Volume V

Health and Aesthetic Impacts of Air Pollution on Property Values in the San Francisco Bay and Los Angeles Areas

EXPERIMENTAL METHODS FOR ASSESSING ENVIRONMENTAL BENEFITS

Volume V

Health and Aesthetic Impacts of Air Pollution on Property Values in the San Francisco Bay and Los Angeles Areas

by

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EXECUTIVE SUMMARY

The purpose of the research presented in this chapter is to contribute to the growing literature concerning the value of air quality in urban areas. The hedonic housing value method, based primarily on the writings of Rosen (1974) and Freeman (1974, 1979a, 1979b), is the valuation approach utilized. Three specific tasks were undertaken and are reported here.

The initial objective is to estimate a hedonic housing value equation which includes separate estimates for the health and aesthetic components of air quality. In the air quality components study aesthetics are represented by a visibility variable which measures what individuals actually perceive. The health component is measured by ozone concentrations. Ozone is a colorless gas that produces physical discomfort yet cannot be visually perceived.

The second task is to examine the importance of functional form in benefit estimation. Numerous authors have suggested that the benefits of environmental improvements are highly susceptible to functional form. This is an especially damaging criticism since it implies that (almost) any benefit figure is obtainable. The results reported here are more encouraging for hedonic price estimation in that they suggest that for some variables functional form is unimportant. In addition, the importance of functional form can be reduced in other cases through the use of prior information.

The third issue concerns demand estimation in the hedonic housing value method. Two alternative estimation approaches -- single market and multiple market -- are used. The results are then compared.

The remainder of this summary is organized as follows. The basic hedonic housing value method is reviewed in the next section. The data utilized in the hedonic analysis is specified in the following section. In Sections 4 through 6 the empirical analysis and associated results of the three studies are reported. The final section offers concluding remarks.

METHODOLOGICAL REVIEW

The economic analysis used herein follows the Freeman-Rosen approach for identifying demand curves of commodities not normally traded in markets. The essential element of the Freeman-Rosen approach, as applied to housing data, is the hedonic price function which relates the price of a home to its characteristics (structural, locational, neighborhood, and environmental aspects). This functional allows determination of the implicit or hedonic price of each characteristic (i.e. visual air quality), which can be interpreted as the individual's marginal willingness to pay for that characteristic.

The individual's marginal willingness to pay for air quality depends upon other housing characteristics and the individual's characteristics, especially income. The second stage of the hedonic procedure is to estimate the relationship between marginal willingness to pay and these other characteristics. This latter relationship can be interpreted as the (inverse) demand curve for air quality, since it relates price to quantity and other shift variables. The benefits of a specific air quality change can be determined by integrating the inverse demand curve over the proposed improvement.

Until recently, the basic Freeman-Rosen framework has been widely accepted as a means of estimating the benefits of environmental improvements. However, the procedure has lately been criticized as being inappropriate under certain conditions. The criticisms have focused on two issues: (1) the functional form of the hedonic equation in the first stage, and (2) the identification of the (inverse) demand curve in the second stage.

With respect to the first issue, the traditional hedonic approach provides no clues as to the correct shape of the hedonic function. Therefore, two approaches are used here. First, sensitivity analysis is employed to determine a range of benefit estimates. Second, a detailed analysis of the theoretical structure is undertaken. This reduces the range of the benefit estimates. With respect to the second issue, various authors have questioned whether sufficient information exists for estimating the demand curve. Two possible solutions are utilized here: (1) combining data from multiple markets to yield information on how individuals respond to different price sets, and (2) using data from a single market but imposing further restrictions on possible functional forms.

DATA SPECIFICS

Implementation of the hedonic approach requires two data sets. The first data set includes the sale prices of numerous homes and their attributes (structure, neighborhood, community, and environment). The data on sale price and house structure were obtained from the Market Data Cooperative for the 1978-79 time period. Structural variables pertain to both quantity (square footage, number of bathrooms, etc.) and quality (pool, fireplaces, view, etc.). A very large number of observations were used to provide robust statistical estimation properties. Neighborhood refers to the surrounding census tract and includes the variables -- population, age, ethnic composition, distance to work, and distance to the beach. Community (city level) variables encompass density, school quality, crime rate, and others. The final variables included in the hedonic modeling are the air quality variables, visibility and ozone concentrations. The neighborhood, community, and air quality data were matched with the household data using Thomas Brothers maps (4 x 4 km grid squares).

Once hedonic prices (marginal willingness to pay) for air quality improvements have been determined from the first data set, the second step of the approach is to determine the shape of the inverse demand curve. This is done by relating the hedonic prices to air quality and income.

HEALTH/AESTHETIC COMPONENTS OF AIR QUALITY

In order to examine the aesthetic/health component parts of air quality two separate measures of air quality are used in the hedonic procedure. Aesthetic air quality is measured as actual visibility (annual median miles). Various visibility measures are utilized (all hours, all days without precipitation or fog, see haze adjusted) but the results are essentially invariant to any particular one. The health component is measured by average ozone concentrations. Since ozone is a colorless gas, it has no visual effect. The health effects are primarily chest discomfort, headaches and an assortment of lung associated problems.

A previous attempt to separate these influences conducted in the Los Angeles area was only marginally successful. Multicollinearity between the air pollution measures and access to the beach made estimation of an accurate hedonic equation difficult. Thus, even though the Los Angeles hedonic results seemed consistent with a survey of households, the instability of these results prevents placing undue emphasis on them. For this reason a different study area, the San Francisco air basin, was chosen for the study.

In the San Francisco area the estimated hedonic housing equations indicated that air quality can be divided into its component parts: aesthetics and health. Both visibility and ozone concentrations are significant determinants of home sale price. These results are quite insensitive to various sample sizes, functional forms and model formulations.

The monetary impact of a hypothetical ten percent improvement in ozone concentrations ranges from approximately 1.03-1.3 percent of home sale price, dependent upon functional form. The monetary impact of visibility improvement diminishes as visibility increases. Thus, the health component of air quality increases in relative importance for households with relatively greater visibility.

Inverse demand curves for both ozone and visibility are estimated using the classic hedonic price model. The equations yield annual household benefits in the range of 119-127 dollars for a hypothetical ten percent reduction in annual ozone concentrations. Annual household benefits for a ten percent visibility improvement are between 110-217 dollars.

THE IMPORTANCE OF FUNCTIONAL FORM FOR BENEFIT ESTIMATION

In the San Francisco air quality components study it was indicated that the benefit estimates were essentially invariant with respect to functional form. This is not the usual case. Numerous authors have found that the benefit estimates generated from the hedonic approach vary widely, dependent upon estimated functional form. In the most detailed analysis of the importance of functional form, Bender et al (1980) confirm the result. The sensitivity of benefit estimates to functional form is especially damaging since the accuracy of the benefit figures depends on some statistical criterion. Previous researchers have correctly concluded that in the absence of prior information concerning the hedonic price equation, the form is purely a statistical question. The purpose of the detailed study of the Los Angeles area is to indicate that prior information may be used to improve the accuracy of the benefit estimates from the hedonic methodology and reduce the significance of functional form.

The results of this study do not dispute the conclusions regarding the apparent importance of functional form. For instance, the initial investigation found that benefit estimates for visibility improvements (10%) varied by an approximate six to one ratio. However, the results also indicate that, whereas functional form seems important on the surface, this may be a symptom rather than a cause of unstable benefit estimates. Thus, the major finding of this study help to determine <u>why</u> benefit estimation is so sensitive to functional form. This constitutes an attempt to explain why benefits are sensitive to functional form for visibility but not for interior living area (benefits vary by a 1.4/1 ratio).

In addition to the purely statistical reason (a variety of forms fit the data), two potential explanations for the importance of functional form are examined. These are poor quality data and an inadequate theoretical foundation.

The first of the alternative causes is addressed through the use of an outstanding data set. The hedonic price technique is used to estimate the benefits from visibility improvements in the Los Angeles (South Coast) air basin. Air quality is measured as actual visibility (median miles), the housing data is at the micro level and a large number of observations are utilized. The empirical results indicate that instability of benefit estimates for visibility improvements still occurs and is therefore not traceable to poor quality data.

The theoretical foundation of the hedonic price technique are also analyzed. A general theoretical model of the air quality/location decision is presented. A model differs from the standard Freeman-Rosen model in that an additional constraint on the choice of air quality is imposed. The model yields a set of testable hypotheses concerning the behavior of households and the resultant shape of the hedonic price function. Our empirical findings are not inconsistent with the model. By imposing additional econometric restrictions, the variation in the benefit estimates with respect to functional form is reduced. Therefore, the relationship between benefit estimates and functional form is not purely statistical but may be related to the underlying behavioral model.

The results of this study have important implications for determining the benefits of environmental improvements. They suggest that where functional form has a large impact on benefit estimation, a modified hedonic price procedure may be appropriate. This latter procedure, which imposes additional structure on the hedonic model produced a narrower range of benefit estimates.

THE MULTI-MARKET HEDONIC APPROACH

The results of the San Francisco air quality components and Los Angeles functional form studies employed the traditional hedonic approach, modified only by an additional restriction on the functional relationship between the hedonic equation and the inverse demand curve (see Brown and Rosen [1982]). This restriction allows identification of the inverse demand curve. However, there exists an alternative approach to demand identification, suggested by both Mendelsohn (1980) and Palmquist (1981). Their suggestion is to utilize multi-market data to obtain price variation, thereby permitting identification.

In the final study the multi-market approach is empirically implemented using data from two markets, San Francisco and Los Angeles. This analysis provides: (1) evidence on the efficacy of the multi-market approach, and (2) justification for the single market analysis of the previous two sections.

The initial step in the single and multi-market approaches is estimation of the hedonic equation for each area. This set of air quality improvements. In order to complete the benefit estimation procedure, the following steps are required. First, the hedonic equations are differentiated to determine the marginal willingness to pay for a change in extinction. The marginal willingness to pay is evaluated for each individual point in the data set. Given these implicit prices, an inverse demand curve can be estimated by regressing price against quantity (extinction) and other household (homeowner) shift variables (income, etc.).

The difference between the single and multiple market approaches occurs at this point. In the single market case the inverse demand curve is estimated using data from only one market. An alternative is to pool the data across markets and estimate one multi-market inverse demand curve. The theoretical reasoning for this approach is associated with Mendelsohn (1980) and others. This approach requires the assumption that individual preferences must be identical across the markets. It is felt that this is a very unreasonable assumption because individuals tend to gravitate to their own kind. For example, those who are relatively adverse to pollution might not live in the Los Angeles area.

A comparison of the single market result to the multi-market results can best be completed by calculating benefit figures from each approach. The use of multi-market data adjusts the single market benefit estimates in an expected manner. For instance, adding San Francisco area households into an analysis of the Los Angeles air basin increases the benefit estimates since San Francisco area households seem to have a greater aversion to air pollution. This implies that the multi-market approach may be inappropriate since it ignores location self-selection.

CONCLUDING REMARKS

The research reported in this chapter was designed to use and extend the hedonic housing value approach to estimate the benefits of air quality improvements. Three specific issues were examined: the health/aesthetic component values of air quality, the importance of functional form in hedonic estimation and demand curve identification.

In general, it was determined that the traditional hedonic housing approach is a viable method for estimating the benefits of environmental improvements. Recent criticisms concerning demand curve identification and the importance of functional form were found not to be as serious as previously thought. The demand curve can be accurately estimated by imposing a restriction on the functional relationship between the hedonic equation and the inverse demand curve. A multi-market approach can also be used but it is considered inferior. Functional form was found to be relatively unimportant in San Francisco. In addition, the effect of functional form can be reduced by using prior knowledge. Finally, the analysis in San Francisco suggests that for a ten percent air quality improvement, approximately one-third to one-half is accounted for by health aspects, with the remainder being attributed to aesthetic factors.

SECTION 1

INTRODUCTION

The purpose of the research presented in this chapter is to contribute to the growing literature concerning the value of air quality in urban areas. The hedonic housing value method, based primarily on the writings of Rosen (1974) and Freeman (1974, 1979a, 1979b), is the valuation approach utilized. Three specific tasks were undertaken and are reported here.

The initial objective is to estimate a hedonic housing value equation which includes separate estimates for the health and aesthetic components of air quality. Previous research has used a proxy variable to represent the overall level of air quality (see Harrison and Rubinfeld [1978] and Brookshire, et al [1982]). This approach provides little information on the separate impacts of the various pollutants. In addition, a previous attempt to value the separate components of air quality in the Los Angeles region was beset with collinearity problems, especially between the pollution measures and access to the beach (Brookshire, et al 1983). Therefore, even though the reported results were consistent with a survey analysis, little emphasis can be placed on these results. In the study reported here, the San Francisco air basin is examined. The area performs much better than the Los Angeles region since collinearity is not as pronounced. Thus, San Francisco is an ideal location to study the value components of air quality.

In the air quality components study aesthetics are represented by a visibility variable which measures what individuals actually perceive. The health component is measured by ozone concentrations. Ozone is a colorless gas that produces physical discomfort yet cannot be visually perceived.

The second task is to examine the importance of functional form in benefit estimation. Bender, et al (1980) and others (Harrison and Rubinfeld [1978], Nelson [1978], Bloomquist and Worley [1981] and Linneman [1980]) have suggested that the benefits of environmental improvements are highly susceptible to functional form. This is an especially damaging criticism since it implies that (almost) any benefit figure is obtainable. The results reported here are more encouraging for hedonic price estimation in that they suggest that for some variables functional form is unimportant. In addition, the importance of functional form can be reduced in other cases through the use of prior information.

The third issue concerns demand estimation in the hedonic housing value method. This approach is a multistage procedure (see Rosen, 1974; Freeman, 1979). The initial step is to estimate the hedonic price gradient which explains home sale price as a function of its structural characteristics as well as the characteristics of the community and neighborhood in which it is located. The second step is to determine the implicit price of environmental change by differentiating the hedonic price gradient with respect to the variable of interest. Subsequent steps include estimation of the inverse demand curve and integration to obtain benefit estimates.

The hedonic procedure as outlined above has been generally well received by the economics profession. Recently, however, a number of authors, including Brown and Rosen (1982), Mendelsohn (1981), and Palmquist (1982) have criticized the approach as not possessing sufficient information to identify the (inverse) demand curve in the subsequent steps. A possible solution is to constrain the functional form of the hedonic and inverse demand equations. This is the approach used by Harrison and Rubinfeld (1978) and formally suggested by Quigley (1982). An alternative approach associated with Mendelsohn (1980) and Palmquist (1981) is to utilize multi-market data. Each of these approaches is analyzed.

