EXHIBIT H

A Primer on Nonmarket Valuation

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Chapter 10

THE HEDONIC METHOD

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1. INTRODUCTION

Heterogeneous or differentiated goods are products whose characteristics vary in such a way that there are distinct product varieties even though the commodity is sold in one market (e.g., cars, computers, houses). The variation in product variety gives rise to variations in product prices within each market. The hedonic method for non-market valuation relies on market transactions for these differentiated goods to determine the value of key underlying characteristics. For instance, by observing the price differential between two product varieties that vary only by one characteristic (e.g., two identical cars, but with one having more horsepower than the other), we indirectly observe the monetary trade-offs individuals are willing to make with respect to the changes in this characteristic. As such, the hedonic method is an "indirect" valuation method in which we do not observe the value consumers have for the characteristic directly, but infer it from observable market transactions.

The most common application of hedonic theory to environmental valuation involves housing markets. Analyzing the choices consumers make over housing is particularly well suited to many valuation exercises. The choices of housing location, and therefore neighborhood amenities, are observable. Often location choice is directly linked to an environmental amenity of interest. For example, housing locations can offer different scenic vistas (Patterson and Boyle, forthcoming). As such, the choice of a house and its associated price, implies

an implicit choice over the environmental amenities linked to the house and their implicit prices.

Imagine the following hypothetical scenario in which there are two identical lakes, each with 100 identical homes surrounding them. All homes are lake-front, and all the characteristics of the homes themselves, the land, and the neighborhoods are identical across the properties. At the current equilibrium price of $200,000 per house, all 200 homes on either lake are equally preferred. Now, lets imagine that water clarity at one lake, Lake A for example, is improved. We assume that the improved water clarity is preferred by all households. Now if any home on Lake A were offered at the original equilibrium price of $200,000, consumers would uniformly prefer this house to any house on Lake B. In other words, at the current prices, there would be excess demand for the houses located on Lake A, and as such, the price of these houses must rise to bring the market into equilibrium. The price differential that results from the change in water clarity at Lake A is the implicit price consumers are willing to pay for that incremental increase in water clarity. This willingness to pay for water clarity is indirectly revealed to us through the market prices of the homes. For instance, if in the new equilibrium, houses on Lake A sell for $210,000, while houses at Lake B sell for $200,000, the "implicit price" associated with the increased water clarity is $10,000.

Of course, housing markets aren't so simple: housing choice depends on many characteristics such as structure of the house, amenities of the land, neighborhood and location. Yet, the fundamental intuition behind the hedonic method extends easily. By observing the choices consumers make over heterogenous commodities with varying prices, we can estimate the implicit price of one of the component characteristics of the commodity. These implicit prices or hedonic prices, under certain conditions, are equal to WTP or allow us to recover WTP.

Hedonic analyses have been reported as early as Fred Waugh's (1928) analysis of quality factors influencing asparagus pricing, and have been applied to markets as varied as automobiles, computers, VCRs, and appliances, and agricultural commodities.[1] Beach and Carlson (1993) estimated the factors affecting herbicide choice by farmers. Nimon and Beghin (1999) applied hedonic pricing to the apparel market to determine if consumers place a premium on clothes made from organically grown cotton.

Hedonic price functions have also been used to determine factors influencing the pricing of prescription drugs (Danzon and Chao 2000; Cockburn and Anis 1998) and to evaluate the treatment of clinical treatment of illnesses such as depression (Berndt, Busch, and Frank 1998). Cultural applications of the hedonic method have been used to analyze market sales for Picasso paintings (Czujack 1997), Impressionist paintings (Chanel, Gerard-Varet, and Ginsburgh 1996), classical music (Harchaoui and Hamdad 2000), and have even been extended to examining the factors that influence dowries in South Asia (Rao 1993).

This chapter focuses primarily on housing markets and how they may be used to value environmental amenities. The application of the hedonic method to labor markets is also briefly reviewed in section 6. Other reviews of the hedonic method can be found in Palmquist (1991, 2000) and Freeman (1993).

Hedonic analysis of markets for differentiated goods consists of two related steps often referred to as a first-stage and second-stage analysis. In a first-stage analysis, the hedonic price function is estimated using information about the prices of a differentiated commodity and the characteristics of the commodity. This analysis allows researchers to recover the implicit prices of characteristics and reveals information on the underlying preferences for these characteristics as discussed in section 4. Once the first-stage analysis is completed, researchers may then use the implicit prices obtained in the first stage to estimate the demand functions for the *characteristics* of the commodity. This step is referred to as a second-stage analysis and is discussed in section 5. First-stage analyses are the most common application of the hedonic method because the data requirements are minimal and the needed economic insights often only require marginal price information. Second-stage analyses require significantly more data that are often difficult to obtain, and the modeling is more complex.

For the purposes of non-market valuation, Rosen's (1974) seminal article was important because it developed a utility theoretic framework for understanding the market process generating a hedonic equilibrium, and thus established the connections between consumers' preferences for characteristics of heterogeneous goods and the equilibrium price function. Next we review this theory to provide the basis for our later discussion of implementing the method and the econometric issues related to a first- or second-stage analysis.

2. THE HEDONIC PRICE FUNCTION: THEORY

An example of hedonic price function for housing is presented to facilitate discussions throughout this chapter. This example has common elements with almost every hedonic price function estimated with housing markets for the purposes of non-market valuation. The example is based on a study by Boyle, Poor, and Taylor (1999), but I will present some of their results in this chapter that were not directly reported in the journal article.

Boyle, Poor, and Taylor estimated hedonic price functions for lakefront properties in Maine. Sales prices of properties, mostly summer cottages, were analyzed as a function of the characteristics of the structure on the property and important characteristics of the land such as its location relative to the nearest town and the water quality of the lake on which the property is located. Maine lakes are known for their high water quality, however this quality is being compromised in many Maine lakes by eutrophication resulting from nonpoint pollution. The physical manifestation of eutrophication is reduced water clarity. Thus, water clarity is the measure of lake water quality that is used by the authors in the hedonic price function.

Boyle, Poor, and Taylor (1999) estimate a hedonic price function for each of four geographically distinct markets. The estimated hedonic price function for one market is:

$$P = 25{,}899 + 6{,}790 \cdot \ln(SQFT) + 83 \cdot FRONT - 3{,}919 \cdot DNSTY + 1{,}516 \cdot DIST + 11{,}572 \cdot HEAT + 23{,}465 \cdot BATH - 17{,}579 \cdot LKWATER + 2.057 \cdot WQ, \quad (1)$$

where the dependent variable is the sales price of a property, and the independent variables are, respectively: square feet of the structure on the property (mean = 750 square feet); the length of the property's frontage on the lake (mean = 143 feet); the number of lots per 1000 feet of frontage adjacent to either side of the property (mean = 8.9 lots); the distance between the property and the nearest town (mean = 9.4 miles); dummy variables included that designate whether or not the structure has central heating, a full-bath, or if the property uses lake-water as its primary source of water. The last independent variable in equation (1) is a measure of water quality (WQ) which is equal to LKAREA*ln(WC), where LKAREA is area of the lake on which the

property is located (mean = 4,756 acres), and WC is the depth of water clarity of lake (mean = 3.9 meters).

This application of the hedonic method to value lake water clarity in Maine will be used to illustrate conceptual issues discussed throughout this chapter. Next, the theoretical underpinnings of the hedonic method are presented which allows us to precisely interpret the hedonic price function coefficient estimates. Section 3 summarizes the steps involved in implementing the theory and these steps are then discussed in detail in the following sections.

2.1 The Hedonic Equilibrium

The basic utility maximization problem including the consumer's choice over a differentiated product is presented in chapter 2, section 3.4. In this chapter, we will discuss this theory in more depth using the following notation and assumptions. Let Z represent the differentiated commodity with characteristics $\underline{z} = z_1, z_2, z_3, \ldots z_n$. The differentiated commodity is assumed to be sold in a perfectly competitive market and the interactions of the many producers and consumers together determine an equilibrium price schedule for the differentiated commodity, $P(\underline{z})$.[2] The equilibrium price for any one model of the differentiated good is a function of the characteristics of that particular model. As such, the consumer can determine the price he/she pays for the good by choosing which model to purchase. However, it is important to note that the consumer takes the entire price schedule $P(\underline{z})$ as exogenous.

Consumer utility is defined over two goods: Z, the differentiated good, and x, a composite commodity representing all other goods (i.e., income left over after purchasing Z). Consumer j, with demographic characteristics α^j has utility defined as:

$$U^j(x, z_1, z_2, \ldots, z_n; \alpha^j). \quad (2)$$

If we assume that the consumer purchases only one unit of the differentiated commodity, a reasonable assumption for the housing market, the budget constraint is $y^j = x + P(\underline{z})$. The consumer seeks to maximize utility by choosing the model of the differentiated product, $\underline{z}$, and the amount of x to purchase, subject to this budget constraint. The consumer will choose $\underline{z}$ and x such that the following is satisfied for each z_i:

(3) $$\frac{\partial P}{\partial z_i} = \frac{\partial U/\partial z_i}{\partial U/\partial x},$$

which is equivalent to equation (32) in chapter 2, and indicates that the marginal rate of substitution between any characteristic, z_i, and the composite numeraire commodity, x, is equal to the rate at which the consumer can trade z_i for x in the market (i.e., the ratio of the implicit price for z_i and the price of the numeraire =1)).

For our purposes, it is convenient to describe the optimal bid a consumer will make for any specific product variety. The bid function, θ, describes the relationship between the dollar bid consumer j will make for Z as one or more of its component characteristics are changed while utility and income remain constant. Equation (2) can be used to define the bid function formally by recognizing that income less the bid a consumer makes for Z is the amount of money left over to spend on the numeraire, x. Thus, the relationship:

(4) $$U^j(y_0 - \theta,\ \underline{z},\ \alpha^j) = U_0$$

indicates how a consumer's optimal bid must vary in response to changes in $\underline{z}$ if utility and income are held constant. Solving equation (4) for θ indicates that $\theta^j = \theta(\underline{z},\ y_0,\ U_0^j,\ \alpha^j)$, where y is exogenous income and U_0^j is a fixed level of utility. Maximizing utility in (4) yields the result that the the marginal bid a consumer is willing to make for z_i ($=\partial\theta/\partial z_i$, which is denoted as θ_{zi}), will equal the marginal rate of substitution between any characteristic, z_i, and x. Relating this result to that in equation (3) indicates that the necessary conditions for utility maximization are that the marginal bid a consumer places for a characteristic must equal the marginal price of that characteristic ($=\partial P(\underline{z})/\partial z_i$, which is denoted as P_{zi}).

For the supply-side of the market, we can describe a firm with characteristics δ^k as seeking to maximize profits, $\Pi = H^*P(\underline{z}) - C(H,\ \underline{z},\ \delta^k)$, where H is the number of units of Z that the firm produces and C(·) is a well-behaved cost function. Again, the firm faces the exogenous, equilibrium price schedule $P(\underline{z})$ when determining its choices. Although firms can affect the prices they receive for their products by varying the characteristics of the product, no single firm can affect the price schedule. In this formulation, we assume the firm produces only one model of Z. Thus, the firm chooses what type to produce, Z^k, and then chooses how many of that type to produce.[3] Similar to the consumer's problem, we may describe the behavior of a firm in

this differentiated goods market by an offer function: $\varphi^k = \varphi(\underline{z};\ H,\ \Pi_0,\ \delta^k)$, which describes the amount of money a firm is willing to accept for any particular variety of Z, holding constant the number of units of that variety the firm produces, H, and its level of profit, Π_0. The offer function is defined by: $\Pi_0 = H^*\varphi^k - C(H,\ \underline{z},\ \delta^k)$, and at the optimum, it will be the case that the marginal price a firm is willing to accept for z_i, φ_{zi}, will equal the marginal cost of producing that characteristic per unit of the differentiated good, C_{zi}/H.

The bid and offer functions, and their properties may be easily described using Figure 1, which originally appears in Rosen (1974). Figure 1 illustrates the equilibrium price schedule, $P(\underline{z})$ as it varies with changes in z_1, holding the level of all other characteristics constant. $P(\underline{z})$ is drawn such that the total price paid for z_1 increases at a decreasing rate. We might expect this relationship in many cases.

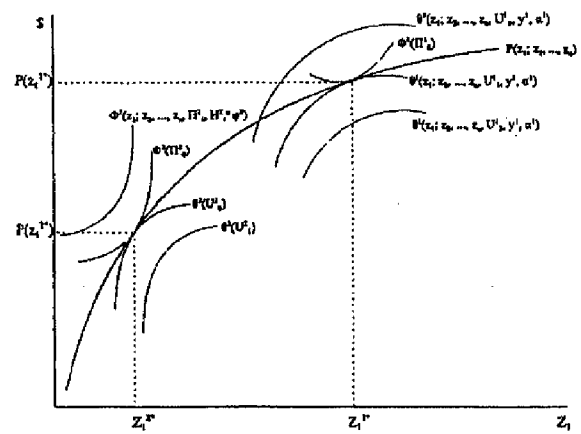

Figure 1. The Hedonic Price Function

For instance, let's say z_1 represents the square feet of living space in a house. We might expect a smaller price differential between a 5,000 and a 5,300 square foot house as compared to the price differential between a 1,000

and a 1,300 square foot house. However, the equilibrium price schedule P(z) may theoretically take any form, a point discussed in more detail later.

