VALUING PRODUCT ATTRIBUTES USING SINGLE MARKET DATA: A COMPARISON OF HEDONIC AND DISCRETE CHOICE APPROACHES

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Abstract—This paper compares, via simulation, the performance of the multinomial logit and hedonic models in estimating consumer preferences for product attributes. We ascribe preferences over the attributes of houses to a population of consumers, and, by having them bid for a set of houses, calculate equilibrium prices. The resulting data are used to estimate the two models.

We find that the gradient of a linear Box-Cox hedonic price function estimates marginal attribute bids at least as well as a linear logit model, although the difference between the two is small when some variables are not observed or are replaced by proxies. The logit model, however, outperforms the hedonic model in valuing non-marginal attribute changes. This is true when the researcher knows the true form of consumers' utility functions and when the utility function must be approximated.

Introduction

TWO models that are typically used to value product attributes are the hedonic model (Rosen, 1974) and the multinomial logit (McFadden, 1973). The hedonic model assumes that there is a continuous function relating the price of a good to its attributes—the hedonic price function —and that people select a house or car by equating the marginal utility of each attribute of the product to its marginal price. The discrete choice approach views the individual as choosing the house or car that gives him the highest utility out of all houses or cars in a universal choice set, with utility a function of product attributes.

A difficulty in using the hedonic model to estimate the demand for attributes is the fact that marginal prices are endogenous (they depend on the levels of attributes consumed) and that they must be estimated from a hedonic price function rather than being observed directly. This causes two problems. The first is an identification problem (Brown and Rosen, 1982; Epple, 1987; Mendlesohn, 1985) which arises because both the marginal price of an attribute and the inverse marginal bid depend on the levels of attributes consumed.

A second problem is that the gradient of the hedonic price function is likely to measure marginal attribute prices with error. This may occur because the form of the true hedonic price function is unknown, because the attributes are observed with error, or because some attributes are not observed. Unlike errors in measuring conventional prices, errors in measuring marginal prices are likely to be correlated with the endogenous variables in the hedonic model and may be correlated with income and taste variables as well. This implies that OLS estimates of marginal bid functions are inconsistent, and that instrumental variable estimation of these functions may be difficult, especially if one has data from only a single market.

The discrete choice model avoids the problems created by predicting marginal prices, but only by imposing a good deal of structure on the preference function. It is based on the assumption of the independence of irrelevant alternatives, which may not be satisfied in practice.[1]

These problems lead us to ask whether the hedonic or logit model is more likely to produce reliable estimates of consumers' preferences for product attributes. We have investigated this question by simulating equilibria in housing markets and using the data to estimate utility function parameters with the logit and hedonic models. Because the true parameters are known, each model can be judged on the basis of how closely it estimates true preferences.

Our findings are as follows. The two models perform equally well in estimating the marginal value of an attribute. The finding is robust to specification error. When valuing non-marginal

Received for publication July 20, 1990. Revision accepted for publication December 17, 1991.

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Drs. Deck and Kishor contributed to this paper in a private capacity.

[1] One way of handling this problem when the choice problem has a tree structure is to use the nested logit model (Quigley, 1986).

attribute changes, however, the logit model performs better than 3SLS estimation of the hedonic model. This holds when the true form of the utility function is known, and when it is unknown and must be approximated. It thus appears that when one has data from a single market, the logit model is a better choice for valuing non-marginal attribute changes.

Simulation of Housing Market Equilibria

We simulate behavior in housing markets by constructing a population of households with utility functions defined over housing attributes **Z**, and other goods, x, and having them bid for a housing stock with known attributes. The resulting equilibrium provides data on housing prices, and vectors of housing attributes consumed by each household. Complete details of this simulation can be found in Cropper et al. (1988) and in an appendix available from the authors.

To define a housing market equilibrium let $B_{hj}(u_h)$ denote household h's bid for house j when its utility level is u_h. $B_{hj}(u_h)$ is defined implicitly by

$$u_h = U_h(y_h - B_{hj}, \mathbf{Z}_j; \mathbf{C}_h), \tag{1}$$

where y_h is income and $\mathbf{C}_h$ is a vector of personal characteristics describing the household. An equilibrium in the housing market is a set of utilities $u^* = (u_1^*, u_2^*, \ldots, u_N^*)$ and prices $P^* = (P_1^*, P_2^*, \ldots, P_N^*)$ such that the equilibrium rent on house j equals the maximum willingness to pay (at utility u_h^*) of the household h occupying j and that no household h' is willing to pay more for house j than the household buying the house:

$$\begin{aligned} B_{hj}(u_h^*) &= P_j^* \\ B_{h'j}(u_{h'}^*) &\le P_j^* \qquad h' \neq h. \end{aligned} \tag{2}$$

Equilibrium prices may be computed by iteratively solving an assignment problem (Koopmans and Beckmann, 1957; Wheaton, 1974). The housing shadow prices, P_j^*, then constitute equilibrium rents. The data that result from the simulations—the price and attributes of the chosen house, and observed household characteristics—are the hedonic data typically used to value neighborhood attributes.