The major results of this inquiry can be summarized as follows:

o In the San Francisco basin air quality can be divided into its component parts: aesthetics and health. Both visibility and ozone concentrations are significant determinants of home sale price. These results are quite insensitive to various sample sizes, functional forms and model formulations.

o The monetary impact of a hypothetical ten percent improvement in ozone concentrations ranges from approximately 1.03 - 1.3 percent of home sale price, dependent upon functional form. The monetary impact of visibility improvement diminishes as visibility increases. Thus, the health component of air quality increases in relative importance for households with relatively greater visibility.

o Inverse demand curves for both ozone and visibility are estimated using the classic hedonic price model. The equations yield annual household benefits in the range of 119 - 127 dollars for a hypothetical ten percent reduction in annual ozone concentrations. Annual household benefits for a ten percent visibility improvement are between 110 - 217 dollars.

o Functional form is relatively unimportant for the ozone and visibility results in San Francisco.

o In an extended study of the Los Angeles region the impact of functional form is quite small for variables such as square footage of interior living space. However, functional form seems important for visibility in Los Angeles. But this impact can be reduced through the use of prior information concerning the shape of the hedonic equation.

o The use of multi-market data adjusts the single market benefit estimates in an expected manner. For instance, adding San Francisco area households into an analysis of the Los Angeles air basin increases the benefit estimates since San Francisco area households seem to have a greater aversion to air pollution. This implies that the multi-market approach may be inappropriate since it ignores location self-selection.

The remainder of this chapter is organized as follows. The basic hedonic housing value method is reviewed in the next section. Possible problem areas are also examined. In Section III the results of the attempt to divide air quality into its component parts is discussed. Included in this section is a discussion of the data utilized, the empirical results and their implications. Sections IV and V present experimental work into the hedonic price method. In the former section the importance of functional form is analyzed for a data set of Los Angeles homes. Section V contains an analysis of the use of multi-market data. Concluding remarks are offered in Section VI.

SECTION II

METHODOLOGICAL REVIEW

The benefits of environmental improvements estimated herein employ a methodology derived from ideas originally proposed by A. Myrick Freeman (1974, 1979a, and 1979b) and Sherwin-Rosen (1974). Their approach, referred to here as the Freeman, Rosen (F-R) technique, facilitates the identification of demand curves for commodities which are not normally traded in markets. Despite numerous professional comments (especially those appearing in the Review of Economics and Statistics), the basic framework of the F-R technique has become accepted by economists and applied to a wide range of problems. Several researchers have used this technique to estimate the benefits (whether marginal or total) of changes in various environmental commodities, among which are air pollution (Brookshire et al 1982; Harrison and Rubinfeld 1978; and Nelson 1978) and shoreline (Brown and Pollakowski 1977), indicating its applicability in the field of environmental economics.

However, the F-R technique has recently been criticized for being inappropriate under some very general conditions. Through the work of Brown and Rosen (1982), Mendelsohn (1980), Palmquist (1981), and Quigley (1982), it has become increasingly clear that implementation of the F-R approach requires more assumptions and/or data than originally anticipated by Freeman and Rosen.

The purpose of this section is to review the F-R technique and reconcile it with these recent criticisms so that the methodology used in obtaining the benefit estimates can be completely specified. The major conclusion of this section is that the benefits from improving the environment in the San Francisco area can be estimated using the F-R framework, modified by additional assumptions. Although more restrictive, these assumptions do not make the F-R technique unrealistically abstract or unusable.

The fundamental importance of the F-R model is that it provides a methodology for estimating demands for the characteristics of implicit commodities. For example, an automobile can be described by various characteristics, such as color, number of doors, type of seats, etc. The F-R methodology could, in theory, be used to determine the demand for, say, doors (e.g. two or four) on an automobile. Likewise, the technique can be used to determine the demands for the differing characteristics of homes. It is this application that we consider below, and, because our concern is with the environmental quality characteristics, much of the discussion focuses on it.

The F-R model, as applied to housing markets, can be examined using the following notation. Let:

P = the price of housing.

S = a vector of site specific characteristics of homes. For example, living area, number of bathrooms, and the age of the home would be represented in S.

N = a vector of neighborhood characteristics of the home. These include, for example, age of the surrounding population, locational parameters, public services, and racial make-up.

E = the environmental quality associated with the home. For our purposes, E is visibility and ozone concentrations.

X = a composite commodity. The variable represents consumption on all goods and services except housing. The price of X is set equal to one for simplicity.

Y = income.

The measures in S, N, and E completely describe the housing prices provided by homes and therefore determine P for each unit. More formally, this relationship,

$$P = P(S, N, E), \tag{1}$$

is defined as the hedonic price function, assumed to be continuous and twice differentiable. Since S, N, E, and P are observable during market transactions, Equation (1) is theoretically observable as well. Unfortunately, there are no clues to the shape of this function, requiring that its functional form be determined statistically through some type of estimation procedure. It is, however, improbable that the function will be linear in all of its arguments. This would imply, for example, that a home with 2000 square feet of living area would always be worth a certain amount more than one with 1000 square feet, an unlikely situation.

Equation (1) determines the total cost of a bundle of attributes represented by S, N, and E. The marginal cost due to an additional amount of some characteristic (e.g., E) is $P_E = dP/dE$. P_E is referred to as the implicit price of E or the hedonic price of E. An example will help clarify why P_E is, in fact, the implicit price of additional units of E. Imagine that P represents the total cost of a shopping basket containing various items represented by S, N, and E. If one of the items is soup, then we can calculate the change in P (the total cost) due to an additional container of soup, holding constant the other items in the basket. Obviously this is the same as the price of an additional container of soup. Similarly, P_E is the price of additional units of environmental quality.

Inasmuch as Equation (1) is observed (or estimated) from data accumulated during market transactions, the implicit prices can be calculated. Thus, the existence of the hedonic price function necessarily implies that the implicit prices for the characteristics can be obtained.

Next consider a consumer whose preferences over housing characteristics and other goods are represented by the following utility function:

$$U = U(X, S, N, E) \tag{2}$$

The behavior of the consumer is characterized by maximizing (2) subject to a budget constraint:

$$\begin{aligned} \text{Maximize: } & U = U(X, S, N, E) \\ \text{Subject to: } & Y = X + P(S, N, E). \end{aligned}$$

The first order necessary conditions for utility maximization yield

$$U_E/U_X = MRS_{EX} = P_E \tag{3}$$

where subscripts denote partial differentiation. The implicit prices reveal marginal rates of substitution (MRS), a fundamental result of the F-R model, especially important for E since E is a public good.

Define W as the amount an individual is willing to pay for alternative amounts of S, N, and E given a level of satisfaction and some amount of income. W is an implicit function defined by:

$$U(Y-W, S, N, E) = \overline{U} \tag{4}$$

where $\overline{U}$ is arbitrarily fixed. Thus,

$$W = W(S, N, E, Y, \overline{U}). \tag{5}$$

The <u>marginal</u> willingness to pay for some characteristics (say E) is $dW/dE = W_E$ and

$$W_E = f(S, N, E, \overline{U}, Y) \tag{6}$$

is the consumer's compensated (inverse) demand curve for E. In equilibrium, $W_E = P_E = MRS_{EX}$, and therefore P_E reveals the consumer's marginal willingness to pay for E, given the other characteristics, utility, and income. Moreover, data can be obtained for all the variables (except, of course, $\overline{U}$) in the equation. Under what conditions then, can (6) be identified empirically?

Following Freeman (1979) and Harrison and Rubinfeld (1978), a reasonable assumption is that the supply of E is exogenous or fixed, particularly in short run. Given this, and a nonlinear Equation (1), there is variation in the price ($P_E = W_E$) and quantity (E) data, and applying ordinary least squares to Equation (6) should identify the inverse demand curve for E. On the other hand, if the supply of E cannot reasonably be assumed to be independent of P_E, then the demand and supply relationships should be estimated jointly (Nelson 1978). In light of the fact that E is mainly determined by exogenous influences such as topography and wind patterns, we have chosen to ignore the supply side of E.

It appears as though the F-R model does provide a workable framework for estimating the benefits from discrete changes in E. An estimated version of (6) would be an ordinary inverse demand curve, even though the theory suggests that (6) is the utility compensated demand curve. This is because observations on $\bar{U}$ are not generally available, meaning that there is no way to empirically hold utility constant. If, however, the utility function is known a priori, or assumed, then compensated demand curves can be estimated. Quigley (1982) assumed a generalized utility function with constant elasticity of substitution and was able to identify compensated demand curves. In practice, when an ordinary demand curve is estimated, benefits are calculated as changes in willingness to pay and, when compensated demand curves are estimated, benefits are calculated as the measure of compensating variation. The difference between the two will be minor as long as the income elasticity is relatively small and the ratio of the consumer's surplus to income is small (Willig 1976). To the extent that E is a relatively minor item for most individuals, the distinction between willingness to pay and compensating variation (or, for that matter, between ordinary and compensated demand curves) can be ignored.

As is the case whenever demand curves are estimated, it is necessary to assume that all individuals in the market are identical except for income and measurable taste shift parameters. The shift parameters are usually socioeconomic variables such as education, sex, race, age, and political beliefs. Below, we have assumed that individuals within a market are identical except for differences in income levels.

Recent Criticisms and Comments

Criticism of the F-R model revolve around two issues. The first concerns the functional form of the hedonic equation. As indicated above, no clues as to the appropriate functional form, except that it is nonlinear, are provided. Further, a number of authors (Bender, et al [1980], Harrison and Rubinfeld [1978], Bloomquist and Worley [1981], and others) have found benefit estimates to vary dependent upon functional form. The approach utilized in the empirical work of the following section is to examine the importance of functional form through the use of sensitivity analysis. Functional form is found to be relatively unimportant for ozone and visibility in San Francisco. Thus, for this data set functional form considerations are deemed relatively insignificant. In addition, a detailed analysis of Los Angeles households suggests that the importance of functional form can be reduced through the use of prior information.

The second suspected flaw in the F-R technique is associated with the writings of Brown and Rosen (1982), Mendelsohn (1980), Palmquist (1981), and Quigley (1982). Their argument is that the implicit prices (e.g., P_E) are endogenous in the model, rather than given to consumers. As a matter of fact, the consumer actually chooses P_E when making his locational decision. To see this, assume that the hedonic price function depends on only three arguments represented by S, N, and E. In general, then, implementation of the F-R approach requires the estimation of the following equations.

$$P = P(S, N, E)$$
$$P_E = f(S, N, E, Y)$$
$$P_S = g(S, N, E, Y)$$
$$P_N = h(S, N, E, Y)$$

where subscripts again denote partial derivatives. Since P_E, P_S, and P_N are deterministic functions of S, N, and E (according to the hedonic price function), it is impossible to estimate f, g, and h. Only when P_E, P_S, and P_N are exogenous will any new information be gained by estimating f, g, and h. Since this point is crucial to the implementation of the F-R technique, some additional comments and suggestions are warranted.

Following Mendelsohn, within a market (e.g., an SMSA) all individuals face the same set of prices for the characteristic under consideration. The price set given by P_E represents the array of prices faced by individuals when choosing optimal levels of E. The implication of this can be realized by comparing two individuals, A and B. Individual A chooses a different level of E than does B, only if his demand for E is different than B's (perhaps due to different income or tastes). Their quantity choices are not different because of differences in P_E. It seems as though the observed data reveal information about how different individuals respond to the same set of prices, rather than the desired situation of identical individuals responding to different prices. In essence, the data give us one point on each demand curve which, without some additional structure, is not enough information to estimate the shape of the underlying relationship between price and quantity.

Figure 1 visually highlights this issue. In the figure, P^1_{AE} is the implicit price set faced by all individuals in the market and W^A_E and W^B_E are the demand curves for A and B, respectively. The demand curves illustrate that different individuals choose different levels of E and, therefore a different P_E. The information revealed by the F-R approach is (P^A_1, E^A_1) and $P^B_1, E^B_1)$. Now, unfortunately, exactly the same information is revealed by the demand curves $\bar{W}^A_E$ and $\bar{W}^B_E$. And, in general, there will be no way to discern whether the shape implied by W^A_E and W^B_E is correct or the shape of $\bar{W}^A_E$ and $\bar{W}^B_E$ is the appropriate representation of reality.

Brown and Rosen have examined the econometric implications of the endogeneity of the implicit prices in greater detail. Assume that the hedonic price function is estimated as the following polynomial:

$$P = a_0 + a_1N + a_2S + a_3E + a_4E^2 \tag{7}$$

Then

$$P_E = a_3 + 2a_4E \tag{8}$$

If we try to estimate a demand equation that is linear in E, say

$$W_E = B_0 + B_1E + B_2Y \tag{9}$$

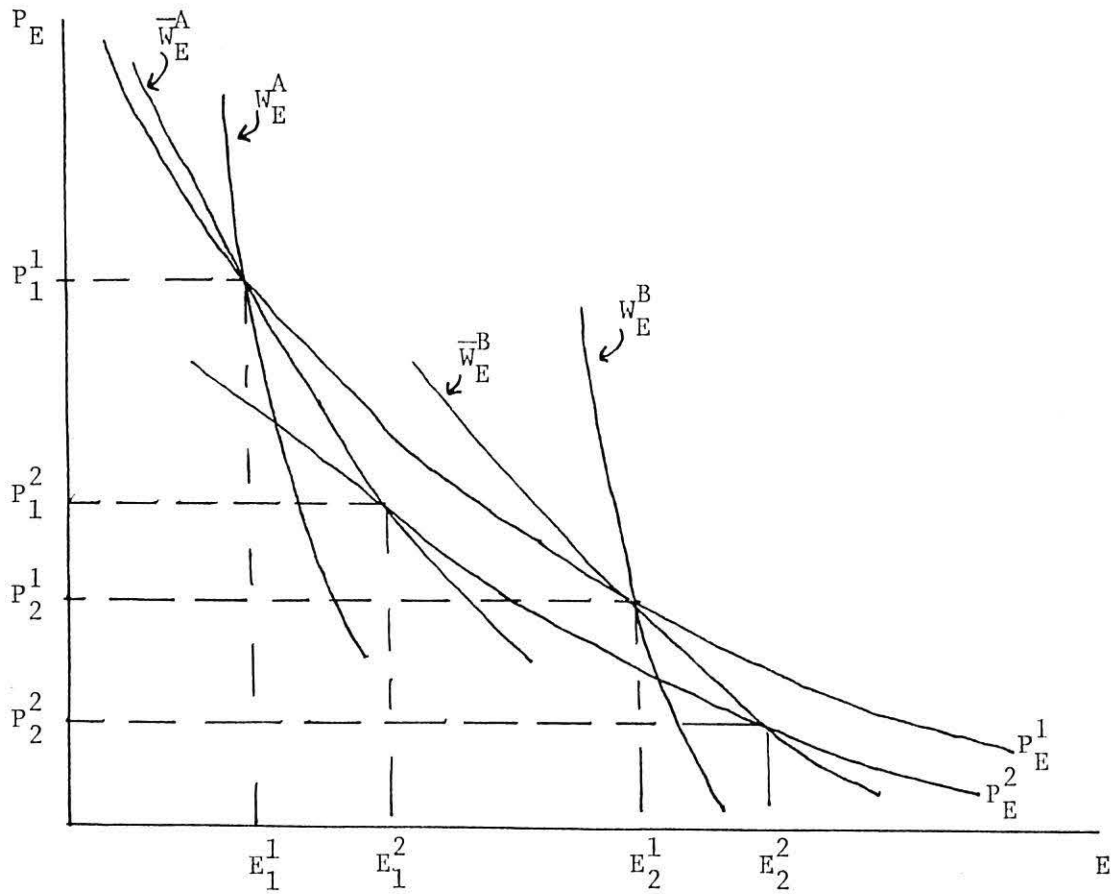

Figure 1: Alternate environmental demand curves for two individuals.

we would find that the R-square is one, $B_0 = a_3$, $B_1 = 2a_4$, and B_2 is insignificant. Clearly, demand estimation cannot reveal any additional information other than that contained in (7) in this case. At first this may seem to be a fatal blow to the F-R technique; however, when the demand equation is not a deterministic function of the hedonic price equation, then estimation is still possible. The problem is a drawback, though, since it requires researchers to assume away the problem and avoid these situations.

