AN ABSTRACT OF THE THESIS OF

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Rebecca L. Johnson

This thesis investigated the contribution of the forest to neighboring property prices and explored the possible impacts from different neighboring forest characteristics with the hedonic property price model.

The quadratic Box-Cox model was applied to choose the proper functional form. The square root model was chosen to be the interpretable functional form that best explained the data. To check the strength of the regression estimation, the linear model and a weighted regression were also applied.

The distance from the forest has a significant negative relationship with property prices in all of the estimations. The implicit price of proximity to the forest increases as distance decreases and this relationship is stronger for closer houses in the estimated square root model. For example, the property price change is $6.13 per foot for a house 100 ft away, while it is $1.94 per foot for a house 1000 ft away. In the linear model, for each one foot closer to the forest, the house price is worth about $2.87 more at any distance.

After accounting for the contribution of proximity to McDonald-Dunn Forest, the variables for the neighboring forest characteristics were applied to the hedonic price model. Being close to even-aged forests results in a negative contribution to the property price, while being close to shelterwood stands with taller trees has positive impacts.

When the property is close to agricultural pasture rather than to forestland, property prices tend to be much lower. Neighboring pure conifer stands have higher contribution to the property price than hardwood or mixed stands.

The visibility of clearcut sites in the forest was analyzed by using GIS and the elevation of the area. If all other characteristics of a property are identical, the sales price is lower for the property where clearcut sites are visible at the time of purchase.

This study applied the hedonic price model to the near urban forest area and expanded the possibility of GIS application in measuring locational amenities. Results of this study could be used to negotiate arguments between forest owners and neighboring homeowners to produce forest characteristics that are acceptable to neighbors, while providing compensation to the forest owners.

Measuring the Economic Impact of Forests on Neighboring Properties

by

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1. INTRODUCTION

1.1 Background

The market value of commercial forest products can be just the "tip of the iceberg" if we consider the various benefits we get from forests. Without seeing the whole iceberg, it is difficult to compare benefits and costs in the decision-making process for conflicting uses of forests.

Total value of forests includes use and nonuse values. Use value is based on actual enjoyment of a commodity or a service from forests, whereas nonuse value is the desire to preserve the potential future uses or simply to know that something exists. When one consumes a commodity such as timber, that use excludes use by others and reduces the opportunity for possible uses by others. Therefore, competition for its use and the resulting market price can be an indicator of consumptive use value. For other commodities or service flows from forests, such as recreation opportunities or environmental amenities, one's enjoyment is neither exclusive nor reduced by the use of others (non-rival). These are nonconsumptive uses, and their market prices are often absent or underestimate their real values. Neighboring forest homeowners derive recreational opportunities, scenic views, clean water and air, etc., which are nonconsumptive use values. Even though they may derive other values from the forest, most are likely to be nonconsumptive. One way to estimate this value is by simply asking people how much they are willing to pay for it. By creating a hypothetical market, we may capture the nonuse as well as nonconsumptive use values. An alternative is to observe what people are paying directly and/or indirectly in an actual market, reflecting the nonconsumptive use value.

The hedonic price model, an indirect value estimation method, is a way to observe an implicit price for a characteristic in the market price of a commodity such as housing. This regression analysis estimates the contribution of each explanatory variable of housing prices such as the housing structure and surrounding locational amenities. For example, forest-neighboring homeowners have better access to recreation opportunities and more beautiful views of the neighboring forest. The hedonic price method can measure the value of proximity to the forest and can compare the differences in economic value of forests with respect to distinct management schemes. Based on actual market transactions, this method avoids some of the problems inherent in hypothetical markets used in contingent valuation.

In earlier years, the hedonic price method was developed and applied primarily to measure the value of clean air in metropolitan areas. Here it was possible to observe quarterly updated sale records on properties that have similar attributes. In this study, the forest-neighboring properties have different housing characteristics and the number of market transactions is small. Different data characteristics affect the process of model estimation and variable selection. Because economic theory does not adequately address the functional form of the hedonic price model, a flexible functional form, the quadratic Box-Cox model, will be applied to choose the proper functional form.

1.2 Study Area

McDonald-Dunn Forest near Corvallis, Oregon, was chosen for this study because it provides unique amenities to the surrounding community as well as to adjacent suburban residential properties. Johnson et al. (1992) showed that neighbors adjacent to the forest were very concerned about the effect of forest management activities on their property values. Over 80% of interviewed homeowners said that the adjacent forest was important in their decision to purchase their house. In addition, a majority of surveyed neighbors said that they would be willing to pay a substantial amount of money to the adjacent forestland owner to avoid having a clearcut in their "backyard." These results suggest that proximity to the forest as well as the types of forest management practiced, can have an effect on property prices.

To investigate the relationship between the forest and the neighboring residential properties more carefully, the hedonic price model was applied to the housing market surrounding McDonald-Dunn Forest. The contribution of the surrounding forest to neighboring property prices was estimated, and the values derived from different forest characteristics were compared.

1.3 Objectives

The objectives of this study are as follows:

1) to explore the nature of price data in properties surrounding the McDonald-Dunn Forest for the best estimate of the hedonic price model.

2) to estimate the hedonic price models.

3) to systematically compare the results from different hedonic price functional forms and explanatory variable selections.

4) to estimate the forest's contributions to neighboring property values and compare them with respect to different neighboring forest characteristics and management schemes.

2. LITERATURE REVIEW

2.1 Theory

The idea of measuring the marginal price of a certain implicit characteristic of property dates back many years. For example, highly productive farmlands produce more crops and can be sold (or rented) at a higher price than low-productivity lands. That difference in price is the implicit price of productivity. The first application of the hedonic method in residential properties was by Ridker and Henning (1967), where they investigated the association between air quality and property values.

Rosen (1974) and Freeman (1979) expanded this idea as a possible tool for welfare measure and established the conceptual theory of the hedonic price model. The first stage estimation of the hedonic price model is to estimate the marginal price for the characteristic of interest by regressing a commodity price on its attributes. Rosen demonstrated that the price function of a certain commodity is not linear for some component characteristics when repackaging is impossible. For example, a four-bedroom house is not equivalent to two two-bedroom houses. When the price function of housing is not linear in a certain characteristic, its implicit price is not a constant but is a function of its quantity. If there is a relationship between price and quantity, the implicit demand function for the characteristic can be established as for a normal commodity. However, it is observed with present income and utility levels of individuals in the market. When people make more money, they may want a better house and the marginal willingness to pay for a certain implicit characteristic can change. People's tastes for a house can also change as they get older and the form of the underlying utility function may differ.

The second stage estimation is to identify the inverse demand curve or the marginal willingness to pay function, from the implicit price function estimated in the first stage. The inverse demand function takes the changes in income and utility levels into account. Rosen suggested that the inverse demand function of an implicit characteristic could be estimated by using its marginal price as an endogenous variable in the second-stage simultaneous equation with the supply function. If it is possible to trace back the inverse demand function from the implicit marginal price function, it is also possible to measure the utility change with respect to certain quality changes by integrating the inverse demand. However, Rosen realized that there would be "garden varieties of identification problems" when identifying the inverse demand function. The ensuing discussion describes the conditions under which an inverse demand curve may be identified, although there seems to be some disagreement. Because the necessary conditions seemed unrealistic for this study area, I did not attempt to recover the inverse demand function from the estimated implicit marginal price function.

One of the identification problems in Rosen's framework is from the interaction between supply and demand of a characteristic when the inverse demand function is estimated. Freeman (1979) earlier suggested an examination of the supply side of a certain characteristic. This can be simplified in two special cases. One is when the supply of a commodity is perfectly elastic, and an infinite amount of a characteristic can be obtained at the same price. The second case is when the supply of a characteristic is fixed. In both cases, the marginal price of a characteristic becomes exogenous in the estimation of the inverse demand function. Bartik (1987) criticized this Rosen-Freeman approach of estimating the hedonic price model. He argued that the hedonic estimation problem is not due to the interaction between demand and supply, and that an individual consumer cannot affect suppliers in the hedonic model because an individual buyer's demand for an implicit characteristic cannot affect the hedonic price function. Therefore, "the hedonic estimation problem is instead caused by the endogeneity of both prices and quantities when the household faces a non-linear budget constraint" and he proposed "an instrumental variable solution using instruments that exogenously shift the budget constraint." Freeman (1993) said that because our interest was in the values of characteristics to homebuyers, there was no need to formally model the supply side of this market. Consistent with Bartik's argument, this means that an individual consumer's decision cannot affect suppliers in the hedonic model.

Freeman (1979; 1993) criticized Rosen's argument (1974) that implicit price and quantity data from a single market could be used to estimate this inverse demand function. He indicated that using a single market data could be enough in only two special cases. First, when repackaging is possible and the price function is linear, the implicit price is constant, and nothing can be revealed about the relationship between implicit price of a characteristic and its quantity. Second, when the hedonic price model is not linear but all the individuals in the market are identical in their income and utility, the marginal willingness to pay is the same for all individuals. The inverse demand function can be identified immediately by the marginal implicit price function in this case. He suggested two ways to estimate the inverse demand functions of a certain characteristic of a commodity:

> The first is to increase the quantity of information obtained from marginal implicit prices by estimating hedonic price functions for several separate markets, and then pooling the cross-sectional data on the assumption that the underlying structure of demand is the same in all markets (also Freeman, 1974; Brown and Rosen, 1982; Palmquist, 1984). The second approach is to impose additional structure on the problem by invoking a *priori* assumptions about the form of the underlying utility function. (Freeman, 1993; p. 131)

Another problem is identifying whether the housing market is actually in equilibrium. When homebuyers don't have full information or the market is still in the adjustment period, the marginal implicit price is a biased estimate of the marginal willingness to pay. Freeman (1993) suggested that in many cases divergences from full equilibrium could only introduce random errors. Palmquist (1991) showed that aggregation over time should be considered with caution and problems with temporal stability of the hedonic equation could be tested empirically. An F-test can be used to detect a change in the market structure over the range of the aggregated time period.

Defining the geographical market for estimating a hedonic price model has been controversial as well. Should a metropolitan area be defined as a housing market with a single price function? Should we identify the submarkets with locational and political boundaries or with individual characteristics like race and income? Market segmentation studies by Michaels and Smith (1990) found differences in submarkets. Freeman (1993) suggested that two conditions must be met for different hedonic price functions to exist in an urban area.

> The first is that either the structure of demand, the structure of supply, or both, must be different across segments...The second condition is that purchasers in one market segment must not participate significantly

> in other market segments...Such barriers could be due to geography, discrimination, lack of information, or a desire for ethnically homogeneous neighborhoods. (p. 386)

In this study, the main interest is to know the connection between a certain characteristic and property values, which can be shown as its implicit price. Many real estate appraisal studies adopted the hedonic price model to break down the components of the housing price and to evaluate the value of each housing characteristic. The identification problems in economic theory stated above are not important when only the structure of the price function is of interest and the inverse demand is not being recovered. However, there are issues related to functional form that must be considered when estimating the hedonic price model.

2.2 Functional Forms and Model Estimations

After establishing the theoretical background for using cross-sectional demand-side information, identifying a correct functional form is the major task for applying the hedonic price model. Economic theory has very little to say about the functional form of the hedonic price equation. Rather conventional functional forms are suggested by Halvorsen and Pollakowski (1981). They proposed a procedure to choose a functional form for hedonic price equations by applying the quadratic Box-Cox model. They rejected the most common functional forms such as the linear, log-linear, and semilog, because the log-likelihood values from these functional forms were significantly smaller than that of the optimal functional form. However, the comparison of log-likelihood values is only meaningful if we can assume normally distributed errors. Depending on the results, the optimal estimates of the quadratic Box-Cox parameters are sometimes hard to interpret.

Box and Cox (1964) suggested that the choice of the Box-Cox parameter (λ) should be meaningful and interpretable. They considered the transformation of the response variable (*y*) only and the functional form was determined by the value of the estimated Box-Cox parameter (λ).

> Having chosen a suitable λ, I should make the usual detailed estimation and interpretation of effects on this transformed scale. Thus in our two examples I recommended that the detailed interpretation should be in terms of a standard analysis of respectively *1/y* ($\lambda = -1$) and *log y* ($\lambda = 0$), since the value of λ used is selected at least partly in the light of the data, the question arises of a possible need to allow for this selection when interpreting the factor effects. (p. 239)

In many cases, the main purpose of the hedonic study is to know the implicit price of a factor, which is the partial derivative of the estimated hedonic price function. For a meaningful and interpretable partial derivative, i.e., the implicit price function, we need to choose suitable Box-Cox parameters in the range of the estimated optimal parameters.

Box and Cox's original intention was that when the assumptions for multiple regression analysis were not satisfied in terms of original observations, a non-linear transformation might be beneficial. Cropper et al. (1988) showed that when some attributes for the hedonic price function were unobserved or were replaced by proxies, linear and linear Box-Cox models performed better than the quadratic Box-Cox model in their Monte Carlo study.

Graves et al. (1988) did a systematic comparative analysis of functional forms and variable selections with three categories of explanatory variables. The "focus" variable group included the variables of primary interest in the investigation, but whose relationship with property value was unknown. The other variables known to be related to the property price were called "free" variables. The "doubtful" variables included other potential explanatory variables. They indicated that the reaction of the parameters on focus variables under different free and doubtful variables should be considered, because of the interest in the marginal price of focus variables. They found that the specification of the model and outlying observations greatly affected the results even within the very sophisticated statistical model, and suggested the minimum absolute deviation estimator instead of least squares.

Dubin (1988) suggested that spatial autocorrelation occurred in hedonic price studies, especially when the studied area was non-urban. Distance between observations performed a function similar to that of time in a time series. For example, properties tend to be bigger in rural areas than in urban areas. The distance from a city is highly correlated with the other explanatory variables for property prices such as lot size and total number of rooms. Dubin presented a maximum likelihood procedure for simultaneously estimating the correlation and regression function.