The motivation for valuing attributes such as air pollution or crime rates is to estimate the benefits of government programs that affect these disamenities. Suppose the housing market is in equilibrium and the government alters some elements of **Z**. In the short run, before any adjustments to this change in attribute supply, the value of the attribute change to an affected household is the most the household would bid for the new attribute vector **Z′** and keep its utility at its equilibrium value,[2]

$$\int_{\mathbf{Z}_i^0}^{\mathbf{Z}_i'} \partial B_h/\partial z_i \, dz_i = \int_{\mathbf{Z}_i^0}^{\mathbf{Z}_i'} \frac{\partial U_h/\partial z_i}{\partial U_h/\partial x} \, dz_i. \tag{3}$$

For a marginal change in z_i the household's marginal bid is $\partial B_h/\partial z_i$.

Valuing Product Attributes

The multinomial logit model and the hedonic model approach the problem of estimating the welfare effects of an attribute change differently. In the logit model, the household chooses the house that yields the highest utility of all houses in some feasible set K_h. The utility received by household h from house j is written as the sum of deterministic and random components,

$$U_{hj} = V_{hj}\left(y_h - P_j, \tilde{\mathbf{Z}}_j, \tilde{\mathbf{C}}_h; \boldsymbol{\beta}\right) + e_{hj}, \tag{4}$$

where $\boldsymbol{\beta}$ is a parameter vector to be estimated, $\tilde{\mathbf{Z}}_j$ is the vector of observed housing attributes and $\tilde{\mathbf{C}}_h$ the vector of observed household characteristics. The error term e_{hj} may reflect attributes of the household or house not observed by the researcher, or deviations in household h's preference vector $\boldsymbol{\beta}_h$ from the mean preference vector $\boldsymbol{\beta}$ (unobserved heterogeneity in preferences). If the e_{hj} are IID Type I Extreme Value, the probability that household h chooses house j is of the logit form,

$$\begin{aligned} &P(V_{hj} + e_{hj} \geq V_{hk} + e_{hk}, k \in K_h) \\ &\quad = \exp(V_{hj}) \Big/ \sum_k \exp(V_{hk}). \end{aligned} \tag{5}$$

[2] The short-run welfare effects in (3) are what is most often estimated in the literature. Bartik (1988) has shown that these constitute lower bounds to the value of attribute changes after markets adjust to these changes.

The parameter vector $\boldsymbol{\beta}$ may be estimated by maximum likelihood techniques, and marginal and non-marginal welfare measures calculated from the household's utility function.

In the hedonic model, the individual selects a house by choosing the utility-maximizing $\mathbf{Z}$ vector subject to the budget constraint $x_h + P(\mathbf{Z}) = y_h$, where $P(\mathbf{Z})$ is the hedonic price function. Optimality conditions require the household to equate the marginal price of each attribute to the marginal bid,

$$\frac{\partial P(\mathbf{Z})}{\partial z_i} = \frac{\partial U_h/\partial z_i}{\partial U_h/\partial x} = \frac{\partial B_h}{\partial z_i}, \qquad i = 1,\ldots,n. \tag{6}$$

Estimation of the bid function $B_h(\mathbf{Z})$ requires that one estimate the set of marginal bid functions,

$$\frac{\partial U_h/\partial z_i}{\partial U_h/\partial x} = f_i\left(\tilde{\mathbf{Z}}, y_h - P, \tilde{\mathbf{C}}_h\right) + \epsilon_{ih}, \qquad i = 1,\ldots,n. \tag{7}$$

which can then be integrated to yield $B_h(\mathbf{Z})$. The parameters of (7) are typically estimated by regressing $\partial P/\partial z_i$, on the right-hand side of (7).