Mendelsohn and Palmquist suggest that a way to overcome these difficulties may be to use hedonic price functions from several different markets. The effect of this is to add additional price sets into the problem and obtain information on how like individuals respond to different price sets. An example is illustrated by P^2_E in Figure 1. P^2_E is the set of implicit prices calculated from another market; with the additional information denoted by (P^2_1, E^2_1) and (P^2_2, E^2_2) it is possible to discover the appropriate price and quantity relationships. (In the figure, W^A_E and W^B_E reflect the true relationship between price and quantity.) Obviously, more precision will be gained by adding in more and more markets.

The use of multi-market data revolves around two issues; first, we need to determine what, if any, additional assumptions are required for estimation. Then, we need to be able to identify the different markets.

As noted above, demand estimation using the traditional hedonic approach requires the assumption of like preferences for individuals within the market. The multi-market approach requires an assumption of like preferences across markets. For example, individuals in Boston will have the same shaped demand curve for environmental quality as individuals in Los Angeles. This assumption describes how similar people respond to different price sets and, if appropriate, facilitates estimation of demand curves.

In order to identify the different markets, Mendelsohn suggests that a sufficient condition for hedonic functions to vary across markets is "that the underlying array of suppliers changes across the markets." An example would be different supply arrangements induced by building codes and realtor boards. Another sufficient condition noted by Mendelsohn is, "if the number of demanders in a market is independent of the market prices, the supply curves are not perfectly elastic, and the number of demanders varies across markets." This can result when the transportation costs between markets prohibit consumers from locating in either area (Palmquist). Therefore, we have some guidelines on defining different markets within a geographic region, which, coupled with the assumption of identical individuals across markets, enable us to implement the multi-market approach.

An alternative the the Mendelsohn and Palmquist suggestion is the approach taken by Harrison and Rubinfeld (1978) and formally suggested by Quigley (1982). In this case, the endogenous nature of the implicit prices is eliminated by taking the hedonic price function as given (or determined in a prior step) and use the nonlinear budget constraint to empirically determine preferences. The choice of these two procedures is examined below.

In order to implement the F-R technique, two different assumption sets can be imposed. The first requires the use of multi-market data, while the second, although operational with data from a single market, requires restrictions on the functional forms of the hedonic price equation and the demand curves. Even though there are good and bad points about each set of assumptions, we have concluded that the estimates from single market data will be more appropriate in this study (see Section V for an extensive discussion of this point). There were several reasons for this conclusion.

Foremost in our reasoning was the requirement that individual preferences needed to be identical across markets in order to use multi-market data. Indeed, since people tend to gravitate toward others who have similar preferences, we expect San Franciscans to be similar and Los Angeles area residents to be similar, but there is no reason to suspect that the two groups are similar to each other. There does not seem to be an empirical test of this hypothesis, although we have found that hedonic price equations and the demand equations are different across the two areas (see Section V). Thus, our initial empirical investigations seemed inconsistent with the multi-market approach.

Another consideration was the amount of data required for multi-market estimation. We have two viable markets but doubt that two is a sufficient number to adequately implement Mendelsohn's suggestion. More confidence could be achieved by obtaining data from more markets. Perhaps San Diego, Portland, and Seattle would be reasonable choices to combine with Los Angeles and San Francisco.

As noted above, Brown and Rosen have illustrated that some functional form combinations must be eliminated. This type of assumption may be not overly restrictive. For example, if the demand curve is going to be linear in E, the only forms ruled out for the hedonic price equation are polynomials of degree two in E. Basically, this is what we have done in the San Francisco analysis below.

The approach used herein is essentially the same as that taken by Quigley. We assume that the individuals within each market are identical with the exception of income and that they take as given the nonlinear hedonic price function. Then, since the budget constraint is nonlinear, differences in income are sufficient to identify consumer's preferences. For a graphical presentation of this, see Quigley's Figure 1. Harrison and Rubinfeld appear to have used the same approach as well.

Given the review of the F-R model and recent criticisms, the following is a formal categorization of the procedures followed in the next section for determining the benefits of the separate components of air quality.

1. Determine the appropriate set of variables to be entered into the hedonic price equation. Included in this evaluation are the suitable health and aesthetic measures of air quality.

2. Examine the importance of functional form using sensitivity analysis.

3. Assume that all individuals within a market are similar except for income and that air quality is neither a substitute for nor a complement with other characteristics. Thus demand is given by

$$W_E = f(E, Y).$$

4. Assume that the demand equation is not a deterministic function of the hedonic price equation. Thus, all variation in P_E is not due entirely to differences in E.

5. Calculate P_E for each individual and regress E and Y on these calculations.

6. Use the results from (5) to calculate the benefits of various programs.

Implementation of this methodology is described in the next section of this chapter.

SECTION III

SAN FRANCISCO EMPIRICAL ANALYSIS

Numerous hedonic housing studies have examined the relationship between housing values and air quality. These studies have been conducted for different cities, have used different air quality measures, and pertain to various time periods (see Freeman [1979a] for a review). The consensus of these studies is that air pollution is a significant negative determinant of home sale price. In addition, benefit estimates from these studies are generally consistent and replicable.

The research reported in this section is designed to contribute to this previous literature through an examination of the aesthetic/health division of air quality. Previous analysis has generally employed a proxy variable to measure the overall level of air quality. While this approach eliminates collinearity among the various pollutants, it provides little information on the benefits of reducing individual pollutants.

In order to examine the aesthetic/health component parts of air quality two separate measures of air quality are used in the hedonic procedure. Aesthetic air quality is measured as actual visibility (annual median miles).[1] Various visibility measures are utilized (all hours, all days without precipitation or fog, see haze adjusted) but the results are essentially invariant to any particular one. The health component is measured by average ozone concentrations. Since ozone is a colorless gas, it has no visual effect. The health effects are primarily chest discomfort, headaches and an assortment of lung associated problems (frequency of asthma attacks, etc.).[2] Further, there is evidence that individuals in low ozone areas have the effects at concentrations that would not produce effects among individuals used to higher concentrations (National Research Council, 1977).

A previous attempt to separate these influences conducted in the Los Angeles area was only marginally successful. Multicollinearity between the air pollution measures and access to the beach made estimation of an accurate hedonic equation difficult. Thus, even though the Los Angeles hedonic results seemed consistent with a survey of households, the instability of these results prevents placing undue emphasis on them. For this reason a different study area, the San Francisco air basin, was chosen for study.

The objective of this section is to describe the data base, procedures and empirical results of this inquiry. Consider first the data utilized in the study.

Data Specifics

The initial procedural step of the hedonic housing value approach is to estimate a hedonic housing equation which relates home sale price to the attributes of the home. Of particular interest is the relationship of home sale price to air quality levels. The estimation is particularly concerned with testing the hypothesis of whether or not air quality levels are a significant determinant of home prices.

The study area consists of San Francisco, Alameda, Contra Costa, San Mateo, and Santa Clara counties. The analysis is specifically confined to single family residences in these areas. Thus, not considered is the impact of air quality variations upon other structures (multiple family dwellings, mobile homes, commercial, etc.) or other ownership types (rental leasing, etc.). Therefore, within our sample, this research asks if households will pay a premium in price for single family homes located in clean air areas and what is the magnitude of that willingness to pay.

The data base was constructed to enable the testing of hypotheses concerning the impact of air quality levels on housing sale price. The dependent variable in the entire analysis is the sale price of owner occupied single family residences.[3] The independent variable set consists of variables which correspond to three levels of aggregation: house, neighborhood, and community. Table 1 describes further the data employed in the study.

The housing characteristics data, obtained from the Market Data Cooperative (a data clearinghouse centered in Los Angeles), pertain to homes sold in the 1978-79 time period and contain information on nearly every important structural and/or quality attribute. Included in the list of available variables are those that pertain to both quantity (lot size, total number of rooms, square footage of living area) and quality (pool, view, number of fireplaces, parking, stories, etc.) of each particular house. This list was pared to those variables presented in Table 1 in order to reduce collinearity problems. But not that both home quantity and quality are covered by the variables chosen.

It should be emphasized that housing data of such quality (e.g., micro level of detail over time) are rarely available for studies of this nature. Usually outdated data which are overly aggregated and collected irregularly (for instance census tract averages only in census years) are employed. Our data set yield results relevant at the household (micro) level.

The Market Data Cooperative provided data tapes listing all homes sold in the counties specified above during the 1978-79 time period. The number of entries was unmanageably large (in excess of 100,000 observations), so the data sets were reduced using a random number matching system. The selection criteria satisfied a desire to maintain: (1) a large data set (greater than 1000 observations), and (2) the relative proportions of homes sold in the counties.

In addition to the immediate characteristics of a home, other variables which could significantly affect its sale price are those that reflect the condition of the neighborhood and community in which it is located. In order to capture those impacts and to isolate the independent

TABLE 1: VARIABLES USED IN ANALYSIS OF HOUSING MARKET

Variable	Definition (hypothesized effect on housing sale price)	Unit	Source
Dependent:			
Sale Price	Sale price of owner occupied single family residences	($100)	Market Data Cooperative
Independent-Housing:			
Sale Date	Month the home was sold (positive)	January 1978 = 1 December 1979 = 24	Market Data Cooperative
Age	Age of home (negative)	Years	Market Data Cooperative
Bathrooms	Number of bathrooms (positive)	Number	Market Data Cooperative
Living Area	Square feet of living area (positive)	Hundreds of square feet	Market Data Cooperative
Pool	1 if pool, 0 if no pool (positive)	0 = no pool 1 = pool	Market Data Cooperative
Fireplaces	Number of fireplaces (positive)	Number	Market Data Cooperative
View	1 if view present, 0 if not (positive)	0 = no view 1 = view	Market Data Cooperative
Independent-Neighborhood:			
Distance to Beach	Miles to nearest beach (negative)	Miles	Calculated
Age Composition	Percent greater than 62 in census tract (positive)	Percent	1980 Census
Ethnic Composition	Percent white in census tract (positive)	Percent	1980 Census
Time to Work	Average time to employment from census tract (negative)	Minutes	1980 Census

TABLE 1 (Continued)

Variable	Definition (hypothesized effect on housing sale price)	Unit	Source
Independent-Community:			
School Quality	Community's 12th grade math score (positive)	Percent	California Assessment Program (1979)
Population Density	Population per square mile in surrounding community	Persons/square mile	1980 Census, Thomas Brothers Grid Maps
Miles to Central Business District	Distance from census tract to dominant city in county (negative)	Miles	Thomas Brothers Grid Maps
Crime	Seven major crimes per 1000 people in surrounding communities (negative)	Crimes/persons	Summary Characteristics 1980 Census
Age	Median age of population in surrounding community (positive)	Years	Summary Characteristics 1980 Census
Race	White percentage of population in surrounding community (positive)	Percent	Summary Characteristics 1980 Census
Unemployment	Unemployment rate in surrounding community (negative)	Percent	Summary Characteristics 1980 Census
Education	Percentage of population in community with High School Diploma (positive)	Percent	Summary Characteristics 1980 Census
Poverty	Percentage of population in community below poverty level (negative)	Percent	Summary Characteristics 1980 Census
Home Density	Hundreds of people per square mile (negative)	Homes/square mile	Calculated
Population per Household	Persons per household (negative)	People/home	Summary Characteristics 1980 Census

TABLE 1 (Continued)

Variable	Definition (hypothesized effect on housing sale price)	Unit	Source
Independent-Air Quality:			
Visibility (1)	Median annual visibility level (positive)	Miles	Trijonis, et al (1984)
Visibility (2)	Median annual visibility level disregarding hours with fog or precipitation (positive)	Miles	Trijonis, et al (1984)
Visibility (3)	Median annual visibility subtracting sea haze contribution (positive)	Miles	Trijonis, et al (1984)
Ozone (1)	Annual arithmetic average of daily maxima (negative)	pphm	California Air Resources Board
Ozone (2)	Days exceeding 12 pphm (negative)	Days	California Air Resources Board

influence of location vis-a-vis extinction differences, several neighborhood and community variables were included in the econometric modeling.

Neighborhood refers to the surrounding census tract and includes the variables -- population, age, ethnic composition, distance to work, and distance to the beach. Given the large number of census tracts (for example over 1500 in the Los Angeles area) variation in this data are quite substantial. Pertinent community (city level) variables include density measure, school quality, crime rate, and others. However, in contrast to the house and neighborhood characteristics, there are only a limited number of communities. Thus, collinearity between community measures presents empirical difficulties (see following subsection).

The neighborhood and community data were matched to the household characteristic data using the transformation from Thomas Brothers grid maps to the relevant census tracts and communities. Thus, each household was matched with its corresponding neighborhood and community characteristics. Summary statistics for the variables used in the hedonic housing equation are presented in Table 2.

The final variable input into the hedonic equations are the air quality measures. Three different visibility measures are examined. The first and second visibility variables (annual median and annual median excluding hours of precipitation or fog) are nearly equivalent. Also, as Table 2 illustrates, their means and standard deviations are quite close. Furthermore, the simple correlation between these measures is 0.98. Therefore, in the empirical analysis that follows, the results for these two variables are essentially interchangeable. However, this is not the case with the relationship between the third visibility variable (annual median subtracting sea haze) and either of the other measures. Thus, visibility (3) is treated as a parameter which measures something different from the other measures. In addition, two different ozone variables are examined. As indicated below, the results are quite insensitive to the particular measure.

The data base assembled for the housing value study is appropriate to test the hypothesis outlined above for two reasons. First, the housing characteristic data are extremely detailed at the household level of aggregation and extensive in that a relatively large number of observations are considered. Second, a variety of neighborhood and community variables have been included to help isolate the specific effect of air quality on housing values.