Also depicted in Figure 1 are the bid functions for two consumers, θ^1 and θ^2. Along any bid function contour, only the level of z_1 changes; the level of all other characteristics, income, and utility are constant. Bid functions are concave in $\underline{z}$ (i.e., optimal bids increase at a decreasing rate in $\underline{z}$) and higher levels of utility for a consumer are represented by bid function contours closer to the horizontal axis. Intuitively, a lower bid for the same level of z_1, implies a higher level of utility because more money is left over to spend on x.[4] The optimal choice of z_1 is where the consumer reaches the lowest possible bid function while still being able to participate in the market. For consumer 1, this occurs at a quantity z_1^{1*} and a total bid price of $P(z_1^{1*})$, which is the point at which the bid function is tangent to the equilibrium price schedule in Figure 1. For consumer 2, this optimal choice occurs at z_1^{2*} and the consumer pays a total price of $P(z_1^{2*})$. At each consumer's optimal choice of z_1, the marginal bid $(\partial\theta/\partial z_1)$ equals the marginal price $(\partial P(\underline{z})/\partial z_1)$.

Offer functions for two firms, φ^1 and φ^2, are also depicted in Figure 1. Offer functions are convex in $\underline{z}$ as optimal offers increase at an increasing rate, holding profits and all else constant. Offer functions further away from the horizontal axis represent higher levels of total profit. The firm's optimal choice of what level of z_1 to produce in each of its H units of the differentiated product is where the firm reaches the highest possible offer function while still being able to participate in the market. For firm 2, this occurs at quantity z_1^{2*} and a total offer price of $P(z_1^{2*})$.

Figure 1 illustrates that the hedonic price function is simply an envelope of the equilibrium interactions between all buyers and sellers of a differentiated good. As such, it is possible for the hedonic price function to take any shape. The key point is that with relatively small data requirements, such as information on product types and their sales prices, we can recover the marginal implicit prices for any component characteristic of Z. The marginal price is equal to the marginal WTP for that characteristic by consumers, $\partial\theta/\partial z_1$. In the Maine lakes example, equation (1) indicates that consumers' value for a one-unit (one foot) increase in a property's feet of lake frontage is $\partial\theta/\partial FRONT = \partial P/\partial FRONT = \$83$. This is the fundamental insight underlying the hedonic method. We seek to estimate the parameters of the hedonic price function so we may recover information about the marginal value consumers place on characteristics.

3. THE HEDONIC PRICE FUNCTION: ESTIMATION

The data needs for estimating the marginal implicit prices through the hedonic price function are fairly simple. In this section, we discuss the details of estimating the hedonic price function and some important considerations. Table 1 summarizes the steps and considerations for estimating the hedonic price function.

Table 1. Summary of Steps for Estimating the Hedonic Price Function

Define Value to be Estimated
- Marginal willingness to pay as revealed by marginal implicit prices.

Collect Data on Property Value (Dependent Variable)
- Sales Price: preferred measure of value, may need to consider selection bias.
- Tax Assessment or Homeowner Survey of Value: measurement error may be a significant concern.
- Rental or Lease Prices: appropriate for some applications, timing issues can be of concern, care should be taken when interpreting the implicit prices.

Choose Functional Form for the Hedonic Price Function
- Linear usually not appropriate. Non-linear functions imply non-constant marginal prices.
- Semi-log functional form often used, care must be taken when interpreting the coefficient estimates for the dummy variables.
- Researcher judgement must be applied, and expectations about relationships between certain characteristics and sales price will guide choice of functional form.

Address Spatial Dependence and Correlation
- Spatial relationships among properties similar to autocorrelation in time-series is likely. Tests and corrections for spatial dependence are available pre-packaged statistical packages and should be implemented when possible. These packages require properties to be spatially-located (i.e., assigned latitude/longitude markers).

Compute Welfare Measures (Section 4)
- For localized changes in amenities, the change in sales price resulting from the change in the amenity is the measure of net-benefits if there are no transactions costs associated with moving between properties. If there are transactions costs, the change in price net of transactions costs measures net-benefits (or is an upper-bound on net benefits).
- For non-localized changes in amenities, a second-stage demand analysis is most appropriate for computing a bound on net-benefits.

3.1 Dependent Variables

We seek to estimate the equilibrium price schedule, P(z), which is the function relating transaction prices (sales price) to the characteristics of the product. Thus, the appropriate dependent variable is sales price, which is the observed outcome of a market assumed to be in equilibrium. As with any durable asset, sales price of a property represents the discounted present value (PV) of all future rents (R) from the property:

$$PV = \sum_{t=1}^{T} \frac{R_t}{(1+r)^t} \tag{5}$$

where r is the discount rate, and T is the expected life of the property. The implicit price for a characteristic of a house can then be thought of as representing the discounted presented value of the stream of benefits expected from that characteristic. Thus, expected changes in future benefits of the house would be incorporated into current sales prices.

Sales prices may be obtained from several sources. First, local government offices such as county courthouses record each deed transfer and its transfer price. This information is publicly available; however, these records are almost never recorded electronically by these government offices. The data used by Boyle, Poor, and Taylor (1999) were collected at town offices using researchers' laptop computers. Collection of sales price data in this manner can be quite time consuming, if not prohibitive when large numbers of observations are needed. For larger metropolitan areas, private firms have begun recording local sales data for re-sale in electronic formats. A recent internet search revealed many private vendors of property data. While prices vary, one company's price for academic purchasers was $1,000 per county in the Atlanta, Georgia metropolitan area for a data file containing the most recent sales price of every property in the county (well over 250,000 observations in one county alone).

When sales prices are too difficult to obtain, other estimates of housing value may be used such as homeowner or tax assessor estimates of value. Tax assessors values are often more readily available. Often, county tax assessor offices maintain electronic databases of every property's assessed value within the county. These records are public information and generally are available upon request.

Surveys of homeowners may also be used to estimate property values. For instance, a researcher may conduct a mail survey and ask owners the price they paid for their house and the purchase year. National surveys of homeowners are available which ask homeowners to estimate the value of their homes. Example databases include the American Housing Survey collected by the U.S. Census Bureau (www.census.gov/hhes/www/ahs.html) and the Panel Study of Income Dynamics, which is collected annually by the University of Michigan (www.isr.umich.edu/src/psid/pdf.html).

Tax assessor and homeowner estimates of value may not correspond exactly with actual sales prices, but it is hoped they are reasonably good approximations. As approximations, the potential for measurement error must be considered as discussed in Section 3.1.1. Also, in the case of tax-assessed prices, it is of some concern that the implicit price estimated in a hedonic price function may not reflect the owners' (or market) value of these characteristics, but rather the values of a handful of tax assessors who work for a county.

Rental prices of properties have also been used as the dependent variable in some hedonic analyses of housing markets (Pollard, 1980). Taylor and Smith (2000), Osborne (1995), and Wilman (1984) used rental prices of vacation properties to estimate values for proximity to the shoreline. In this case, implicit prices are actually implicit rents, representing the additional value to rent from an additional unit of a particular characteristic. As such, it is important to note that while future changes in amenities may be capitalized into sales prices, they are not expected to be capitalized into current rents (as equation 5 makes clear). Although this does not diminish the usefulness of rental prices for hedonic analysis, the researcher has to be clear in the interpretation of the hedonic price function that implicit prices represent current-period values, rather than changes in asset values.

3.1.1 Measurement Error in the Dependent Variable

In terms of estimating the hedonic price function, measurement error in the dependent variable is not a problem if the measurement error is uncorrelated with the set of independent variables. In this case, the estimated implicit prices would remain unbiased, although efficiency will be reduced. The empirical question is whether tax assessor or homeowner estimates of value (sale prices) are uncorrelated with the characteristics of the properties. Ihlanfeldt and Martinez-Vazquez (1986) investigate this question and compare tax assessor

and homeowner estimates of property values to actual sales prices. Their results indicate that the errors in both tax assessor and homeowner data were related to a number of structural characteristics, thus causing potentially biased estimates. In the sample used by Ihlanfeldt and Martinez-Vazquez, a smaller number of variables was affected by tax assessor estimates (5 of 22 variables) as compared to homeowner estimates (10 of 22 variables).

Kiel and Zabel (1999) provided a comparison of owner assessments with actual sales prices for 3 metropolitan areas over approximately an 11-year period. Their results indicate that although owners generally overestimate the value of their homes by approximately 5%, the difference in owner valuation and actual sales price is not related to any housing or owner characteristic other than the tenure in the home (those living longer periods of time in their house at the time of the survey provided more accurate values). These results held regardless of housing cycles, and they suggest a considerable promise for the use of data from owner surveys, such as the American Housing Survey and the Panel Study of Income and Dynamics, for estimating unbiased implicit prices for housing characteristics.

It seems likely that the appropriateness of survey or assessor data will be case specific, and one can only be assured of the appropriateness of these measures of housing value if sales prices are available for comparison. Unfortunately, this prescription is not particularly helpful for the researcher who does not have actual sales prices available.

Also, sales prices themselves are not without shortcomings. While sales prices may be recorded without error by county transfer deed records, not all sales are "arms-length" transactions. In some cases, properties may be transferred to family members or from one business entity to another at prices much less than market value. These observations would not be appropriate for inclusion in the data set as the hedonic price function is an equilibrium function arising from competitive market bidding for each property. Unfortunately, recognizing transactions that are not arms-length is not always easy. An intuitive approach is to omit any observations on prices that are implausibly low. However, the researcher must be carefully define what is "too low" and should have a good understanding of the market.

3.1.2 Sample Selection Bias

A second issue with sales prices, which the use of homeowner or tax assessor values may overcome, is the potential for sample selection bias. Here, the concern is that properties with specific unobservable characteristics may be less likely to be placed on the market for sale, or less likely to sell once placed on the market. Thus, sales prices for these properties are never observed, so they are systematically not included in the hedonic data. In this case, Ordinary Least Squares (OLS) estimation produces biased coefficient estimates.

One way to test for sample selection bias in sales price data is to compare hedonic implicit price estimates obtained from a database of sales prices to those obtained from a database of all property values. Ihlanfeldt and Martinez-Vazquez (1986) took this approach and found no evidence of selection bias in a large, general sample of Atlanta, Georgia homeowners.

Sample selection bias may be particularly important in studies focusing on housing that are proximate to amenities or dis-amenities. If the selection criteria for what properties are included in the analysis (e.g., homes that are located within a certain distance of a hazardous waste site) are related to unobserved characteristics that determine if we observe a sales price, then OLS estimation of the implicit prices based on this truncated sample will be biased. To my knowledge, an explicit consideration of this issue has not been undertaken. Huang and Palmquist (2001) developed a related model in which they explicitly consider the simultaneity between the duration a property is on the market and its sales price. They argued that housing located near a disamenity may suffer two impacts: reduced sales prices and reduced probability of sales. They found that location near a noisy highway does not adversely affect duration on the market, but does adversely affect sales prices. However, they do not test for selection effects among the mix of properties offered for sale near the highways as compared to those further away, clearly an area where further research is warranted.

3.1.3 Aggregation Level

Ideally, one would use observations on individual house transactions to estimate a hedonic price function. While most hedonic studies do use data on individual housing units, some studies still use census-level data (e.g., median

house value in a census tract or block, and associated median housing characteristics). If available, information on individual units is preferable, especially when a study is focusing on externalities that are likely to be localized. For instance, the effects of an environmentally contaminated site on nearby property values may be limited to a small geographic area. Aggregate housing data might not be able to distinguish these price effects if the geographic extent of the negative impacts is small relative to the geographic area that is aggregated.

The potential shortcomings of aggregated data are highlighted by Schultz and King (2001), who compared the results of hedonic regressions using census block-level and tract-level information to value open space in Tucson, Arizona. Although the authors did not find significant variations in implicit price estimates across these two data, they did find important variations between their results, and those of King, White, and Shaw (1991) who estimated a similar hedonic using individual house-sale information for the same market. As compared to the implicit prices estimated with house-level sales data, the implicit prices estimated using Census data understated the value of regional or district parks and overstated the value of neighborhood parks, golf courses, and some types of natural habitats (up to three-fold), and had the opposite sign for some types of wildlife habitat.

3.2 Independent Variables

As discussed in section 2.1, the hedonic price function is an envelope function relating sales price of a differentiated good to its characteristics. As such, the independent variables in a hedonic price regression are only those product characteristics that affect price. Characteristics of the consumers and sellers of the product *do not* belong in the hedonic price regression. Not all product characteristics belong in the regression either. Characteristics that vary across product types, but do not affect price are not included as a regressor (e.g., the color of a product type often does not affect its price).

There is no simple way to determine exactly what characteristics belong in a particular hedonic regression. Researchers must use their knowledge of the market to determine what characteristics are relevant for determining price in their market. In general, most property value studies include three types of characteristics: (1) the house and the lot, (2) features of the neighborhood such as the quality of the school district, the level of crime, and the environmental

health and (3) the property's location such as its proximity to a recreation area or an employment center. How a researcher might assemble these three categories of information follows. Also discussed in more detail regarding the choice of characteristics and how to formally model the hedonic price function.

Housing and lot characteristics are typically gathered from tax assessor records or homeowner surveys. The retail vendors of property data typically begin with the tax assessor database and then append the most recent sales price of each property. For instance, the vendor mentioned in section 3.1 (charging $1,000 per county for the most recent sales price of every property on the tax-assessor's roles) also included in the database the address and all property characteristics as recorded by the county tax assessors. The Panel Study on Income Dynamics survey of homeowners (see section 3.1) includes information on housing characteristics. Housing characteristics are also available at the census tract level from the U.S. Census Bureau (each observation is an average of the individual houses within a census tract). As micro-level data has become so widely available, census-level data is seldom applied in the recent studies (see section 3.3 for more on this point).

As with all secondary data, the researcher should carefully examine the data for apparent errors and outliers. For example, a house with 1 bedroom and 6 baths is likely a data error. This information should be verified by the researcher, and if it cannot be verified, the observation can be dropped from analysis. However, considerable controversy exists about data trimming, and observations should only be dropped judiciously.