In some studies, the generalized method of moments approach was applied to overcome this spatial correlation (Can, 1992; Bell et al., 1997). In these spatial hedonic models, the correlation between distance and other explanatory variables was introduced in the regression, and the linear regression model was usually applied. According to Dubin (1988), a linear hedonic regression function was unrealistic and violated basic tenets in economic theory, because it assumed no change in the marginal price of an implicit characteristic when its quantity changed.

Parsons (1990) examined the exogenously fixed supply of locational attributes of housing and suggested the use of weighted regression by lot size. He argued that a 2-acre house had twice the locational attributes of a 1-acre house and this bigger house should be weighted more in the count of the locational attribute variables in the regression. This was true when the existing houses are perfect substitutes for new houses and there was no barrier for subdividing a lot. If air quality was good in an area where lots tended to be large, the implicit price of air quality would be overestimated without weighted regression.

A procedure or a single functional form should not be a general rule for the hedonic price model. The right application should be based on the nature of the data. Halstead et al. (1997) investigated the issues of functional form choice in hedonic price functions to estimate effects of landfills on local property values. They found that the proper functional form varied by problem and case study.

2.3 Applications

The hedonic price model has been expansively applied to estimate the value of air quality and visibility deterioration in metropolitan areas. Smith and Huang (1993) did a meta analysis of the hedonic price model in air quality studies from 1967 to 1990. They found 37 studies and more than 160 separate estimates of the effect of air quality variables on housing prices. They concluded that "those hedonic models have been successful in supporting the connection between air quality conditions at different residential sites within a city and housing prices, but most of the research did not seek to establish more than this connection." Some studies tried to recover the inverse demand function and measure welfare changes. Palmquist (1984) applied the hedonic model of housing characteristics in seven large U.S. cities to eliminate identification problems. He found that the own and cross price elasticities of demand for each characteristic of a house, as well as expenditure and income elasticities, had the expected signs and accorded well with the original expectation from economic theory.

It is difficult, if not impossible, to gain sufficient data and identify the demand function of a certain implicit characteristic in several similar housing markets when the subject areas are not metropolitan. However, it is possible to estimate the implicit price of attributes for a house without the welfare measure. The hedonic price method estimated the values for various locational amenities or disamenities in housing markets, from the effect of earthquakes (Beron et al., 1997) to having a hog farm as a neighbor (Palmquist et al., 1997). Galster and Williams (1994) investigated the effect of dwellings occupied exclusively by severely mentally disabled tenants on sales prices of nearby homes. Pompe and Rinehart (1995) applied the hedonic price model to examine the contribution of beach quality (e.g. beach width) to property value. Roos (1996) analyzed the price of forestland primarily used for timber production in Sweden. He found that the per-hectare price of forestland had positive relationships with the proportion of productive forestland, the mean standing volume and mean site productivity.

Garrod and Willis (1991; 1992) measured the amenity value of forests in Britain, using a Box-Cox model and a two stage hedonic price model. They found that the two most important land attributes in the countryside landscape of Britain were proximity of woodland and water, which raised house prices by 7% and 4% respectively. They also examined the effect on housing prices with higher proportions of neighborhood forestland and compared the contributions of lands of different forest types. They examined the contributions of three tree covers. The focus variables were the percentages of Forestry Commission forested area in km square taken by 1) all broad-leaved trees, 2) larch, Scots pine and Corsican pine planted before 1920, 3) all other conifers, mainly Sitka spruce planted before 1940. They found that an increase of Sitka spruce in relative cover depressed house prices while more broad-leaved trees added to prices.

Price (1995) argued that the hedonic price model was not applicable to scenic beauty because the quality of a scenic view is hard to measure quantitatively. However, Powe et al. (1997) used a geographic information system to estimate an hedonic price model in woodlands, thereby measuring the benefits of woodland access. They argued that the distance from forests can be a quantitative measure of forest amenity even though the quality of a scenic view was ambiguous. While estimating total benefits, they did not distinguish the marginal price function, marginal willingness to pay, or inverse demand.

Therefore their comparison of benefits and costs of planting and felling may have been biased, unless every person in that region had the same income and utility.

Despite this wide range of applications, this method has not been widely applied to properties surrounding forests in the U.S. The hedonic price model drew some attention in natural resource management in recent years. Geoghegan et al.(1997) applied the landscape indices developed by landscape ecologists to the pattern of surrounding land uses by using a geographical information system. They used a double log ordinary least square model (OLS) and the spatial hedonic model to estimate the implicit value of ecosystem dynamics of surrounding land uses in a 30 mile radius of Washington D.C. From the double log OLS model, they found the percent of open space in the area had a significant positive contribution in a smaller measure of area, but it became negative in the larger measure. More open space in one's immediate neighborhood was valued. None of the landscape diversity and fragmentation indices was significant in their initial model. In the spatial expansion model, they assumed the contribution of landscape to a property's value changed over space and applied the interactions of focus variables with distance and quadratic distance from Washington D.C. to the model. The landscape diversity and fragmentation indices became significant. They found that the marginal contribution to selling price of increased diversity and fragmentation changes in different landscape settings.

Many previous hedonic studies concerned urban housing markets, especially in metropolitan areas. Metropolitan dwellings may have had more similar characteristics than suburban or rural settings. Sufficient transactions in a relatively short time can also be observed. In suburban or rural areas, some housing prices can be unusually high or low due to some locational amenities, so the possibility of outlying observations is higher and aggregation of data over time also can be more problematic. Application of the hedonic method in nonmetropolitan areas requires more theoretical and empirical development including choices of functional form, spatial autocorrelation and aggregation of the data over time, as well as the development of amenity measures.

3. CONCEPTUAL FRAMEWORK

3.1 Background Theory

In this study, the hedonic price model was applied for measuring the contribution of forests to the price of neighboring residential properties. To construct the hedonic price model, I assume the housing market is in equilibrium and the homeowner is maximizing utility by choosing an optimal residential property. I also assume that divergences from the equilibrium condition generated only random errors in the estimation of the price function.

A house can be thought as a package of many characteristics. For example, the price of a house is determined by size, number of rooms, view and proximity to the business center or school. In other words, the i[th] house price (p_{hi}^{0}) is a function of housing structure vectors (S_i), lot size (l_i), location-specific environmental amenity vectors (Q_i), and other neighboring characteristic vectors (N_i).

$$p_{hi}^{0} = p_h(S_i, l_i, Q_i, N_i) \qquad [1]$$

In addition, when people decide to purchase a house, they compare the cost of ownership as an investment versus paying rent. If people expect a higher future price while the current mortgage interest rate is relatively low, buying a house is a lucrative investment and it affects housing demand. The user cost of capital, which is the cost of holding a house against expected future earnings, should be included as a factor of housing price change. It is determined by the mortgage interest rate, depreciation rate, income tax, and expected price change. In previous hedonic studies, these factors in the user cost of capital were assumed to be the same for all observations for the cross-sectional analysis. Aggregation over time is, however, unavoidable for many hedonic studies especially in non-metropolitan areas. Some factors in the user cost of capital may be stable over time, such as depreciation rate or income tax rate. Severe changes in the expected future price, or in the mortgage interest rate can affect the housing price even in a relatively short time period.

Equation [2] shows the rental price of a house, when the income tax rate is not changed. The rental price is equal to the homeowner's expense to own a house at a period of time, if the housing market is in equilibrium. It is a simplified version of the rental price of capital services for structure from investment theory (Clark, 1979; p.112-3)

$$RC_{hi} = p_{hi}^{0} * (r + \delta - \rho) \qquad [2]$$

$$UCC = r + \delta - \rho \qquad [3]$$

where RC_{hi} : the rental price for the ith house

UCC : the user cost of capital

p_{hi}^{0} : the ith house price

r : mortgage interest rate

δ : depreciation rate

ρ : expected real house price growth rate

A simplistic model for ρ is that the expected future price in a time period ahead is the same as the price now, so that ρ is zero. When the local economic conditions are good and the population of the region is expected to grow continuously, the expected rate of housing price change (ρ) is positive. Higher expected price change or a lower mortgage rate will induce lower user cost of capital and lower rental price. The demand for housing will be increased as the rental price goes down. To meet the increased demand in the housing market, more houses will be demanded and the housing price will rise. Therefore, the house price in Equation [1] will be affected by the user cost of capital over the time period and Equation [1] should include at least mortgage interest rates and population growth . We can reasonably assume that there is no interaction between housing characteristics and interest rate or expected future price change. The i^{th} house price function with an account of the user cost of capital can be defined as Equation [4].

$$p_{hi}^{ucc} \approx p_h(S_i, l_i, Q_i, N_i, r, \rho) \qquad [4]$$

where p_{hi}^{ucc} : the i^{th} house price
S_i : housing structure vectors
l_i : lot size
Q_i : location-specific environmental amenity vectors
N_i : other neighboring characteristic vectors
r : mortgage interest rate
δ : depreciation rate
ρ : expected real house price growth rate

The owner of this i^{th} house also consumes other commodities (X) to maximize utility within a constrained budget (M). Assume that the owner has only one house and the price of X is standardized to one. The i^{th} house price is really p_{hi}^{ucc} in Equation [4] at a time period, but I will use p_{hi} for simplicity. Then the owner's objective is to maximize utility (U) under a budget constraint:

$$Max \quad U(X, S_i, l_i, Q_i, N_i)$$
$$s.t. \quad M = X + p_{h_i} \qquad [5]$$

where M: the i[th] homeowner's income
X : all other commodities vectors
p_{h_i} : the i[th] house price at a time period

Selecting the optimal combination of all these commodities, the first order conditions of the LaGrange function (L) should be satisfied for x and q_j.

$$L = U(X, S_i, l_i, Q_i, N_i) + \lambda(M - X - p_{h_i}) \qquad [6]$$
$$\partial L / \partial q_j = \partial U / \partial q_j - \lambda \partial p_{h_i} / \partial q_j = 0 \qquad [7]$$
$$\partial L / \partial x = \partial U / \partial x - \lambda = 0 \qquad [8]$$

where λ : the LaGrange multiplier
q_j : j[th] locational amenity
x: a normal commodity

From these first order conditions of utility maximization and general equilibrium theory, the marginal substitution rate of x for q_j is the same as their price ratio. It also means that the more utility one gets from q_j, the more one is willing to pay for it.

$$\frac{\partial U / \partial q_j}{\partial U / \partial x} = \partial p_{h_i} / \partial q_j \qquad [9]$$

The implicit price function of the j[th] locational amenity (q_j) is not constant unless the house price function is linear. For example, we can reasonably assume that the housing price function is concave to cleaner air quality. An improvement in air quality

The implicit price function of the j[th] locational amenity (q_j) is not constant unless the house price function is linear. For example, we can reasonably assume that the housing price function is concave to cleaner air quality. An improvement in air quality leads to a lower increase in utility when the air is already relatively clear rather than when the air quality is very poor.

In this study, our focus variables were the attributes from the forest, measured in several ways including the distance from the forest to a property. A house adjacent to the forest had the upper limit (q_j^u) of a locational amenity; a house one mile away had the lower limit (q_j^l). We cannot necessarily assume that the marginal utility of a homeowner will diminish faster by increasing q_j at lower levels. In other words, increasing proximity to the forest may not be more desirable for the homeowner living farther away than for those living close by. Utility might increase much more when one is already experiencing a certain quantity of forest attribute, e.g. at the higher level of q_j. Conversely, a house one mile from the forest differs little from a house slightly closer if one cannot see or easily access the forest anyway. The i[th] house price function in this study could take any form, convex, linear, or concave. The implicit price function of q_j, a partial derivative of Equation [9] ($\partial p_{h_i} / \partial q_j$), could be a constant, concave, or convex (Figure 1). When the hedonic price is linear, however, the implicit price is constant. The marginal price for q_j remains the same no matter the quantity; this is probably not realistic.

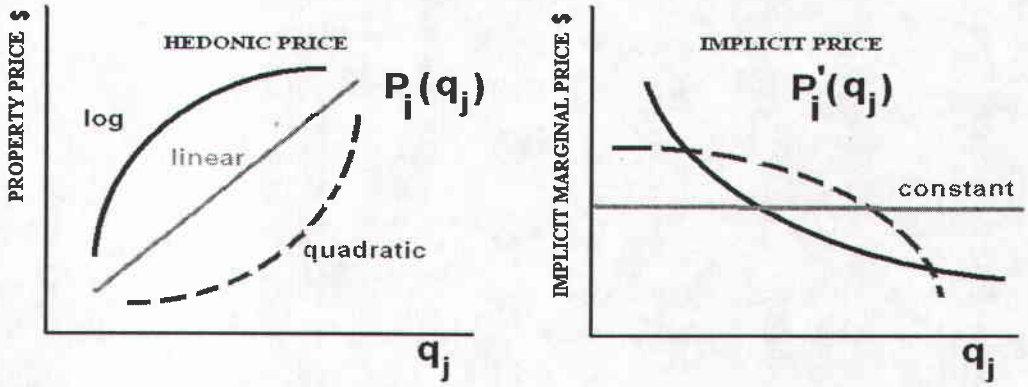

Figure 1. The hedonic and implicit price functions

If we assume that the utility function is weakly separable for q_j, the inverse demand function or marginal willingness-to-pay function for the i[th] house location is as follows:

$$b_{ij} = b_{ij}(q_j, Q_i^*, l_i, S_i, N_i, U^*) \qquad [10]$$

where Q_i^* is all other location specific environmental amenity vectors.
b_{ij} is the inverse demand, or bid function (Freeman, 1993; p.374)

The inverse demand function, b_{ij}, is the i[th] person's maximum willingness to pay for the j[th] environmental amenity. It depends on the level of other locational amenities as well as that person's income and taste. The marginal willingness to pay differs by individual unless we assume all individuals in the market have the same income and utility. Because I had only a single market's data and did not know the underlying structure of the utility function, I did not attempt to recover this inverse demand function from the hedonic price function.