Empirical Results: Hedonic Housing Equations

The initial task in the hedonic housing value analysis is to determine the relationship between air quality levels and home sale price. The underlying structure of this hypothesis test is an empirical equation which attempts to explain the variation in home prices located in the San Francisco area for the years 1978-1979.[4] The estimated coefficients of these hedonic equations represent the effects that changes in the independent variables have on sale price. In reference to the air quality

TABLE 2

SUMMARY STATISTICS FOR VARIABLES USED IN ANALYSIS OF HOUSING MARKET FOR THE SAN FRANCISCO AREA

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
HOUSING				
Home Sale Price	89,175	54,119	16,500	850,000
Sale Date	11.68	6.28	1.00	23.00
Age of Home	25.46	18.34	1.00	79.00
Bathrooms	1.67	0.63	1.00	5.00
Living Area	14.34	5.37	4.23	54.7
Pool	0.054	0.23	0.00	1.00
Fireplaces	0.81	0.54	0.00	3.00
View	0.10	0.30	0.00	1.00
NEIGHBORHOOD				
Distance to Beach	26.16	12.84	6.64	64.67
Age Composition	9.91	5.73	0.7	35.8
Ethnic Composition	74.43	21.96	2.7	99.3
Time to Work	24.12	3.80	14.00	35.00
COMMUNITY				
School Quality	68.07	4.34	52.30	81.00
Population Density	59.27	45.52	4.33	151.73
Miles to Business District	7.90	8.86	0.00	27.84
Crime	45.51	22.46	6.01	201.95
Age	31.72	3.50	26.30	40.90
Race	72.24	17.10	38.14	97.53
Unemployment	6.42	2.24	1.20	12.80
Education	78.62	6.72	58.70	97.50
Poverty	9.05	5.03	2.20	21.00
Home Density	24.49	20.84	1.35	66.81
Population Per Household	2.58	0.34	1.74	3.49
AIR QUALITY				
Visibility (1)	17.38	3.15	12.00	24.00
Visibility (2)	18.88	3.20	13.00	26.00
Visibility (3)	31.05	8.13	17.00	42.00
Ozone (1)	2.86	0.90	0.00	4.00
Ozone (2)	0.84	1.33	0.00	4.00

variables, this procedure allows one to focus on their significance while separating out the influence of other extraneous variables. Therefore, this analysis yields two outputs concerning the relationship of air quality differentials to housing price. The relative significance of location with respect to air quality is determined, and the estimated coefficients implicitly measure their monetary value at the margin.

In this section initial estimated hedonic price gradients are presented for the study area. The stability of these results is then analyzed by altering sample size, air quality measures, and functional form. In the latter case, both the independent variable set (other than extinction) and the mathematical form of the relationship are allowed to vary. The initial hedonic price gradients do not necessarily provide the best statistical fit of the data nor the most suitable relationship for subsequent analyses. Rather, only after all possible influences are analyzed do we choose the most appropriate relationship to utilize in the subsequent steps of the hedonic price method. Finally, it should be noted that the order in which we have chosen to analyze these potential destabilizing influences has no effect on the ultimate choice of the best estimated price gradients. Thus, for instance, sample size has essentially no effect whether it is analyzed first or last.

The estimated hedonic price gradient which serves as the base results are presented in Table 3. A number of aspects of the equation are worth noting. First, the independent variable set was chosen to account for all the different characteristics of a home. Thus, square feet of living area represents the quantity of a home, whereas pool, house age, and the number of bathrooms and fireplaces describe the quality. In addition, characteristics which reflect the immediate neighborhood (ethnic and age composition) and the location (time to employment and distance to beach) were included. Also, variables such as school quality, crime, and population density were included to represent overall community attributes. In this latter category, only a few of the available community variables were used because of collinearity difficulties. Collinearity is especially problematical because only a relatively few communities exist (51 in the San Francisco area). There is insufficient variation to allow the inclusion of more community variables. However, as is seen below, this problem can be successfully overcome using principal components analysis. The final variables of interest represent counties. These are zero-one dichotomous variables. San Francisco County is omitted in the San Francisco area. The coefficients yield information as to the home sale price differences between the omitted county and the included counties.

The second noteworthy aspect of the equations is that the nonlinear specification (semi-log for the San Francisco area) is a significant improvement over the linear form. As Rosen (1974) pointed out, this is to be expected since consumers cannot always arbitrage by dividing and repackaging bundles of housing attributes. Third, approximately 80 percent of the variation in home sale price is explained by the independent variable set. Fourth, with the exception of some of the community variables, all variables possess the expected relationship to home sale price and are significantly different from zero at the one percent level ($|t|>2.326$).[5]

TABLE 3

ESTIMATED HEDONIC EQUATION (SEMI-LOG)
FOR THE SAN FRANCISCO AREA

Dependent variable = ℓn (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	.015	14.34
Age of Home	-.0017	-3.53
Square Feet of Living Area	.04	20.88
Number of Bathrooms	.05	3.04
Number of Fireplaces	.097	6.89
Pool	.104	3.54
View	.074	3.25
Neighborhood Characteristics:		
Percent Greater than 64	.0046	3.27
Percent White	.006	15.39
Location Characteristics:		
Distance to Beach	-.003	-2.12
Distance to Business District	-.002	-1.65
Alameda County	-.33	-5.84
Contra Costa County	-.38	-5.73
San Mateo County	-.22	-4.11
Santa Clara County	-.22	-3.81
Community Characteristics:		
Population Density	-.0006	-1.37
School Quality	.014	6.15
Crime	-.0008	-1.92
Air Quality:		
Visibility	.11	3.66
$(\text{Visibility})^2$	-.006	-3.59
Ozone	-.031	-2.53
Constant	3.81	10.97

R-Squared	0.80
Number of Observations	1035

However, the most important result from the perspective of this study is that the air quality variables are significantly different from zero and possess the expected relationship to home sale price. These results indicate that individuals are acting upon air quality information when making locational choices and this action is translated into a measurable hedonic gradient. As is described below, these results are essentially invariant with respect to various sample sizes, air quality measures, model formulations, and functional forms.

Regarding the monetary impact of housing sale price of a change in an independent variable, the semi-log form is particularly amenable to interpretation. Thus, from Table 3 it is evident that for the San Francisco area in 1978-79, home sale prices were rising at 1.5 percent per month, 100 ft^2 of living area was worth four percent of price, and a pool had a value of 10.4 percent of price. In addition, a one unit change in ozone had a value of 3.1 percent of home sale price. Thus, a ten percent change in ozone would alter home sale price by 0.89 percent. Based on a mean home sale price of approximately $83,000, this latter figure translates into $740.

The monetary impact of the visibility variable, because of the estimated polynomial form, is dependent upon where one evaluates the function. If all variables are assigned their mean values and a 10% visibility improvement to its mean is analyzed, then the monetary impact is $1,630. Therefore, it seems that in the hedonic equation, visibility is worth relatively more than the health aspects of air quality. However, the relative value of the health aspects increases as the household's visibility increases.

Given these benchmark results, their stability is the next subject considered. Possible influences include sample size, model formulation, and functional form. As an initial test of the stability of the results presented above, hedonic equations were estimated for various sample sizes. Although the degree of significance increased with sample size, all the basic conclusions drawn above continue to be relevant. Insensitivity with respect to various sample sizes is a general characteristic of our results.[6]

Another possible destabilizing influence is the set of variables included in the hedonic equation. Two separate impacts are analyzed: (i) the effect of different community variables; and (ii) the effect of different air quality measures. With respect to the list of community variables, the benchmark results include three: crime rate, population density, and school quality. It could be argued that this limited number of variables does not account for all important community characteristics. If so, then the air quality variables, in addition to representing air quality, could be serving as a proxy for one of the missing variables. In that case, the coefficients on air quality would be biased.

To test for such a bias, we should add in more community variables. However, additional community variables would introduce the problem of multi-collinearity. In order to overcome this latter problem, the method of principal components is utilized.

Principal component analysis is a method of transforming a given set of variables into a new set of composite indices or principal components that are orthogonal (uncorrelated) to each other. Because of the severe collinearity among the community variables, a transformation that yields uncorrelated variables is particularly useful. The transformation is accomplished by choosing the best linear combination of variables as the first principal component. In this context, "best" implies that the combination chosen accounts for more of the variance in the data than any other linear combination of variables. The first principal component is therefore viewed as the single best summary of linear relationships exhibited in the data. The second component is defined as the second best linear combination of variables, given the condition that the second is orthogonal to the first. This continues until as much variation as possible is explained.

The principal component method can be expressed as:

$$N_i = a_{i1}F_1 + a_{i2}F_2 + \dots + a_{iK}F_K \tag{10}$$

where

N_i = the community variables included in the principal component analysis ($i = 1, 2, \dots M$),
F_j = the principal components or factors ($j = 1, 2, \dots, K$), $K<M$,
and a_{ij} = estimated coefficients.

If the number of factors equals the number of variables ($K=M$), then the entire variation in the variables is explained by the factors. However, it is the usual case to use fewer factors than variables because, if the two are equal, then the procedure is identical to not using principal components analysis (Johnston, 1972).

The estimated coefficients are important in that they indicate the relative importance of each factor. The importance of a given factor for a given variable can be expressed in terms of the variance in the variable that is explained by the factor. Mathematically this is the square of the estimated coefficient (a_{ij}^2). The total variation of a variable explained by all factors is obtained by summing the squared coefficients,

$$\left(\sum_{j=1}^{K} a_{ij}^2 \right).$$

Given the relationships described in equation (10), the original variables are transformed into a set of composite scales or factor scores that represent the relative importance of the respective factors or principal components. In order to do this, the matrix of a_{ij} is transformed into a factor score coefficient matrix (b_{ij}). The composite scales or factor scores are then calculated as:

$$Z_j = b_{1j}(N_1 - \overline{N}_1)/\sigma_1 + b_{2j}(N_2 - \overline{N}_2)/\sigma_2 + \dots + b_{Mj}(N_M - \overline{N}_M)/\sigma_M \qquad (11)$$

where

Z_j = factor score representing the j^{th} factor ($j = 1, 2, \dots, K$),
b_{ij} = factor score coefficient ($i = 1, 2, \dots, M$),
N_i = original variable ($i = 1, 2, \dots, M$),
$\overline{N}_i$ = mean of the i^{th} independent variable
and σ_i = standard deviation of the i^{th} independent variable.

Note that the original variables are normalized to be nondimensional (Johnson 1972).

The factor scores represent the transformed data set in which orthogonality is preserved. These new data are then input into the home sale price hedonic equation as explanatory variables. In essence, a set of highly correlated variables are replaced by a new set of uncorrelated variables which measure precisely the same information. However, it should be noted that the initial variables have been constrained to a linear relationship. Essentially, the procedure represents the imposition of a linear restriction, where the linear relationship is not based on a priori information but is chosen as the one which best fits the data.

In the semi-log form, the hedonic equation can be written as:

$$\ell n(P) = \beta_0 + \sum_{j=1}^{K} \beta_j Z_j + \sum_{\ell=j+1}^{L} \beta_\ell S_\ell + \beta_{L+1} E \qquad (12)$$

where

P = home sale price
Z_j = factor scores representing the principal components ($j = 1, 2, \dots, K$),
S_ℓ = remaining explanatory variables (site influences) not included in the principal component analysis ($\ell=j+1, \dots, L$),
and β_0, β_j, β_1, β_{L+1} = estimated coefficients.

Since the principal components are linear combinations of other variables, no precise interpretation can be given to the factor score variables. However, one can still determine the relative effect of a change in a variable included in the principal component analysis by differentiating equation (12) with respect to that variable. For instance, consider the impact of N_1, a variable included in the principal component analysis. Substituting equation (11) into (12) and differentiating, we obtain

$$\frac{dP}{dN_1} = \left(\sum_{j=1}^{K} \frac{b_{ij}}{\sigma_j} \cdot \beta_j \right) \cdot P \qquad (13)$$

Thus, although N_1 does not enter the hedonic housing equation directly its relative importance can still be determined.

In the particular situation under study, a severe collinearity exists between the community variables. Thus, it was decided to perform principal component analysis on these troublesome variables to transform them into a set of uncorrelated variables. In the study area, eight community variables -- school quality, crime rate, unemployment rate, educational level, poverty rate, population per household, population per square mile, and miles to the business district -- were transformed into three factors or principal components.

The initial factor matrix (a_{ij}) is presented in Table 4. As is illustrated, the first factor or principal component largely explains school quality, crime, unemployment, education, and poverty. Because of the distribution of signs on these variables the expected relationship of Factor 1 to home sale price is negative. A similar analysis can be conducted for the other factors. Finally, in the San Francisco area, the three factors explain approximately 83 percent of the variation in the community variables.

As outlined above, the initial factor matrix is transformed in a factor score coefficient matrix. The relevant matrix is presented in Table 4. These factor score coefficients are used to compute factor scores or composite scales which represent the relative importance of each factor for each variable. This is accomplished in accordance with equation (12). The factor scores are input data (explanatory variables) into the hedonic housing equation.

The hedonic equations which include the three factors to account for eight community variables are presented in Table 5. These results are quite consistent with the benchmark results. All variables remain significant, R^2 is essentially the same, etc. Although there is little change in the overall results, the equations presented in Table 5 are considered superior because they include more community variables. In addition, it is noteworthy that the coefficients on the air quality variables remain quite stable. The monetary impact of a ten percent change in ozone is equal to \$860. A ten percent visibility improvement evaluated as above produces a monetary impact of \$1,580.

The principal component analysis is considered an improvement over the previous results. Thus, the equation presented in Table 5 is the basis for further analysis.

Another test of the stability of the model formulation is to examine other air quality measures. For comparison purposes;, hedonic equations were estimated using days exceeding the ozone standard, and the various visibility measures. In Table 6, the first of these experiments is illustrated. As is evident, all variables perform as previously noted. Distance to the beach is the only insignificant variable. However, previous (and later) results also suggest the weakness of the beach/home sale price relationship in San Francisco. This demonstrates that beach is

TABLE 4

FACTOR COEFFICIENT AND FACTOR SCORE COEFFICIENT MATRICES

Factor Coefficient Matrix

Variable	Factor 1	Factor 2	Factor 3
School Quality	-.713	.543	.195
Miles to Business District	-.582	-.362	.659
Crime	.786	.120	.382
Unemployment	.887	-.328	.078
Education	-.817	.409	.027
Poverty	.902	.016	.139
Population Per Household	-.559	-.650	-.311
Population Per Square Mile	.628	.526	-.196

Factor Score Coefficient Matrix

Variable	Factor 1	Factor 2	Factor 3
School Quality	-.161	.384	.251
Miles to Business District	-.131	-.256	.846
Crime	.177	.085	.490
Unemployment	.120	-.232	.101
Education	-.184	.289	.035
Poverty	.203	.011	.178
Population Per Household	-.126	-.459	-.399
Population Per Square Mile	.141	.372	-.252

TABLE 5

ESTIMATED HEDONIC EQUATION (SEMI-LOG) FOR THE SAN FRANCISCO AREA WITH PRINCIPAL COMPONENT VARIABLES

Dependent variable = (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	.015	14.51
Age of Home	-.0016	-3.29
Square Feet of Living Area	.041	21.16
Number of Bathrooms	.049	2.88
Number of Fireplaces	.096	6.88
Pool	.092	3.13
View	.075	3.29
Neighborhood Characteristics:		
Percent Greater than 64	.0055	3.87
Percent White	.0058	14.43
Location Characteristics:		
Distance to Beach	-.0029	-2.16
Alameda County	-.26	-4.73
Contra Costa County	-.266	-4.06
San Mateo County	-.188	-3.68
Santa Clara County	-.130	-2.47
Community Characteristics:		
Factor 1	-.076	-7.09
Factor 2	.034	6.71
Factor 3	.007	1.06
Air Quality:		
Visibility	.134	4.35
$(\text{Visibility})^2$	-.0074	-4.33
Ozone	-.0362	-3.00
Constant	4.50	16.23

R-Squared	0.80
Number of Observations	1035

TABLE 6

ESTIMATED HEDONIC EQUATION (SEMI-LOG) FOR THE SAN FRANCISCO AREA WITH DAYS EXCEEDING FEDERAL STANDARD

Dependent variable = ℓn (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	.015	14.55
Age of Home	-.0015	-3.31
Square Feet of Living Area	.04	21.17
Number of Bathrooms	.05	3.11
Number of Fireplaces	.092	6.66
Pool	.086	2.97
View	.071	3.11
Neighborhood Characteristics:		
Percent Greater than 64	.005	3.68
Percent White	.006	15.04
Location Characteristics:		
Distance to Beach	-.001	-.75
Alameda County	-.293	-5.34
Contra Costa County	-.399	-6.00
San Mateo County	-.211	-4.15
Santa Clara County	-.115	-2.24
Community Characteristics:		
Factor 1	-.065	-6.16
Factor 2	.021	3.73
Factor 3	-.0059	-.82
Air Quality:		
Visibility	.129	4.28
$(\text{Visibility})^2$	-.007	-4.22
Days Exceeding 12 pphm ozone	-.0507	-5.26
Constant	4.43	16.14

R-Squared	0.80
Number of Observations	1035

relatively unimportant in San Francisco rather than anything particularly deficient about this model.