Lastly, variables may have missing observations for a significant portion of the data. There are two ways to handle missing observations. The first is to allow these observations to be dropped from your statistical analysis. Dropping these observations is a problem only if there is a systematic process determining which observations have missing data, thus introducing selection bias. Alternatively, it is possible to replace missing values with the mean value for this variable in the sample. This approach is suggested in Maddalla (1988), but it is not common in the hedonic housing literature.

Neighborhood and location-related characteristics are usually sparse in tax assessor files, and so this information is generally appended to each property's record by the researcher. A common source of neighborhood information is the U.S. Census Bureau, which publishes information such as racial and income composition of neighborhoods by census tracts (www.census.gov). Census data may be matched to property data using either zip codes (a cross-walk between

zip codes and census tracts may be found at the Census website) or with a base map of census tract boundaries (also available at the Census website). Of course, a researcher may have other sources of neighborhood information, such as school district test scores or environmental quality of a neighborhood (e.g., ambient air quality conditions), that is available from state and local governmental or non-governmental sources.

Location-related characteristics are generally created by the researcher and are specific to each application. For instance, the only location-related characteristic in the Boyle, Poor, and Taylor (1999) study was the distance of the property to the nearest town. Ihlanfeldt and Taylor (2001) conducted a study of commercial and industrial property sales in Atlanta, Georgia and location-oriented variables included the distance from each property to the central business district, the nearest highway exit, the airport, and the nearest light rail station. Also included was the distance from each property to the nearest site with known environmental contamination. Each variable was created using a geographic information systems software package (see section 3.5).

In addition to specifying which characteristics belong in a hedonic price function, the researcher must consider how the relevant characteristics should be measured and how they should enter the hedonic price function. Major considerations for choosing regressors and developing the hedonic price function specification for estimation are outlined below.

3.2.1 Selection of Independent Variables

What characteristics are relevant to include in a hedonic price function? There is no easy answer to this question. Basic components are common to all studies: size of the lot, size of the structure, neighborhood descriptors, and location descriptors. The variables used to describe each feature varies, but typically at least one element of each category is included in a hedonic price function for housing. Lot size is typically measured in acres, and is commonly available. The structure size is typically measured by square footage of the house or the number of bedrooms and baths. Quality indicators can include the age of the structure and amenities, such as the presence of a fireplace. Quality indicators are often sparse. Neighborhood characteristics often include the quality of the school district and census information about the neighborhood such as racial composition and median household income. Neighborhood characteristics may also include an environmental amenity such as ambient air

quality. Lastly, locational variables such as the proximity to downtown (important for urban property markets), proximity to amenities and disamenities such as open space, shopping centers, mass transit station, and landfills are often included.

Which variables within a category should a researcher include? Should as many variables as possible be included within each category? While a "kitchen sink" approach might be tempting, it is not necessarily advisable. Adding irrelevant variables to a regression, if they are systematically related to other independent variables, can lead to increased standard errors and Type II errors in hypothesis testing (failing to reject the null hypothesis of no significant influence of a characteristic on price when it indeed *does* influence price). On the other hand, using too few variables can lead to dropping relevant variables, which would bias the coefficient estimates. Previous research by Atkinson and Crocker (1987) found that including large numbers of housing characteristics in hedonic price functions may result in increased unreliability of parameter estimates. However, Ihlanfeldt and Taylor (2001) found that increasing the number of explanatory variables introduces little bias with respect to the coefficient estimates of the environmental variables of interest.

Standard diagnostic methods for evaluating multi-collinearity exist (e.g., Belsley, Kuh, and Welsch 1980), and remedies that can be applied when variables in the hedonic price specification are suspect (e.g., principle component methods (Greene 1994)). Unfortunately, no simple analytic answer exists, and the researcher must thoughtfully develop a modeling approach, review related hedonic studies, and test the robustness of results to assumptions regarding which variables to include whenever possible.

3.2.2 Measurement Error in the Independent Variables

In addition to choosing the variables that determine price, the researcher has to be concerned with how the variables are measured. Ideally, one would have each characteristic measured in a manner consistent with the perceptions or understanding of the characteristic by the market participants. Again, this is because the hedonic price function is capturing the equilibrium outcomes of the real-world interactions between buyers and sellers of a commodity. Thus, the manner in which each characteristic is measured and used by the researcher should be consistent with the measures perceived by the market participants. For many structural or lot characteristics, this is a relatively straightforward

task. For instance, the number of bedrooms as measured in a current tax assessor database is likely to be equal to the homeowner's assessment of the number of bedrooms in the house at the time of purchase. However, for other characteristics important to sales prices, such as ambient environmental conditions (e.g., air quality at the site), it may be difficult to quantify this characteristic in a manner that accurately reflects buyers' and sellers' perceptions of the characteristic. For instance, in the Boyle, Poor, and Taylor (1999) study of Maine freshwater lakes, the measure of lake water clarity was provided by the Maine Department of Environmental Protection (DEP), and the clarity was measured monthly at a specific site on each lake during the summer months. Prospective purchasers may not have visited the lake during those months (and water clarity varies throughout the year on Maine lakes), or the properties may not have been located near the site where the DEP took measurements. As such, the objective or scientific measures of clarity collected by the DEP may not have coincided with water clarity as perceived by prospective property purchasers (see Poor et. al. 2001).

Although scientific measures or the proxy variables used by researchers are hoped to be reasonably well correlated with the "true" factors that are capitalized into a property's value, the use of proxy variables can nonetheless introduce the potential for errors-in-variables problems leading to biased estimates of *all* coefficients. If only one variable is measured with error, it is the case that improving the measurement of that variable will reduce the bias in all coefficients. However, when more than one variable is measured with error, reducing measurement error in one variable will not necessarily reduce the bias in the other regression coefficients (Garber and Klepper 1980).

Several studies have focused on the impacts of measurement error on hedonic price estimates (e.g., Atkinson and Crocker 1987, Graves et al. 1988). Graves et al. (1988) assumed that the proxy variables used for neighborhood characteristics were measured with error and tested to determine the extent to which these measurement errors may bias the coefficients of two variables measuring air quality: an index of visibility and a measure of the total suspended particulates (TSP). Their results indicated that measurement error in the neighborhood characteristics affected the index of visibility, changing both sign and significance of the variable, but did not affect measures of TSP. Boyle and Taylor (2001) also found that measurement error in structural and property characteristics of lakefront properties in Maine did not affect hedonic price estimates of the impacts of lake water clarity on sales price.

Results from previous research are more mixed when the measurement error is in the environmental variable of interest. Graves et al. (1988), find that even small measurement error in the two air quality measures resulted in unstable coefficient estimates such that even qualitative conclusions were "dubious," indicating "the need for additional efforts to ensure that the environmental quality variables are carefully measured" (p. 232). More recently, Poor et al. (2001) used the Maine lake data described earlier to compare scientific readings of water clarity with subjective measures of clarity gathered from a survey of property owners. Both the objective and subjective measures of quality were measured as linear feet of water clarity, and so the objective and subjective measurements were directly comparable. Their data suggested that property owners tended to *under*-report water clarity as compared to objective measures, and non-nested *J*-tests indicated that the objective measures were better predictors of sales prices than were the subjective measures. Although this finding is encouraging for the use of objective measures of environmental quality in hedonic regressions, clearly additional research is needed to determine whether or not this result extends to situations in which the objective measures of quality may be very different than consumer perceptions of the amenities.

Again, no definitive answer can be offered with respect to building the data needed for the hedonic model. Common sense, research and knowledge about the study market, and an understanding of the consequences of the choices (assumptions) made are key to conducting a thoughtful and careful hedonic price study.

3.3 Sample Frame

When choosing a sample frame for a hedonic analysis, one must consider the geographic coverage of the data selected as well as the time period. First, consider the geographic coverage of the data. If the study focus is an environmental good, then the data has to have geographic coverage sufficient to ensure variation in the environmental amenity or disamenity across properties. Depending on the amenity, variation may be in the form of proximity of each property to the amenity (e.g., proximity to a park), or the variation may be the ambient level of the amenity (e.g., the level of air quality at the site). While variation of the first type is typically easy to ensure, ambient environmental quality can sometimes be more difficult to ensure in a sample frame. Geographic dispersion of properties sufficient to ensure variation in an

ambient environmental variable may result in a sample frame that is comprised of properties from multiple markets. If, in order to get sufficient variation in a environmental variable, the geographic dispersion of properties in a sample is increased so that properties are now drawn from different markets, estimating one hedonic price function for the entire sample is inappropriate. This is because a hedonic price function is an equilibrium function describing a specific market. As such, all properties used in a hedonic regression must be part of the same housing market. The question that arises is how to determine what set of properties comprise a single market. In other words, we wish to know the extent of the market.

Markets are truly separate if participants in one market do not consider houses in the other market when making purchase decisions. One common assumption is that each urban area represents a separate housing market. If the focus of the study is proximity to an amenity or disamenity, each urban area typically has sufficient variation for estimation. Although considering each urban area a separate market is likely a reasonable assumption, it may also be the case that additional market segments exist within a city.[5] For instance, markets may be segmented by time, product variety, and perhaps social barriers such as income and race.

The evidence for clear market segmentation across any barrier is mixed across applications, including whether or not markets are segmented across urban areas. Palmquist (1991) reviewed early studies with evidence for market segments across urban areas (Butler 1980) and within urban areas because of geography (Straszheim 1974), and income or accessibility (Schnare and Struyk 1976). Michaels and Smith (1990) asked realtors in the Boston area to specify what they thought were different market segments and then used this as a basis for segmentation. A similar reasoning was employed by Boyle, Poor and Taylor (1999) in the Maine lakes example (see section 2). They segmented markets according to areas served by different multiple-listing services that were also geographically separate.

It is difficult to test conclusively for market segmentation, but there are commonly employed methods that are used as supporting (or refuting) evidence for the researcher's priors about segmentation. The most common approach is to apply F-tests to determine if the hedonic price functions differ across segments. Taylor and Smith (2000) used a variant of the F-test, the Tiao-Goldberger F-test, which allowed them to test easily for differences in the hedonic price functions by individual characteristics — a particularly useful

extension to determine if there are key characteristics that are priced differently across markets. The problem with F-tests, however, is that results indicating that market segmentation exists may be due to mis-specification of the hedonic price function, and not actual segmentation. F-tests are also likely to reject aggregation with large samples (Ohta and Griliches 1979). Once again, we see that there are no definitive answers. However, researcher judgement along with supporting statistical tests can be used as a guide for determining the market extent in a particular study.

In addition to needing sufficient geographic variation in the data, it may be important to have appropriate time-variations in the data. Often, a researcher may be interested in how the valuation of an amenity changes over time. Or the researcher is interested in how prices changed in response to the creation of an amenity or disamenity (such as the siting of a landfill near a neighborhood). In some instances, the researcher may simply need observations from multiple years in order to increase sample sizes if sales in a market are sparse. In each case, several issues must be considered when drawing a sample frame from multiple years.

First, equation (5) makes clear the importance of considering the nature of the cross section of observations used in the analysis with respect to timing of changes in amenity levels. Future changes in amenity levels will be capitalized into current housing prices. As the expectations about the quality of the amenity or the impact of a disamenity change, so too will the housing prices. Thus, the same amenity or disamenity may have differential impacts on sales prices over time. A researcher may estimate different implicit prices depending on the sample frame chosen. Kiel and McClain (1995) underscore this point with their research on property sales prices around an incineration plant in North Andover, Massachusetts. Their results indicated that negative expectations regarding the impacts of the incinerator were capitalized into nearby housing prices prior to operation of the incinerator. However, the negative effects of the incinerator were greatest within the first three years of operation, attenuating thereafter. Being located one mile closer to the incinerator decreased property sales prices by $2,283 during the construction phase; $8,100 during the first three years of operation; and $6,607 in the following three years of operation.[6]

The study by Keil and McClain (1995) highlights how the timing of events relative to a sample of property sales can be quite important for properly interpreting the long-run impacts of environmental amenities or disamenities

on property values (see also Kohlhase 1991). This is especially important for amenities and disamenities that have announcement effects associated with them, such as the discovery of hazardous waste sites, or for those amenities and disamenities that may be finite in duration (i.e., the disamenity may be removed at some point in the future). Timing effects are likely to be less important for amenities/disamenities that vary spatially, but not over time, such as proximity to urban parks.

When multiple years of data are needed, either for variation in the amenity of interest or to increase sample sizes, one must be careful to consider whether or not the hedonic price function is stable over the time period considered. In the simplest case, one only need adjust for general inflation in a market over time. Prices may be deflated prior to estimation by an appropriate, preferably local price index. If an appropriate price index is not available, a series of dummy variables may be included in the hedonic regression to control for the year in which each property was sold. Either of these methods is reasonable to use when general inflationary trends exist in the market. They essentially control for changes in the intercept of the hedonic price function. In this approach, all implicit prices are assumed to change by the same factor, and thus adjusting the intercept of the hedonic price function is all that is needed.

The more complicated case is when changes in supply and demand conditions occur over time. If structural changes in the market have occurred, implicit prices of characteristics will change, and prices may change by different amounts for each characteristic. In this case, simple price deflators are not sufficient. While F-tests or Tiao-Goldberger F-tests may be applied to test for the stability of the hedonic function and the marginal prices of individual characteristics over time, the same weaknesses in the tests applies as stated above. Ohta & Griliches (1975) suggest a less stringent rule in which the standard errors for the constrained and unconstrained regressions are compared, and aggregation over time is rejected if errors increase by more than 10% (Palmquist 2000). A similar rationale may be applied to Tiao-Goldberger F-tests.

