056	0.395***
		(0.315)	(0.098)
Interior Space	1,000 ft^2	0.989*	0.668***
		(0.528)	(0.100)
Style	Cape Cod (= −1) vs.	−2.226	−0.029
	Colonial (= 1)	0.981***	0.149***
		(0.257)	(0.058)
	Ranch (= 1)	0.313	−0.120**
	Other (= 1)	0.932***	N/A
		(0.261)	
Age	Years	−0.008	−0.004***
		(0.006)	(0.002)
Lot Size	Acres	−0.034	0.869***
		(0.142)	(0.244)
Flooding	Minimal (= −1) vs.	0.072	0.065
	500-year Flood (= 1)	−0.672	N/A
		(0.425)	
	100-year Flood (= 1)	0.600	−0.065
		(0.425)	(0.051)
Price	$1,000	−0.019**	−0.0017
		(0.010)	(0.0018)
Census Tract	Other = −1) vs.	−0.591	N/A
	Beach area (= 1)	−0.319	N/A
		(0.402)	
	Greenfield Hills (= 1)	0.910**	N/A
		(0.401)	
Residual Quality[d]	$1	5.348***	N/A
		(1.694)	

(*table continued on following page*)

TABLE 2

MULTINOMIAL LOGIT REGRESSION OF REVEALED DATA AND STATED DATA SEPARATELY (*continued*)

Variable[a]	Description	Coefficient Estimate: Revealed Data	Coefficient Estimate: Stated Data
Household Characteristics Interacted with House Price			
Marital Status	Married (= 1) vs. Single (= −1) [per $1,000]	0.003 (0.004)	−0.001* (0.0007)
Children	Yes (= 1) vs. No (= −1) [per $1,000]	−0.0001 (0.002)	−0.0002 (0.0006)
Household Size	Number [per $1,000]	0.003 (0.002)	0.0004 (0.0006)
Income[e]	Low (= −1) vs.	−0.002	−0.005
	Medium (= 1) [per $1,000]	0.008*** (0.003)	0.001*** (0.0005)
	High (= 1) [per $1,000]	0.010*** (0.004)	0.004*** (0.0006)
Current Natural Features Interacted with Broad Natural Features			
Interactions with Water-Based Feature			
Current Natural Feature	None (= −1) vs.	N/A	−0.526
	Water (= 1)	N/A	0.792*** (0.225)
	Land (= 1)	N/A	−0.266** (0.128)
Interactions with Land-Based Feature			
Current Natural Feature	None (= −1) vs.	N/A	−0.869
	Water (= 1)	N/A	0.834*** (0.224)
	Land (= 1)	N/A	0.035 (0.120)
No. of Observations		404	2,727
Log-Likelihood		−94.935	−791.043
Likelihood ratio statistic (χ^2)		95.41	407.253
McFadden's ρ^2		0.33	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] Observations involving lakes/ponds in revealed data 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.

Notes: Standard errors in parentheses; * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level; *** indicates statistical significance at the 1% level.

preference structures. However, this finding may equally indicate that the errors and biases in one preference method differ from those in the other method, as described in Section 2. Combining the two methods does not eliminate these underlying differences. Regardless of the interpretation, one need not conclude that the two data sets differ in all parameters. Even though the full set of parameters are not compatible, the effects of certain parameters may be comparable between the two data sets, while the effects of other parameters may be 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. 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. Selecting a smaller subset of constrained variables would exclude otherwise statistically similar variables; selecting a larger subset would reject the hypothesis of equal parameters. This procedure distinguishes the most statistically similar variables from the least statistically similar variables.[14,15] It 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. Table 3 identifies the classification of each variable.

Estimation of this specification for combining revealed and stated data generates the results shown in Table 3. 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 according to the revealed-specific coefficient, yet relatively (and insignificantly) lower utility according to the stated-specific coefficient. Regardless of the coefficient, restored marshes generate higher utility than disturbed marshes, indicating that marsh restoration increases utility. These results 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 rivers/streams.

Welfare Measures of Environmental Amenities and Wetland Restoration

From each set of parameter estimates reported above, I calculate welfare measures of benefits generated by environmental amenities. The standard measure is the compensating variation (CV) associated with the change from one type of natural feature to another. In the discrete-choice framework, economic studies generally base the level of welfare benefits (CV) on a change in expected utility: $CV = (1/\alpha)\,[\ln(\sum_{i \in K} \exp(V_{in1})) - \ln(\sum_{i \in K} \exp(V_{in0}))]$, where α represents the negative of the coefficient on the housing purchase price term (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 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 in state.