The air quality variables continue to perform as expected, both in relationship to home sale price and in significance. In regard to the monetary impact of one less day exceeding twelve pphm, the home sale price differential is approximately $4,400.[7] Alternatively, a ten percent improvement in ozone days exceeding the standard is valued at $370. For visibility, a ten percent improvement to the mean is valued at $1,380. Therefore, as a general statement, the hedonic equations are quite insensitive to the particular air quality measures.[8]

The final destabilizing influence is the functional form of the hedonic equation. As previously mentioned, a priori information about the functional form of the hedonic price equation is unavailable. This requires that some consideration be given to correct form, especially since the estimated benefits depend heavily upon the implicit prices calculated from the equation. As an aid in determining the appropriate functional form, the Box-Cox transformation has been employed. This has become a fairly standard approach and has been used by Bender et al (1980), Quigley (1982), and others. Moreover, most researchers have found that benefits are indeed sensitive to functional form, adding importance to these considerations.

Our search ranged over numerous forms: linear, semi-log, log-linear, classical Box-Cox, extended Box-Cox, semi-log exponential, translog, and semi-log quadratic. Two general trends emerged from this search. First, the list of functional forms can be divided into two groups: (1) those with left hand side only transformations (semi-log, classical Box-Cox, etc.), and (2) those with transformations of all the data (log-linear, extended Box-Cox, etc.). Within a group there exists little variation in the estimated results. Between groups is where any differences arise. Therefore, since semi-log equations have been specified previously, the other extreme can be illustrated by the log-linear functional form.

The log-linear results are presented in Table 7.[9] In general, the performance characteristics (R^2, t-values) of the log-linear equations are quite similar to the semi-log equations. In addition, the air quality variables possess the expected signs and are statistically significant.

The second major trend is that the equations with left side only transformations consistently outperform the other equations. In order to choose among the alternatives, the value of the likelihood function for each form was computed (see Spitzer, 1983). The form that achieves the highest likelihood (i.e., that is most probable) is generally considered the most appropriate. On this basis, the semi-log equation would be considered much better than the log-linear. However, for comparison purposes both will be used to calculate the benefits of improved air quality.

Therefore, the hedonic equations estimated for San Francisco are robust in every respect. In addition, they are quite insensitive to the

TABLE 7

ESTIMATED HEDONIC EQUATION (LOG-LINEAR) FOR THE SAN FRANCISCO AREA WITH PRINCIPAL COMPONENT COMMUNITY VARIABLES

Dependent variable = ℓn (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	.015	14.63
ℓn (Age of Home)	-.016	-2.34
ℓn (Square Feet of Living Area)	.67	22.73
ℓn (Number of Bathrooms)	.078	2.94
Number of Fireplaces	.087	6.11
Pool	.123	4.19
View	.102	4.46
Neighborhood Characteristics:		
ℓn (Percent Greater than 64)	.053	4.22
ℓn (Percent White)	.242	15.05
Location Characteristics:		
ℓn (Distance to Beach)	-.035	-.89
Alameda County	-.293	-5.32
Contra Costa County	-.269	-4.20
San Mateo County	-.212	-4.22
Santa Clara County	-.207	-3.68
Community Characteristics:		
Factor 1	-.089	-8.63
Factor 2	.0413	8.00
Factor 3	.013	1.89
Air Quality:		
ℓn (Visibility)	6.67	4.20
ℓn ((Visibility)^2)	-2.38	-4.23
Ozone	-.044	-3.49
Constant	-8.43	-3.77

R-Squared	0.80
Number of Observations	1035

influences of sample size, model formulation and estimated functional form. The next test is to examine the resulting benefit figures. This is accomplished in the next subsection.

Empirical Results: Inverse Demand Equations

The hedonic equations presented in Tables 5-7 are the basis for determining the benefits of air quality improvements. In order to complete the benefit estimation procedure, the following steps are required. First, the hedonic equations are differentiated to determined the marginal willingness to pay for a change in air quality. The marginal willingness to pay is evaluated for each individual point in the data set. These values represent the implicit price of air quality for each individual and are dependent upon all the other characteristics of the home. Given these implicit prices, an inverse demand curve[10] can be estimated by regressing price against quantity (extinction) and other household (homeowner) shift variables (income, etc.). Integrating under these inverse demand curves for any proposed air quality change yields the benefits attributable to the change. In this subsection, estimated inverse demand curves are presented for the San Francisco area following the approach set out by Freeman (1974, 1979) and Rosen (1974) with the additional restriction on functional form (Brown and Rosen [1982]).[11]

The demand curve estimation utilizes the following data. Marginal willingness to pay (in hundreds of dollars) is the implicit price of air quality improvements. It is the derivative of the hedonic equation evaluated for each data point, and it represents the average home sale price differential attributable to a unit air quality difference. The quantity variable is the initial average community air quality level. Income represents average community income in hundreds of dollars per year.

The estimated inverse demand curves for the San Francisco area are presented in Table 8. There are a number of noteworthy aspects. First, only quantity (air quality) and income are employed to describe the variation in price. A large proportion of the variation is explained, so additional variables would be of marginal significance. Second, the linear forms presented for the inverse demand curve perform as well as alternative nonlinear forms. But this is not a crucial point since the resulting benefit figures are quite insensitive to the functional form of the inverse demand curve. The third aspect concerns the lack of significance on the ozone variable in the first equation. Ozone performs better in different functional forms (demand) so it is not considered a serious drawback. Fourth, the ozone variable changes sign dependent upon the particular model. However, no sign can be attached *a priori* (Bartik and Smith [1984]), so this is not considered problematical either. Fifth, the income variable is always significantly different from zero and possess the correct relationship to marginal willingness to pay.

A deeper understanding of the inverse demand relationships can be obtained by calculating the annual household benefits associated with a hypothetical ten percent improvement in the air quality variables. These benefit figures are obtained by integrating the inverse demand curves over

TABLE 8

ESTIMATED LINEAR DEMAND CURVES FOR THE SAN FRANCISCO AREA

Dependent variable = marginal willingness to pay for air quality improvements in hundreds of 1978-79 dollars

Air Quality Variable	Functional Form of Hedonic Price Gradient	Independent Variable Coefficients (t-statistics) Constant	Air Quality	Income	R^2	Number of Observations
Ozone	Semi-log	-59.96 (-15.65)	1.10 (1.09)	.403 (31.52)	.51	1035
Ozone	Log-linear	15.88 (7.47)	-4.21 (-7.53)	.16 (22.46)	.33	1035
Days Exceeding 12 pphm Ozone	Semi-log	.29 (.13)	-2.96 (-6.56)	.188 (22.29)	.33	1035
Visibility	Semi-log	112.00 (31.40)	-8.06 (-48.92)	.138 (18.79)	.74	1035
Visibility	Log-linear	101.73 (41.93)	-6.13 (-54.67)	.024 (4.75)	.75	1035

the proposed change. The range of benefits for a ten percent improvement in ozone are between \$119-\$127/year.[12] The corresponding values for a ten percent visibility improvement are \$110-\$217. Thus, the health aspects of air quality account for between one-third and one-half of the total benefits of marginal air quality improvements.

Concluding Remarks

The analysis reported in this section was designed to determine the value that individuals place on air quality improvements. The information required to conduct this calculation was obtained from the market for single family residences in San Francisco using the hedonic price procedure.

The hedonic equation estimation indicates that air quality, as measured by visibility and ozone concentrations, is a significant determinant of home sale price. This implies that decreases in air quality cause housing values to decrease. Further, this result is independent of sample size, model formulation, and functional form.

Given the hedonic equations, inverse demand curves for air quality have been estimated. Integration of these demand curves over a proposed improvement yields the total benefit associated with the improvement. As an example benefits were estimated for a hypothetical ten percent improvement in air quality. The sum of the health and aesthetic components ranged from \$229-\$344/year/household. Of this amount, the health aspects produced between one-third and one-half of the total. This is a significant portion of total benefits and implies that the threshold for ozone damage is somewhat below the ozone levels generally experienced in San Francisco.

SECTION IV

THE IMPORTANCE OF FUNCTIONAL FORM FOR BENEFIT ESTIMATION

In the previous section it was indicated that the benefit estimates were essentially invariant with respect to functional form. This is not the usual case. For instance, Harrison and Rubinfeld [1978], Nelson [1978], Bloomquist and Worley [1981], Linneman [1980] and others find that the benefit estimates generated from the hedonic approach vary widely, dependent upon estimated functional form. In the most detailed analysis of the importance of functional form, Bender et al (1980) confirm the result. The sensitivity of benefit estimates to functional form is especially damaging since the accuracy of the benefit figures depends on some statistical criterion. Previous researchers have correctly concluded that in the absence of prior information concerning the hedonic price equation, the form is purely a statistical question. The major purpose of this section is to indicate that prior information may be used to improve the accuracy of the benefit estimates from the hedonic methodology and reduce the significance of functional form.

The results in this section do not dispute the conclusions regarding the apparent importance of functional form. However, they indicate that whereas functional form seems important on the surface, this may be a symptom rather than a cause of unstable benefit estimates. Thus, the major findings of this section help to determine <u>why</u> benefit estimation is so sensitive to functional form. In addition to the purely statistical reason (a variety of forms fit the data), two potential explanations for the importance of functional form are examined. These are poor quality data and an inadequate theoretical foundation.

The first of the alternative causes is addressed through the use of an outstanding data set. The hedonic price technique is used to estimate the benefits from visibility improvements in the Los Angeles (South Coast) air basin.[13] Air quality is measured as actual visibility (median miles), the housing data is at the micro level and a large number of observations are utilized. The empirical results indicate that instability of benefit estimates for visibility improvements still occurs and is therefore not traceable to poor quality data.

The theoretical foundation of the hedonic price technique are also analyzed. A general theoretical model of the air quality/location decision is presented. A model differs from the standard Freeman-Rosen model (see Section II) in that an additional constraint on the choice of air quality is imposed. The model yields a set of testable hypotheses concerning the behavior of households and the resultant shape of the hedonic price function. Our empirical findings are not inconsistent with the model. By imposing additional econometric restrictions, the variation in the benefit estimates with respect to functional form is reduced. Therefore, the relationship between benefit estimates and functional form is not purely statistical but may be related to the underlying behavioral model.

The results of this section have important implications for determining the benefits of environmental improvements. They suggest that where functional form has a large impact on benefit estimation, a modified hedonic price procedure may be appropriate. This latter procedure, outlined here, produced a narrower range of benefit estimates.

The remainder of this section is organized as follows. In the next subsection, the base empirical results for visibility are presented. These are consistent with other results that demonstrate the sensitivity of benefit estimates to functional form. However, empirical results for living area are also presented. These indicate that the relationship between functional form and benefits may not be purely statistical but rather a symptom of some underlying problem. The alternative causes for benefit sensitivity are explored in Subsection III. In Subsection IV, the empirical results are presented. The importance of our empirical findings is demonstrated through an example policy application in Subsection V. In Subsection VI, concluding remarks are offered.

The Importance of Functional Form

In this subsection, base empirical results for the benefits of visibility improvements in the Los Angeles air basin are presented. These results are consistent with the previous conclusions concerning the importance of functional form. However, the results for square feet of living area are found to be quite insensitive to functional form. This produces a dilemma concerning the true cause of benefit sensitivity to functional form.

The data base, constructed to enable the estimation of a hedonic price equation, includes observations from Los Angeles, Orange, Riverside, and San Bernardino counties. As in the previous San Francisco analysis, the dependent variable is the sale price of owner occupied single family residences and the independent variable set consists of variables which correspond to three levels of aggregation: site, neighborhood, and community. Variable definitions are consistent with those outlined in Table 1. Summary statistics for this data set are presented in Table 9.

In order to test for the importance of functional form, the hedonic housing value equations were estimated using a variety of functional forms. These include the relatively simple forms such as linear, semi-log and log-linear and the more complex forms translog, semi-log quadratic and the Box-Cox transformations. The list of possible functional forms was reduced using the following procedures. First, previous empirical results indicate that the Box-Cox transformations (classical Box-Cox, Box-Cox extended) and other forms (semi-log, log-linear) yield very similar benefit values for this data set (see Trijonis et al, 1984). In addition, Bender et al (1980) found the translog to be statistically equivalent to the quadratic Box-Cox. Thus, the Box-Cox transformations were eliminated to prevent duplication of results. The second procedural rule was to eliminate those functional

TABLE 9

SUMMARY STATISTICS FOR VARIABLES USED IN ANALYSIS OF HOUSING MARKET FOR THE LOS ANGELES AREA

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
Home Sale Price	93060.00	60508.00	9000.00	725000.00
Sale Date	11.63	6.45	1.00	24.00
Age of Home	20.61	16.15	1.00	77.00
Bathrooms	1.86	0.42	0.50	7.50
Living Area	1524.00	608.90	371.00	9942.00
Pool	0.13	0.34	0.00	1.00
Fireplaces	0.72	0.61	0.00	5.00
View	0.078	0.27	0.00	1.00
Distance to Beach	14.53	11.99	0.13	59.80
Age Composition	9.33	5.48	1.30	60.70
Ethnic Composition	83.77	15.49	2.10	99.10
Time to Work	23.33	3.40	10.00	38.00
School Quality	66.07	4.56	45.60	81.00
Population Density	58.65	22.13	1.38	190.00
Miles to Business District	15.56	7.90	0.00	34.00
Crime	48.06	13.28	15.47	212.62
Age	29.87	2.68	22.00	49.00
Race	75.63	13.93	6.22	97.49
Unemployment	5.99	1.64	1.60	12.50
Education	73.74	9.48	30.70	97.00
Poverty	10.92	4.66	1.90	29.40
Home Density	10.61	3.53	0.19	26.99
Population Per Household	2.72	0.30	1.91	4.00
Visibility (2)	10.89	2.64	7.00	30.20

forms in which the variable of interest was insignificant. This rule was generally unimportant but was utilized to eliminate restricted versions of the translog and the semi-log quadratic.[14] Third, the more complex forms were tested to determine whether or not they constituted as improvement over the simpler forms. A likelihood ratio test was utilized. If the more complex forms did not constitute an improvement they were not considered. Finally, the linear functional form was not examined due to the theoretical argument of Rosen (1974) who suggested that linearity will occur only if consumers can arbitrage activities by untying and repackaging bundles of attributes. This is an overly restrictive assumption for the housing market.