The error terms in the hedonic and logit models depend on the form of consumers' utility functions and on which variables the researcher does not observe or observes with error. We assume that utility for household h is a quadratic function of either the natural logarithm or square root of housing attributes, $g(\;)$,

$$U_h = g(x) + \sum_i a_{ih}(\mathbf{C}_h) g(z_i) + 0.5 \sum_i \sum_j b_{ij} g(z_i) g(z_j). \tag{8}$$

The parameters of the utility function depend on observed household characteristics, $\mathbf{C}_h$, but also reflect unmeasured, individual-specific taste factors. Specifically,

$$a_{ih} = \alpha_{ih} + \delta_i \mathbf{C}_h, \qquad i = 1,\ldots,n, \tag{9}$$

where $\alpha_h = (\alpha_{1h},\ldots,\alpha_{nh})$ are assumed to be identically $N(\alpha, \Sigma)$ distributed for all buyers, with Σ diagonal. The remaining parameters b_{ij} are assumed identical for all persons. The researcher has only a single cross section of data and thus seeks to estimate the mean parameter vector $\boldsymbol{\beta} = (\alpha, b_{11},\ldots, b_{nn}, \delta)$.

Estimation of Parameters Using the Logit Model

If the researcher observes without error all household characteristics $\mathbf{C}_h$ and all attributes $\mathbf{Z}_j$, the random and deterministic components of utility may be written,

$$V_{hj} = g(x) + \sum_i (\alpha_i + \delta_i \mathbf{C}_h) g(z_i) + 0.5 \sum_i \sum_j b_{ij} g(z_i) g(z_j) \tag{10a}$$

$$e_{hj} = \sum_i (\alpha_{ih} - \alpha_i) g(z_{ij}). \tag{10b}$$

Equation (10b) violates the distributional assumptions underlying the logit model in two respects: the e_{hj} are normally distributed, and they are correlated.[3] Since we believe that the error distribution arising from unobserved heterogeneity is reasonable (Hausman and Wise, 1978), it is of interest to see how well the logit model performs when its underlying assumptions are violated.

Estimation of Parameters Using the Hedonic Model

Our assumptions about utility imply that the first-order conditions for the hedonic model are of the form (assuming $\delta_i = 0$ for simplicity)

$$\frac{\partial P(\mathbf{Z})}{\partial z_i} = \frac{g'(z_i)}{g'(x)}\left[\alpha_i + \sum_j b_{ij} g(z_j)\right] + w_{ih}, \qquad i = 1,\ldots,n, \tag{11a}$$

where the error term w_{ih} reflects unobserved heterogeneity in preferences and errors in measuring marginal attribute price, ζ_i,

$$w_{ih} = (\alpha_{ih} - \alpha_i)[g'(z_i)/g'(x)] + \zeta_i = \epsilon_{ih} + \zeta_i. \tag{11b}$$

The two hedonic problems of errors correlated with instruments and identification of parameters can be assessed in (11). Because the utility function underlying our simulations is a quadratic function of the square root or logarithm of the attributes, (11a) satisfies the necessary conditions for identification of a system of equations linear in parameters but nonlinear in variables. How-

[3] $E(e_{hk} e_{hj}) = \Sigma \sigma_i^2 g(z_{ik}) g(z_{ij})$.

ever, applying OLS to (11) yields inconsistent parameter estimates. Households with above average tastes for an attribute $(\alpha_{ih} - \alpha_i > 0)$ will tend to purchase more of the attribute; *ceteribus paribus*, ϵ_{ih} is correlated with z_{ih}. Possible instruments for $\mathbf{Z}_h$ are household characteristics $\mathbf{C}_h$ and income y_h, which are, by construction, uncorrelated with $(\alpha_{ih} - \alpha_i)$ and, hence, with ϵ_{ih}. However, there is no way to determine whether the ζ_i are correlated with $\mathbf{C}_h$ and y_h. Thus how well $\mathbf{C}_h$ and y_h perform as instruments remains an open question.

Description of the Simulations

The simulations require information on preferences, households and houses. The true utility function parameters are fixed to represent realistic preferences for attributes. Fixing the utility function also requires the distribution of α_h to be determined. The joint distribution of y_h and $\mathbf{C}_h$ comes from the Baltimore Travel Demand Dataset (1980). The housing data are drawn from houses actually sold in Baltimore City or County in 1976–1977. Characteristics of the houses come from Multiple Listing data, and neighborhood attributes from the 1980 Census of Housing and Population.[4] We report results for the six scenarios in figure 1. Housing attributes and household characteristics for the six scenarios are given in table 1 of Cropper et al. (1988).