3.4 Functional Form of the Hedonic Price Function

In addition to specifying which variables belong in the hedonic regression, researchers must determine how the characteristics influence price. In other words, the researcher must decide on the functional form of the hedonic price

function that is estimated. Little theoretical guidance exists for the choice of functional form for the hedonic price function because the price schedule is determined in the marketplace by the interactions between many different buyers and sellers. If a product can be costlessly repackaged, the total price of the product would simply be the sum of the implicit prices of its component characteristics.[7] In this case, the appropriate specification for the hedonic price function would be a simple linear function, as illustrated for the case of housing:

$$P = \alpha_0 + \sum_{i=1}^{h} \beta_i H_i + \sum_{j=1}^{n} \beta_j N_j + \sum_{k=1}^{L} \beta_k L_k + \varepsilon, \tag{6}$$

where P is the sales price of a house; H represents structural and property characteristics of the house, such as number of bedrooms and lotsize; N represents neighborhood characteristics, such as median income and quality of schools, and could include amenities such as ambient air quality; and L represents locational characteristics, such as proximity to the central business district, and could include proximity to environmental amenities and disamenities. In the case of the linear functional form, the implicit price for any specific characteristic, z_i, is simply equal to the estimated coefficient for that variable (i.e., $\partial P(\underline{z})/\partial z_i = \beta_i$). With a linear hedonic price function, the incremental price of the house induced by an incremental increase in a characteristic is constant across levels of the characteristic. This implies, for example, that the incremental value of lakeshore frontage would be the same for lakefront houses with 50 feet of frontage as for houses with 150 feet of frontage.

Of course, marginal prices are not likely to be constant for all characteristics, and so alternative functional forms are often used where some or all of the variables are transformed. For instance, most researchers assume that a home's price is related non-linearly to its square footage. In particular, it is generally assumed that the total price of a house increases at a decreasing rate with square footage (see section 2.1, figure 2.1 and its associated discussion). To capture this empirically, price may be estimated as a function of the natural log of square footage or price may be estimated as a function of square feet and (square feet)^2.

A hedonic price function that allows for sales price to be affected non-linearly by the characteristics of the property may be specified in many possible ways. Some common functional forms are given in Table 2. Also shown for

each functional form of the price function is the specific form for computing the marginal implicit price, $\partial P(\underline{z})/\partial z_i$. As can be seen from Table 2, these formulas can be complicated, and involve not only the estimated coefficients from the hedonic price function but also the levels of the characteristics themselves.

Two possible approaches may be used for computing implicit prices when the formula involves the level of a variable. Consider the semi-log functional form in which $\partial P(\underline{z})/\partial z_i = \beta_i P$. In this case, the implicit price must be evaluated at some level of sales price. Most commonly, the mean or median housing price of the sample over which the coefficients were estimated is chosen. Alternatively, the implicit price may be computed for each house in the sample and then the mean of these prices may be used.No one way is correct, and it is researcher judgement guided by the application at hand that determines the appropriate level of price (or any variable) at which one evaluates the implicit price.

Product characteristics are often described by categorical variables. For instance, rather than recording the number of fireplaces in a home, a variable

Table 2. Functional Forms for the Hedonic Price Function

Name	Equation	Implicit Prices
Linear:	$P = \alpha_0 + \sum \beta_i z_i$	$\partial P/\partial z_i = \beta_i$
Semi-Log:	$\ln P = \alpha_0 + \sum \beta_i z_i$	$\partial P/\partial z_i = \beta_i \cdot P$
Double-Log:	$\ln P = \alpha_0 + \sum \beta_i \ln z_i$	$\partial P/\partial z_i = \beta_i \cdot P/z_i$
Quadratic:	$P = \alpha + \sum_{i=1}^{N} \beta_i z_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \delta_{ij} z_i z_j$	$\partial P/\partial z_i = \beta_i + \frac{1}{2} \sum_{j \neq i} \delta_{ij} z_j + \delta_{ii} z_i$
Quadratic Box-Cox:[a]	$P^{(\theta)} = \alpha + \sum_{i=1}^{N} \beta_i z_i^{(\lambda)} + \frac{1}{2} \sum_{i,j=1}^{N} \delta_{ij} z_i^{(\lambda)} z_j^{(\lambda)}$	$\partial P/\partial z_i = \left(\beta_i z_i^{\lambda-1} + \sum_{j=1}^{N} \delta_{ij} z_i^{\lambda-1} z_j^{(\lambda)} \right) P^{1-\theta}$

[a] The transformation function is $P^{(\theta)} = (P^{\theta}-1)/\theta$ for $\theta \neq 0$, and $P^{(\theta)} = \ln(P)$ for $\theta = 0$. The same transformation applies to lambda. The marginal effect is computed for $\theta \neq 0$. The marginal effect when $\theta = 0$ and $\lambda = 0$ is the same as for the double-log. The quadratic Box-Cox is equivalent to the linear Box-Cox, another common functional form when $\delta_{ij} = 0$ for all i and j. The marginal price of the linear Box-Cox is simply $\beta_i z_i^{\lambda-1} P^{1-\theta}$.

may be created to equal one if there are any fireplaces in the home and equal to zero if there are none. If the dependent variable is log of sales price, then the interpretation of the coefficient estimate is the approximate percentage change in price when the characteristic in question is present. It is an approximation because the coefficients estimated for the dummy variables are transformations of the percentage effect (Halvorsen and Palmquist 1980 and Kennedy 1982). For a coefficient estimate, b, the percentage effect, g, is given by $100 \cdot g = 100(e^b - 1)$. When b is small, the error in interpretation (without adjustment) is small. For instance, a coefficient estimate of 0.10 implies that the percentage change in price is actually 10.5%.

To examine the potential impact of functional form choices, Cropper, Deck, and McConnell (1988) conducted simulations in which the true marginal bid functions of households and equilibrium marginal prices were known and could be compared to the estimated implicit prices from hedonic regressions. Comparisons were made for each of the functional forms are listed in table 2. Results indicated that when all attributes of housing are observed without error, the more complicated functional forms (quadratic, linear Box-Cox, and quadratic Box-Cox) can be used to most accurately estimate implicit prices. However, when some variables are not observed or are replaced by proxy variables, the quadratic and quadratic Box-Cox produced biased estimates of the marginal prices. Instead, it was the simpler forms of the linear, semi-log, double-log and linear Box-Cox that performed best. The linear Box-Cox provides accurate marginal price estimates when all attributes are measured correctly and also performs well in the presence of mis-specification of the hedonic function, so it is the preferred functional form of Cropper, Deck, and McConnell (1988).

Recent improvements allow the transformation parameter in a Box-Cox specification to vary across independent variables as done in Israngkura (1994) and Cheshire and Sheppard (1995). Palmquist and Israngkura (1999) also allow a flexible Box-Cox specification in a study focusing on air quality in 13 major cities. They use an iterative procedure in which they first estimated the Box-Cox parameter for the non-environmental characteristics of housing. This parameter is then imposed, and the Box-Cox parameter for air-quality is estimated.

What can serve as a guide for choice in functional form? First, one should be careful not to rely on a linear hedonic (with no transformed variables) unless there are compelling theoretical reasons to do so. In general, non-linear relationships between size attributes and some quality attributes are expected.

For this reason, there is a preponderance of empirical studies that rely on the semi-log functional form. The semi-log allows for incremental changes in characteristics to have a constant effect on the percentage change in price and a non-linear relationship on the price-level.

Second, researchers should pay particular attention to the relationship between price and the key characteristics of the study. For example, studies that have investigated the relationship between the sales prices of single-family residences and distance to a contaminated site have assumed that price increases with distance at a constant rate (i.e., a linear relationship; see Michaels and Smith 1990 and Kiel 1995) or that prices increase with distance at a declining rate (i.e., price increases, peaks, and then decreases with additional distance; see Kohlhase 1991). Neither of these functional forms is consistent with the expectation that price increases with greater distance from a contaminated site at a declining rate, with the effect of distance disappearing completely beyond some distance. Ihlanfeldt and Taylor (2001) instead implement a reciprocal transformation in which sales prices of commercial and industrial properties are modeled as a function of the inverse of distance to a site with known environmental contamination. This specification is more attractive *a-priori* than what has been used in the past because it is consistent with our expectations regarding how sales prices will be impacted by proximity to a contaminated site: sales prices for properties near contaminated sites are negatively impacted, and prices asymptotically increase to some baseline level as distance from the site increases.

3.5 Spatial Considerations

Specific spatial relationships, such as proximity of a property to a specific amenity such as a park or a shoreline, have been directly addressed in hedonic models for over 30 years. However, more general intrinsic spatial relationships among properties have only been taken into account more recently. Spatial effects that require specific econometric tools (often referred to as spatial econometrics) are spatial dependence and spatial heterogeneity. The following is a necessarily brief introduction to the topic, and the reader is directed to a series of reference books and articles by Luc Anselin providing a comprehensive overview of spatial econometric techniques (Anselin 1988, Anselin and Florax 1995, Anselin et al. 1996, and Anselin and Bera 1998).

Spatial dependence or spatial autocorrelation implies a lack of independence across observations in cross-sectional, spatially organized data. With spatial dependence, a functional relationship exists between what happens at one location and what happens at another location. Spatial autocorrelation is similar in concept to autocorrelation in time-series data; however, spatial correlation is multi-directional while correlation in time-series data is uni-directional. In time series data, only past events are assumed to affect current events and a single direction of dependence exists. But in spatial data, a property is likely to be related to other properties in a multitude of directions. For a variable, say sales price, associated with property i, p_i, there is a general spatial process that can be written as $p_i = f(p_1, p_2, \ldots p_N)$, where N is the number of properties in total. This relationship is modeled parametrically so that the process may be estimated and tested empirically.

Spatial heterogeneity is a related concept and refers to spatial correlation of the error terms of a regression model. Here, the unobservable components of one dependent variable are related to those of a neighboring dependent variable. Again, as with spatial dependence, the spatial relationship between errors must be specified.

Following Anselin (1988), a general model of housing price determination including spatial effects is:

$$
\begin{aligned}
P &= \rho W_1 P + ZB + \varepsilon \\
\varepsilon &= \lambda W_2 \varepsilon + \mu \qquad (7) \\
\mu &\sim N(0, \sigma^2 I)
\end{aligned}
$$

where Z is a NxK matrix of property characteristics, P is sales price, B is a Kx1 vector of coefficients, W_1 and W_2 are NxN spatial weight matrices, ε is a Nx1 spatial autoregressive error, μ is a Nx1 random error term with variance σ^2, and ρ and λ are coefficients on the spatially lagged variables, P and ε. The equations in (7) may be rewritten as:

$$P = \rho W_1 P + ZB + (I - \lambda W_2)^{-1}\mu, \qquad (8)$$

and if ρ and λ are estimated to be equal to zero, equation (8) reduces to a simple linear regression model.

In (8), ρ, λ, and B are estimated and W_1 and W_2 are arbitrarily chosen by the researcher. Specification of the spatial weights matrices are one of the more controversial aspects of spatial econometrics. The spatial weight matrix defines the sense in which properties are believed to be neighbors and determines the

importance of any one observation of the variable of interest (sales price in our example) for another observation. The spatial weights matrix is akin to a lag operator in time series, except for spatial lags are more complicated as they are multi-directional. Several possible structures for this matrix might be specified. One could use distance between observations as the weights. In this approach, the importance of each property on the current property decays as distance increases. Often, the rows of the weight matrix are standardized to sum to one, which eases the statistical computation of ρ and λ. Another approach imposes a lattice structure on the relationship between properties. Here, elements of the spatial weight matrix, w_{ij} equal one if a property shares a border with the observation of interest, and equals zero otherwise. Other lattice structures may be imposed. For instance, weights may equal one if properties are contained within some predefined radius of the property of interest. In equation (8), the matrices W_1 and W_2 are allowed to differ, implying differences in the autoregressive processes of the dependent variable and the error term.

Lagrange multiplier tests, Moran's I statistics (Anselin 1988), and Kelejian and Robinson tests (Kelejian and Robinson 1992) may be used to test for the presence of either spatial dependence or spatial heterogeneity or both. Both tests are pre-packaged and easily implemented using the software package SpaceStat Software for Spatial Data Analysis (Allen, Texas; SpaceStat http://www.spacestat.com 1998). Given evidence of spatial dependence or spatial heterogeneity, spatial weights matrices must be specified and estimation may be done using maximum likelihood or generalized moments estimators. Estimation of models with spatial dependence, but not spatial heterogeneity (i.e., λ=0 in equation 8) are computationally straightforward; however, spatial heterogeneity estimation of λ via maximum likelihood becomes problematic with large samples sizes.[8] Indeed, maximum likelihood estimates with sample sizes over 400 observations may not produce reliable estimates of λ (Kelejian and Prucha 1999). An alternative, suggested by Kelejian and Prucha (1999), and implemented in a hedonic property value model by Bell and Bockstael (2000) is a generalized moments estimator that reduces the computational burden and allows more flexibility in the specification of the weight matrix.

Recent hedonic applications that explicitly control for spatial effects as discussed above are Gwande and Jenkins-Smith (2001), Leggett and Bockstael (2000), Geoghegan, Wainger, and Bockstael (1997), and Bockstael (1996). Gwande and Jenkins-Smith estimate a hedonic property value model to examine the impacts of nuclear waste transport on property values near the

transportation route. Using several test statistics, Gwande and Jenkins-Smith (2001) found significant evidence of spatial correlation in the data. Because they had a large data set (over 9,000 observations), they estimated a model with spatially lagged dependent variables and assumed the proper specification of the spatial weights matrix (W_1) results in no residual spatial heterogeneity in the error terms. Leggett and Bockstael (2000) on the other hand, allowed for spatial heterogeneity in the error terms but no spatial dependence (i.e., ρ=0 in equation (8)). Each element of their spatial weights matrix, w_{ij}, is defined as the inverse distance between observations i and j, and following Bell and Bockstael (2000), this measure is set equal to zero if distance is greater than one mile. Their application is to water quality effects on property values around Chesapeake Bay. Results indicated that fecal coliform counts negatively impact property values, and these results were *not* sensitive to whether or not they corrected for spatial heterogeneity. However, some descriptive variables of the properties, such as density of development that were significant when spatial heterogeneity was not taken into account, are not significant in the spatially-corrected model.