3.2 The Hedonic Price Model

3.2.1 Functional forms

To estimate the hedonic price function, I needed to select a proper specification for the model. In the linear form, the price of a house is simply the sum of contributions from each attraction component (X_i), such as housing structure characteristics, locational amenities, the user cost of capital, and other variables.

$$P = a_0 + \sum_{i=1}^{m} a_i X_i + \varepsilon$$
$$\varepsilon \sim N(0,\sigma^2) \qquad [11]$$

where p : housing price
X : explanatory variables
ε : random error

This is not the case, however, when we cannot repackage a commodity by each component. Even if it were possible, we cannot ignore the repackaging cost of a house. Therefore the marginal price for each component is not constant. The property price function has an upward slope as the quantity of a implicit component increased, but its shape is unknown with the increase. The quadratic Box-Cox model has been widely accepted for choosing the proper functional form of the hedonic price model, because it allows the comparison of many different functional forms. The general form of the quadratic Box-Cox model is as follows:

$$P(\theta) = a_0 + \sum_{i=1}^{m} a_i X_i(\pi) + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} X_i(\pi) X_j(\pi) + \varepsilon$$
$$\varepsilon \sim N(0,\sigma^2) \qquad [12]$$

$$P(\theta) = \frac{(P^{\theta} - 1)}{\theta}, \text{ where } \theta > 0$$
$$= Log\ (P), \text{ where } \theta = 0$$

$$X_i(\pi) = \frac{(X_i^{\pi} - 1)}{\pi}, \text{ where } \pi > 0$$
$$= Log\ (X_i), \text{ where } \pi = 0$$

Depending on the values of θ and π, this flexible functional form can take many shapes. By comparing the log-likelihood values of each form we can choose the optimal functional form that best explains the data.

With the known form of the probability density function for normal distribution, the concentrated log-likelihood function is as follows:

$$L(\theta,\Pi) = -\frac{1}{2} n \log \sigma^2(\theta,\Pi) + (\theta - 1)\sum_{1}^{n} \log P_i \qquad [13]$$

where n is the sample size

$\sigma^2(\theta,\pi)$ is the ordinary least square estimate of variance of the transformed model. To estimate of $\sigma^2(\theta,\pi)$:

$$\hat{\sigma}^2(\theta,\pi) = \frac{SSR}{n}, \text{ where SSR is the residual sum of squares}$$

P_i is i[th] observation of the housing price

(Halvorsen and Pollakowski, 1981; p.43)

We can compare the efficiency of many functional forms defined by the values of θ and π with the quadratic Box-Cox model. When the shape of the hedonic price model is unknown and not supported by economic theory, the quadratic Box-Cox model is best for determining the proper functional form. We still must assume the same value of π for all X_i, however, which means all explanatory variables are raised to the same power. As Graves et al. (1988) also demonstrated, this procedure may not be the best choice when the requirements for the central limit theorem are not met.

The optimal values of θ and π estimated by maximum likelihood methods can generate a functional form that is hard to interpret, such as θ=0.06 and π=0.28 in Halvorsen and Pollakowski (1981), or θ=0.1 and π=1.10 in Graves et al. (1988). It becomes more complicated, and can not be interpreted easily, when trying to get the implicit price of a certain characteristic that is the partial derivative of the functional form. Some special cases of the Box-Cox model that are interpretable are showed in Table 1 and Figure 2.

Table 1. Special functional forms in the quadratic Box-Cox model

Translog $\theta = \pi = 0$	$\log(P) = a_0 + \sum_{i=1}^{m} a_i \log(X_i) + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} \log(X_i) \log(X_j) + \varepsilon$
Semilog $\theta = 0,\ \pi = 1$	$\log(P) = a_0 + \sum_{i=1}^{m} a_i X_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} X_i X_j + \varepsilon$
Quadratic $\theta = \pi = 1$	$P = a_0 + \sum_{i=1}^{m} a_i X_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} X_i X_j + \varepsilon$
Quadratic $\theta = 1,\ \pi = 2$	$P = a_0 + \sum_{i=1}^{m} a_i X^2 i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} X^2 i X^2 j + \varepsilon$
Square root quadratic form $\theta = 1,\ \pi = 1/2$	$P = a_0 + \sum_{i=1}^{m} a_i \sqrt{X_i}) + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} \sqrt{X_i} \sqrt{X_j} + \varepsilon$
Generalized square root quadratic $\theta = 2,\ \pi = 1$	$P^2 = a_0 + \sum_{i=1}^{m} a_i X_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} b_{ij} X_i \log X_j + \varepsilon$

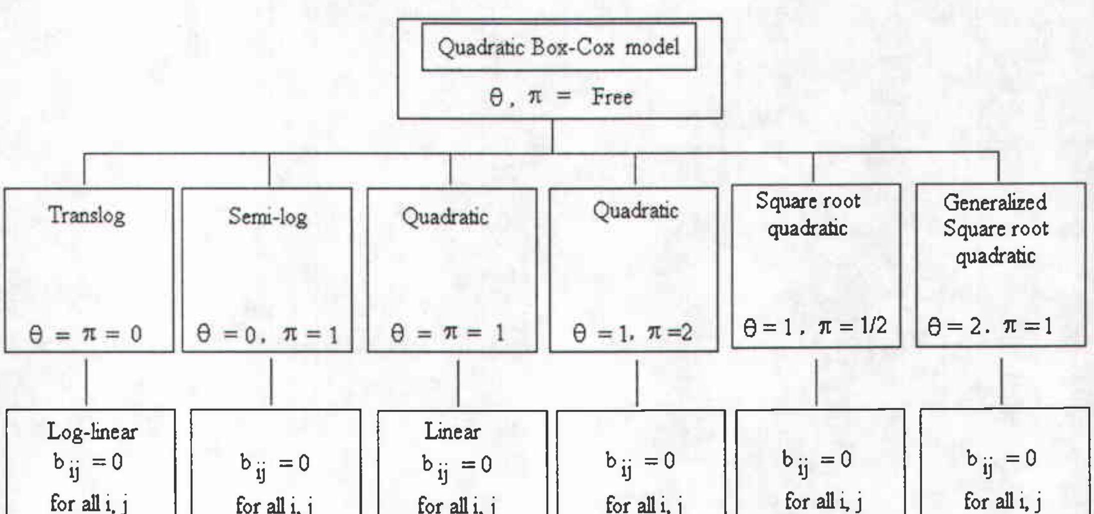

Figure 2. Special functional forms with $b_{ij} = 0$

(Halvorsen and Pollakowski, 1981; p.47)

Other considerations in the regression, besides the functional form, include heteroskedasticity and multicollinearity among the explanatory variables. Multicollinearity, meaning two or more explanatory variables are highly correlated together, does not have a general solution. Because the interest of this study is only in the relationship between the attributes from the forest and their effect on the property values, it can serve as a partial solution to observe the changes in coefficients of focus variables when selecting other explanatory variables. Although we cannot find the perfect solution, we can still test the robustness of the relationship of interest.

Heteroskedasticity, which means the error variance for the regression is not constant for all observations, should be also examined. Tests for detecting heteroskedasticity include White's test and Breusch-Pagan statistic, and are suggested when the structure of uneven variances is unknown (Griffin et al., 1993, p.501). These tests use an auxiliary regression to see how much of the error can be accounted for by the explanatory variables. If a significant portion of the error variance is associated with the explanatory variables, the error variances from the regression are significantly different over the observations. If heteroskedasticity is detected, the feasible generalized least square model (FGLS) can be a solution. White's correction is an asymptotic solution for estimating consistent variances. Alternatively, when subsample groups have different variances and no serial correlation, these group variances can be standardized by weighted regression.

3.2.2 Variables

The response variable of the hedonic price model (Equation [1]; Section 3.1) is simply the price of a house, but the data that represent this price must be determined with minimum measurement errors. The price of a house can be represented by the purchase price, or by assessed values from the county appraiser. Purchase prices reflect real market transactions, whereas the assessed value data contain annual records of land and improvement values. The observation set was selected from all the sales records in the Benton county database. The trade-off between having small number of observations and avoiding time series data sets should be considered carefully. In this study, an F-test (Chow test) was applied to examine if there were significant structural changes in the hedonic price model over time. The results are described in Section 4.2.1.

The assessed value was also considered as a possible response variable, because of some possibly significant reflections on market transactions. Benton county properties are assessed on a six-year cycle. Between assessments, property values are adjusted by the average sales price change in that area. Although the assessed values reflect the market sales of properties, it may be problematic to aggregate assessments from different years. In the preliminary analysis, I used the assessed value of properties as a response variable and found no fundamental differences in the regression estimation. The purchase price was later used as the primary response variable.

Palmquist (1984) and Graves et al. (1988) illustrated the selection of explanatory variables. The "free" or "doubtful" variables are the housing structure variables and other local attributes related to property prices. The free variables in this study included most of the variables related to property prices, such as lot size, size of living area, total number of rooms, and the attributes of the house. Because Palmquist's study sites were in major metropolitan areas, some of his variables were not available or appropriate for this study. This doubtful variables included a time dummy and sale types. These variables seemed to affect property price, although they have not yet been proven to be significant in other studies. These explanatory variables are described in Section 4.2.2.

The "focus" variables were the neighboring forest amenities. The first measure was the distance from the forest. Having a residential property near the forest provides various attractions, such as a beautiful view, better access to the forest, and more privacy for the backyard. Distance can represent all these attributes.

The contribution of the forest to neighboring property prices depends on forest types and forest management practices around the property. The forest characteristics surrounding a property were gathered in three ways to see if this could account for some unexplained part of the original regression with the distance variable. First, the neighboring properties were grouped with respect to the nearby forest management areas. The north, central, and south portions of the McDonald-Dunn Forest have been managed under a distinct management plan. The northern section is mostly even-aged, whereas the central and southern portions are shelterwood-managed and uneven-aged, respectively. Second, I used information from the stand nearest the property. This included the average number of trees per acre, tree species, average height of dominant species, etc. Third, I did visibility analysis to see if clearcut sites were visible at the time of the property purchase. This was done with ArcView 3.0 and its programming language Avenue, and ArcInfo GRID command.

4. DATA AND VARIABLE SELECTION

4.1 Data

McDonald-Dunn Forest covers about 11,500 acres of forest and meadow to the north and west of Corvallis, Oregon. Conifers, especially Douglas-fir (*Pseudotsuga menziesii*), dominate, but oak and poison oak (*Rhus diversiloba*) can also be found. Most of the forest is less than 70 years old. All the forests aged 160 years or older are withdrawn from harvest (McDonald-Dunn Forest Plan, 1993).

The forest provides various recreational opportunities such as hiking, mountain biking, and horseback riding. It also provides nature education for public school students and teachers. Annual use of the forest was about 33,000 in 1989 (Finley, 1990) and about 65,000 in 1994 (Wing, 1996); it has grown rapidly as the population has increased in Corvallis and in Benton County. One of the management goals is to be a good neighbor, i.e. to "a. maintain communications with faculty, neighbors, and the public to convey information, to identify issues of interest and concern, and to receive suggestions regarding management of the forest; b. be sensitive that the Forest provides a visual backdrop to the city of Corvallis; and c. provide managed public access to the Forest" (McDonald-Dunn Forest Plan, 1993). As a popular recreation destination of the growing city and as the backyard of neighbors, the forest is obligated to these roles when forest management decisions are made.

A total of 3,283 properties lie within one mile of the forest. Among these, I chose 2,095 properties of primary residential uses after excluding vacant lots, residential properties on farm or forestland, and multiple-family houses. For this study, sale prices and other general information about the neighboring residential properties around the forest were collected from Benton County information resources; information about forest quality variables was obtained from the OSU Research Forest office.

By combining the geographic information system (GIS) layers of Benton County and McDonald-Dunn Forest, I was able to measure the distance from each property to the forest boundary, and other neighboring forest characteristics of that property. Figure 3 shows the study area and the location of the selected samples, which are residential properties traded more than once since 1990 that have all the relevant information available.

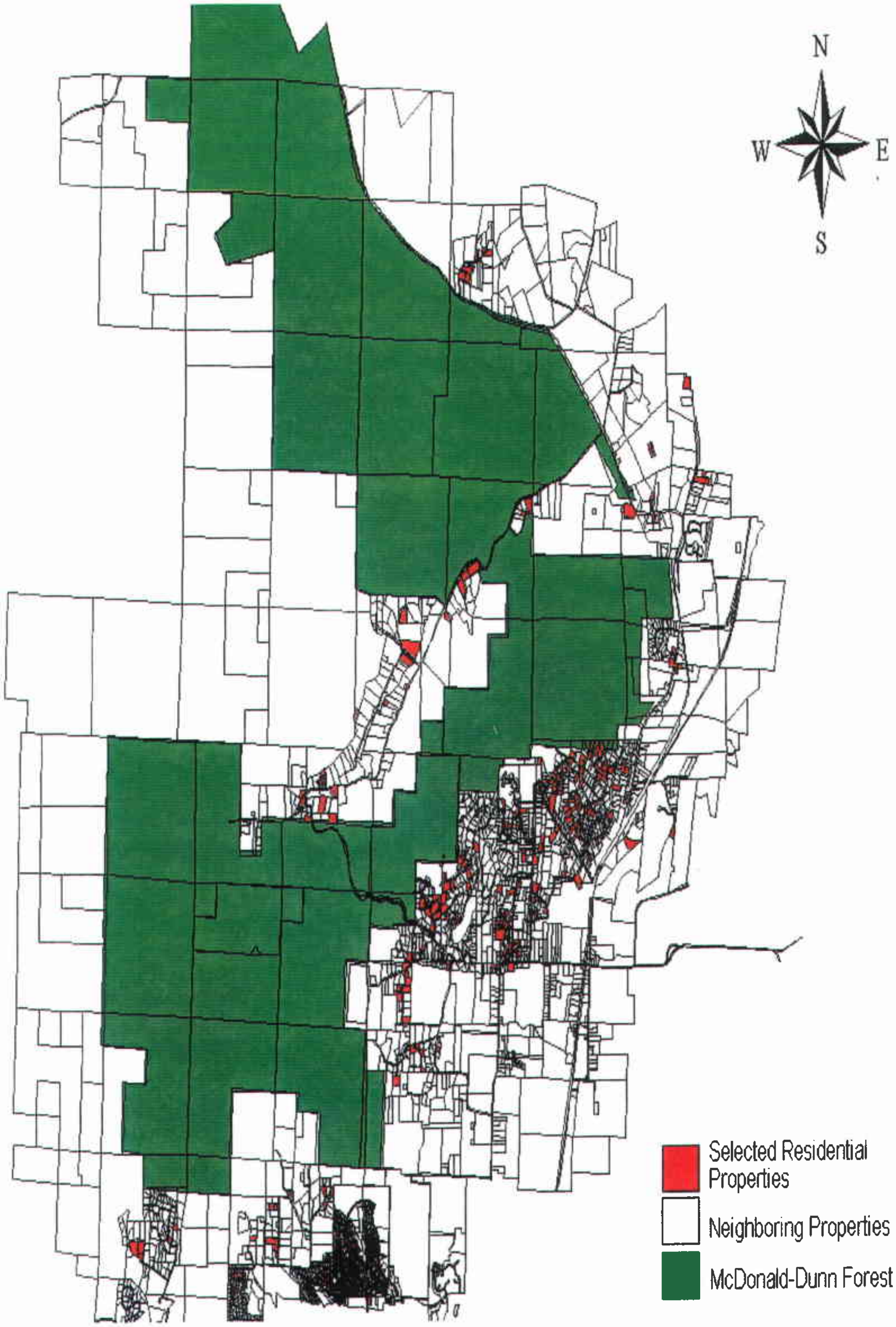

Figure 3. Neighboring properties around McDonald-Dunn Forest

4.2 Variable Selection

4.2.1 The response variable

The response variable for the hedonic price model in this study is the purchase price of selected residential properties. Sales in different years were adjusted to 1987 dollars according to the Consumer Price Index-All Urban Consumers for All Items less Shelter to account for the price inflation outside of the housing market over time. Some internal transactions were among family members, so I excluded those sales below $1,000.