Empirical Results

For each of the 6 scenarios, 20 housing market equilibria were computed, each corresponding to a different draw of the parameter vector α_h, $h = 1, \ldots, 200$. The data from these equilibria were used to estimate the parameters of the hedonic and logit models under two sets of assumptions:

(1) $\mathbf{Z}_j$ and $(\mathbf{C}_h, y_h)$ were observed without error;

(2) $(\mathbf{C}_h, y_h)$ was observed without error, but some elements of $\mathbf{Z}_j$ were not observed, or were replaced by proxies. For example, Sq. Ft. of Interior Space was replaced by No. of Rooms. There were 6 scenarios in which all variables were observed without error and 10 misspecification scenarios.

FIGURE 1.—HOUSING MARKET SCENARIOS

Form of Utility Function	Housing Stock	
	Baltimore City	Baltimore County
Translog	Attribute List #1	Attribute List #1
Diewert	Attribute List #1	Attribute List #1
	Attribute List #2	Attribute List #2

Estimation of the Hedonic Model

We estimated the hedonic model by first estimating the hedonic price function, computing marginal prices from the gradient of this function, and then estimating the set of marginal bid functions. The marginal bid functions were also estimated using true marginal bids as the dependent variables to examine the identification problem. In estimating the hedonic price function we used six functional forms: linear, semi-log, double-log, linear Box-Cox, quadratic, and Box-Cox quadratic. Three of these forms—the linear, semi-log, and double-log—have no interaction terms. In the last three forms—linear and quadratic functions of Box-Cox transformed variables, and a quadratic function—the marginal price of each attribute depends on more than one coefficient. For the Box-Cox functions, all independent variables have the same transformation, which differs from the transformation of the dependent variable. Dummy variables were not transformed. The parameters of marginal bid functions were estimated by applying 3SLS to the set of equilibrium conditions in (11).[5] Income, (income)^2, household size, (household size)^2 and the set of additional socioeconomic variables $(\mathbf{C}_h)$ were used as instruments. These variables are, by construction, uncorrelated with errors that arise due to unobserved heterogeneity in preferences.

Marginal attribute bid functions were estimated only for the 6 full-information cases. To test the robustness of the hedonic model to specification error, the linear marginal attribute bid functions on the right-hand side of (12) were also

[4] Because the α_h are random, each draw produces a new equilibrium. For each of the six scenarios, 20 Monte Carlo simulations were run, each for a different draw of α_h. An appendix describing the data and computation of equilibrium is available from the authors.

[5] Before estimation the equations (11a) were multiplied by $g'(x)/g'(z_i)$ to reduce heteroskedasticity in the error terms.

estimated using the same set of instruments

$$\frac{\partial P}{\partial z_i} = \gamma_i + \psi_i z_{th} + w_{th}, \qquad i = 1, \ldots, n. \tag{12}$$

Estimation of the Logit Model

The parameters of the logit model were estimated by maximum likelihood methods for all 6 full-information scenarios and for the 10 scenarios in which housing attributes were observed with error. Estimation was performed using the true form of the utility function and three approximations to the true function:

$$V_{hj} = \theta_0 g(x_{hj}) + \sum_i \theta_i h(z_{ij}). \tag{13}$$

The three approximations were: (1) g and h the square root function, (2) g and h the logarithmic function and (3) g square root and h linear. The log-linear and linear-in-square-roots forms of the utility function are natural approximations to the translog and Diewert utility functions.

Comparison in Estimating Welfare Effects

Marginal Welfare Changes

We judge the relative performance of the models in estimating marginal attribute bids by examining the resulting distributions of errors. The error in estimating household h's marginal bid for attribute i on trial t is the difference between the predicted and actual marginal attribute bids. To summarize the distribution of errors across buyers, we calculate for each trial the mean error for each attribute as a fraction of the mean true bid for each attribute,

$$\mu_{it} = \sum_h \left(\partial \hat{B}_{ht}/\partial z_i - \partial B_{ht}/\partial z_i\right) \Big/ \sum_h \partial B_{ht}/\partial z_i. \tag{14}$$

Table 1 contrasts errors in estimating marginal attribute bids using the logit model with errors that occur when marginal attribute bids are estimated using the gradient of the hedonic price function. When all attributes are observed without error, averaging the absolute value of errors, μ_{it}, across all attributes and trials shows that the best-performing forms of the hedonic price function—the linear and quadratic Box-Cox functions—produce errors approximately equal in magnitude to the logit model when the researcher knows the true form of the utility function. The linear Box-Cox hedonic price function produces average errors ranging from 10% to 14% of true marginal attribute bids, while the logit model, using the true form of the utility function, produces average errors that range from 3% to 11%.