To implement the spatial models described, the databases must be spatially referenced or geocoded. In geocoding, typically latitude and longitude markers are assigned to the center-point of each property. Geographic information systems software may be used to compute spatial variables, such as the linear distance between properties, quite easily. The accuracy of the spatial relationships depends critically on the accuracy of the geocoding. The most common method of geocoding data is to use address matching which is available in software packages such as ArcView and Maptitude (www.caliper.com/maptovu.htm). These programs use base maps, such as the TIGER files (www.census.gov/geo/www/tiger/index.html), to assign latitude and longitude markers to each property. Address matching is not exact because the location of a property is only approximate along the street segment in which the property is located. For highly localized externalities, address matching may not place properties accurately enough. Fortunately, many urban areas have developed, or are developing, base maps of their tax parcels that are accurate to within a few feet by combining geo-referenced aerial photos with digitized tax maps.

As spatially referenced property value data sets are becoming increasingly available, there is likely to be a continued expansion of spatial econometric techniques applied to hedonic property value studies. Indeed, tests and correction for spatial correlation are likely to become as commonplace as tests and corrections for heteroskedasticity in cross-sectional data.

4. WELFARE MEASUREMENT WITH THE HEDONIC PRICE FUNCTION

Our model indicates that the implicit price of amenity i ($p_{zi} = \partial P(\underline{z})/\partial z_i$) is equal to the consumer's marginal WTP for the amenity ($\theta_{zi} = \partial\theta(\underline{z}, y, U)/\partial z_i$). Implicit prices are the most commonly reported result from hedonic studies. If one is interested in whether or not a current stock of an amenity is capitalized into the market for housing, estimates of the marginal implicit prices (sign, magnitude, and statistical significance) are the appropriate measures to report. In the context of expenditures on other aspects of housing, these relative prices can provide interesting insights about the importance of various housing amenities.

In instances where we want to know the value consumers might place on a *change* in an environmental amenity, the relationship between implicit prices and appropriate measure of WTP for the change depends on the situation. To examine this issue, we will consider the owners of properties and the renters of these properties separately. Even though the owner and renter can be the same person (implicitly renting from oneself), this discussion considers these two sides of the market separately. Two types of changes are considered: a change in a localized amenity and a change in a non-localized amenity. Examples of localized externalities that have been studied in the hedonic context are highway noise (Palmquist 1992a), a hazardous waste site (Kohlhase 1991), an incinerator (Kiel and McClain 1995), and local parks (Shultz and King 2001). In these cases, a change in the amenity affects a relatively small number of properties, and so the equilibrium hedonic price function for the entire market is unaffected. When changes in non-localized amenities such as the air quality of a city occur (Zabel and Kiel 2000, Sieg et al. 2000), the amenity change affects a large enough number of houses to reflect a marketwide shift in supply, and thus we would expect a change in the market-clearing equilibrium hedonic price function.

For a localized change in an amenity, first consider the effects on renters of the property if no transactions costs are associated with moving. When a decrease of an amenity occurs, the renter is no longer at their optimal bundle of housing given that they face the same hedonic price schedule as before the

change at their home. If renters can move costlessly to a house with the original bundle of characteristics, there will be no change in welfare for the renter. However, the owners of the property realize a capital loss on the property because of the decrease in the amenity level associated with the property. The owner would be WTP an amount of money up to the value loss of the property value to avoid the amenity change. If, in addition to being a localized change, the amenity change is marginal (i.e., a one-unit change), then WTP is simply the implicit price, $\partial P(\underline{z})/\partial z_i$, for each property owner. The total WTP is the sum of the implicit prices across property owners that receive a change in the amenity.

If the amenity change is localized and non-marginal in the magnitude of change, owners would be willing to pay an amount equal to $P^1 - P^0$, where P represents the sales price of the property with the initial level of the amenity (P^0) and the new level of the amenity (P^1). The total WTP is the sum of the price changes for houses that receive the amenity change. If the analysis is *ex-ante*, as is typical for policy analyses, the price change is forecast using the estimated hedonic price function.[9] Thus, for a change in an amenity, say characteristic z_1, the total change in welfare or net benefit (NB) is computed in the following way:

$$NB = \sum_{k=1}^{N} P_k(z_{1k}^1, z_{2k}^0, \ldots, z_{nk}^0) - P_k(z_{1k}^0, z_{2k}^0, \ldots, z_{nk}^0). \tag{9}$$

where $P_k(z_{1k}, z_{2k}, \ldots, z_{nk})$ is the *ex-ante* hedonic price function evaluated at the characteristics associated with k^{th} property in either the initial or new state.

For example, using the estimated hedonic price function in equation (1), a property with characteristics equal to the sample means (see discussion following equation (1) for those means) is predicted to sell for $110,466 (the mean sales price in the data is $97,761). If the water clarity at the lake where the property is located (a small part of the overall market) were increased from 3.9 to 6.3 meters (the highest observation for this data) this property would be predicted to sell for $115,133. The NB for this house is $4,667. The total NB would be the sum of the net benefits estimated for each house located on this particular lake.

If we relax the assumption of costless moving on the part of renters, then the computation above represents an upper bound on the welfare change associated with the amenity change (i.e., overstate gains and understate losses). From the price change given in equation (9), one would need to subtract the transactions costs (TC) associated with each renter having to move to their new optimal

location to compute the total change in welfare. For each property, net benefits are given by $P^1 - P^0 - TC$. Palmquist (1992b) summarizes the manner in which transactions and moving costs may be quantified and incorporated empirically into a hedonic analysis.

The above analysis assumes consumer utility is unchanged as a result of the change in the amenity (Δz_i) since renters move to a new house with the exact same bundle of characteristics as before the amenity change. This follows from our assumption that the change in the amenity does not affect the overall hedonic price function in the market, but only affects the price of houses experiencing Δz_i. Thus, in optimizing utility, a house identical to the original dwelling before the amenity change will be chosen. If identical housing is not available, and utility changes as a result of the move, then the correct welfare measure would require quantifying the difference in utility arising from the consumer no longer being at the optimal consumption bundle (see Bartik 1988 for a complete description of this problem). While this computation is not possible using information from only the hedonic price function, the change in rents less transactions costs would provide a upper bound on the resulting net benefits from an amenity change. The degree to which this bound is close to the true net benefits will depend on the degree of substitutability between the housing affected by the amenity change and the amenity level at the housing renters move to.

Table 3 summarizes the benefit estimates possible with the first-stage hedonic price function when the change in the amenity is localized. Note that the amenity change that occurs locally may be marginal or non-marginal. The table highlights that simply computing the change in property values at locations will overstate the benefits of an amenity improvement and will understate the losses of an amenity decline when transactions costs are associated with moving (Bartik 1986).

The last case to consider for a localized externality is when transactions costs (TC) are great enough to prohibit moving. For a homeowner, closing costs, changes in interest rates on mortgages, and a tight housing market may make transactions costs prohibitively high, especially in the short run when costs associated with searching for suitable new housing would be high. For owner-occupied housing, the short run may be as much as six months to a year or possibly longer. For renters, it is more likely that the short run would be a few months.

Table 3. Summary of Welfare Computations Appropriate with 1st Stage

Computation	Appropriate Situation
$\partial P/\partial z_i$	Net benefits of an 1/1 in the amenity by one-unit in a localized context with zero transactions costs associated with moving.
$P^1 - P^0$	Net benefits of an 1/1 in the amenity in a localized context with zero transactions costs associated with moving.
$P^1 - P^0 - TC$	Net benefits of an 1/1 in the amenity in a localized context when transactions costs are positive, but do not prohibit moving. Household can relocate to an identical house as before the amenity change.
$P^1 - P^0 - TC$	*Upper-bound* on net benefits of an 1/1 in an amenity in a localized context when (1) moving is possible, but households cannot relocate to an identical house as before the amenity change or (2) when it is *not* possible to move because transactions costs are prohibitively high.

When transactions costs prohibit moving, the net benefits of an amenity change cannot be exactly measured, but an upper bound can again be computed as the price differential for the property minus the transactions costs associated with moving. Consider a decline in an amenity. The landlord's capital loss as a result of the amenity change is exactly offset by the tenant's capital gain associated with paying a lower rent (recall, the tenant does not move). Thus, the price change is a transfer between owner and tenant, and no net benefit is associated with the change in rent. However, the reduction in rent only partially offsets the consumer's utility loss. Transactions costs provide an upper bound on the remaining utility loss (after the change in rent is taken into account). Thus, the difference between the change in rent and transactions costs associated with moving will provide an upper bound on the total welfare change associated with the change in the amenity for a consumer (Table 2). Palmquist (1992b) presents a graphical exposition of this point.

In the case of *non-localized* amenities an exact measure of welfare change cannot be computed with only information from the hedonic price function. This is because a non-localized change implies a shift in the overall supply, and the hedonic equilibrium itself will change. The new hedonic price function cannot be forecast using information from only the current price function. However, as Bartik (1988) demonstrates, the change in hedonic rent at sites

which are improved, as predicted by the *ex-ante* hedonic price function (call this measure ΔHP), is likely to be an upper bound for the net benefit of the amenity change. This bound is computed as given in equation (9) and is, therefore, quite easy to implement. However, ΔHP is only an upper bound under some conditions on the profit changes landlords may experience when allowed to make equilibrium adjustments to housing characteristics in response to the amenity change (Bartik 1988, 179). These profit changes are likely to be in a range such that ΔHP will be an upper bound only if no transactions costs are associated with moving. If there are significant transactions costs, this measure is less likely to be an upper bound.

Unfortunately, one cannot know *a-priori* if ΔHP is an upper bound, and empirical tests have not determined how likely it is to be an upper bound. In the next section, we discuss methods for estimating the *demands* for amenities by households and associated WTP measures. While more complicated and data-intensive, there are several reasons why estimating the demand for a characteristic is desirable. In the case of localized externalities, if transactions costs cannot be measured and are expected to be significant, then household WTP must be computed. This is easily computed using estimates of the demand parameters. In the case of non-localized amenity changes where the hedonic price function is expected to shift, household WTP provides a definite lower bound, as compared to the ambiguous bound provided by ΔHP. Lastly, estimating the demand for an amenity allows us to explore the relationships between WTP and the characteristics of a household such as income, race, gender, and family composition.

5. SECOND-STAGE DEMAND ANALYSIS

To estimate uncompensated demands for the *characteristics* of the differentiated good, information on the quantities of characteristics purchased and the marginal implicit prices of those characteristics from a hedonic analysis are combined with information on the socio-economic characteristics of the purchasers. Estimating the demand for characteristics of a differentiated product using hedonic prices is often referred to as a second-stage analysis (estimating the hedonic price function was described as the first stage in the previous section). Rosen's (1974) seminal article provided the framework for

this method, however, some confusion exists in the literature regarding the nature of, and proper estimation of, these characteristic demand functions. This section provides an overview of second stage methods. See Palmquist (2000) for a more technical discussion of the method.

For welfare measurement, we are typically interested in compensated demands, which indicate the WTP for z_i holding the levels of all other goods/characteristics and utility constant. Recall that the bid function for each individual, θ^j, is a function describing the maximum WTP for an specific bundle of characteristics, holding utility and income constant. Because bid functions change directly with income (i.e., $\partial\theta/\partial y = 1$), the marginal bid function for characteristic z_i, θ_{zi}, only depends on z, utility, and exogenous consumer characteristics, α^j (Palmquist 2000). As such, the marginal bid function is equivalent to an inverse compensated demand function for characteristic z_i. It describes the change in WTP for z_i as the level of z_i changes, holding utility and all other characteristics and goods constant. Figure 2 illustrates the marginal bid function for two individuals, θ^1_{zi} and θ^2_{zi}. For the moment, consider only the marginal bid function for consumer 1 as depicted by the heavy dark line passing through points AB and the associated implicit price function P^A_{zi}. We can see

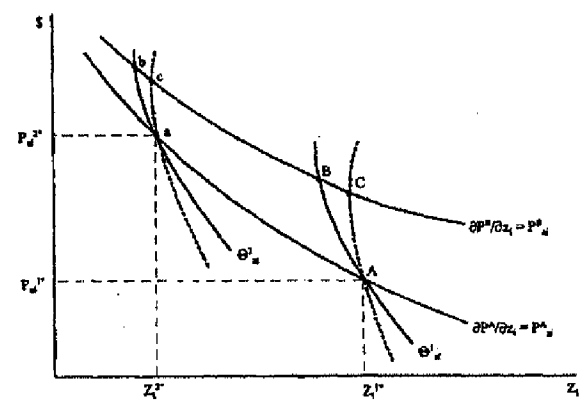

Figure 2. Demand Identification with the Hedonic Price Function

that the marginal bid function is equal to the implicit price function at the optimal level of consumption for consumer 1, z_i^{1*} (point A). This point

corresponds in Figure 1 to the optimal consumption level where the bid function is tangent to the hedonic price function.