Figure 4 shows yearly nominal purchase prices of the residential properties within one mile of the forest. This housing market has been growing rapidly since 1990. Any significant shock that changed the structure of this housing market could be problematic when aggregating the data over time. This would require treating the two different markets separately.

To decide the proper range of aggregation over time, an F-test (the Chow test) was applied to see if the estimated regression coefficients differed with the time period. The explanatory variables were selected from the preliminary regressions on all observations. The selected record in the study area included sales from 1978 to 1996. Data before and after 1990 were aggregated into two groups.

The null hypothesis of the Chow test was that the estimated regression coefficients from the two separated groups were not significantly different ($H_0 : \beta_{period1} = \beta_{period2}$), which indicated no structural change in the relationship between

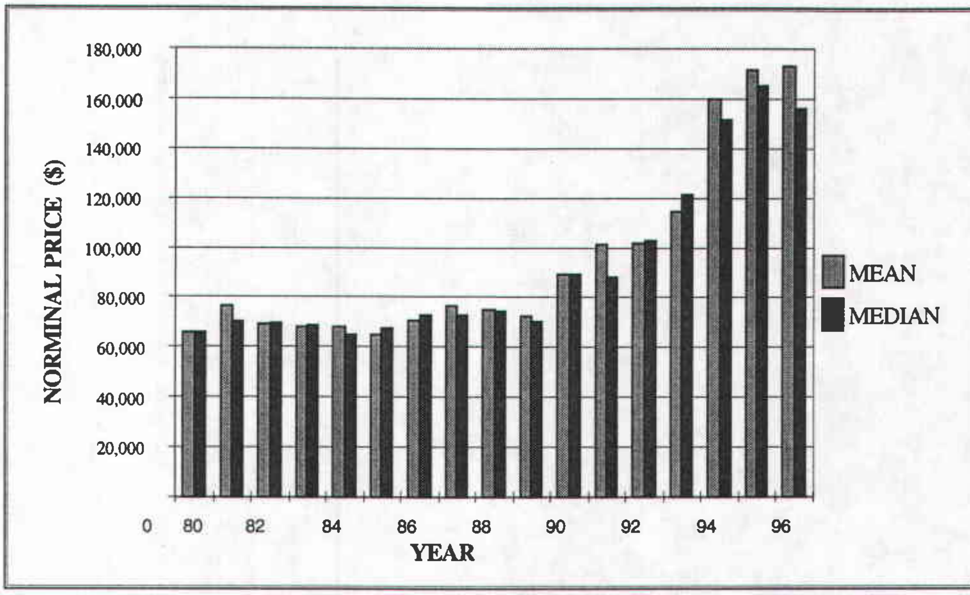

Figure 4. Nominal purchase price changes in neighboring properties

the response variable and explanatory variables. This was rejected in the comparison of the sales data before and after 1990 (F-Statistic=20.88; P-value=0.00). These two groups of observations were more likely from two different populations, with some notable structural change in this housing market over time.

Among the 2,095 residential properties within one mile of the McDonald-Dunn Forest, I found 1,289 sales with all relevant information available. After selecting the period from 1990 to 1996, I had 752 observations. In choosing a relatively short period of time, the number of observations is decreased, but problems from a structural change in the housing market are avoided. For cross-sectional analysis, I chose the sales between 1990 and 1996.

4.2.2. The explanatory variables

Following Palmquist (1984) and Graves et al. (1988), I considered "free" variables known to be significant in determining the property price, such as lot size, size of living area, total number of rooms, age of house at time of purchase, public access to roads, garage or basement, and so on. Table 2 includes the explanatory variables used in the hedonic price model estimation. Because the study area was relatively small and outside of an urban area, some free variables important in metropolitan areas were not applicable here. For example, the distance from the Corvallis city center to each property did not have a significant impact on the property price.

Some variables not considered in other hedonic studies were significant factors in the property prices in this study. These "doubtful" variables included the dummy variable for the year of the property purchase. When the housing market is growing fast, owning a house is an important investment. Because the opportunity cost of owning a property changes, the user cost of capital can explain some variation in the property price change. Population growth and mortgage interest rates are the key factors of the user cost of capital in predicting future housing prices and the decision to retain a house and can be explanatory variables in the hedonic price estimation.

Population growth in Benton county was about 2,600 over 10 years from 1980 to 1990, but was about 4,400 over the next 5 years. Figure 5 illustrates the conventional mortgage interest rate (30 year fixed term) along with population growth in Benton County since 1990. These two factors were tested as explanatory variables in the regression estimation for the hedonic price model and they were significantly correlated

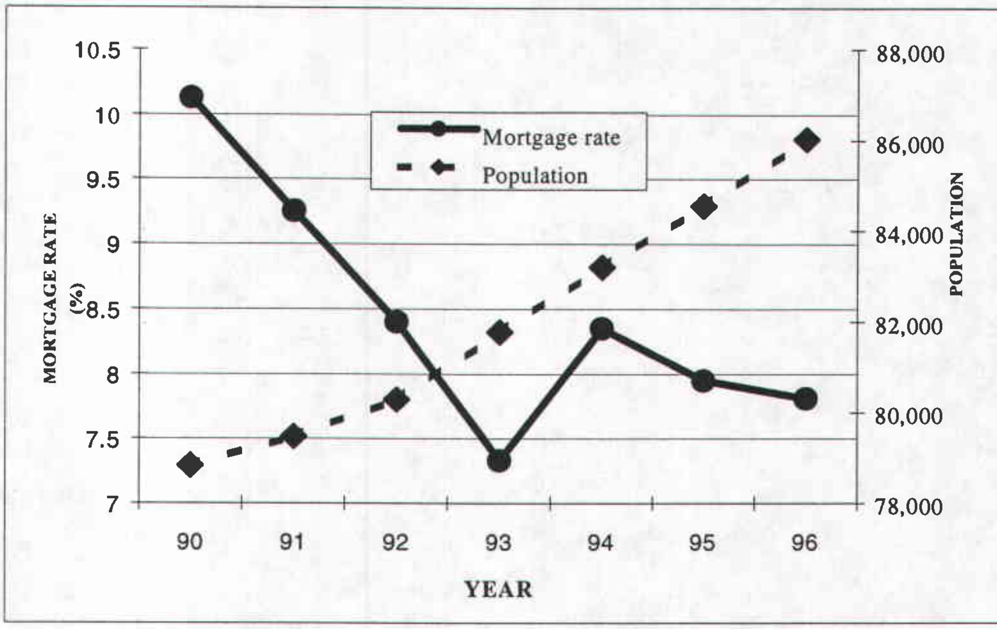

Figure 5. Mortgage interest rate and population change

individually with property prices. However, there was high correlation between the two factors, because both had a time trend. A dummy variable for each year was applied to capture the fluctuation of both population growth and mortgage interest rates over time.

Other doubtful variables were the sales type and housing index. Most houses were sold under warranty deed, but some were cases of 'bargain or sale' or 'quit claimed'. I checked if these different types of deeds affected the sales price of the properties. The housing index was from the factor book code in the property assessment. The factor book code is a three-digit number. The first digit represents housing types. In this study, all the selected observations were single residential houses. The second digit designates the quality of housing, on a scale of 1 to 8 for the residential quality classification. This is a judgement made by the assessor based on the shapes, stories and the materials used. For example, 1 represents a simple single-story, smaller home; 8 is for a larger and higher quality house. I used this second digit as an explanatory variable. The third digit represented the number of units in the house.

The primary "focus" variable was the distance from the McDonald-Dunn Research Forest boundary to each property. Whether the property was adjacent to the forest was considered a dummy variable. Most adjacent properties, however, were not for primary residential use, such as on farmland or forestland and few had changed ownership since 1990. Some properties were adjacent to agricultural pastures in the forest with fewer forest attributes than those adjacent to forest stands. In this study, I was unable to find any significant contribution of adjacency to the forest in the property price because of the small number of observations in that category.

To determine what forest type might cause a significant gain in property values when proximity to the forest was an important factor, I tried the following ways to represent forest types. First, the areas around McDonald-Dunn Forest were grouped according to the neighboring forest areas under distinct management plans: even-aged, shelterwood, or uneven-aged stands. Since the forest provides various services to the neighboring homeowners, such as recreational opportunities and beautiful views, these services may vary by the forest types. The area groups around the forest also have different levels of accessibility and quality as well as different forest management goals.

Table 2. Selected explanatory variables for the hedonic price model estimation

Name	The Description
S96	For houses purchased in 1996 S96=1, otherwise S96=0
S95	For houses purchased in 1995 S95=1, otherwise S95=0
S94	For houses purchased in 1994 S94=1, otherwise S94=0
S93	For houses purchased in 1993 S93=1, otherwise S93=0
S92	For houses purchased in 1992 S92=1, otherwise S92=0
S91	For houses purchased in 1991 S91=1, otherwise S91=0
SALETY_QC	If the sale type is "Quit claimed" then QC=1
SALETY_BS	If the sale type is " Bargain or Sale" then BS=1
URBAN	If the house is located in urban area, then URBAN=1
PUBLIC ACCESS	If the house has public access, then PUBA=1
FAN_COOL	If air conditioner is installed, then FAN_COOL=1
FIREPLACE	If the house has fireplace, then FIREPLACE=1
BASEMENT	If the house has basement, then BASEMENT=1
GARAGE	If the house has garage, then GARAGE=1
STORIES	Number of stories in house
HOUSINGINDEX	The housing quality index 1-8 in the factor book code
LOT SIZE	Lot size
LIVING AREA	Total living area size
ROOM	Total number of rooms
AGE	The age of house when it was purchased
DISTANCE	The distance from McDonald-Dunn Forest boundary (ft)

Second, information on the stand closest to each property was applied. More detailed forest stands data were used, such as the number of trees, the dominant species, and if the closest site is an agricultural pasture or a meadow instead of a forested land. Third, I examined any impact on property price when clearcut sites were visible from the property at the time of purchase. This was done in two ways. A dummy variable of either 0 or 1 depended on whether the clearcut sites could be seen from the property. The density of visibility was also specified how many points along the boundary of clearcut could see sites. Elevation of the study area (30 m resolution Digital Elevation Model (DEM)) was obtained from the United State Geological Survey database. Elevation of

McDonald-Dunn Forest was increased by mean tree height of dominant and codominant species in each forest site to account for the fact that intervening trees might block the view of any clearcuts. The visibility analysis was done by using the programming language Avenue in ArcView and ArcInfo GRID. These variables for neighboring forest characteristics around each property are further explained in section 5.4.1.

5. RESULTS

To choose the proper functional form for the hedonic price model (Equation [4], section 3.1), the quadratic Box-Cox model was applied with the primary focus variable being the distance from the McDonald-Dunn Forest boundary to each property. Although some characteristics of the neighboring forest may have affected the property price individually, their contribution was highly correlated with proximity to the forest. The distance from the forest can be a quantitative measure representing the various forest attributes of each property.

The hedonic price model with the distance variable was estimated in three ways. First, the square root model was applied because it was the closest interpretable model to the optimal functional form suggested by the estimated quadratic Box-Cox parameters. All significant explanatory variables were considered and the function form that best explained the data was applied. It is, however, impossible to be absolutely sure that all of the preconditions are met. The linear functional form was used for comparison to see the robustness of the estimated relationship between the distance from the forest and the property price. This simple functional form provided more intuitive interpretations without a sophisticated statistical procedure. The implicit price for being close to the forest was drawn from each model and interpreted according to economic theory. Third, a weighted regression was applied to improve the data distribution in the regression estimation, and the results were compared with those from the ordinary least square regression model.

The significance of individual forest characteristic variables in the property price were determined in a separate regression. I investigated whether the unexplained part (residuals) of the square root regression with the distance variable could be explained by the difference in the neighboring forest characteristics around the property. Because the contribution of those variables depended on the distance from the forest and were highly correlated with one another, I first checked the partial correlation between the residuals and the forest characteristic variables. Variables that appeared to be significant in the partial correlation were integrated into the square root regression model. I found some forest characteristics variables which have significant contributions to the neighboring properties regardless of the proximity to the forest. The applied forest characteristic variables, however, were proxies of the specific forest attributes of each property and the results should be considered as exploratory.