TABLE 1.—NORMALIZED ERRORS IN MEASURING MARGINAL ATTRIBUTE BIDS

	Variables Observed without Error							Imperfect Information Cases
	Diewert		Diewert		Translog			
	City		County		City	County	Average	Average
	#1	#2	#1	#2	#1	#1	Error	Error
Form of the Hedonic Price Function	Hedonic Model							
Linear	0.478	0.283	0.272	0.224	0.649	0.384	0.382	0.756
Semi-Log	0.543	0.505	0.466	0.324	0.624	0.553	0.503	0.742
Double-Log	0.493	0.878	0.239	0.220	0.255	0.189	0.379	0.763
Box-Cox Linear	0.137	0.115	0.104	0.109	0.138	0.120	0.119	0.612
Quadratic	0.238	0.455	0.119	0.253	0.439	0.224	0.288	1.095
Box-Cox Quadratic	0.129	0.199	0.079	0.110	0.171	0.086	0.129	1.277
Form of the Utility Function	Logit Model							
True	0.056	0.032	0.054	0.110	0.083	0.089	0.071	0.609
Linear	0.642	0.374	0.481	0.352	0.700	0.592	0.524	0.695
Loglinear	0.438	0.938	0.198	0.141	0.127	0.080	0.320	0.824
Square Root	0.175	0.075	0.099	0.138	0.286	0.251	0.171	0.595

Note: The errors above were computed as $\Sigma_i \Sigma_t |\mu_{it}|/nT$ where μ_{it} is the average error in estimating the value of attribute i on trial t, T is the number of Monte Carlo trials and n the number of attributes.

TABLE 2.—NORMALIZED ERRORS IN WILLINGNESS-TO-PAY FOR A 25% AND A 100% ATTRIBUTE CHANGE: TRUE UTILITY FUNCTION KNOWN

Form of the Hedonic Price Function		Diewert City #1	Diewert City #2	Diewert County #1	Average Error
			Hedonic Model		
Linear	(25%)	0.537	0.221	0.296	0.351
	(100%)	0.490	0.183	0.282	0.318
Semi-Log	(25%)	0.456	0.521	0.562	0.513
	(100%)	0.385	0.428	0.562	0.458
Double Log	(25%)	0.477	0.965	0.217	0.553
	(100%)	0.512	0.957	0.198	0.556
Box-Cox Linear	(25%)	0.084	0.097	0.064	0.082
	(100%)	0.098	0.088	0.074	0.087
Quadratic	(25%)	0.243	0.749	0.167	0.386
	(100%)	0.296	1.360	0.324	0.660
Box-Cox	(25%)	0.143	0.398	0.062	0.201
Quadratic	(100%)	0.173	0.730	0.111	0.338
True Marginal	(25%)	0.017	0.013	0.022	0.017
Bids	(100%)	0.034	0.021	0.041	0.032
			Logit Model		
True Utility	(25%)	0.048	0.030	0.049	0.042
Function	(100%)	0.058	0.069	0.062	0.063

Note: The errors above were computed as $\Sigma_i \Sigma_t |\mu_{it}|/nT$ where μ_{it} is the average error in estimating the value of attribute i on trial t, T is the number of Monte Carlo trials and n the number of attributes.

The logit model, however, produces larger errors than the linear Box-Cox hedonic price function when the utility function is approximated by a linear or log-linear function. Specifically, errors average 52% for the linear function and 32% for the log-linear. A linear function of the square roots of the attributes does only slightly worse than the linear Box-Cox function, with an average error of 17%.[6]

When some attributes are not observed or are replaced by proxies (see the last column of table 1), the best versions of each model continue to produce similar errors, though greater than in the full information case. Averaging errors across all scenarios, the linear Box-Cox function and the logit model, using the true form of the utility function, produce errors that are 61% of true bids. With the logit model, knowing the true utility function helps little. Indeed, the square root approximation performs slightly better than the true utility function—a finding that parallels our conclusion that simpler forms of the hedonic price function produce lower errors than more complicated forms (Cropper et al., 1988). The linear utility function produces average errors of 70%, only slightly worse than those produced by the linear Box-Cox hedonic price function.

[6] This result is in part due to the fact that the true utility function is a quadratic function of the square roots of the attributes; however, the linear-in-square roots function does fairly well (producing errors of 25% to 29%) when the true utility function is translog.