Considerable confusion exists in the literature regarding the interpretation of the marginal bid function as related to the inverse uncompensated and compensated demand functions. It has been suggested that the marginal bid function is actually akin to a marginal rate of substitution function given by $(\partial U/\partial z_i)/(\partial U/\partial x)$, which is incorrect. It is true that, at the *optimal level of consumption*, the marginal rate of substitution is equal to the marginal bid and the marginal price $(\partial U/\partial z_i)/(\partial U/\partial x) = \partial P/\partial z_i = \partial\theta/\partial z_i$ as discussed in section 2.1. In other words, the two functions cross at the optimal consumption level, but they are not equivalent functions. The marginal rate of substitution function may be combined with either utility or the budget constraint to derive the compensated or uncompensated inverse demand function, respectively (Palmquist 2000). This parallels the derivation of these two functions for any homogenous good.[10]

Theoretically correct measures of welfare change for a characteristic of a differentiated good are no different than as described for a quantity change in an amenity in Chapter 2. The literature typically makes the distinction between measures of welfare change when consumers face a price change (compensating and equivalent variation) and when consumers face an exogenous quantity change (compensating and equivalent surplus). These are analogous measures (see Chapter 2). In the case of an exogenous change for consumers who cannot move, compensating and equivalent surplus would be the appropriate measure. In the case of an exogenous change in z_i in which moving is possible, compensating and equivalent variation would be more appropriate. However, these measures will only measure the benefits to homeowners. If the change in the amenity affects consumers in other ways (say, increases recreation benefits to consumers who do not own nearby property, but visit the park after it is improved), these benefits will not be captured using the measures discussed in this chapter.

Here, we focus on compensating and equivalent surplus, as one typically assumes households cannot move in response to a change and compute WTP of the households as a lower bound to the true welfare change (see section 4). Measures of compensating or equivalent surplus are simply computed by integrating under the compensated inverse demand or the marginal bid function:

$$W(\Delta z_i) = \int_{z_{i0}}^{z_{i1}} \frac{\partial\theta(z_i; \underline{z}, U^j)}{\partial z_i}\, dz_i, \tag{10}$$

where $W(\Delta z_i)$ is compensating or equivalent surplus for a change in z_i depending on whether U^j is equal to the initial level of utility or the level of utility after the amenity change, respectively. This measure of welfare change is appropriate for the situation in which consumers receive an exogenous quantity change in an amenity, and consumers are compensated in terms of the numeraire (holding $\underline{z}$ constant). Palmquist (2000) discusses welfare measures when other types of compensation are used to return consumers to their original (or new) level of utility.

Of course, estimating the marginal bid function directly is not possible, because the marginal bid depends on unobserved utility. However, two alternatives allow us to recover the information necessary to compute welfare measures. The first is to estimate an uncompensated demand and use duality to recover estimates of welfare change. The second is to estimate the equilibrium condition given in equation (3) and use the estimated parameters of the marginal rate of substitution function to recover estimates of welfare change. Each method is described next.

5.1 Uncompensated Demands for Characteristics

Uncompensated demand functions can be derived analytically in a manner analogous to a homogenous goods market if the hedonic price function is linear so that the marginal prices are constant. However, we often expect the hedonic price function to be non-linear and the marginal prices to be non-constant. In this instance, the budget constraint is no longer an exogenous constraint; the marginal price of any characteristic is simultaneously determined by the choice of the amount of that characteristic to purchase. Traditional optimization methods are inappropriate in this case.

Uncompensated demands with non-constant marginal prices can be derived, however, if we linearize the budget constraint around the optimal consumption bundle of the consumer. Palmquist (1988), demonstrates that utility maximization with this constraint set yields the same choices as would be observed with the original, non-linear budget constraint. The linear budget constraint is of the form:

(11) $$Y_a^j = x + \sum_{i=1}^{n} p_i^* z_i,$$

where Y_a^j is consumer j's income adjusted in the following manner:

(12) $$Y_a^j = y - P(Z^*) + \sum_{i=1}^{n} p_i^* z_i^*.$$

The linearized budget constraint in (11) is exogenous as the implicit prices, p_i^*, faced by consumer j are held constant at the level associated with js this consumer's actual purchase, z_i^*. Income must be adjusted as shown in equation (12) because a linear budget constraint will imply a larger consumption set than is affordable for the consumer with income y facing a non-linear budget constraint in which prices for z_i are decreasing as amounts of z_i are increased.

The linearized budget constraint in (11) may be used in conjunction with the first-order condition for utility maximization (given in equation (3) above) to solve for the inverse uncompensated demand in a manner analogous to that for homogeneous goods:

(13) $$p_1^j = f(z_1, z_2, \ldots z_n, x, Y_a, \alpha^j).$$

This demand function can be estimated using quantities of characteristics chosen, the implicit prices of those characteristics, adjusted income, and other socio-economic characteristics assumed to affect demand.

Consumer surplus estimates for a change in z_i may be computed by integrating vertically under the inverse demand curve for z_i between the initial and new level of z_i (Parsons 1986). For example, suppose the following simple linear demand for z_1 is estimated (note, this is not an inverse demand function):

(14) $$z_1 = \alpha + \beta_1 p_1 + \beta_2 p_2 + \delta y,$$

where p_2 is the implicit price of a substitute/complement for z_1 and y is adjusted income. The integral of the inverse demand between the initial level z_{10} and new level z_{11} is:

(15) $$\int_{z_{10}}^{z_{11}} \frac{1}{\beta_1}(z_1 - k)\, dz_1 = \left[\frac{1}{\beta_1} z_1^2 - \frac{k}{\beta_1} z_1\right]\Bigg|_{z_{10}}^{z_{11}}$$

where k is a constant equal to $\alpha + \beta_2 z_2 + \delta y$ evaluated at some appropriate level, such as the mean observed in the data.

The demand function estimated should include relevant substitute and complement characteristics to the characteristic of interest. Choosing the appropriate set of substitutes and complements may be somewhat *ad hoc* because no theoretical guidance defines exactly what is a substitute or complement for any one characteristic. A reasonable approach is to assume that the major characteristics of a property (such as house and lot size and a few key neighborhood characteristics) are likely substitutes and complements to include. Boyle, Poor, and Taylor (1999) estimated the following uncompensated demand for water clarity (Q_{wc}):

(16) $$Q_{WC} = f(P_{WC}, P_{SQFT}, P_{FRONT}, Y_{adj}, \Gamma),$$

and computed consumer surplus for changes in water clarity as described in equations (14) and (15). In equation (16), Y is income as adjusted in equation (12) and P_{WC}, P_{SQFT}, P_{FRONT} are the marginal implicit prices of water clarity, square feet of living space, and lake frontage of the property, respectively. They chose two major characteristics of the property: size of the house and the amount of lake frontage. Results indicated that both characteristics were substitutes for water clarity as the price coefficients for house size and lake-frontage were positive and significant.

In addition to income, the researcher must determine the other relevant factors expected to shift demand, represented by the vector Γ in equation (16). As with any demand function, typical factors might include the age and education of the purchaser. For property markets, factors such as the number of children under 18 years old would also be expected to be important demand shifters. Other factors specific to each application might be included. For example, in the Maine lakes example, Boyle, Poor, and Taylor (1999) included a dummy variable indicating whether or not the owner had friends who had bought property at the lake prior to their own purchase of property.

After the set of substitute and complements and demand shifters are chosen, the researcher must still specify the function to be estimated. A common functional form for demand is the semi-log functional form. Boyle, Poor, and Taylor (1999) estimate a linear, semi-log, and Cobb-Douglass specification for equation (16), preferring the non-linear specifications. Based on the semi-log specification, the estimated own-price elasticity for water clarity was -0.158, and the estimated surplus for an improvement in lake water clarity from 3.78

to 5.15 meters was $3,765. The estimated surplus for the same change in quality was $12,870 using linear specifications and $3,677 using Cobb-Douglas specifications. As might be expected, the results are sensitive to the choice of functional form. A careful researcher investigates how sensitive their results are to choice of functional form (and specification of variables included). If they have a preferred equation for reporting, reasons for this preference should be explained.

Consumer surplus measures can be computed using estimates of the parameters of the uncompensated demand. However, consumer surplus is only an approximation of the theoretically correct measures of welfare change (see Chapter 2 and Freeman 1993). Two approaches may be used to recover compensating or equivalent variation when uncompensated demands are estimated. In the first, utility is specified and a system of uncompensated demands are derived analytically and estimated. Given estimates of the demand parameters, duality may be used to analytically recover estimates of compensating or equivalent variation by solving for indirect utility or expenditure functions. This approach is taken by Palmquist and Israankura (1999) and Parsons (1986).

Alternatively, one can estimate a single demand for a characteristic of interest and use differential equation methods to recover an associated utility or indirect utility function. Hausman (1981) and Vartia (1983) demonstrate how this may be accomplished when prices are changing. Palmquist (2000) demonstrates this method for quantity changes to solve for the bid function.

Consider the inverse uncompensated demand in equation (13). Recognizing that the marginal implicit price is equal to the marginal bid function at the optimal level of consumption, we can substitute $\partial\theta/\partial z_i$ for left hand side of equation (13). Also, since our numeraire x is identically equal to Y - θ, we can substitute for x in the RHS, and equation (13) becomes a differential equation in θ. Solving this differential equation for the bid function allows us to compute welfare measures as follows:

$$(17) \qquad W(\Delta z_i) = \int_{z_i^0}^{z_i^1} \frac{\partial\theta(z_i, z, U^j)}{\partial z_i}\, dz_i = \int_{z_i^0}^{z_i^1} MRS(z_i, z, x(z_i, z, U^j)).$$

which is equal to compensating surplus if utility is held constant at the original level of utility, and equal to equivalent surplus if utility is held constant at the level of utility after the change (note, income is held constant).

5.2 MRS Function Approach

An alternative method for recovering the information necessary to compute compensating and equivalent variation is to directly specify the functional form for household utility and derive the functions to be estimated (see Quigley 1982). In other words, the exact specification of the regression is determined by the analytical solution to the utility maximization problem. What function is estimated depends on the goal of the research. For estimating welfare changes, Cropper et al. (1993) and Chattopadhyay (1999) estimate the equilibrium condition given in equation (3) in which marginal prices (computed from the first stage hedonic regression) are equal to the marginal rate of substitution (MRS) function. While this function may not be used directly for computing welfare changes, it is useful for estimating demand parameters that can then be used to recover estimates of welfare.

Chattopadhyay (1999) provides a recent example of this approach for estimating the welfare change associated with changes in air quality in Chicago. He tried two alternative forms for utility: the translog and Diewert utility function. The translog utility he specifies is of the form:

$$(18) \qquad U(Z, x) = \ln x + \sum_{i=1}^{k} (\alpha_i + \delta_i C + \tau_i R) \ln z_i + \frac{1}{2} \sum_{i,j=1}^{k} \gamma_{ij} \ln z_i \ln z_j,$$

where x is the numeraire, Z is the vector of z_i housing characteristics, C and R are demographic characteristics of the owners (C, number of dependent children; R, race of owner), and k is the number of housing characteristics (Chattopadhyay 1999, 24). If a linear Box-Cox functional form for the hedonic price function is assumed, then the marginal rate of substitution function to be estimated is given by[11]:

$$(19) \qquad \beta_i P^{1-\theta} z_i^{\lambda-1} = \frac{x}{z_i}\left[(\alpha_i + \delta_i C + \tau_i R) + \sum_{j=1}^{k} \gamma_{ij} \ln z_j\right],$$

where the regressand is the implicit price of z_i as derived from a linear Box-Cox hedonic price equation (see table 2, footnote a), and the right-hand side is equal to $(\partial U/\partial z_i)/(\partial U/\partial x)$.[12] The estimated hedonic equation is used to compute the dependent variable for each observation, $\beta_i P^{1-\theta} z_i^{\lambda-1}$. This information is combined with information on the chosen levels of characteristics, the numeraire, and homeowner demographics to estimate equation (19) and recover

the parameters of the utility function α, δ, τ, and γ. The level of the numeraire x is equal to income less the price of housing. Typically, one would compute this with annual income and annualized housing expenditures.

Recall that $\theta_{zi}(z_i, \underline{z}, U) = MRS_{zi,x}(z_i, \underline{z}, x)$ at the optimal level of consumption, where θ_{zi} is the marginal bid function for characteristic z_i, and $MRS_{zi,x}$ is the marginal rate of substitution between z_i and the numeraire x. It is also true that $\theta_{zi}(z_i, \underline{z}, U)$ is identically equal to $MRS_{zi,x}(z_i, \underline{z}, x(z_i, \underline{z}, U))$, where $x(z_i, \underline{z}, U)$ is derived by solving the utility function for x. In other words, if we substitute utility into the marginal rate of substitution function, we recover the compensated demand curve. If a MRS function such as that given in (19) is estimated, welfare measures are given by[13]:

$$(20) \qquad W(\Delta z_i) = \int_{z_i^0}^{z_i^1} \frac{\partial \theta(z_i, \underline{z}, U^J)}{\partial z_i} dz_i = \int_{z_i^0}^{z_i^1} MRS(z_i, \underline{z}, x(z_i, \underline{z}, U^J))\, dz_i .$$

In equation (20), utility at either the original level of consumption or the new level of consumption may be computed directly from the utility function since its parameters have been estimated.

5.3 Identification of Demand

Recall, each consumer will choose an optimal level of each characteristic by finding the level of consumption at which the marginal bid for z_i equals the implicit price of z_i. By estimating the parameters of $P(\underline{z})$, and computing $\partial P(\underline{z})/\partial z$, we observe one point on each consumer's uncompensated demand, as well as their compensated demand function or marginal bid function. (The term, marginal bid function, rather than inverse compensated demand function, is used for consistency with past discussions.) However, no other information on the shape of the bid function is observed. Consider Figure 2 again, which shows the marginal bid functions for two consumers and the marginal price function P^A_{zi} (ignore for the moment the second marginal price function, P^B_{zi}). For reasons discussed in section 3.4, the hedonic price function is likely to be non-linear, and so the marginal price function is likely to be non-constant. In Figure 2, the marginal price of z_i is shown to decrease as more of z_i is consumed.