5.1 Quadratic Box-Cox Model

This flexible functional form allowed us to compare the log likelihood values from each model defined by the values of θ and π (Equation [9], section 3.2.1). I chose the model that had the largest log-likelihood value, which could best explain the data. The optimal values of θ and π were 0.82 and 0.52, respectively, from the iterated ordinary least square model. Its log-likelihood value was – 7,539.95. The implicit price of the focus variable was the partial derivative of this optimal functional form ($\partial P / \partial X = 0.52bX^{0.52-1} / 0.82P^{0.82-1}$). The implicit price depends on not only on the focus

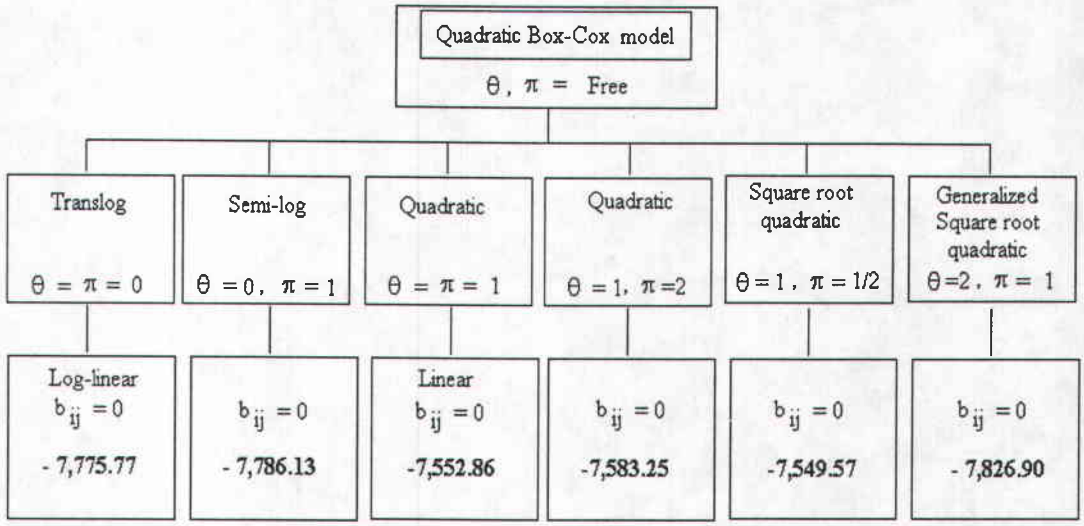

Figure 6. Log-likelihood values: purchase prices from 1990 to beginning of 1996

variable (*X*) but also the response variable (*P*) and becomes very difficult to interpret the factor effect from this model.

Among the more interpretable functional forms, the square root model was chosen to have the largest log-likelihood value (smallest in absolute value) close to the optimal model (Figure 6). Because there was no a priori reason to include the interactions among the explanatory variables, the models without the interaction term (b_{ij} =0) were selected for simplification. However, I also statistically tested for the significance of the interaction terms in the linear model with an F-test (F-Statistic=3.02; P-value=0.00). It seems there are some interactions among the explanatory variables that are significantly affecting the response variable. When I tested individual interaction terms in the regression, some interactions between distance and housing structure variables were significant, but the estimated coefficients were very small or had unexpected signs. The interaction of distance with the time dummy variable for 1996 was significant in the regression, and the proximity to McDonald-Dunn Forest tends to have more impact on neighboring property prices in 1996. Since I only had the purchase price records until the beginning of 1996, I did not include that in the main analysis. The contribution of the forest to neighboring property values may have changed over time and this needs further consideration with more observations.

5.2 Regression Estimates

5.2.1 Square root model

The square root model was selected as the closest to the optimal functional form suggested by the quadratic Box-Cox model, with an interpretable partial derivative (Table 3). The explanatory variables describe 75.28% of the variation in the property price; most show the expected signs. The dummy variables for each year explain the changes in the user cost of capital. The mortgage interest rate has decreased over time, while the expected future price has risen because of the population growth in the region (Figure 5). This tendency of higher housing price is captured by the time dummy variables. The properties in urban areas have higher prices; a public access to the property also has a positive impact. When the properties are not sold under warranty deed, purchase prices are lower. A house with more features such as an air conditioner or fireplace is more

Table 3. Regression estimates: Square root model

Purchase prices from 1990 to 1996 ($)				**(N=752) Adj. R^2 = 75.28 %**
Explanatory Variables	**Estimates**	**Standard Error**	**T-statistic**	**Prob>[T]**
Intercept	-128,993.00	13,847.20	-9.32	0.00
S96	40,392.00	2,963.92	13.63	0.00
S95	42,141.00	2,848.78	14.79	0.00
S94	33,844.00	2,633.62	12.85	0.00
S93	17,567.00	2,458.17	7.15	0.00
URBAN	6,864.75	2,532.56	2.71	0.01
PUBLIC ACCESS	5,793.11	2,177.16	2.66	0.01
SALETY_QC	-81,534.00	8,399.33	-9.71	0.00
SALETY_BS	-74,883.00	6,376.25	-11.74	0.00
FAN_COOL	7,506.00	3,626.79	2.07	0.04
FIRE PLACE	3,366.69	2,149.27	1.57	0.12
STORIES	378.54	220.10	1.72	0.09
HOUSING INDEX	14,523.00	1,969.01	7.38	0.00
BASEMENT	-4,384.32	2,548.97	-1.72	0.09
GARAGE	17,535.00	3,126.74	5.61	0.00
Square root of AGE	-4,090.49	836.57	-4.89	0.00
Square root of LOT SIZE	61.10	13.91	4.39	0.00
Square root of LIVING AREA	3,214.26	228.51	14.07	0.00
Square root of ROOM	6,782.68	4,198.57	1.62	0.11
Square root of DISTANCE	-123.00	82.11	-1.50	0.13
Breusch-Pagan statistic: 206.26 (Prob>[X] = 0.00) White's statistic: 283.80 (Prob>[X] = 0.00)				

expensive. A larger living area is significantly related to higher property price, but when it includes the living area in a basement, it has less of a contribution.

Some explanatory variables that were tested originally were highly correlated with others or were not significant in the regression. For example, the distance from each property to the Corvallis business center was not significant in the regression because the study area is small and the commute time is not highly variable. The size of the main floor area in a house is highly correlated with total living area. Between these two, I chose total living area size, because it could explained more of the variation in property price. Most of the free variables expected to be significant were included in comparisons across functional forms. A different selection of explanatory variables, however, did not greatly affect the significance of the squared distance variable in the regression estimation.

In the ordinary least square regression, evidence of heteroskedasticity was significant in the Breusch-Pagan statistic and White's statistic. When heteroskedasticity is detected, the estimated coefficients are still unbiased but have relatively large variances. A weighted regression to estimate more efficient regression coefficients can be somewhat subjective. Results for a weighted regression will be presented in Section 5.3. The results were only used for comparisons with the ordinary least square regressions.

The distance variable had a negative relationship with the property price. When one unit of square root distance increases, the estimated mean of property price decreases by $123. The contribution of proximity to neighboring property prices depends on the distance from the property to the forest boundary. For a house 100 ft away, the property price change is $6.13 per foot while it is $1.94 per foot for a house 1000 ft away. If a house is a mile away, the change in the property price is only $0.85 per foot. Recall that if a property is farther away, the attribute from the forest decreases and therefore the distance from the forest (d_j) is a negative measure of locational amenity (q_j). The marginal implicit price of the distance is as follows:

$$\frac{\partial P}{\partial d_j} = \frac{-61.5}{\sqrt{d_j}} \quad [14]$$

where p = purchase prices (1990 to 1996), and
d_j = the distance from the forest boundary to the property j
(for all equations , $d_j = -q_j$)

5.2.2 Linear model

The procedure to estimate the parameters for the quadratic Box-Cox model involved a sophisticated statistical procedure, under the assumption of normal distribution. Satisfying all the assumptions for the central limit theorem can be problematic. To check the robustness of the estimation, I compared the estimated regression coefficients from the square root model chosen by the quadratic Box-Cox model with those from the simpler functional form. The linear model was applied because it provided simple and more intuitive interpretation without a complicated estimation process. When the hedonic price function is linear, however, the implicit price becomes constant with no change in its marginal price when the quantity of the implicit characteristic changes.

Table 4 shows the estimated coefficients from the linear regression model. The explanatory variables described 74.87% of the response variable. Most of them that were significant in the square root model were significant in the linear model; the signs of explanatory variables did not change. Error variance for the regression was not constant for all observations, so heteroskedasticity was a problem in the linear model.

Table 4. Regression estimates: Linear model

Purchase prices from 1990 to 1996 ($)				**(N=752) Adj. R^2 = 74.87 %**
Explanatory Variables	**Estimates**	**Standard Error**	**T-statistic**	**Prob>[T]**
Intercept	-45,799.00	10,078.84	-4.54	0.00
S96	40,010.00	2,991.33	13.38	0.00
S95	42,542.00	2,873.83	14.80	0.00
S94	33,455.00	2,662.31	12.57	0.00
S93	17,882.00	2,479.60	7.21	0.00
URBAN	5,917.70	2,544.38	2.33	0.02
PUBLIC ACCESS	6,617.01	2,166.24	3.06	0.00
SALETY_QC	-80,610.00	8,475.82	-9.51	0.00
SALETY_BS	-72,678.00	6,429.56	-11.30	0.00
FAN_COOL	7,738.15	3,655.61	2.12	0.03
FIRE PLACE	2,546.23	2,125.67	1.20	0.23
STORIES	508.59	219.47	2.32	0.02
HOUSING INDEX	13,483.00	2,016.01	6.69	0.00
BASEMENT	-5,313.81	2,581.75	-2.06	0.04
GARAGE	17,964.00	3,166.48	5.67	0.00
AGE	-411.98	96.09	-4.29	0.00
LOT SIZE	0.07	0.02	2.98	0.00
LIVING AREA	34.22	2.40	14.28	0.00
ROOM	1,439.74	651.17	2.21	0.03
DISTANCE	-2.81	0.84	-3.33	0.00
Breusch-Pagan statistic: 198.30 (Prob>[X] = 0.00) White's statistic: 297.34 (Prob>[X] = 0.00)				

The focus variable, distance from the forest, had a significantly negative impact on the property price. For a house farther from McDonald-Dunn Forest, its property price decreased about $2.81 per foot. The following equation shows the marginal implicit price of distance and it remains the same at any distance.

$$\frac{\partial P}{\partial d_j} = -2.81 \qquad [15]$$

where p = purchase prices (1990 to 1996), and
d_j = the distance from the forest boundary to the property j
(for all equations , $d_j = -q_j$)

5.2.3 The implicit price of being close to the forest

Increased distance from McDonald-Dunn Forest is the negative measure of the forest attribute of each property. With distance, the property's locational amenity from the forest decreases along with the price. Figure 7 shows the changes in the average sale price of the selected residential properties converted to 1997 price level. The linear model is shown for comparison with the square root model.

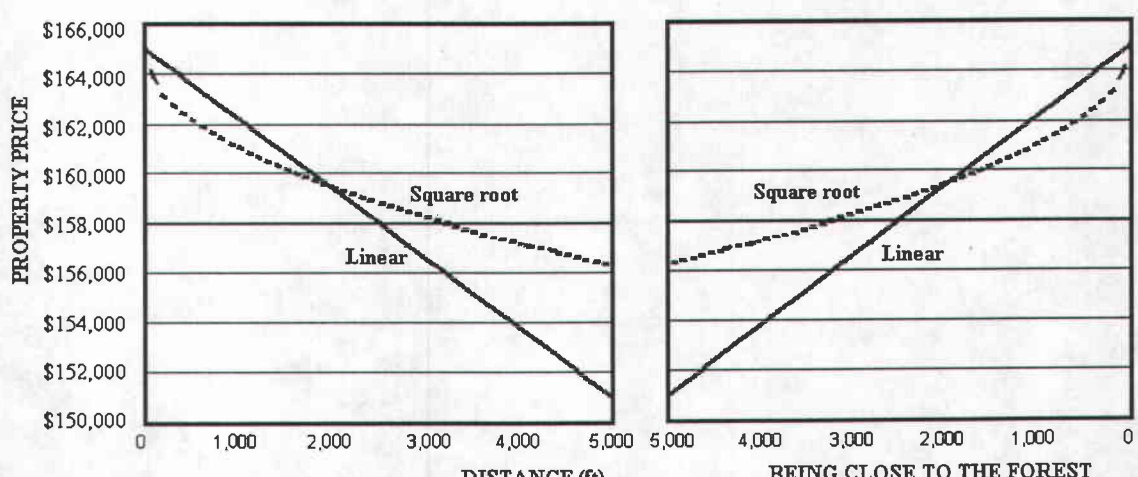

Figure 7. The hedonic price functions from the square root and linear models

The square root functional form indicates that the hedonic price function is convex to an increase in the locational amenities from McDonald-Dunn Forest, which is a decrease in the distance. The property price rises with greater forest attributes in both models. The marginal rate of the price change, however, differs in the square root model with respect to the distance, i.e. the level of locational amenity from the forest. The homeowner's utility actually increases more rapidly with additional forest attributes when they are already close to the forest. If a house is far from the forest and does not have many forest amenities, increasing the proximity does not make big difference in the property price. The marginal price change in the linear model is the same at any distance.

Implicit price functions are the partial derivative of the hedonic price functions (Figure 8). The right hand figure is the implicit price functions of neighboring homeowners for proximity to the forest. For a normal commodity, the demand does not decrease a lot as the price rise if one has none to start with. At the lower level of proximity to the forest, however, the demand decreases very fast when the implicit price rises. With the linear price model, the implicit marginal price of distance is constant.

The implicit price increases as houses get closer to the forest. This relationship is even stronger for houses in closer distances in the square root model. For example, when all other characteristics of a house are identical, a house 100 ft away from the forest is worth about $1,520 more in its purchase price than a house 500 ft away, while a house 500 ft away is worth about $1,139 more than a house 1,000 ft away. In the linear model, for each one foot closer to the forest, the property price is about $2.87 more. This contribution of the forest to the property price remains the same for any distance.