CV measures based on expected utility are unfortunately sensitive to the contents of each choice set—attributes of affected and *unaffected* housing sites (Freeman 1993). Since each household very likely faces a distinctively different choice set, this sensitivity

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14 Unlike a stepwise regression approach, this method does not confound the testing of statistical significance for coefficients (Greene 1997) since the criterion for selecting the best specification concerns the differences between paired coefficients not the coefficients' statistical significance.

15 Earnhart (1998) more fully describes this strategy. One alternative strategy would examine the statistical differences between individual parameters from the separately estimated models. This strategy is flawed since the estimated parameters are unique only up to the scale factor μ, which may differ between the two data sets. Another alternative strategy would postulate that a specific subset of variables is represented by compatible parameters, while the remaining variables is represented by incompatible parameters, and then confirm that the first subset does not reject the hypothesis of equal (after rescaling) parameter estimates. This limited strategy does not allow the data to identify the compatible and incompatible parameters.

TABLE 3

MULTINOMIAL LOGIT REGRESSION OF COMBINED REVEALED AND STATED DATA

Variable[a,b]	Description	Coefficient Estimate[c]		
		Revealed Data		Stated Data
Attributes				
Broad Natural Feature[e]	None (= 0) vs.			0
	Water (= 1)		1.714***	
			(0.311)	
	Land (= 1)		1.014***	
			(0.198)	
Water Feature	Disturbed Marsh (= −1) vs.	−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) vs. 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)		−4.454	
			(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)

(*table continued on following page*)

TABLE 3

MULTINOMIAL LOGIT REGRESSION OF COMBINED REVEALED AND STATED DATA (*continued*)

Variable[a,b]	Description	Coefficient Estimate[c] Revealed Data	Stated Data
Household Characteristics Interacted with House Price			
Income[f]	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] Stated data are re-scaled by a factor of 0.85.
[e] Broad natural features are coded as 1, 0 dummy variables.
[f] Low: < $100,000; Medium: $100,000–$200,000; High: > $200,000.
Notes: Standard errors in parentheses; *, indicates statistical significance at the 10% level; ** indicates statistical significance at the 5% level; *** indicates statistical significance at the 1% level.

may substantially affect CV calculations. Thus, the CV measure 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 muted in other discrete-choice contexts examined by environmental economics, such as recreational choice, since the analyses treat individuals as sharing identical or similar choice sets.

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 *either* the revealed data *or* the stated data. Similarly, the price coefficient may be specific to *either* the revealed data *or* the stated data. Table 4 reports the possible combinations, except 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 4 reports the welfare measures for each broad and individual category of natural feature generated by each estimation model: revealed data, stated data, and combined data. CV measures based on revealed data are noteworthy. Long Island Sound and rivers/streams generate benefits of $ 7,924 and $ 6,137, respectively, representing 3.2% and 2.5% of the median house price, which equals $ 245,000. Restored marshes generate $ 40,578 in benefits and disturbed marshes generate *negative* benefits of $ 32,412, representing 16.6% and 13.2% of the median house price, respectively. These latter welfare measures seem disproportionately large. Collinearity between explanatory variables appears to confound somewhat the calculation of CV measures, as expected.

The first set of measurements is roughly comparable to results from previous studies, while the wetland values are higher than previous measures. For the category of coastline (e.g., Long Island Sound), Milon, Gressel, and Mulkey (1984) find that a parcel's value declines an average of 36.2% in the first 500 feet from the Gulf of Mexico coast, while

TABLE 4A
WELFARE MEASURES OF NATURAL FEATURES

Feature Categories	Type of Data used for Estimation				
			Combined ($)[a]		
	Revealed ($)	Stated ($)	Revealed Utility Revealed MU	Stated Utility Revealed MU	Stated Utility Stated MU
Broad Categories					
Water	8,990	237,904	12,557	14,135	406,107
Land	9,804	286,572	15,034	17,520	503,355
Individual Categories					
Water-Based					
Disturbed Marsh	−32,412	230,702	−5,754	11,073	318,134
Restored Marsh	40,578	210,551	45,871	11,905	342,048
Sound	7,924	209,058	8,565	14,785	424,776
River/Stream	6,137	265,805	906	15,889	456,500
Lake/Pond	N/A	300,106	369	21,308	612,196
Land-Based					
Forest	10,967	292,706	15,080	18,652	535,892
Open Field	2,208	192,985	12,894	8,032	230,765

[a] 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.