Figure 2 indicates that each marginal price reveals only one point on each consumer's marginal bid function, and so we cannot make inferences about the

shape of the marginal bid function using only information on marginal prices. By observing P_{zi}, we know that one point on the marginal bid function of consumer 1 is $\{P_{zi}^{1*}, z_i^{1*}\}$; however, we cannot determine if the demand function is shaped as shown by the solid line, or the dashed line. Indeed, an infinite number of possible functions could pass through the point $\{P_{zi}^{1*}, z_i^{1*}\}$. This is the standard identification problem of any demand analysis: additional information besides the market-clearing prices for each property in a market is needed to identify demand.

One approach to identifying demand is to use information from separate markets, such as different cities that are geographically distinct. In this approach, one assumes that individuals in one market do not consider housing in the other markets as substitutes when making their purchase decisions. Thus, the hedonic price function in each market is distinct and arises from interactions of only those buyers and sellers located in that market. Individuals with any given vector of socio-economic characteristics are assumed to have preferences over attributes that are identical across markets. However, because of differences in supply, or perhaps the distribution of socio-economic characteristics among individuals within a market, the equilibrium hedonic price functions will vary across markets, and so similar people will be observed making different housing choices across the different markets. If this is the case, estimating separate hedonic price functions in each market will identify demand. This point is illustrated in Figure 2. In figure 2, P^B_{zi} represents the marginal price function from a separate market. Given this additional information, we can now determine if it is point B or C that is the optimal choice for that type of consumer, and whether the marginal bid function is represented by the dashed or solid line.

Thus, to estimate an inverse uncompensated demand (such as in equation (13)) or a system of demands, hedonic price functions are estimated for multiple markets. The marginal prices from each market are pooled with information on property owners demographics and characteristics of their properties to estimate demand. For example, to estimate the demand given in (16), Boyle, Poor, and Taylor (1999) specified a hedonic price function like that given in (1) for four markets in Maine. Each market was distinguished by distances between each other, by unique regional characteristics, and by different real estate multiple listing service regions. The estimated marginal implicit prices, along with corresponding quantities purchased, were pooled with demographic information from a survey of property owners.

The use of multiple markets to identify demand for housing attributes has also been used by Palmquist (1984), Parsons (1986), Bartik (1987), Cheshire and Sheppard (1998), Palmquist and Israngkura (1999), and Zabel and Kiel (2000), with the latter two studies focusing on environmental amenities. The number of markets used to identify demand has varied from two (Cheshire and Sheppard 1998; Bartik 1987) to seven (Palmquist 1984; Parsons 1986), to thirteen (Palmquist and Israngkura 1999). There is no established correct minimum number of individual markets required. Of course, what must be established is that the hedonic price functions do vary across markets, and thus researchers must provide for statistically significant differences in the implicit prices across markets. The issues associated with determining appropriate assumptions for market segmentation are the same here as discussed in section 3.3.

For estimation purposes, some key characteristics are typically assumed to be separable in consumption so that the dimensionality of the problem is reduced. For example, Palmquist (1984) estimates the demand for four housing characteristics, and includes the price of five substitute/complement variables in each demand equation. Cheshire and Sheppard (1998) estimate demand equations for twelve housing characteristics and include eleven possible substitutes and/or complements in each demand equation.[14] Systems methods have been estimated by Palmquist and Israngkura (1999), Parsons (1986), and Stewart and Jones (1998), although the latter study was in a non-housing framework. Regardless of approach, when making weak separability assumptions about utility to reduce the dimensionality of the demand system, one has to recognize that the welfare measures estimated are a lower bound on the true measures (Hanemann and Morey 1998). This is, of course, in addition to the welfare measure being a lower bound to total net benefits in the housing market if one is assuming (say) no moving among residents in response to the amenity change.

If the alternative approach of estimating an MRS function is taken, data from only a single market is needed because the exact specification of the regression is determined by the analytical solution to the utility maximization problem. Here, the researcher simply specifies a different form for the hedonic price function and the MRS function to achieve identification. The researcher must still make sure that the functional forms chosen imply the rank conditions for identification are met (see Quigley 1982 and Chattopadhyay 1999, Appendix 1).

The utility restrictions that must be imposed when estimating the MRS function are not testable, and so this approach is often considered less desirable particularly when data from multiple markets are available. Alternatively, the multiple market approach requires consideration of the appropriateness of the market segments.

5.4 Endogeneity of Prices and Income in Demands

In addition to identifying demand, an important econometric issue that must be taken into account is the possible endogeneity of implicit prices and income. Recall, that for any functional form of the hedonic price function other than linear as given in equation (6), implicit prices may be non-constant. If prices are non-constant, then they are endogenous because consumers can choose the marginal price they pay per unit of the characteristic by choosing the level of the characteristic they consume. Also, in the case of non-constant implicit prices, we linearized the budget constraint to analytically derive the demand function, which involved adjusting income by the implicit prices (equations (11) and (12)). When including this adjusted income in the demand specification, it too will be endogenous because the adjusted income relies on the non-constant implicit prices.

For instance, the hedonic price function estimated by Boyle, Poor, and Taylor (1999) in equation (1) indicates that the marginal price for water clarity and square feet of living space are non-constant. Thus, by choosing the quantity of living area, for instance, the purchasers are also choosing the marginal price per foot of living area they must pay. The marginal price of living area and the choice of square feet of living area are both endogenous.

Endogeneity is typically handled by instrumental variable techniques. First, each price that is endogenous and adjusted income is regressed on a set of exogenous explanatory variables. These exogenous variables should be related to the endogenous variable of interest, but exogenous to the system. The instruments must be (1) correlated with the regressors, (2) uncorrelated with the error term, and (3) of full-rank (add new information). The resulting parameter estimates are used to predict values for the endogenous prices and income. The predicted prices and predicted income are then included in the demand equation, and they are expected to have less correlation with the error term than the original variables (see Greene 1994 for a standard discussion of two-stage least squares).

Choosing proper instruments for the endogenous variables can be a difficult task. For the demand given in equation (16), Boyle, Poor, and Taylor (1999) developed nine instruments for the marginal prices that described factors such as number of lakes in a market area, distance of the market to Boston, a time trend, and local economic and demographic conditions (e.g., an index of real estate activity in the area and the percentage of the current population that is employed). For adjusted income, the instruments were socio-economic characteristics of the property purchasers (as reported in a survey of the owners) and included age and gender of the owner, number of children under 18 years old, educational level, retirement status, the number of people in the household. Also included were the squared terms for age, the number of children under 18 years old, and the number of people in the household.

Palmquist (1984) estimated the demand for four housing characteristics and uses exogenous socio-economic characteristics (age, marital status, number of dependents, race, and their square where appropriate) and used a set of dummy variables for each of his seven urban areas to instrument for the non-constant implicit prices and adjusted income. In his single market, utility restriction approach, Chattopadhay (1999) uses household attributes such as income, income squared, number of dependent children and its square, race, and marital status as instruments for the levels of housing characteristics.

Cheshire and Sheppard (1998) used an innovative approach with "spatially lagged" variables as their instruments. The authors developed a spatial relationship between each house in their data set, and each next "closest" house.[15] For each observation, the characteristic prices and income levels associated with the two houses closest to the house in question were used as instruments. The authors argue that these variables clearly meet requirements (1) and (3) above for instrumental variables, and are likely to meet requirement (2) as they argue there is enough variability in neighborhood housing characteristics (and individual characteristics within a neighborhood). Palmquist (2000) makes the point that because this approach is not unidirectional (i.e., the spatial lags are not unidirectional in the same way time lags are), these instruments are invalid. To alleviate this problem, one might combine time and the spatial lags to create an instrument for the implicit price that is the closest house sold prior to the current house.

A common issue is that instruments do not explain the variation in the endogenous variables very well. In finite samples, weak instruments result in biased estimates of the demand parameters just as in the case of using simple

ordinary least squares (Bound, Jaeger, and Baker 1995). Thus, with weak instruments, one may be accepting higher variance of the parameter estimates without reducing the bias. Also if instruments are weak and the loss of efficiency is large, common tests for endogeneity (Hausman 1978) are likely to have weak power (Nakamura and Nakamura 1998). Lastly, a "loss of relevance" can occur when the instruments chosen for the endogenous regressors do not adequately capture the type of variation in the regressor for the application at hand. For these reasons, Nakamura and Nakamura (1998) reject the "always instrument" policy, especially for variables that are not of primary interest to the application or when it is not clear that the potential instruments are truly exogenous. While there is no clear guidance for what are "weak" instruments, R^2 values for the auxiliary equations of less than 0.2 caused concern for Nakamura and Nakamura (1998) in earlier research on female labor supply.

5.5 Summary of Demand Estimation

Table 4 summarizes the steps involved in estimating a demand function for a characteristics of a differentiated good and highlights a few of the main issues to be considered in each step. These steps apply regardless of whether utility restrictions in a single market are used to identify demand or multiple markets are used to identify demand. For a single market, steps 3 and 4 must still be undertaken if the hedonic price function in the first stage (step 1) is non-linear. Also, in the single market approach, the functional form for the equation to be estimated in step 6 is derived from an underlying utility specification and is usually the marginal rate of substitution function. Exact welfare measures are then easily obtained (step 7) as described in section 5.2.

6. LABOR MARKETS AND OTHER HEDONIC APPLICATIONS

Hedonic theory has been applied to differentiated goods markets as varied as labor markets, child care services, agricultural products, and computers. Most often, these applications are first-stage analyses estimating only the hedonic price function, and not underlying demands for characteristics of the

Table 4. Steps for Conducting a Hedonic Demand Analysis when Multiple Markets are Used to Identify Demand

1. Estimate hedonic price function for each market.
   - Choose functional form (see section 3.4)
   - Test for market segmentation (see section 3.3)
2. Obtain marginal prices for characteristics of interest (see Table 2) for each observation in each market, p_i, including price of the characteristic of interest and all relevant substitutes and complements.
   - Test for price differences across markets
3. Instrument non-constant (endogenous) prices to obtain predicted prices: **p-hat**$_i$. This is accomplished by pooling data across markets and estimating p_i as a function of exogenous variables that are related to p_i.
   - Choose of instrumental variables (see section 5.4)
   - Choose of functional form
4. Adjust income if hedonic price function is non-linear by computing the following for each observation:
   Y_{adj} = Y - Price of House + Sum over characteristics of: marginal implicit price of characteristic multiplied by the chosen characteristic level (see equation 12)
5. Instrument adjusted income to obtain predicted adjusted income: **Y-hat**$_{adj}$. This is accomplished by pooling income data across markets and estimating Y_{adj} as a function of exogenous variables that are related to income.
   - Choose instrumental variables (see section 5.4)
   - Choose functional form
6. Estimate demand: $z_i = z(p_i, p_{j \neq i}, \text{Y-hat}_{adj}, \tau)$, where τ are a set of demand shifters. Data from all markets are pooled.
   - Choose functional form
   - Choose relevant demand shifters
7. Compute welfare measures (see sections 5.1 and 5.2):
   a) Integrate under demand for consumer surplus changes. Levels of all other variables (besides own-price and quantity) must be fixed at some level, often the mean of the observed data.
   b) Use duality to obtain exact welfare changes.

good. This section provides an overview of hedonic applications to markets other than housing with particular attention to labor markets.

6.1 Labor Market Applications

The hedonic approach to understanding equilibrium pricing in markets for differentiated goods can easily be applied to the labor market. The hedonic wage equation is the envelope of individual firm's offer functions and worker's indifference curves. Reconsider Figure 1, and let z_1 represent the risk of on-the-job injury. In this case, Φ now represents the wage tradeoffs workers are willing to make for additional units of risk of on-the-job injury, holding utility constant. Higher contour levels of Φ would represent higher levels of utility. Similarly, θ are now iso-profit curves of the firm, representing the tradeoffs the firm can make between higher wages and expenditures to reduce the risk of on-the-job injury, holding profit constant. Lower contour levels of θ represent higher levels of profits (see Rosen 1979 for a more detailed treatment).

Using a wage hedonic to estimate the tradeoffs workers are willing to make between wages and the risk of death on the job is an area of nonmarket valuation that has stimulated much research over the past 30 years. Estimates of these dollar tradeoffs are used to compute the value of a statistical life; not on the value of a particular individual (an "identified life"), but the value society places on a statistical reduction in the probability of one death among them (see Viscusi 1992, 1993). For instance, consider the following simple wage hedonic:

$$wage_k = \alpha + \beta_r risk_k + \sum_{n=1}^{N} \lambda_n X_{kn} + \sum_{m=1}^{M} \gamma_m D_{km} + \varepsilon_k, \tag{21}$$

in which the wage of the kth worker is estimated to be a function of the risk of death on the job ($risk_k$), N variables describing human capital and demographic characteristics of the worker (X_{kn}) such as age and education, and M job characteristics (D_{km}) other than the risk of death such as whether or not supervisory activities are associated with the job.[16] In a linear specification such as (21), the implicit wage for risk, $\partial w/\partial r = \beta_r$, is the additional wages a worker would require to assume an additional increment of risk of death on the job. By normalizing over risk, the compensating wage differential for risk is converted to the value of a statistical life (VSL). For instance, suppose risk is measured in units of deaths per 10,000 workers, wages are hourly earnings, and a simple linear compensating wage equation is estimated as illustrated in (21). To compute the value of a statistical life, $\hat{\beta}_r$ is multiplied by 2000 hours/year to

arrive at the annual compensation required for an additional unit of risk, and then by 10,000, the number of workers over which the risk is spread. In this example, an estimate of $\hat{\beta}$, equal to 0.35 would imply a value of statistical life estimate of $7 million.