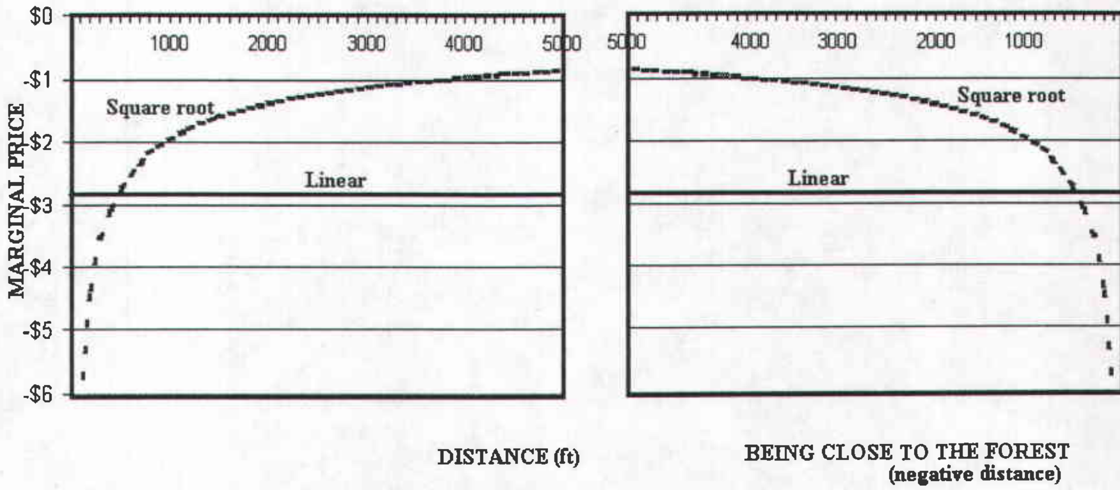

Figure 8. The implicit price functions from the square root and linear models

5.3 Heteroskedasticity and an Example of Weighted Regression

To estimate the price function, I applied the ordinary least square (OLS) regression model. The estimated coefficients from OLS are efficient and unbiased, when the errors are normally distributed and their variances are the same for all observations with no correlation across the observations. The following equation shows a simple OLS model.

$$\begin{aligned} E(y \mid X) &= \beta_0 + \beta X \\ \beta &= (X'X)^{-1}X'y \\ E(e) &= 0,\ E(e'e) = \sigma^2 \end{aligned} \qquad [16]$$

where y = Adjusted purchase price
X = The explanatory variable matrix

When heteroskedasticity exists, which means uneven variances for the observations ($E(e'e) \neq \sigma^2$), economic theory suggests using the general least squares model (GLS) to normalize the different variances. White's corrected standard errors are the asymptotic results from the feasible GLS. Because of some heteroskedasticity in the regression estimation, I applied White's correction. The efficiency of the estimated models was not greatly increased, which means White's corrected standard errors were not smaller than the ones from the ordinary least square estimations.

I then grouped the observations with respect to similar variance levels to normalize the differences in the error variances. In this data set, the error variances tend to depend on more than one explanatory variable. For a weighted regression model, I needed to estimate the variances with respect to different groups. The "factor book code" is a representative variable for many different housing characteristics. Recall that the three-digit code represents housing type, housing quality and the number of units in the house (Section 4.2.2). Houses with the same code have similar housing structure characteristics. The bigger and higher quality houses seem to vary more in purchase price than do the smaller and lower quality houses. The estimated variance of each group was used as the weight in the regression.

$$
\begin{aligned}
&E(y \mid X) = \beta_0 + \beta X \\
&\beta = (X'W^{-1}X)^{-1}X'W^{-1}y \qquad\qquad [17] \\
&\quad E(e) = 0,\ \mathrm{E(e'e)} = \sigma^2 \mathrm{W}
\end{aligned}
$$

where y = Adjusted purchase price
X = The explanatory variable matrix
W = The diagonal matrix of estimated variances of each factor book code group

As I grouped the observations and normalized the variances, some explanatory variables became insignificant in explaining the variation of the property price, such as the total number of rooms and lot size. Because this grouping of observations could be somewhat subjective, I only used this result of the weighted regression to check the robustness of the previous regression estimation.

In the weighted regression, the coefficient of the focus variable seems to have a more efficient estimate. Table 5 shows the coefficients from the weighted regression of the adjusted purchase price in the square root model. The coefficient of the focus variable, the distance from McDonald-Dunn Forest, is consistently significant in all regression estimations, meaning that the proximity of a property to the forest has a robust and positive contribution to the property price. In the weighted regressions, most of the coefficients had expected signs, even though some variables became insignificant after normalizing the variances of similar houses. Explanatory variables accounted for about 76.4% of the purchase price differences.

From the weighted square root model, the estimated mean of property price decreases by $151.05 as one unit of square root distance increases. The implicit price of distance changes more for houses in closer distances. For a house 100 ft away, the property price change is $7.53 per foot while it is $2.39 per foot for a house 1000 ft away. The estimated implicit price of proximity is slightly bigger in the weighted square root model, but it significantly reduces the confidence interval of the estimated coefficient for the distance variable. The following equation shows the implicit price function for distance:

$$\frac{\partial P}{\partial d_j} = \frac{-75.53}{\sqrt{d_j}} \qquad [18]$$

where p = purchase prices (1990 to 1996), and

d_j = the distance from the forest boundary to the property j

(for all equations , $d_j = -q_j$)

Table 5. Weighted regression estimates: Square root model

Purchase prices from 1990 to 1996 ($)				**(N=752) Adj. R^2 =76.4%**
Explanatory Variables	**Estimates**	**Standard Error**	**T-statistic**	**Prob>[T]**
Intercept	-108,187.00	13,643.81	-7.93	0.00
S96	29,492.00	2,666.99	11.06	0.00
S95	39,502.00	2,799.07	14.11	0.00
S94	29,329.00	2,432.48	12.06	0.00
S93	19,282.00	2,303.58	8.37	0.00
URBAN	6,504.16	2,382.51	2.73	0.01
PUBLIC ACCESS	8,954.08	2,040.44	4.39	0.00
SALETY_QC	-81,889.00	8,460.49	-9.68	0.00
SALETY_BS	-65,074.00	6,744.24	-9.65	0.00
FAN_COOL	4,340.57	3,370.08	1.29	0.20
FIRE PLACE	4,565.73	2,017.56	2.26	0.02
STORIES	458.10	236.90	1.93	0.05
HOUSING INDEX	14,603.00	1,998.60	7.31	0.00
BASEMENT	-656.42	2,851.99	-0.23	0.82
GARAGE	26,519.00	2,902.88	9.14	0.00
Square root of AGE	-4,806.46	739.16	-6.50	0.00
Square root of LOT SIZE	14.71	13.90	1.06	0.29
Square root of LIVING AREA	3,280.89	241.58	13.58	0.00
Square root of ROOM	-816.58	4,233.89	-0.19	0.85
Square root of DISTANCE	-151.05	68.20	-2.22	0.03

For comparison, a weighted regression was also applied to the linear model. In the weighted linear model, the property price change is about \$2.5 more, which is similar to the OLS estimation (Table 6). The explanatory variables show expected signs and explain about 77.33% of variation in the purchase price. The marginal implicit price of distance is as follows:

$$\frac{\partial P}{\partial d_j} = -2.50 \qquad [19]$$

where p = purchase prices (1990 to 1996), and
d_j = the distance from the forest boundary to the property j
(for all equations, $d_j = -q_j$)

Table 6. Weighted regression estimates: Linear model

Purchase prices from 1990 to 1996 ($)				**(N=752) Adj. R^2 =77.33 %**
Explanatory Variables	**Estimates**	**Standard Error**	**T-statistic**	**Prob>[T]**
Intercept	-31,281.00	10,016.05	-3.12	0.00
S96	30,793.00	2,622.57	11.74	0.00
S95	40,212.00	2,745.40	14.65	0.00
S94	30,263.00	2,385.34	12.69	0.00
S93	19,614.00	2,259.81	8.68	0.00
URBAN	6,191.61	2,330.28	2.66	0.01
PUBLIC ACCESS	8,752.06	2,002.46	4.37	0.00
SALETY_QC	-80,406.00	8,285.02	-9.71	0.00
SALETY_BS	-66,119.00	6,613.36	-10.00	0.00
FAN_COOL	5,445.52	3,307.64	1.65	0.10
FIRE PLACE	2,859.19	1,947.26	1.47	0.14
STORIES	635.87	234.68	2.71	0.01
HOUSING INDEX	10,146.00	2,030.40	5.00	0.00
BASEMENT	-4,455.52	2,841.81	-1.57	0.12
GARAGE	23,382.00	2,891.92	8.09	0.00
AGE	-508.41	68.29	-7.45	0.00
LOT SIZE	-0.01	0.02	-0.54	0.59
LIVING AREA	37.68	2.55	14.80	0.00
ROOM	221.70	650.52	0.34	0.73
DISTANCE	-2.50	0.70	-3.59	0.00

5.4 Regression Estimates with Forest Characteristics

5.4.1 Measures of the forest characteristics

It was difficult to separate out the contribution of a single neighboring forest characteristic to the property price after accounting for the effect of being close to the forest. However, there are differences in locational amenities even at the same distance from the forest; some variation in property price was not explained by distance.

I first grouped the properties in this study area to get the neighboring forest characteristics information of each property (Figure 9). Area groups were divided by distinct forest management plans in nearby forest zones. The northern zone of the forest is generally managed to maintain younger, more structurally uniform stands with an even-aged regime, using clearcutting and commercial thinning. The central zone is managed to create two-story stands using an even-aged approach with longer rotation. This plan involves regeneration methods of clearcutting and shelterwood. The goal in the southern zone is to achieve species composition and structure similar to an older, mid- to late-successional forest. Management here stresses multi-layer, uneven-aged stands incorporating harvest methods of single tree and group selection. Table 7 shows the average forest stand information in each zone. There are some agricultural pastures in the northern zone. Those were not included in averaging the forest information of the zone. The northern zone has younger stands with lesser trees per acre than other two zones. The southern zone has the oldest stands, while the central zone has taller stands.

The properties in these area groups also differ by accessibility to the forest. Oak Creek with its meadows and hardwood stands, is most popular with hikers and mountain bikers, while Peavy Arboretum attracts people with duck ponds and hiking trails through old-growth stands. The Jackson area is the major equestrian access point and also provides access for other recreationists.

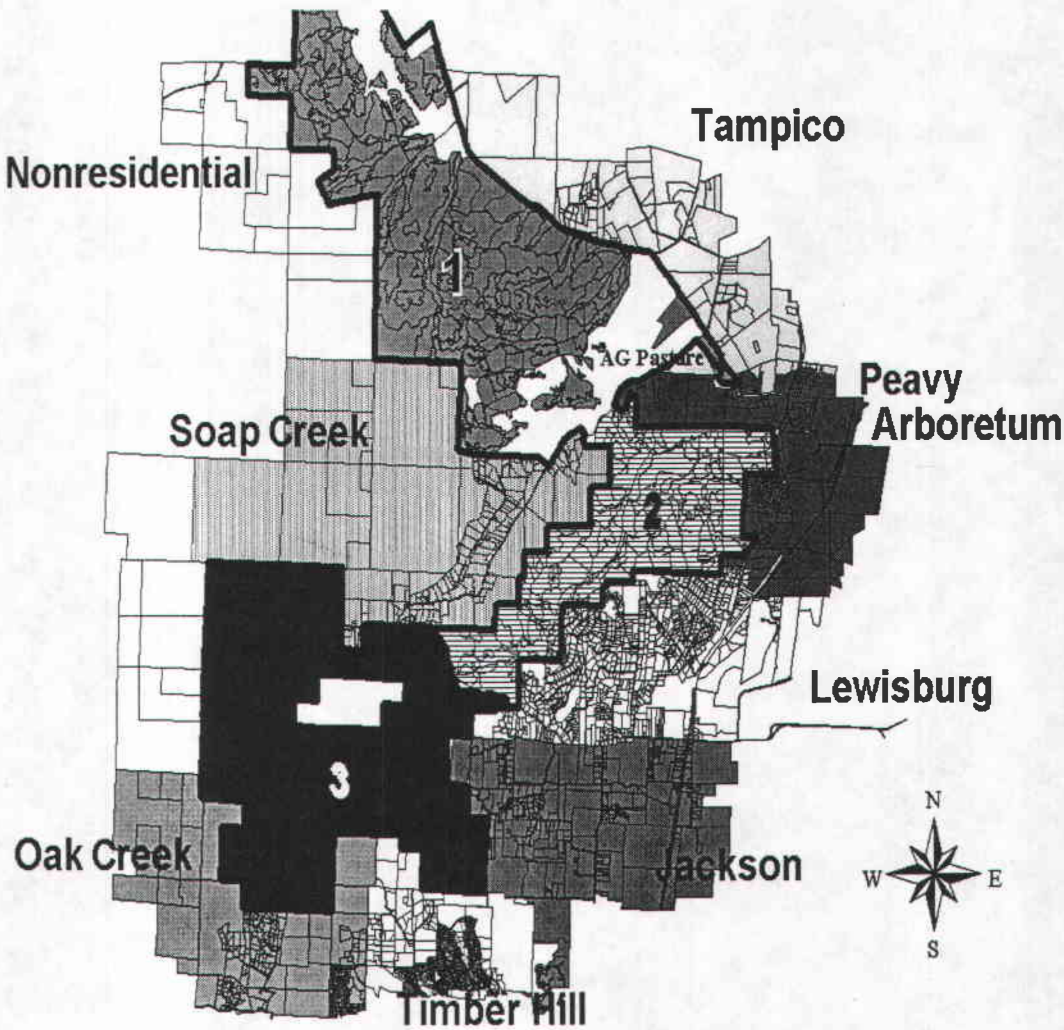

Figure 9. Residential area groupings around McDonald-Dunn Forest

Table 7. Description of forest zones

	Northern Zone (1)	Central Zone (2)	Southern Zone (3)	Total
Management scheme	Even aged	Two story	Uneven-aged	
Average number trees per acre	236.88	263.37	263.55	250.77
Average age (year)	52.81	59.95	63.59	58.12
Number of clearcuts over 10 acre since 1985	16	13	16	45
Last clearcut in the area	1996	1991	1992	1996
Average height of dominant and codominant trees (ft)	45.17	47.04	42.57	43.93
Average height of the tallest 40 trees (ft)	69.76	77.98	73.76	72.46
Average diameter (in)	5.79	6.38	6.08	5.97
Average crown closure (%)	54.29	62.03	63.11	58.99
Crown ratio	0.34	0.36	0.34	0.34

I also considered if the visible clearcut sites from a property affected the property price. Figure 10 shows the clearcut sites from 1985 to 1996. Because the height of intervening trees could block the view, I raised the elevation of McDonald-Dunn Forest by the average tree height of dominant and codominant species in each site (Figure 11). With this adjusted elevation data, the visibility of the clearcut sites for each year was calculated in a two-mile radius by using ArcView and Avenue. Avenue is a programming language that is fully integrated with ArcView. One of uses for Avenue is to direct ArcView to perform a specific task. It allows the users to calculate whether a given point is visible from another point accounting for intervening slope and elevation. I can also specify vertical and horizontal angle limits to the scan and limit the search distance when identifying areas visible from each observation point. I excluded some isolated clearcut sites under 10 acres in the visibility analysis, because those small patch cuts might not significantly affect the scenic view. Figure 12 illustrates the visibility of clearcut sites from 1990 to 1996. The measure of visibility is how many points generated along the boundaries of clearcut sites can be seen. There were no clearcuts in 1993 and 1994.