Estimated hedonic equations for two of the forms -- log-linear and the semi-log quadratic -- are presented in column one of the Tables 10 and 11. As measured by any objective criteria (R^2, log of likelihood values) the estimated equations provide a very good fit of the data. In addition, the independent variables are generally significant at the one percent level and possess the expected relationship to home sale price. Of particular relevance is the visibility variable which is significant at the one percent level and is positively related to home sale price.

Following the hedonic procedure as outlined by Freeman and Rosen, these hedonic equations yield, through differentiation, the marginal implicit price of visibility for each individual in the data set. These implicit prices are then related to the characteristics of the household to estimate the inverse demand curve for visibility. A search over functional form in the inverse demand estimation was conducted.[15] Estimated quadratic inverse demand curves, based on the log-linear and semi-log quadratic forms, are presented in the first two columns of Table 12.

The final step of the traditional Freeman-Rosen hedonic approach is to determine the benefits of some environmental improvement. This is accomplished by integrating under the inverse demand curve for some specified change in the environmental good. In order to test the sensitivity of functional form, a ten percent uniform improvement was analyzed. The benefit results are presented in Table 13. As is illustrated, the individual household benefits of a ten percent improvement in visibility range from $1,042-$6,715 over the life of the house. This wide variation in benefit estimates for visibility supports the conclusion of other papers. In addition, the Bender et al analysis would suggest that the log-linear and semi-log forms are inferior on the basis of a likelihood ratio test. This would imply that these forms produce underestimates of the benefits of visibility improvements. Thus, using a statistical criterion (maximum likelihood value) to choose functional form would yield large household benefits.

TABLE 10

ESTIMATED LOG-LINEAR HEDONIC PRICE
EQUATIONS FOR VARIOUS VISIBILITY RANGES

Independent Variables	All Visibility	Visibility 12	Visibility 12 (restricted)	All Visibility (restricted)
ℓn (Age of Home)	-.0159 (-5.03)	-.0253 (-7.64)	-.0019 (-.19)	-.0187 (-5.57)
ℓn (Bathrooms)	-.0930 (6.54)	-.0631 (4.34)	-.1644 (3.96)	-.1040 (7.07)
ℓn (Ethnic Composition)	.2783 (6.16)	.2449 (24.42)	.2468 (7.20)	.2896 (28.59)
ℓn (Age Composition)	.0388 (6.16)	.0083 (1.18)	.1477 (7.66)	.0216 (3.15)
ℓn (Distance to Beach)	-.1166 (-29.10)	-.0910 (-20.85)	-.1912 (-15.11)	-.1021 (-24.04)
ℓn (Living Area)	.7348 (49.33)	.6996 (46.28)	.7553 (15.98)	.7294 (46.86)
ℓn (Visibility)	.1309 (5.82)	.0849 (2.52)	.1295 (.575)	.1824 (7.33)
Sales Date	.0145 (29.86)	.0135 (27.31)	.0189 (12.87)	.0141 (27.98)
View	.1579 (13.01)	.1549 (12.39)	.2072 (5.78)	.1484 (11.72)
Pool	.0746 (7.85)	.0544 (11.19)	.0634 (5.43)	.0682 (12.34)
Fireplaces	.0869 (13.50)	.0747 (11.19)	.0997 (5.43)	.0833 (12.34)
Orange County	-.1372 (-15.80)	-.1116 (-13.45)	----- -----	-.1395 (-16.03)
Riverside County	-.2716 (-13.88)	-.2180 (-10.51)	-.6813 (-3.28)	-.3209 (-15.42)
San Bernardino County	-.1750 (-11.77)	-.1945 (-13.87)	----- -----	-.1999 (-13.18)

TABLE 10 (Continued)

Independent Variables	All Visibility	Visibility 12	Visibility 12 (restricted)	All Visibility (restricted)
Factor 1	-.0276 (-6.84)	-.0503 (-12.30)	-.7020 (-2.25)	-.0403 (-5.70)
Factor 2	.0328 (8.20)	.0204 (4.73)	.0802 (1.43)	.0403 (9.67)
Factor 3	-.0089 (-2.09)	-.0100 (-2.44)	-.1786 (-4.80)	-.0107 (-2.47)
Constant	-.1735 (-1.46)	.3647 (2.61)	-.3174 (.46)	-.2827 (-2.23)
R-square	.80	.79	.84	.79
Number of Observations	4765	3718	637	4355
Residual Sum of Squares	216.87	135.03	35.78	196.72

TABLE 11

ESTIMATED SEMI-LOG QUADRATIC HEDONIC PRICE EQUATIONS FOR VARIOUS VISIBILITY RANGES

Independent Variables	All Visibility	Visibility 12	Visibility 12 (restricted)	All Visibility (restricted)
Age of Home	-.0186 (-9.45)	-.020 (-6.55)	-.006 (-.985)	-.016 (-8.020)
Age of Home Squared	.0001 (3.40)	.00006 (-2.712)	.0001 (1.780)	.00008 (3.124)
Number of Bathrooms	-.172 (-2.65)	-.426 (-4.629)	-.496 (-2.051)	-.176 (-2.569)
Number of Bathrooms Squared	-.007 (-.68)	-.004 (-.400)	.143 (2.745)	-.008 (-.775)
Percent White	.003 (-1.58)	-.008 (-2.253)	-.004 (-.633)	-.008 (-3.439)
Percent White Squared	.00001 (.79)	.00002 (1.526)	.0002 (4.244)	.00003 (1.737)
Percent Greater than 64	-.036 (-6.83)	-.023 (-2.544)	-.048 (-2.434)	-.024 (-4.295)
% Greater than 64 Squared	-.0004 (-3.20)	-.0001 (-.971)	-.0004 (-1.688)	-.0003 (-2.307)
Distance to Beach	.006 (1.91)	.014 (-2.997)	.078 (3.33)	.014 (4.379)
Distance to Beach Squared	.0003 (6.17)	.00005 (.908)	.0002 (.385)	.0001 (2.094)
Square Feet of Living Area	.001 (8.82)	.001 (6.674)	.001 (2.047)	.0006 (7.870)
Square Feet of Living Area Squared	-.0000001 (-18.03)	-.0000002 (-12.398)	-.0000001 (-8.69)	-.0000001 (-3.482)
Visibility	-.033 (-2.23)	-.105 (-1.771)	-.291 (-3.729)	-.055 (-3.482)

TABLE 11 (Continued)

Independent Variables	All Visibility	Visibility 12	Visibility 12 (restricted)	All Visibility (restricted)
Visibility Squared	.004 (5.13)	.002 (.308)	.021 (3.281)	.006 (7.523)
Age of Home X # of Bathrooms	.001 (2.25)	.001 (1.95)	.003 (1.969)	.001 (2.336)
Age of Home X Percent White	.0002 (11.88)	-.0002 (11.41)	.00004 (.88)	.0002 (11.38)
Age of Home X % Greater than 64	.00004 (.97)	.0001 (2.18)	.00002 (.255)	.00005 (1.167)
Age of Home X Distance to Beach	-.0001 (-5.05)	-.00007 (-2.71)	-.0002 (-1.465)	-.0001 (-5.137)
Age of Home X Square Feet of Living Area	-.000001 (-2.13)	-.0000008 (-1.482)	-.000003 (-2.231)	-.000001 (-2.580)
Age of Home X Visibility	.0001 (1.27)	.00009 (.416)	-.00002 (-.351)	-.00006 (-.542)
# of Bathrooms X Percent White	.002 (3.35)	.002 (3.196)	.0002 (.132)	.002 (3.838)
# of Bathrooms X % Greater than 64	.003 (1.90)	.004 (2.204)	.004 (1.077)	.002 (1.394)
# of Bathrooms X Distance to Beach	-.001 (-1.54)	.001 (1.156)	-.009 (-2.02)	-.001 (-1.866)
# of Bathrooms X Square Feet of Living Area	.00002 (3.60)	.00007 (6.897)	-.00009 (-3.183)	.00003 (3.606)
# of Bathrooms X Visibility	.0002 (.08)	.017 (2.396)	.026 (1.656)	-.001 (-.330)
% White X % Greater than 64	.0003 (5.50)	.0001 (2.110)	.0004 (2.465)	.0002 (4.647)
Percent White X Distance to Beach	-.00007 (-2.99)	-.00002 (-.555)	-.0002 (-1.337)	-.00006 (-2.362)

TABLE 11 (Continued)

Independent Variables	All Visibility	Visibility 12	Visibility 12 (restricted)	All Visibility (restricted)
Percent White X Square Feet of Living Area	-.000001 (-1.97)	-.000002 (-2.844)	.000003 (1.059)	-.000001 (-2.390)
Percent White X Visibility	-.000006 (-.05)	.0004 (1.806)	-.001 (-1.090)	.0003 (2.520)
Percent Greater than 64 X Distance to Beach	-.0001 (-2.28)	-.00002 (-2.66)	-.001 (-2.73)	-.0001 (-1.927)
% Greater than 64 X Square Feet of Living Area	.000002 (1.69)	.000001 (.659)	-.000004 (-1.030)	.000003 (1.529)
% Greater than 64 X Visibility	.001 (4.98)	.001 (.815)	.002 (1.734)	.0004 (1.455)
Distance to Beach X Square Feet of Living Area	.000002 (2.38)	.000003 (3.420)	-.000008 (-1.465)	.000002 (3.133)
Distance to Beach X Visibility	-.001 (-9.36)	-.00004 (-.113)	-.005 (-2.979)	-.0018 (-11.274)
Square Feet of Living Area X Visibility	.000008 (2.40)	.000008 (1.134)	.00002 (.811)	.00001 (3.197)
Sales Month	.014 (32.58)	.013 (28.627)	.019 (16.113)	.014 (31.298)
View	.172 (15.13)	.160 (13.225)	.117 (3.844)	.164 (14.002)
Pool	.050 (5.65)	.029 (2.987)	.408 (1.830)	.037 (3.999)
Number of Fireplaces	.084 (14.22)	.076 (12.021)	.063 (4.203)	.079 (12.994)
Orange County	-.114 (-10.92)	-.143 (-11.881)	N/A N/A	-.089 (-8.235)

TABLE 11 (Continued)

Independent Variables	All Visibility	Visibility 12	Visibility 12 (restricted)	All Visibility (restricted)
Riverside County	-.099 (-4.51)	-.142 (-6.208)	-.162 (-2.401)	-.135 (-6.180)
San Bernardino County	-.145 (-7.08)	-.097 (-5.008)	N/A N/A	-.138 (-6.804)
Factor 1	-.047 (-11.44)	-.055 (-12.620)	-.0998 (-3.477)	-.044 (-10.642)
Factor 2	.031 (7.30)	.037 (8.686)	.011 (2.36)	.031 (7.128)
Factor 3	-.013 (-3.20)	-.0120 (-2.945)	-.237 (-6.910)	-.015 (-3.616)
Constant	6.265	7.252	8.126	6.337
R-Square	.83	.82	.91	.83
Number of Observations	4765	3718	637	4355
Residual Sum of Squares	179.83	119.759	21.570	159.558

TABLE 12

ESTIMATED INVERSE DEMAND CURVES FOR VISIBILITY BY FUNCTIONAL FORM OF THE HEDONIC PRICE REGRESSION AND FOR VARIOUS VISIBILITY RANGES*

	FUNCTIONAL FORM							
	Log-Linear	Semi-Log Quadratic	Log Linear	Semi-Log Quadratic	Log-Linear	Semi-Log Quadratic	Log-Linear	Semi-Log Quadratic
	All Visibility		Visibility ≤ 12		Visibility ≥ 12 (Restricted)		All Visibility (Restricted)	
Visibility	44.66	1686.86	-329.70	-262.16	-573.41	-5517.53	-26.90	1075.45
	(1.93)	(10.73)	(-7.67)	(-.72)	(-2.70)	(1.58)	(-.67)	(4.15)
$(\text{Visibility})^2$	-1.63	-93.51	26.61	20.70	1.68	-139.61	.414	-95.17
	(-1.90)	(-16.00)	(6.70)	(.62)	(.291)	(-1.46)	(.308)	(-10.91)
Income	8.02	8.10	2.92	2.539	-48.98	-769.05	8.17	-22.64
	(13.88)	(2.06)	(4.86)	(.50)	(-3.10)	(-2.96)	(6.75)	(-2.88)
$(\text{Income})^2$	-.008	-.043	-.0048	.0016	.036	.1794	-.009	-.065
	(-6.26)	(-4.93)	(-6.41)	(.26)	(1.77)	(.535)	(-4.95)	(-5.61)
Visibility* Income	-.208	1.51	.079	.6406	3.01	56.40	-.082	6.22
	(-3.19)	(3.41)	(1.26)	(1.22)	(3.89)	(4.43)	(-.076)	(8.22)
Constant	-407.94	-15305.13	1900.83	-514.44	9748.83	87912.60	332.41	-10714.70
	(-2.24)	(-12.35)	(7.64)	(-.25)	(2.94)	(1.61)	(.965)	(-4.79)
R-Square	.16	.31	.26	.07	.19	.07	.17	.33
Number of Observations	4765	4765	3718	3718	637	637	4355	4355

*t-statistics in parentheses

TABLE 13
BENEFIT ESTIMATES AND FUNCTIONAL FORM

Functional Form	Benefits of a 10% Improvements in Visibility	Benefits of a 10% Increase in Living Area
1. Log Linear	1170.5	6631.4
2. Translog	6715.4	6327.7
3. Semi-log	1042.9	4722.4
4. Semi-log Quadratic	5345.3	6543.2

However, a similar analysis can be conducted for square feet of living area and the results are markedly different. The estimated quadratic inverse demand curves for living area based on the log-linear and semi-log quadratic hedonic equations are presented in the first two columns of Table 14. Benefits are then calculated for a ten percent change in square footage. As Table 13 indicates, the benefit estimates for this change are relatively insensitive to functional form. Moreover, the range of benefits for a change in the living area is overstated in the table since the semi-log hedonic equation is a poor specification for these data.[16]

The Basis for an Alternative Estimation Procedure

The inconsistency of the importance of functional form suggests that the cause may not be functional form. Rather, the cause of benefit sensitivity is related to the difference between the variables living area and visibility. It is this difference that is the subject of this subsection.

Consider first the quality of the data issue. The data utilized in the hedonic price estimation were obtained from a housing data clearinghouse. Over 100,000 observations were included in the original data set. Included in the list of available variables are those that pertain to both quantity (lot size, total number of rooms, square footage of living area) and quality (pool, view, number of fireplaces, parking, stories, etc.) of each particular house. This list was only pared to those variables presented in the equations in order to reduce collinearity problems. But note that both home quantity and quality are covered by the variables chosen.

It should be emphasized that housing data of such quality (e.g., micro level of detail over time) are rarely available for studies of this nature. Usually outdated data which are overly aggregated and collected irregularly (for instance census tract averages only in census years) are employed. Our data set yields results relevant at the micro level.