In a policy context, the value of statistical life is particularly important for evaluating policies that reduce human mortality. Evaluating these policies in a benefit-cost framework requires an estimate of the value that society places on a life saved as a result of the policy. The appropriate measure of such a value is the value of statistical life (VSL). A recent example of the application of this methodology to benefit/cost analyses is the U.S. Environmental Protection Agency's (EPA) retrospective (1970-1990) and prospective (1990-2010) analyses of the Clean Air Act (Environmental Protection Agency 1997 and 1999). In these analyses, the EPA evaluated the benefit and costs of emissions controls imposed by the Clean Air Act and its associated regulations for the period 1970 to 2010. To monetize the benefits associated with mortality reductions, the single best estimates of the value of a statistical life reported in 26 different studies (21 of which were labor market studies) were used to compute a mean value of $4.8 million (1990 dollars, Environmental Protection Agency, 1997, 44). This value was then aggregated over the number of lives saved to compute the monetized benefit of reduced mortality in both the retrospective and prospective studies. For example, in the retrospective analysis, the mean benefits of reduced mortality were estimated to be $17.97 trillion (1990 dollars; Environmental Protection Agency 1997, 52-53), just over 80% of the total benefits estimated to be associated with the Clean Air Act from 1970 to 1990.

While the VSL is an appropriate value to use in benefit/cost analyses, there is much controversy surrounding the empirical estimates of this value. First, the large variation in the VSL estimates that make the choice of which value is best for any specific policy application difficult. In a recent quantitative review of this literature, Mrozek and Taylor (2002) conducted a meta-analysis drawing on VSL estimates from over 30 studies using labor markets to estimate the VSL. The VSL estimates from these studies ranged from under $100,000 to over $20 million (1998 dollars). Based on their review, Mrozek and Taylor (2002) conclude that the appropriate estimate of the VSL that can be drawn from this past literature, when correcting original studies for design weaknesses, is approximately $2 million (1998 dollars) — a decrease of 50%

or more over the value suggested by previous reviewers of the literature (see for example, Viscusi 1993).

A second, perhaps more important, concern is whether or not a VSL estimate derived from studies of fatal workplace risks is an appropriate value for reducing the risks of death from illnesses, where there may be prolonged reductions in the quality of life or more dread and/or pain involved. As of yet, there is no systematic evidence as to how these latent risks are treated by individuals relative to immediate risks in an economic framework. An important extension to the VSL literature is to estimate the wage tradeoffs workers make for on the job exposure to latent risks of death (such as exposure to cancer-causing agents). However, this may be difficult to implement due to a lack of data and measurement difficulties. A related concern is whether or not the VSL derived from labor market studies, which are based on the working-age population of healthy adults, are appropriate to extend to other populations at risk such as the elderly or children. Again, empirical research is needed to determine the systematic differences, if any, between the different populations' responses to risks in an economic context.

An extension of the wage hedonic is to recognize that not only will characteristics of the individual and the job affect wages, but also the characteristics of the location of the job. The recognition that amenities are capitalized into wages as well as housing prices is the basis of "quality of life indexes" (QOLIs) that have been constructed to rank amenities across urban areas in the U.S. The framework for estimating QOLIs is as follows. Consider two identical jobs, one located in a desirable community in terms of school and environmental quality, the other located in a less desirable community. If the communities are located a distance from each other sufficient to make commuting between them unlikely, then the firm located in the less desirable community will have to offer higher wages, *ceteris paribus*, to attract workers to the firm. The firm location and the amenities associated with that location affect wages and should be included in the compensating wage equation (Rosen 1979; Smith 1983). The important assumption here is that labor markets are large enough so that amenities vary across communities within a market (usually, labor markets are assumed to be national in scope), but the communities are distant enough from each other to prevent commuting between them for work purposes. A single wage hedonic applies to the entire market, and workers face different implicit prices (or wage differentials) for different levels of amenities in various communities.

To compare quantities of amenities across locations, the quantities must be aggregated using consistent units of measurement. A consistent index of the level of amenities at a specific location is one where each amenity is weighted by its full implicit price and then aggregated (Rosen 1979 and Roback 1982). The full implicit price (FP) is equal to the sum of the housing expenditure differential associated with the amenity and the negative of the wage differential associated with the amenity or:

$$FP_k = h_k(\partial P_k / \partial a_k) - \partial w_k / \partial a_k, \tag{22}$$

where $\partial P_k/\partial a_k$ is the implicit price for amenity k in the housing market, h_k is the quantity of k associated with a property, and $\partial w_k/\partial a_k$ is the wage differential associated with amenity k. The full implicit price of locational amenities may then be combined with the levels of amenities at each location to compute the aggregate household expenditure on amenities, which is equal to total household WTP for marginal differences in these amenities (Blomquist, Berger, and Hoehn 1988).

Blomquist, Berger, and Hoehn (1988) computed a quality of life index (QOLI) for 253 urban areas across the U.S. Their index aggregated expenditures (based on full implicit prices) on 15 environmental and social amenities such as air quality, rainfall, violent crime, and teacher-pupil ratios. Based on the average compensation for these amenities, they ranked 253 urban counties, and found Pueblo, Colorado to be ranked highest (with a QOLI = $3,289 in 1980 dollars), and found St. Louis, Missouri to be ranked lowest (with a QOLI = $-1,857 in 1980 dollars). Because the unit of analysis is each county, Blomquist, Berger and Hoehn were also able to identify large QOLI differentials within metropolitan areas. For instance, two counties in Milwaukee, Wisconsin had different QOLIs, differing by over $2,000. One county ranked 68th, and the other ranked 252 (out of 253 total). More recent applications and extensions of this literature include using a revealed preference approach based on hedonic prices to rank quality of life in cities (Kahn 1995) and to examine how firms respond to quality of life measures in their location decisions (Blomquist and Maury 1999).

6.2 Non-Housing Hedonic Demand Applications

The first stage hedonic method has been applied to markets as varied as consumer durables (e.g., automobiles and computers), agricultural commodities, labor markets, and cultural commodities. There are fewer examples of hedonic demand (second stage) analyses outside of housing markets. Hedonic demand applications are sparse likely due to the additional data required: information on the individuals (or firms) who purchased the products. Of course, this is true for estimating demand in the market for a homogeneous good. But in a market for a homogeneous good, one may often rely on aggregate observations such as sales per month, monthly average price, and aggregate demand information such as mean income across households. In a market for differentiated goods, this type of aggregation is undesirable because the individual variation in product variety drives the model. Individual-level sales information is needed and thus, demographic information on individual purchasers is needed.

A non-housing example of a single market approach to estimating demand is Stewart and Jones (1998) who estimated a system of factor demands for the characteristics of major league baseball players. They identified demand by assuming a translog or generalized Leontief cost function. Their estimated system of demands are largely consistent with predictions of economic theory (i.e., demands are homogeneous of degree zero and cross-substitution effects are symmetric), and are not sensitive to the form assumed for the cost function.

Hagy (1998) and Blau and Hagy (1998) used a multiple market approach in a hedonic analysis estimating the demand for attributes of child care. Hagy (1998) focused on staff-to-child ratio, and matches data on households and their choices over the quantity and quality of child care with the estimated implicit price of staff-to-child ratio in their area. She used 55 geographically distinct markets to identify demand. Her results indicate that demand is not sensitive to economic factors such as mother's wage rate and the implicit price of staff-to-child ratio; rather, demand is sensitive to factors such as the age of the youngest child and the availability of a relative near the household. These results are important for public policy because they suggest that government subsidization of child care, which effectively increases income or decreases the implicit prices, is unlikely to have a significant effect on the quality of care purchased.

Although second-stage analyses may be more difficult and data intensive, the demand analysis can provide much richer insights than just a first stage analysis alone as well illustrated by Hagy (1998).

7. SUMMARY

This chapter focused on the possibilities for non-market valuation using hedonic methods, primarily with property markets. Estimation of the hedonic price function alone (a first-stage analysis), is by far the most common hedonic application. Indeed, a search using a popular academic search engine using the keyword "hedonic" revealed over 850 published works in the economics literature. The popularity of the hedonic method is not surprising given the relatively minimal data requirements and straightforward empirical implementation. In addition, the insights we may draw from a first-stage analysis are quite powerful: the of a change in an environmental amenity that accrue to a population of residents in an area.

But, we also saw that many details require careful consideration when estimating the hedonic price function. Choice of the independent variables, their measurement, the functional form of the price function, and sample frame all require thoughtful treatment. Not all issues will require in-depth treatment. The nature of the question being asked and the nature of the data available for estimation will focus the attention of the researcher on the key issues that must be considered in detail.

Even very many first-stage hedonic analyses have been conducted, this is still an exciting area of research. We are just beginning to incorporate the spatial nature of housing data fully into hedonic models. Spatial aspects of markets have always been included in empirical applications in rudimentary manners (such as computing the linear distance of a property to the center of a city), the advent of inexpensive computing and widely available geographic information systems software have made possible the consideration of more complex spatial relationships. In addition, spatial econometric methods are increasingly applied in hedonic studies and are likely to be standard in hedonic analysis in the near future.

Beyond just the first-stage estimation of the hedonic price function, much additional research can be conducted on estimating welfare changes within the hedonic framework. Although welfare analysis in this context has been actively discussed since Rosen's (1979) seminal article, in the twenty-odd years since then, confusion remains as to how, and under what conditions, the hedonic

method may be used to precisely estimate household welfare changes. Relatively few studies have attempted to address this issue. Second-stage analyses that estimate the demand for amenities not directly traded in markets are particularly useful because they provide rich information on the links between demographics and preferences for amenities. Understanding these links is essential for targeting effective policy. Future studies can easily combine property value databases with surveys of homeowners to estimate such models.

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NOTES

1 Examples of hedonic applications are Berry, Kortum, and Pakes (1996) and Dreyfus and Viscusi (1995) for automobiles; Stavins (1997), Berndt, Griliches, and Rappaport (1995) for computers; Liegey and Shepler (1999) for VCRs; and Greening, Sanstad, and McMahon (1997) for appliances. Agricultural commodities to which the hedonic method has been applied are milk, shrimp, wine, and cigars (see, respectively, Gillmeister, Yonders, and Dunn 1996, Salayo, Voon, Selvanathan 1999, Combris, Sebastien, and Visser 1997, and Stover 1996). Examples of applications to crops such as wheat and cotton are Espinosa and Goodwin (1991) and Bowman and Ethridge (1992), respectively.

2 For example, the lakefront cottages used by Boyle, Poor, and Taylor (1999) were assumed to have eight primary characteristics that determined price (as shown in equation 1), which could be labeled with variable names z_1 to z_8. In this case, the equilibrium price schedule for lakefront properties is generally represented by $P(z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8)$ or $P(\underline{z})$ or $P(Z)$. Recall that Z represents houses (so Z^1, Z^2, etc. represent house 1 and house 2, respectively, each with their own unique levels of the characteristics z_1 to z_8). Each of these representations indicates that the price of a house is a function of the characteristics of the house.

3 It may also be assumed that firms produce multiple types of the good, and that the cost function is separable in each type of product. The maximization problem for the firm choosing an entire product line in this case is equivalent to choosing each product type separately as described here.

4 Another property of the bid function is that optimal bids increase proportionally with income $\partial\theta/\partial y = 1$. If income increases by $1, the consumer's optimal bid must increase by the same amount to hold utility constant.

5 Linneman (1980) suggested that housing markets may be national, and compares city-specific hedonic price functions for housing with a hedonic price function estimated on a national sample of housing. His hypothesis of a national market is neither fully supported nor rejected.

6 Other studies focus on the impacts of similar disamenities on property values, but do not consider timing effects are Keil (1995) and Dale, et al. (1999).

7 The common example here is to think of a full grocery cart as "the commodity" which has component characteristics that are the grocery items contained within. In this case, where it is costless to repackage the component characteristics of the grocery cart, so the total price for the product is simply the sum of the prices for each of its component characteristics.

8 Maximum likelihood estimates involve calculating the N eigenvalues of the spatial weight matrix, and the precision of the numerical procedures used to calculate these eigenvalues decreases as the number of observations increases (Kelejian and Prucha, 1999).

9 In the case of a localized amenity, we are able to forecast the change in price prior to the amenity change actually occurring because the hedonic equilibrium does not change. One still must be careful that the magnitude in the change of the amenity is not outside the range observed in the total sample. If so, the prediction is out-of-sample and becomes less reliable the further out-of-sample the change.

10 This derivation requires, for non-constant marginal prices, that the budget constraint be linearized as discussed in the next section.

11 Chattopadhyay notes in his discussion that this function (equation [1b] in his article) is equal to the inverse demand for z_i (Chattopadhyay, 1999, 23). Although the inverse demand and marginal rate of substitution function are equal at one point (the optimal consumption bundle), they are not equivalent functions.

12 This function does not duplicate Chattopadhyay (1999), equation (5b), 25 because of a minor typographical error in the paper.

13 An equivalent to equation (20) is reported in Cropper et al. (1993, p.226, equation (3)). However, Cropper et al. do not make explicit the substitution that must be made in the marginal rate of substitution function for it to be equivalent to the marginal bid function.

14 The choice of substitutes and complements to include is often somewhat ad-hoc and judgements must be applied to determine the important factors to include.

15 Closeness is defined by both geographic proximity and similarity of the structures.

16 The compensating wage equation describes the equilibrium wage as a function of the factors affecting the wage negotiation. This negotiation will be in regard to factors such as job duties and job working conditions, as well as characteristics of the workers themselves that affect expected productivity.

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