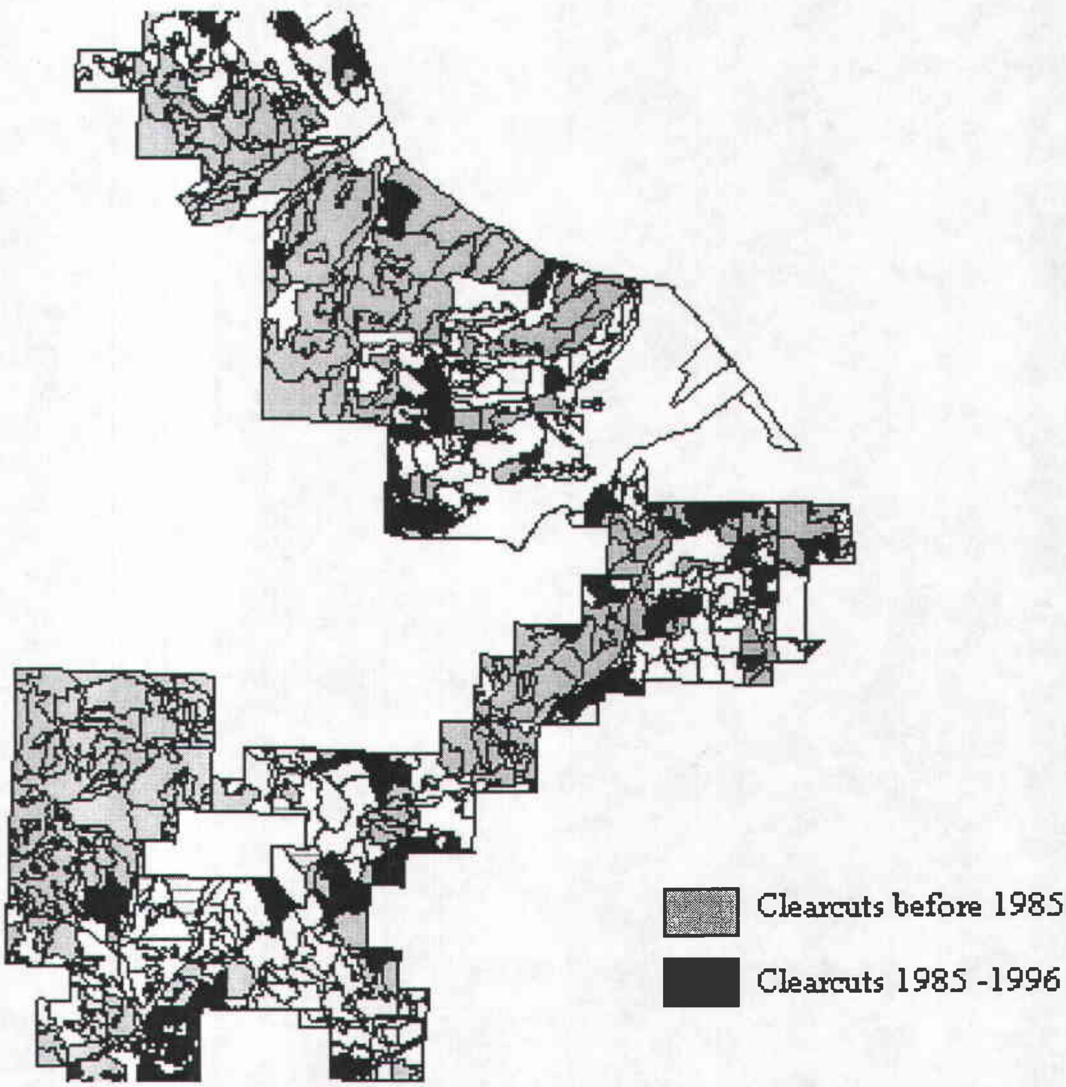

Figure 10. Clearcut sites in McDonald-Dunn Forest

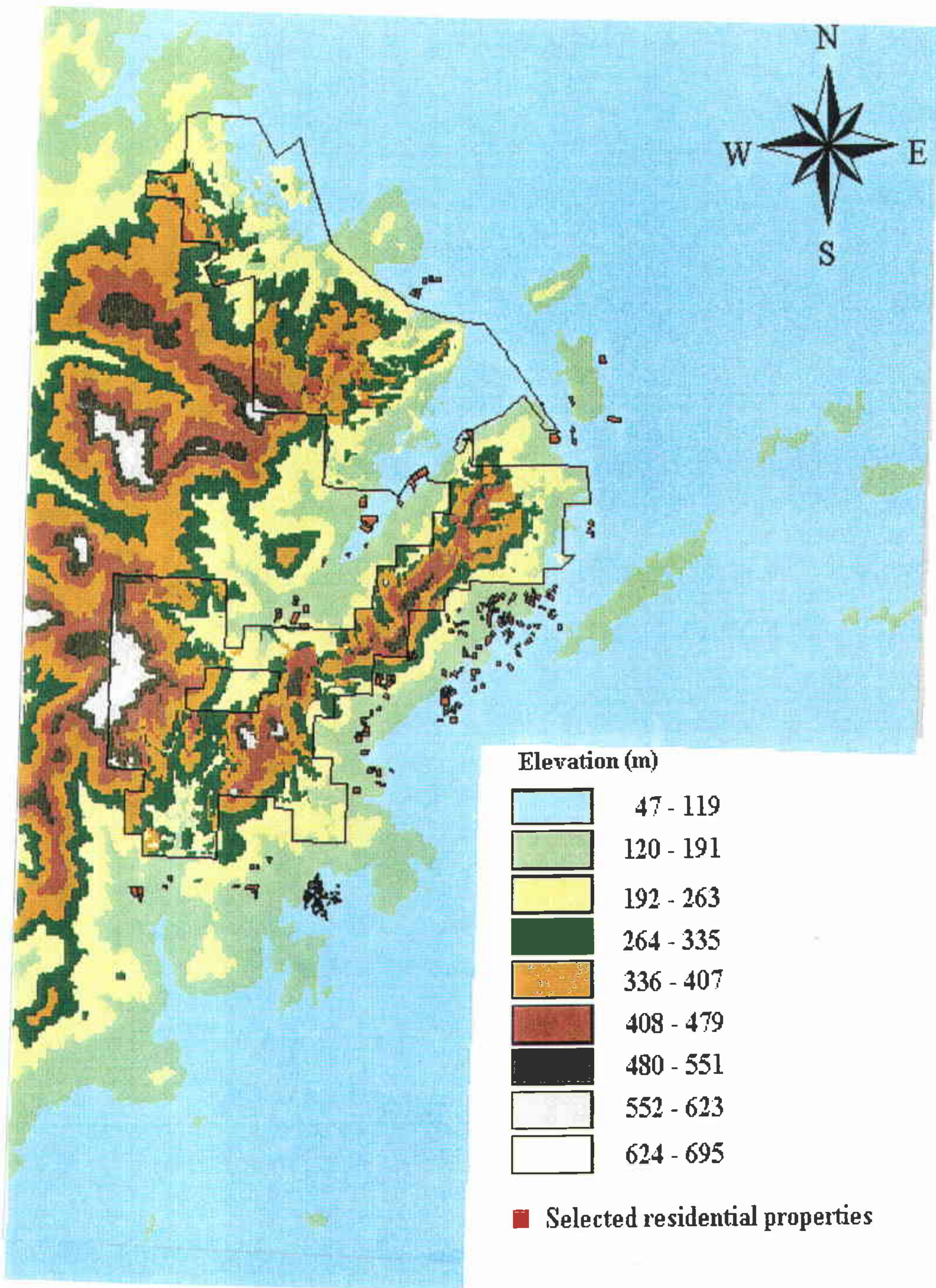

Figure 11. Elevation of the study area after adjusting for average height of dominant and codominant species in each stand

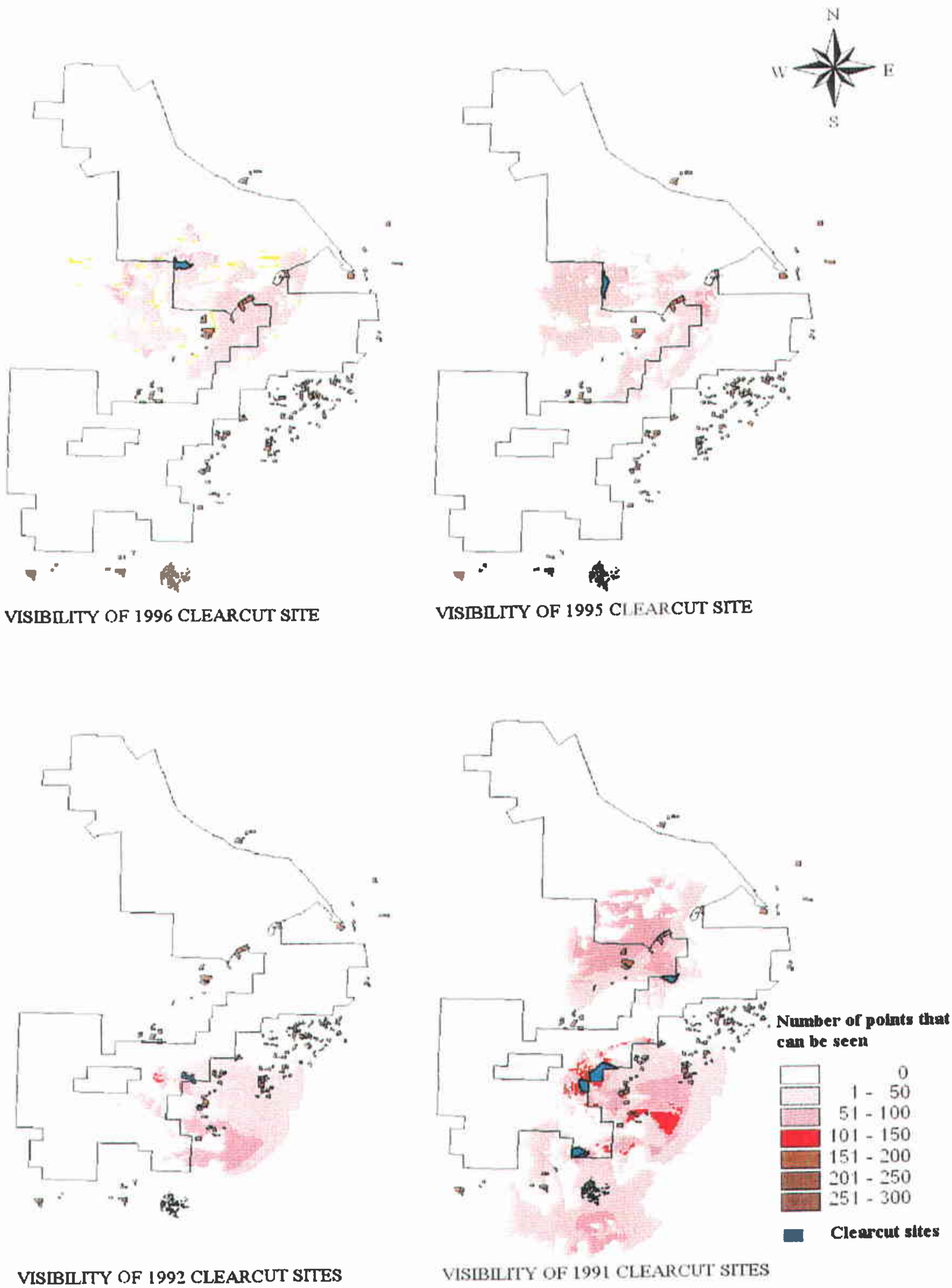

Figure 12. Visibility of clearcut sites

Table 8 shows the explanatory variables describing the neighboring forest characteristics of each property. The residential area group for each property was included as a dummy variable. Stand information for the forest site closest to each property was included to see if there was any contribution to the property price from a certain neighboring forest type. The variables for stand information were collected from

Table 8. Description of selected forest attribute variables

Location/ Stand type	Description
	<u>Area Group Dummy Variables</u>
	If the house is
ARBORETUM	in Peavy Arboretum area, then ARBORETUM=1
TAMPICO	in Tampico area, then TAMPICO=1
SOAP CREEK	in Soap Creek area, then SOAP CREEK=1
LEWISBURG	in Lewisburg area, then LEWISBURG=1
OAK CREEK	in Oak Creek area, then OAK CREEK=1
JACKSON	in Jackson Creek area, then JACKSON =1
TIMBER HILL	in Timber Hill area, then TIMBER HILL=1
	<u>Stand Information of the closest forest site</u>
	If the closest site is
AG PASTURE	agricultural pasture, then AG PASTURE=1
CONIFER	conifer/hardwood (51-85%), CONIFER=1
HARDWOOD	hardwood/conifer (15-50%), HARDWOOD=1
PURECONIFER	pure conifer (>85%), PURE CONIFER=1
OTHERS	meadow or others, OTHERS=1
TREE/ACRE	Total number of trees per acre
HEIGHT 40	Average height of 40 tallest trees
STAND AGE	Total age, overstory (year)
TREE HEIGHT	Mean height of dominant and codominant species (feet)
CCLOSURE	Crown closure
BIGDEAL	If the closest forest site was clearcut within 5 years before the property purchase, then BIGDEAL=1
	<u>Visibility of clearcut site at the time of purchase</u>
VISI	How much of clearcut site can be seen from the property
DVISI	If the clearcut site can be seen from the property, then visibility=1

the McDonald-Dunn Forest database. This database defines the composition of the stand. For example, when a forest site has 15 to 50 % of conifer, it is defined as a hardwood stand. More than half of trees in that site are conifers, it is a conifer stand. If the stand has 85% or more conifers, it is classified as a pure conifer stand. The other characteristics of the forest, such as tree height and stand age, were also included. The visibility of a stand that has been clearcut since 1985 was considered in two ways. The density of visibility is how much of the clearcut site that can be seen from a property at the time of purchase. Alternatively, a dummy variable was used to represent whether or not any part of clearcut site was visible at the time of purchase.