In addition to the housing characteristic data, the census tract variables which delineate the condition of the immediate area around the home were the most recent available (1980). The census tract data matched the housing data very closely. Thus, any shifts in neighborhood patterns were captured by using 1980 data rather than outdated 1970 census data.

TABLE 14

ESTIMATED INVERSE DEMAND CURVES FOR LIVING AREA BY FUNCTIONAL FORM OF THE HEDONIC PRICE REGRESSION AND FOR VARIOUS VISIBILITY RANGES*

	FUNCTIONAL FORM							
	Log-Linear	Semi-Log Quadratic	Log Linear	Semi-Log Quadratic	Log-Linear	Semi-Log Quadratic	Log-Linear	Semi-Log Quadratic
	All Visibility		Visibility ≤ 12		Visibility ≥ 12 (Restricted)		All Visibility (Restricted)	
Living Area Income	-.0032	.03136	-.0097	.0356	.010	.046	-.0035	.0324
	(-3.19)	(30.49)	(-8.88)	(43.01)	(2.34)	(6.43)	(-2.84)	(23.97)
$(\text{Living Area})^2$	.0000017	-.000007	.000003	-.000017	-.0000016	-.000009	.0000016	-.000007
	(6.16)	(-25.77)	(8.74)	(-64.86)	(-3.02)	(-11.03)	(5.81)	(-24.23)
Income	.0863	.0159	.1187	.041	.70	.914	.0722	-.019
	(9.05)	(1.63)	(14.12)	(6.44)	(9.89)	(7.78)	(6.85)	(-1.63)
$(\text{Income})^2$	-.00008	.00008	-.00014	.000016	-.0015	-.002	-.000018	.00022
	(-3.50)	(3.38)	(-5.56)	(6.82)	(7.26)	(-5.76)	(-.56)	(6.27)
Income* Living Area	-.000008	-.000012	-.000003	-.000009	-.000014	-.00005	-.000009	-.000016
	(-2.49)	(-3.70)	(-.94)	(-3.22)	(-.81)	(-1.76)	(-2.16)	(-3.45)
Constant	31.09	-.2693	26.51	-5.78	-64.99	-132.88	32.58	4.03
	(16.88)	(-.14)	(16.16)	(-4.64)	(-5.78)	(-7.13)	(16.21)	(1.82)
R-Squared	.06	.39	.20	.56	.26	.28	.07	.38
Number of Observations	4765	4765	3718	3718	637	637	4355	4355

*t-statistics in parentheses

Finally, a large number of community variables were included in the modeling through the use of principal components analysis. Thus, information on eight community variables was included where collinearity would normally permit many fewer. This improved the stability of our estimates, especially in regard to the visibility variable (see Trijonis, et al [1984] for a comparison).

In summary, the data base assembled the estimation of the hedonic equations is appropriate for three reasons. First, a large number of extremely detailed micro data are utilized. Second, a variety of neighborhood and community variables have been included to help isolate the specific effect of visibility on housing values. Third, this study uses what people actually see (visibility) rather than some proxy variable. Therefore, any sensitivity of the results to functional form because of data limitations has been reduced to the lowest possible level.

The second possible explanation for the apparent importance of functional form is that the traditional theoretical model is inappropriate. The standard Freeman-Rosen model was detailed in Section II. The first order conditions (interior solution) from the standard model imply that the implicit price of any characteristic (say dP/dE for environmental quality) equals the corresponding marginal rate of substitution between the characteristic and the composite good; in equilibrium the implicit price measures precisely an individual's marginal willingness to pay for the characteristic.

This model is probably quite accurate for a commodity like living area in which the underlying assumptions are satisfied. For instance, living area is relatively continuous, so that there exists a wide range of options enabling the home buyer (or producer) to trade off square feet for any other attribute. Differences in living area are also relatively easy to perceive and subsequently act upon. There exist other behavioral assumptions (see Freeman [1979] and Maler [1977] for reviews) but it seems apparent that interior space is an ideal characteristic since it satisfies the assumptions of the model.

When the data are of high quality and the theoretical model is an accurate representation of the choice process, functional form should not be an overwhelming factor but rather should increase slightly the accuracy of the estimates. As evidenced in the second column of Table 13, this is precisely the situation in the Los Angeles area. In addition, the results of the living area analysis provide estimates of the accuracy that can be expected from a hedonic study. The ratio of the largest to the smallest benefit estimate is approximately 1.4 for living area. Additional accuracy is unlikely. Moreover, it seems that the hedonic approach performs quite well for interior living area.

The case for the behavioral model representing consumer behavior with respect to visibility is more tenuous. This occurs even if households are assumed to perceive visibility differences and act on these perceptions. In contrast to living area in which the choice set is complete, the choices over visibility levels are quite limited. Restrictions on choice will occur throughout the range of visibility. However, the problem is most severe at the endpoints, especially in the Los Angeles region which is geographically bounded by ocean water and inland mountains. In these boundary areas individuals may not be able to obtain the visibility levels they desire. Thus, the theoretical model must be amended to account for those boundary areas.

The Los Angeles visibility situation can be represented by the following constraint:

$$\underline{E} \leq E \leq \overline{E}. \tag{4}$$

The inequality constraint illustrates that air quality is bounded from both above and below. E is the only variable treated in this manner. The basic premise is that air quality cannot be modeled accurately using the traditional Freeman-Rosen framework. The implicit assumption concerning square footage is that the choice set is complete. However, since air quality is physically bounded then all choices may not exist even if it is assumed to be continuous over a particular range. Therefore, the model is more general than seems apparent since the choice sets are accurately specified.

This constraint has no effect on households unless they desire an air quality level outside the feasible set. For instance, if $E = \underline{E}$ then the marginal rate of substitution between visibility and the composite good could be less than or equal to the implicit price of visibility. The household will take as little air quality as possible, locating in the most heavily polluted region. Thus, households in these polluted areas may prefer more air quality deteriorations in exchange for any housing price reduction. These households have a low willingness to pay for air quality improvements and will drive the implicit price of air quality toward zero. This corresponds to the possibility of an individual marginal damage function, relating air pollution to associated damage, that goes to zero at some level. Starrett (1972) discussed this possibility in detail.

This lower bound constraint implies that some a priori information about the shape of the hedonic function is available. That is, in the poor air quality areas, the implicit price of visibility will be relatively low and the hedonic functions will be relatively flat (horizontal for the lowest visibility levels).

Consider next the other end of the visibility range. If $E = \overline{E}$ then the relevant marginal rate of substitution could exceed the implicit price. The household may want more clean air than is available. The implications in this case are opposite of those above. In this case the areas with the least pollution will be inhabited by those with relatively large willingness to pay. Consequently, the hedonic function will become increasingly steep as the upper bound of visibility is approached.

Since the theoretical structure suggests that some a priori information is available on the shape of the hedonic function, it is possible to use this information to identify why the estimated benefits for visibility are so sensitive to functional form. The procedure used here is to estimate the lower and upper ranges of the hedonic function and test for consistency with our a priori hypothesis. Inconsistency with the model helps to identify possible breakdowns in the required assumption set. For example, and in the case considered below, this procedure may help to identify a segmented market that should not be contained in the data set.

Empirical Results

If consumers behave as if their maximization problem with respect to visibility is bounded as specified above, then the hedonic function will have two identifiable sections. There will exist a flat section in the relatively polluted region and a steep section in the relatively unpolluted region. Since our base visibility results demonstrate sensitivity of benefit estimates to functional form, the next step is to investigate these extreme regions in more detail. In particular, it must be determined whether or not these two sections are consistent with the theoretical structure based on the physical characteristics of the area.

The initial task is to determine what constitutes a section of the hedonic function. The existence of two quasi-independent regions of the hedonic function can be tested using a likelihood maximization procedure as suggested by Judge et al (1980, p. 389). A series of two equation models are estimated, each using a different visibility level as the factor determining how to divide the data. The level of visibility is found that maximizes the joint likelihood function. For the Los Angeles area sample, this level was 12 miles. Then, the two equation model is compared to the traditional one equation hedonic function model. For these data, the two equation model outperformed the one equation model on the basis of a likelihood ratio test. The results of this test were invariant with respect to functional form, indicating a clear distinction in the data. This explains why the one equation model was so sensitive to functional form; one equation was not general enough to adequately fit the data.

The estimated log-linear and semi-log quadratic hedonic functions for the group with visibility less than twelve miles are presented in the second column of Tables 10 and 11, respectively. The independent variable set performs quite well on the basis of proportion of variation explained and t-statistics. In addition, the coefficient on visibility is much smaller in this data set as compared to the full data set. This is the case in both functional forms even though the complex semi-log quadratic form prevents immediate visual inspection. The relatively small coefficient on visibility corresponds to the theoretical model which suggests the existence of a flat relationship between visibility and home sale price, especially in the areas of greatest pollution.[17] In contrast to these visibility results, the coefficient on living area remains remarkably stable indicating that this subset of data is consistent with the entire data set.

Given these hedonic equations, the corresponding demand curves are estimated (see columns three and four of Tables 12 and 14) and the benefits of a ten percent change in visibility and area are calculated. The range of visibility benefits is between \$200 and \$710 per household. The range for a ten percent change in living area is \$5610 to \$8540. Thus benefits for a change in living area remain insensitive to functional form, varying by approximately a ratio of 1.5 to 1. In addition, visibility is relatively less sensitive to functional form in the region where visibility is less than twelve miles. These results are not inconsistent with the model for the following reasons.

First, the small household benefits for visibility improvements in the area of less than twelve miles of visibility indicates a relatively flat hedonic gradient. Thus, the individuals who inhabit this region demonstrate a relatively small marginal willingness to pay for cleaner air. Second, functional form seems to be less important than when the entire data set is considered. This implies that the cause of benefit sensitivity to functional form is not associated with this range of the data. Third, living area remains insensitive to functional form. Further, the benefit estimates for this group for a ten percent change in living area are quite similar to those obtained using the entire data set; it seems there is little sorting on the basis of square footage.[18]

Consider next the group of households in the least polluted area. The theoretical structure predicts a steep positive relationship between visibility and home sale price. However, the hedonic equations initially estimated for this range of data violated the theoretical construct. In particular, the coefficient on the visibility variable was quite unstable across functional form, ranging from negative to strongly positive. Only the latter case is consistent with the model. The instability of the results indicated that the least polluted areas were the cause of the overall sensitivity to functional form. Therefore, the modelling effect allowed us to isolate the cause as being the upper range of the data.

Further investigation of the high visibility households revealed the presence of a portion of the data inconsistent with the model. This data, when grouped with the other observations, led to the theoretical violation described above. The approach used to overcome this problem was to restrict this data in accordance with the theoretical model. That is, since the model predicts a steep positive relationship between visibility and home sale price, then the inconsistent data was restricted to conform to this prediction. The validity of this restriction was then tested by estimating hedonic equations with and without the restriction. The results of the F-test indicate the restriction imposed by the theoretical model could not be rejected.[19]

Given that the restriction cannot be rejected, then hedonic equations employing the restriction are estimated for those areas with visibility greater than twelve miles. Typical hedonic equations for this group are presented in the third column of Tables 10 and 11. In regard to the coefficient on visibility, those estimates are quite different from those presented for the low visibility group. They demonstrate that visibility has a much greater effect on home sale price in this region.

The inverse demand curves for this group are presented in columns five and six of Tables 12 and 14. Integration of these demand curves for a ten percent change in visibility yields a range of household benefits that varies by a three to one ratio. The benefits associated with a ten percent increase in living area remain quite stable varying by a ratio of 1.2 to 1. Consistency with the theoretical model is demonstrated in a variety of ways. The visibility benefits are quite large indicating large willingness to pay for marginal improvements in this range of the data. The importance of functional forms for visibility is reduced. Finally, living area remains relatively insensitive to estimated functional form.

The value of the theoretical model can be specified as follows. The model yields predictions concerning the shape of the hedonic function. The results using the data in the visibility range less than twelve miles are in accordance with these predictions. However, the results for the high visibility areas are not. A segmented market was identified as the cause of the instability. Thus, the data in this market were dropped from the data set. The validity of the restriction was then tested and found to be statistically appropriate. The theory has allowed us to isolate the cause of benefits sensitive to functional form and to adjust the empirical estimates.

The final step in this hedonic procedure, modified by the inclusion of a restriction based on a behavioral model, is to reestimate the overall hedonic function with the restriction imposed. Examples of hedonic equations are presented in Tables 10 and 11. These equations are quite similar to the estimated equations initially presented, especially regarding the performance of the individual variables. In addition, a high proportion of variation in home sale price is explained by the variation in the independent variable set and all variables are significantly different from zero with the expected sign.

The inverse demand curve for two forms of the hedonic equations are presented in columns seven and eight of Tables 12 and 14. Evaluating these for a ten percent change in visibility yields the benefit values presented in Table 15. The results for a ten percent change in living area are also

TABLE 15
REVISED BENEFIT ESTIMATES AND FUNCTIONAL FORM

Functional Form	Benefits of a 10% Improvements in Visibility	Benefits of a 10% Increase in Living Area
1. Log Linear	1600.9	6352.3
2. Translog	4427.3	6098.0
3. Semi-log	1341.6	4481.4
4. Semi-log Quadratic	4530.5	6358.6

illustrated. As is evident, the living area results remain stable with respect to functional form (ratio of highest to lowest equals 1.4 to 1). In addition, these results are almost identical to those presented in Table

13, providing evidence that the restriction imposed has left these results unaffected. However, the visibility results are much different from those presented earlier. In particular, the impact of functional form yields a 3.38 to 1 ratio rather than the approximate six to one ratio established earlier.

The visibility results presented in Table 15 have two important implications. First, it seems that prior information can be utilized to reduce the variability of the benefit estimates with respect to functional form. The second implication concerns the Bender et al (1980) conclusions. They suggest the use of statistical criteria to determine which functional forms yield the best benefit estimate. Using their criteria, the translog and semi-log quadratic function forms would be considered best in this analysis. This would suggest benefits in the range of $5345 to $6715 per household. However, the imposition of a slightly modified theoretical construct demonstrates that this range overestimates the benefits of visibility improvements. Thus, the accuracy of the benefit estimate can be increased through the use of prior information concerning the shape of the hedonic function.

Concluding Remarks

The basic premise of this section is that benefit estimates sensitive to functional form are not inherent to the hedonic price method. Evidence to support this premise is presented. Thus, as is illustrated, the hedonic price method is quite accurate in some situations and can be improved through the application of prior information in other cases.

In addition to this general conclusion, the empirical results suggest the following conclusions. First, the traditional Freeman-Rosen hedonic approach seems appropriate for square footage of interior living space. The estimated benefits for a ten percent change in living area are quite stable, demonstrating that functional form has only a minor impact. In this instance, functional form produces minimal adjustments to the basic results. It should also be noted that the minimum ratio of highest to lowest estimates is likely 1.4 to 1.

The second implication is that visibility does not correspond to the traditional model. Evidence of this is the sensitivity of the benefit estimates to functional form. A slight modification of the traditional model provides additional structure to the estimation procedure. The hedonic gradient is hypothesized to be relatively flat for the heavily polluted areas and relatively steep in the unpolluted areas. This additional structure reduces the range of benefit estimates from 6/1 to 3.3/1. The minimum ratio has not been reached but the range has narrowed significantly. This result leads to the conclusion that functional form may be the symptom rather than the cause of unstable benefit estimates.