TABLE 4B
WELFARE MEASURES OF MARSH RESTORATION

	Type of Data Used for Estimation				
			Combined		
	Revealed	Stated	Revealed Utility Revealed MU	Stated Utility Revealed MU	Stated Utility Stated MU
CV Measure ($)	50,124	104,140	53,424	6,684	192,036

Shabman and Bertelson (1979) measure the value of a waterfront amenity in Virginia Beach between $ 231 and $3,401 (in 1977 dollars). The value for Long Island Sound is comparable to the second set of measures. For the category of rivers/streams, the CV value is very similar to Mahan, Polasky, and Adams (1998), who implicitly measure the benefits of a river and stream, respectively, at − $1,703 and $1,367 (−1.4% and 1.1% of mean house price).[16] For wetlands, the CV values are somewhat high. Doss and Taff (1996) measure benefits ranging between– $2,077 and $7,304 (−2.0% and 7.0% of mean house price). Mahan, polasky, and Adams (1998) implicitly measure benefits for any wetland type at $2,303 (1.9% of mean house price) and benefits for specific types ranging between − $6,594 and $5,244 (− 5.4% and 4.3% of mean house price). Thibodeau and Ostro (1981) measure benefits at $400 (1.5% of mean house value). For lakes, Doss and Taff (1996), Lansford and Jones (1995), and Mahan, Polasky, and Adams (1998) measure benefits at $45,949, $59,826, and $8,679, respectively, representing 43.8%, 31.8%, and 7.1% of the relevant mean house prices.

CV measures based on stated data are sub-

[16] Each value represents the difference in house value between a house located 0 meters from the specific amenity and a house located the mean distance from the same amenity.

stantially higher than the revealed CV measures. Measured benefits for individual water features range between $209,058 for Long Island Sound and $300,106 for lakes/ponds, representing between 85.3% and 122.5% of the median house price. Contrary to the revealed data, the CV measures for both marsh types are more similar to other CV measures. With the exception of Long Island Sound, these CV measures are much higher than previous results for water features. CV measures for land features also seem quite high at $292,706 and $192,985 for forest and open field, respectively. All these high values are most likely driven by the rather small coefficient on housing price, which is consistent with the expected downward bias on the price effect in the conjoint analysis, as noted in Section 3. Given the construction of the CV measure, a small enough price coefficient will generate large CV values (even values greater than the median house price), regardless of the meaningfulness of the overall utility calculation.

Relative to the CV measures based on each individual data set, combining the revealed and stated data 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 most features fall moderately between the estimates based on revealed and stated data individually. Oddly, estimated benefits for rivers/streams and lakes shrink to practically nothing.

Next, consider the case where utility is calculated using the set of coefficients specific to stated data, plus compatible coefficients, and marginal utility of income is based on the price coefficient specific to stated data. These CV measures seem quite large, spanning from $230,765 for open field to $612,196 for lake/pond, driven by the very small price coefficient.

Nevertheless, calculating utility based on coefficients specific to stated data, plus compatible coefficients, produce relative magnitudes more in line with expectations; Long Island, rivers/streams, and lakes/ponds generate greater benefits than restored or degraded marshes. Dividing this measure of utility by the price coefficient specific to revealed data moderates the CV measures. 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. Oddly, Long Island Sound generates low benefits of $14,785.

Based on these results, combining revealed and stated data improves and moderates the calculation of welfare measures. In particular, inclusion of stated data seems to avoid problems with collinearity and generates more accurate coefficients in general, as noted above. Therefore, analysis should use these coefficients to calculate deterministic utility. On the other hand, estimation of stated data generates a price coefficient that seems somewhat small. The context of the conjoint survey may not adequately capture the tradeoff between housing price and other attributes.[17] In contrast, the real-life context of actual housing purchases seems to capture more effectively this tradeoff. Therefore, analysis should use this price coefficient to represent marginal utility of income.

Combining revealed and stated data similarly improves and moderates the welfare measures for marsh restoration. Welfare measures based separately on revealed and stated data are $50,124 and $104,140, respectively. Both measures represent a sizable proportion of the median house price, 20% and 43%, respectively. Combining the two data sets, while basing utility and marginal utility of income on the set of coefficients specific to the same data set increases the CV measure. As with welfare measures for individual natural features, the small price coefficient specific to stated data drives up the CV measure to $192,036. When deterministic utility is based on coefficients specific to stated data, plus the compatible coefficients, and marginal utility of income is based on

[17] This insensitivity to price should not alter the trade-offs *among* the other attributes and the estimated effects of these other attributes.

the revealed-data-specific price coefficient, combining revealed and stated data generates a much smaller and the most realistic welfare measure for marsh restoration of $6,684 (2.7% of median price).

VI. SUMMARY

In sum, this paper combines the revealed method of discrete-choice hedonic analysis and the stated method of choice-based conjoint analysis to improve the estimation of benefits for environmental amenities and coastal wetland restoration in an urban/suburban setting of southwestern Connecticut. In particular, inclusion of stated data improves estimation of household utility (including environmentally-related utility) associated with housing locations, while inclusion of revealed data improves estimation of the marginal utility of income, as captured by the coefficient on housing price.

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