Non-Marginal Welfare Changes

The value of a non-marginal attribute change or willingness to pay (*WTP*) (equation (3)) is computed by integrating marginal attribute bid function in the case of the hedonic model. In the logit model it is computed directly from the utility function.

Table 2 presents errors in estimating *WTP* for 25% and 100% changes in attribute levels when the true form of the utility function is known to the researcher. When the hedonic model is estimated using true marginal bids, errors are only 1% or 2% of true *WTP*. Identification is thus not a problem in our model. When marginal prices must be estimated from the hedonic price function, however, average errors in estimating welfare measures range from 8% to 66% of true *WTP*. This reflects two problems: errors in estimating marginal prices are biased, and they are correlated with the instruments used in 3SLS

TABLE 3.—NORMALIZED ERRORS IN WILLINGNESS-TO-PAY FOR A 25% AND A 100% ATTRIBUTE CHANGE: TRUE UTILITY FUNCTION UNKNOWN

		Diewert City #1	Diewert City #2	Diewert County #1	Average Error
Form of the Hedonic Price Function			Hedonic Model		
Semi-Log	(25%)	0.445	0.798	1.525	0.922
	(100%)	0.408	0.623	1.180	0.738
Double Log	(25%)	6.976	47.240	1.584	18.116
	(100%)	4.786	32.593	1.139	12.576
Box-Cox Linear	(25%)	1.132	2.761	1.347	1.747
	(100%)	0.891	2.336	0.861	1.363
Quadratic	(25%)	27.944	12.070	1.207	13.741
	(100%)	19.011	8.196	0.845	9.351
Box-Cox	(25%)	21.810	12.070	3.653	12.511
Quadratic	(100%)	13.676	8.493	2.417	8.195
True Marginal	(25%)	17.902	12.293	3.469	11.221
Bids	(100%)	11.102	8.248	2.298	7.216
Form of the Utility Function			Logit Model		
Linear	(25%)	0.582	0.330	0.550	0.487
Function	(100%)	0.478	0.300	0.471	0.416
Loglinear	(25%)	0.397	1.055	0.209	0.554
	(100%)	0.437	1.112	0.237	0.595
Square Root	(25%)	0.144	0.071	0.081	0.099
	(100%)	0.106	0.078	0.096	0.093

Note: The errors above were computed as $\Sigma_i \Sigma_t |\mu_{it}|/nT$ where μ_{it} is the average error in estimating the value of attribute i on trial t, T is the number of Monte Carlo trials and n the number of attributes.

estimation of marginal bid functions. By contrast, errors in estimating *WTP* using the logit model average about 5%.

Matters are even worse when the researcher approximates the true marginal bid functions with linear functions (see table 3). In this case, when equation (11) is replaced by equation (12), even the linear Box-Cox hedonic price function produces average errors of over 100%. Other forms of the hedonic price function produce extremely high errors—of almost 5000%! By contrast, the logit model estimated with a linear approximation to the true utility function produces average errors of no more than 58%. In fact, in each scenario, all versions of the logit model produce smaller errors than the hedonic model using the linear Box-Cox hedonic price function.

The large average errors produced by the hedonic model represent extremely large errors for *MEDIAN AGE OF THE POPULATION*, with smaller errors for the remaining attributes. The very high average errors in table 3 may therefore be misleading. If this attribute is removed from consideration, average errors fall by an order of magnitude. Consider Diewert City #2 for a 25% attribute change. For the Box-Cox linear, Quadratic, and Box-Cox quadratic, excluding the highest error results in average errors of 1.02, 0.097, and 0.544 instead of 2.761, 12.07, and 12.07 (column 2 of table 3).

The fact that the hedonic model misses badly in valuing some attributes cannot, however, be ignored. While it is true that the model also estimates *WTP* for minor neighborhood attributes less accurately than *WTP* for lot size and interior space, it estimates *WTP* for these attributes more accurately than does the hedonic model. The reason for these results is that, with data from a single hedonic market, errors in estimating marginal attribute prices tend to be correlated with the factors (income, socioeconomic variables) that cause individuals to select different housing attributes. Since these are the instruments typically used in estimation of marginal bid functions, instrumental variable estimators are inconsistent. This problem does not arise in estimating the logit model, which in our simulations outperforms the hedonic model in valuing nonmarginal welfare changes.

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Valuing Product Attributes Using Single Market Data: A Comparison of Hedonic and Discrete Choice Approaches
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The Review of Economics and Statistics, Vol. 75, No. 2. (May, 1993), pp. 225-232.
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[2] **Measuring the Benefits of Amenity Improvements in Hedonic Price Models**
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