Finally, the empirical results indicate that a modified procedure may be appropriate. Thus, were sensitivity to functional form is evident, then restrictions based on theoretical considerations may increase the accuracy of the estimates.

SECTION V

THE MULTI-MARKET HEDONIC APPROACH

The results presented in the previous two sections have employed the traditional hedonic approach, modified only by an additional restriction on the functional relationship between the hedonic equation and the inverse demand curve (see Brown and Rosen [1982]). This restriction allows identification of the inverse demand curve. However, there exists an alternative approach to demand identification, suggested by both Mendelsohn (1980) and Palmquist (1981). As outlined in Section II, their suggestion is to utilize multi-market data to obtain price variation, thereby permitting identification.

In this section the multi-market approach is empirically implemented using data from two markets, San Francisco and Los Angeles. This analysis provides: (1) evidence on the efficacy of the multi-market approach, and (2) justification for the single market analysis of the previous two sections.

The data used to estimate the benefits of air quality improvements with the multi-market approach are essentially the same as those employed previously (see Table 1 for variable definitions). However, there are three substantive changes from the previously described data. First, a different random sample was taken in San Francisco. This is somewhat larger (3096 observations) to provide additional robustness. Second, in order to estimate consistent hedonic equations across the different markets, the ozone variable is eliminated from the San Francisco equation.[20] Finally, light extinction is used to measure air quality rather than visibility.[21] This is done since most hedonic equations are estimated in terms of air pollution rather than air quality (see Harrison and Rubinfeld [1978]).

The initial step in the multi-market approach is estimation of the hedonic equations for each area. Two different functional forms, semi-log and classical Box-Cox, are presented in Tables 16 through 19. The equations perform well in every respect. In addition, the extinction variable is negative and significantly different from zero.

This set of hedonic equations is the basis for determining the benefits of extinction improvements. In order to complete the benefit estimation procedure, the following steps are required. First, the hedonic equations are differentiated to determine the marginal willingness to pay for a change in extinction. The marginal willingness to pay is evaluated for each individual point in the data set. Given these implicit prices, an inverse demand curve can be estimated by regressing price against quantity (extinction) and other household (homeowner) shift variables (income, etc.). Integrating under these inverse demand curves for any proposed extinction change yields the benefits attributable to the change.

TABLE 16

ESTIMATED HEDONIC EQUATION (SEMI-LOG)
FOR THE LOS ANGELES AREA

Dependent variable = ℓn (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	0.014	28.93
Age of Home	-0.0018	-7.07
Square Feet of Living Area	0.036	41.58
Number of Bathrooms	0.104	13.02
Number of Fireplaces	0.101	15.64
Pool	0.048	4.99
View	0.162	13.19
Neighborhood Characteristics:		
Percent Greater than 64	0.0060	9.00
Percent White	0.0068	28.42
Location Characteristics:		
Distance to Beach	-0.013	-26.17
Orange County	-0.177	-19.54
Riverside County	-0.095	-4.26
San Bernardino County	-0.0068	-0.39
Community Characteristics:		
Factor 1	-0.037	-9.18
Factor 2	0.027	6.67
Factor 3	-0.117	-2.67
Light Extinction:	-0.038	-2.70
Constant	5.44	152.11

R-Squared	0.795
Number of Observations	4766

TABLE 17

ESTIMATED HEDONIC EQUATION (CLASSICAL BOX-COX)
FOR THE LOS ANGELES AREA

Dependent variable = (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	0.010	28.84
Age of Home	-0.0014	-7.66
Square Feet of Living Area	0.025	40.90
Number of Bathrooms	0.073	12.82
Number of Fireplaces	0.073	15.78
Pool	0.033	4.83
View	0.112	12.81
Neighborhood Characteristics:		
Percent Greater than 64	0.0041	8.70
Percent White	0.0049	28.86
Location Characteristics:		
Distance to Beach	-0.0095	-25.91
Orange County	-0.126	-19.45
Riverside County	-0.069	-4.34
San Bernardino County	-0.0077	-0.63
Community Characteristics:		
Factor 1	-0.027	-9.24
Factor 2	0.0199	6.72
Factor 3	-0.0078	-2.47
Light Extinction:	-0.025	-2.51
Constant	4.79	187.53

R-Squared	0.795
Number of Observations	4766

* Indicates the variable is transformed using the Box-Cox transformation.

TABLE 18

ESTIMATED HEDONIC EQUATION (SEMI-LOG)
FOR THE SAN FRANCISCO AREA

Dependent variable = ℓn (home sale price in hundreds of 1978-79 dollars)

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	0.015	25.57
Age of Home	-0.0022	-8.06
Square Feet of Living Area	0.039	35.60
Number of Bathrooms	0.052	5.31
Number of Fireplaces	0.091	11.33
Pool	0.097	6.11
View	0.068	5.19
Neighborhood Characteristics:		
Percent Greater than 64	0.0039	5.68
Percent White	0.0063	27.27
Location Characteristics:		
Distance to Beach	-0.0056	-8.21
Alameda County	-0.212	-11.38
Contra Costa County	-0.336	-15.34
San Mateo County	-0.121	-6.52
Santa Clara County	-0.097	-4.21
Community Characteristics:		
Factor 1	-0.051	-9.40
Factor 2	0.020	3.15
Factor 3	-0.0067	-1.08
Light Extinction:	-0.127	-2.70
Constant	5.77	76.81

R-Squared	0.797
Number of Observations	3106

TABLE 19

ESTIMATED HEDONIC EQUATION (CLASSICAL BOX-COX)
FOR THE SAN FRANCISCO AREA

Dependent variable = (home sale price in hundreds of 1978-79 dollars)*

Variables	Coefficient	t-Statistic
Site Specific Characteristics:		
Sales Month	0.107	25.64
Age of Home	-0.016	-9.28
Square Feet of Living Area	0.027	35.04
Number of Bathrooms	0.037	5.40
Number of Fireplaces	0.067	11.53
Pool	0.067	5.90
View	0.047	5.05
Neighborhood Characteristics:		
Percent Greater than 64	0.0027	5.46
Percent White	0.0046	27.92
Location Characteristics:		
Distance to Beach	-0.004	-8.18
Alameda County	-0.152	-11.44
Contra Costa County	-0.243	-15.57
San Mateo County	-0.087	-6.60
Santa Clara County	-0.071	-4.35
Community Characteristics:		
Factor 1	-0.036	-9.30
Factor 2	0.148	3.28
Factor 3	-0.0062	-1.41
Light Extinction:	-0.91	-2.70
Constant	5.026	93.94

R-Squared	0.795
Number of Observations	3106

*Indicates the variable is transformed using the Box-Cox transformation.

Estimated inverse demand curves are presented for both the Los Angeles and San Francisco areas following the approach set out by Freeman (1974, 1979) and Rosen (1974). In addition, the alternative using the data pooled from across the two study areas to estimate a multi-market demand is implemented.

Because of data difficulties, the demand curve estimation is performed at the community level, rather than at the individual level. Specifically, because individual homeowner income is not available, the price and quantity data must be aggregated to the community level. The demand curve estimation utilizes the following data. Marginal willingness to pay (in hundreds of dollars) is the implicit price of light extinction improvements per $(10^4 m)^{-1}$. It is the derivative of the hedonic equation evaluated for each data point, and it represents the average home sale price differential attributable to a unit extinction difference. The quantity variable is the initial average community extinction level. Income represents average community income in hundreds of dollars per year.

The inverse demand curves for Los Angeles and San Francisco are presented in Table 20. A large proportion of variation in marginal willingness to pay is explained by extinction level and income. In addition, the variables perform as expected.[22]

An alternative approach to estimating separate demand curves is to pool the data across markets and estimate one multi-market inverse demand curve. The theoretical reasoning for this approach, outlined previously, is associated with Mendelsohn (1980) and others. This approach requires the assumption that individual preferences must be identical across the markets. It is felt that this is a very unreasonable assumption because individuals tend to gravitate to their own kind. For example, those who are relatively adverse to pollution might not live in the Los Angeles area.

The multi-market inverse demand curves are also presented in Table 20 for the common hedonic price equations. The equations seem to be dominated by the negative extinction result for Los Angeles. The coefficients are quite significant, but R^2 values are lower reflecting the difficulty of determining a common demand curve for diverse groups.

A comparison of the single market result to the multi-market results can best be completed by calculating benefit figures from each equation. Consider again a hypothetical ten percent improvement in average visibility over the entire Los Angeles area. Integration of the inverse demand curves for this change yields the household benefits associated with the change.[23] The Los Angeles area inverse demand curve based on the semi-log hedonic equation yields an average annual value of approximately $62 per household. The corresponding pooled estimate is $99 per household annually. The difference may be partly attributed to the use of San Francisco individual preferences in evaluating a Los Angeles policy. Since San Francisco individuals are likely more adverse to pollution, they place a higher value on the improvement.

TABLE 20

ESTIMATED LINEAR DEMAND CURVES
FOR LOS ANGELES AND SAN FRANCISCO

Dependent variable = marginal willingness to pay for light extinction improvements in hundreds of 1978-79 dollars

Functional Form of Hedonic Price Gradient	Independent Variable Coefficients (t-statistics) Constant	Light Extinction	Income	R^2	Number of Observations
		Los Angeles			
Classical Box-Cox	14.75	-3.84 (-2.39)	0.090 (21.39)	0.81	112
Semi-log	17.28	-3.89 (-2.30)	0.092 (21.06)	0.80	112
		San Francisco			
Classical Box-Cox	-22.78	23.49 (1.29)	0.429 (15.50)	0.84	51
Semi-log	-9.68	25.65 (1.73)	0.337 (149.69)	0.84	51
		Multi-Market			
Classical Box-Cox	110.96	-63.62 (-10.02)	0.207 (8.98)	0.56	163
Semi-log	111.39	-60.06 (-10.80)	0.178 (8.82)	0.57	163

This result confirms our reservations about pooling the data across obviously diverse groups. Thus, this approach seems to require assumptions that are overly restrictive in that self-selection in location is ignored. Further, it seems that any result can be obtained through selective choice of the cities to include in the multi-market analysis. A well designed single market analysis seems to be the best hedonic approach.

SECTION VI

CONCLUDING REMARKS

The research reported in this chapter was designed to use and extend the hedonic housing value approach to estimate the benefits of air quality improvements. Three specific issues were examined: the health/aesthetic component values of air quality, the importance of functional form in hedonic estimation and demand curve identification.

In general, it was determined that the traditional hedonic housing approach is a viable method for estimating the benefits of environmental improvements. Recent criticisms concerning demand curve identification and the importance of functional form were found not to be as serious a previously thought. The demand curve can be accurately estimated by imposing a restriction on the functional relationship between the hedonic equation and the inverse demand curve. A multi-market approach can also be used but it is considered inferior. Functional form was found to be relatively unimportant in San Francisco. In addition, the effect of functional form can be reduced by using prior information.

Given that the hedonic housing value approach produces reasonable benefit estimates, it can be utilized to value the individual components of air quality. The analysis in San Francisco suggests that for a ten percent air quality improvement, approximately one-third to one-half is accounted for by health aspects.

FOOTNOTES

1. See J. Trijonis, et al (1984) for a precise definition, as well as construction of the visibility variables.

2. Thus, this research is designed to examine subclinical health effects. This includes all ozone effects and since ozone accounts for most of total oxidant then this variable also proxies for effects of other oxidants. This approach ignores the health effects of the primary pollutants but evidence of these effects is more readily available.

3. The sale price of the discounted value of the flow of rents rather than actual rent is used as the dependent variable. The two are interchangeable given the appropriate discount rate.

4. See Freeman (1979) and Maler (1979) for reviews of estimation techniques for hedonic housing equations.

5. The insignificance of these variables does not present an overwhelming problem because in the final equation they are eliminated using principal components analysis.

6. See Section V for an estimated equation with 3106 observations.

7. The equations using other visibility measures are not reported here because they essentially duplicate the results presented.

8. It should be noted that in Table 6 ozone is measured as days exceeding twelve pphm. An alternative specification using days exceeding ten pphm (correlation between the two being 0.9) was also estimated. In this latter case the coefficient on ozone was -0.0064, significant at the one percent level. The monetary impact of a one day decrease was then estimated at $560. However, the average number of days was 6.66. Therefore, if all days in both specifications are improved below the standards then the value would be approximately $3,700.

9. Note that the ozone variable is not transformed. This is because fifteen observations are zero and cannot be transformed. If those data points are eliminated, then the semi-log and log-linear equations are both adjusted in a similar manner.

10. Demand curves usually represent quantity as a function of price. In this case, price is a function of quantity, so the label is "inverse" demand curve.

11. See Section IV for a comparison of this approach to the multi-market approach proposed by Mendelsohn (1980) and others.

12. Stated differently, one less day exceeding twelve (ten) pphm is valued at \$436/year (\$57.6/year). Thus, improvement in ozone that satisfies the ozone standard produces benefits of approximately \$370/year/household.

13. In this context visibility is treated as a proxy variable for the overall level of air quality. The aesthetic/health division is not considered here due to collinearity among the pollution variables. Thus, this reduces the dimensionality of the problem, allowing us to focus on the functional form issue.

14. The restricted versions include subsets of the total number of interaction variables. In addition to the visibility variable being insignificant, these forms never performed as well as the forms that included all the relevant interaction terms.

15. In general, benefit estimates were quite insensitive to functional form of the inverse demand curve. In addition, Brown and Rosen (1982) have shown that identifying the inverse demand curve with single market data requires some a priori restriction regarding its functional form. We have restricted the inverse demand curves to be quadratic.

16. For instance, on the basis of log of likelihood values the semi-log form is a much poorer form than the log-linear (see Trijonis, et al (1984) for actual calculations).

17. In addition to the generally flat relationship between visibility and home sale price in this range of the data, the model is further supported in that for the worst air quality zones (visibility less than eight miles) the coefficient on visibility is insignificant.

18. There is also no evidence of sorting by income as each subset of households has income statistically equivalent to all others.

19. There were 410 observations (mostly from Santa Monica -- a beach community) that appeared to constitute the segmented market. The F ratios comparing the sum of squared errors of the hedonic equations with and without these data were greater than one for all functional forms. Thus, the restriction that these 410 observations constituted a segmented market was imposed and the equations were estimated without these data (see column four of Tables 10 and 11).

20. This points out a possible problem with the multi-market approach. Ideally, ozone or some other measure of the health aspects should be included in the hedonic equation. However, collinearity prevents its inclusion in Los Angeles and consistency requirements prevent its use in San Francisco.

21. Light Extinction = 18.7/visibility and is measured in $(10^4 \text{ meters})^{-1}$.

22. Note that no sign can be predicted a priori on the extinction variable (Bartik and Smith [1984]).

23. The formula used in these calculations is:

$$\int_{\text{Extinction after}}^{\text{Extinction before}} (MWTP_i)\, d(\text{Extinction})$$

where $(MWTP_i) = f(\text{income, extinction})$.

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