5.4.2 Partial correlation analysis

The partial correlation analysis for each forest characteristic variable was applied to the residuals from the square root model (Table 3 in Section 5.2.1). I tested if any unexplained part of the square root regression estimation with the distance variable could be accounted for by the neighboring forest characteristics around each property. With the partial correlation analysis, the correlation of the forest characteristic variables with the property price can be investigated without multicollinearity among explanatory variables (Table 9).

Among the area groups, the observations from the Tampico and Lewisburg areas show significant correlation with the residuals from the regression. Locations in these areas can explain some variation in the property prices not explained by the distance from the forest and other explanatory variables. For information on the forest site closest to each property, the differences in stand types are significant. Being close to agricultural pasture or meadow instead of forestland explains some part of the residuals. The closest forest site being 85% or more conifer stand also shows significant positive correlation. More trees per acre, older stand age and taller trees in the closest forest stands have positive coefficients even though they are not statistically significant (p-value > 0.1).

Most forest characteristic variables, however, show significant correlation with distance. This means that the properties have different neighboring forest characteristics according to the distances from the forest. Interaction terms between the forest characteristic variables and distance were also considered. The total age of overstory and mean height of dominant and codominant species became significant when those were considered with distance. This means that being close to an older stand or taller trees may not affect the property price directly. However, the locational amenities from the forest may have more lasting impact on the property price as the distance increases when the forest site closest to the property is an older stand or has taller trees.

To investigate the impact of these variables on property price, the variables having significant correlation (p-value<0.1) with the residuals from the square root model were applied to the regression estimation. The forest characteristic variables that are not significantly correlated with distance (p-value>0.1) were also tested in the regression.

Table 9. Pearson correlation coefficients between residuals and forest characteristics

Forest Characteristics	Correlation with Distance		Correlation with Residuals	
	Coefficients	P-value	Coefficients	P-value
ARBORETUM	-0.441	0.00	-0.021	0.57
TAMPICO*	-0.165	0.00	-0.096	0.01
SOAP CREEK	-0.282	0.00	-0.044	0.23
LEWISBURG*	-0.206	0.00	0.075	0.04
OAK CREEK	0.015	0.67	0.000	0.99
JACKSON	-0.087	0.02	0.056	0.12
TIMBER HILL	0.636	0.00	-0.007	0.84
AG PASTURE*	-0.199	0.00	-0.114	0.00
CONIFER	-0.058	0.11	0.033	0.36
HARDWOOD	-0.036	0.31	0.030	0.42
PURE CONIFER*	-0.140	0.00	0.072	0.05
OTHERS*	0.251	0.00	-0.061	0.09
TREE/ACRE	-0.229	0.00	0.048	0.19
HEIGHT 40	-0.344	0.00	0.024	0.52
CCLOSURE	-0.341	0.00	0.033	0.37
BIGDEAL	0.115	0.00	0.031	0.40
STAND AGE	-0.357	0.00	0.045	0.22
TREE HEIGHT	-0.359	0.00	0.054	0.14
VISI	-0.214	0.00	0.046	0.21
DVISI	-0.023	0.51	-0.030	0.41
ARBORETUM*DISTANCE			-0.012	0.74
SOAP CREEK*DISTANCE			-0.033	0.36
TAMPICO*DISTANCE*			-0.129	0.00
LEWISBURG*DISTANCE*			0.080	0.03
OAK CREEK*DISTANCE			-0.002	0.96
JACKSON*DISTANCE			0.059	0.11
TIMBER HILL*DISTANCE			-0.017	0.64
CONIFER*DISTANCE			0.048	0.19
HARDWOOD*DISTANCE			0.026	0.47
AG PASTURE*DISTANCE*			-0.102	0.01
PURE CONIFER*DISTANCE*			0.067	0.06
OTHERS*DISTANCE*			-0.065	0.07
TREE/ACRE*DISTANCE			0.059	0.11
HEIGHT 40*DISTANCE			0.038	0.30
BIGDEAL*DISTANCE			0.023	0.53
STAND AGE*DISTANCE*			0.065	0.08
TREE HEIGHT*DISTANCE*			0.075	0.04
DVISI *DISTANCE			-0.014	0.70

1) The value in parentheses is P-value, which is the probability for accepting the null hypothesis that there is no correlation.
2) * shows the variables with a significant correlation with the residuals at the 90% significant level

5.4.3 Regression estimates with forest characteristics

I applied the selected neighboring forest characteristic variables to the square root model (Table 10). Because of their high correlation with the distance from the forest and with one another, this regression result should be considered as exploratory.

All of the variables that show significant partial correlation with the residuals from the square root model were introduced to the regression analysis. The variables that show no significant correlation with the residuals were also tested to see if they were also not correlated with distance. None of interaction terms with distance are significant in the regression after accounting for the forest characteristic variables. Insignificant variables were eliminated to reduce the biases from multicollinearity. Adding five forest characteristic variables increases 0.69% of adjusted R^2 and all of the explanatory variables explain 75.97% of variation in property price. Most of the variables remain significant and show the same signs. The coefficient for the squared distance variable is smaller (bigger in absolute value) with the forest characteristic variables included. In other words, proximity to the forest shows a bigger contribution to the property price when I account the differences of the neighboring forest.

In the regression, the properties in the Tampico area have significantly lower property prices than those in the other areas. This area neighbors the even-aged industrial forest. It is also a relatively isolated area far from the business center of Corvallis. The Tampico area also happens to be near the city landfill. All these factors can have negative impacts on the property price. Locations in the Lewisburg area have significantly

Table 10. Regression estimates with neighboring forest characteristics

Purchase prices from 1990 to 1996 ($)				**(N=752) Adj. R^2 = 75.97%**
Explanatory Variables	**Estimates**	**Standard Error**	**T-statistic**	**Prob>[T]**
INTERCEPT	-112,158.00	14,719.57	-7.62	0.00
TAMPICO	-15,707.00	7,020.13	-2.24	0.03
LEWISBURG	5,358.57	2,878.55	1.86	0.06
AG PASTURE	-19,663.00	7,377.17	-2.67	0.01
PURE CONIFER	2,827.75	1,823.36	1.55	0.12
VISIBILITY	-12,391.00	5,695.33	-2.18	0.03
S96	39,704.00	2,933.85	13.53	0.00
S95	42,148.00	2,815.97	14.97	0.00
S94	34,526.00	2,610.07	13.23	0.00
S93	17,712.00	2,429.01	7.29	0.00
URBAN	6,587.59	2,510.58	2.62	0.01
PUBLIC ACCESS	2,330.93	2,287.40	1.02	0.31
SALETY_QC	-83,410.00	8,294.87	-10.06	0.00
SALETY_BS	-76,877.00	6,338.92	-12.13	0.00
FAN_COOL	8,053.94	3,586.00	2.25	0.03
FIRE PLACE	3,983.60	2,147.26	1.86	0.06
STORIES	359.69	217.53	1.65	0.10
HOUSING INDEX	14,927.00	1,952.80	7.64	0.00
BASEMENT	-5,884.93	2,550.07	-2.31	0.02
GARAGE	15,520.00	3,148.22	4.93	0.00
Square root of AGE	-3,729.78	846.92	-4.40	0.00
Square root of LOT SIZE	64.13	13.99	4.59	0.00
Square root of LIVING AREA	3,187.91	229.61	13.88	0.00
Square root of ROOM	6,311.22	4,192.99	1.51	0.13
Square root of DISTANCE	-200.94	82.76	-2.43	0.02

positive impacts on the property price. This area is near forest sites managed for shelterwood stands with taller trees.

When the closest forest site to the property is agricultural pasture, the property price is substantially lower. Among the properties near the forest, those close to pure conifer stands, rather than to mixed or hardwood stands, seem to have higher values.

The dummy variable for visible clearcuts from the property does not show significant partial correlation with the residuals or with distance. However, it became significant when it was introduced with other neighboring forest characteristics. In other words, when the forest sites clearcut since 1985 can be seen from the property, the sales prices are lower if all other characteristics of the property are the same including the neighboring forest characteristics.

Although the elevation of the forest sites was raised by the average tree heights, data on the heights of trees and buildings outside the forest which could block the views were not available and could not be included. The visibility target points were generated along the boundaries of clearcut sites in the GIS application, so it may not accurately represent the whole area of clearcuts. Visibility of clearcut sites needs further consideration with more detailed data.

6. CONCLUSIONS

6.1 Summary

This paper investigated the contribution of the forest to neighboring property prices and explored the possible impacts of having different neighboring forest characteristics with the hedonic price model. The sales records of residential properties within one mile of McDonald-Dunn Forest were used for the estimations, after choosing the time period of 1990 to 1996 for cross-sectional analysis and eliminating unreliable sales data.

The quadratic Box-Cox model was applied to choose the optimal functional form with the largest log-likelihood value for the response variable, i.e. purchase prices from 1990 to the beginning of 1996. The optimal values of the quadratic Box-Cox parameters, θ and π, were 0.82 and 0.52 respectively with the log-likelihood value –7,539.95. To interpret the factor effect, the square root model (θ=1, π=0.5; log-likelihood value = –7,549.57) was chosen to be the functional form that best explained the data. To check the robustness of the regression estimation, the linear model and a weighted regression were also applied.

The hedonic price function of the locational amenity from McDonald-Dunn Forest is convex to its quantity in the square root model. The implicit price of proximity to the forest increases as distance decreases; this relationship is even stronger for closer houses in the estimated square root model. For example, a house 100 ft away from the forest is worth about $1,520 more in its purchase price than a house 500 ft away, while a house

500 ft away is about $1,139 more valuable than a house 1,000 ft away, if all other characteristics of the house are identical. In the linear model, for each one foot closer to the forest, the house price is worth about $2.87 more. This contribution of locational amenity from the forest to the property price remains the same for any distance in the linear functional form.

The data set also shows different variances with respect to the factor book code groups. The weighted regression by the variance of each group shows more efficient estimation results than the ordinary least square regressions, but the estimated coefficient of the distance variable is not greatly different. In all of the ordinary least square regressions and weighted regressions, the distance from the forest seems to have a significantly negative relationship with the residential property purchase prices.

After accounting for the contribution of proximity to McDonald-Dunn Forest, the variables for the neighboring forest characteristics were applied to the hedonic price model. First, partial correlation analysis was applied to the residuals from the square root model and each forest characteristic variable to avoid the biases from correlation among explanatory variables. Then, the variables having significant correlation (p-value < 0.1) with the residuals were introduced to the square root model. The variables not correlated with the residuals or with distance were also tested in the regression.

By applying the area group dummy variables, I found that locations close to even-aged forests have negative contribution to the property price, while being close to shelterwood stands with taller trees have positive impacts. Average tree height of dominant and codominant species and stand age are not greatly significant by themselves in the partial correlation analysis, but their interaction with distance are notable. The taller trees and older stand in the neighboring forest seem to have lasting impact to the property price as the distance from the forest increases. However, these are not significant in the regression analysis, due to their correlation with other explanatory variables. When the property is close to agricultural pasture rather than to forestland, property prices tend to be much lower. Among the property near the forest, neighboring pure conifer stands have higher contribution to the property price than hardwood or mixed stands. The visibility of clearcut sites in the forest was analyzed by using GIS and elevation of the area. For the visibility analysis, I analyzed how many points along the boundary of the forest sites clearcut since 1985 could be seen. The visibility variable is highly correlated with other forest characteristics. If all other characteristics of a property including the neighboring forest characteristics are identical, the sales price is lower for the property where clearcut sites are visible at the time of purchase. The intensity of visibility, however, is not significant.

The neighboring forest characteristics are highly correlated among one another and with distance. Although these variables can explain some variation in the neighboring property price unexplained by the distance, they need to be measured in more comprehensive terms and the results should be considered as exploratory.

6.2 Implications

One of the management goals of McDonald-Dunn Research Forest is to be a good neighbor. The forest management plan is also concerned with the view of the forest from neighboring properties as well as providing recreational opportunities. It is important for the forest managers to know if the forest has any positive or negative impacts on neighboring property values and what kinds of forest conditions neighboring homeowners prefer.

In this study, I found that having McDonald-Dunn Forest as a neighbor has a significant positive impact on residential property values. The contribution of the forest seems to fade out as the distance from the forest increases. A certain forest management practice in the neighboring forest, such as a clearcut, may change the relationship between proximity to the forest and the property price and have a greater affect on the neighbors in closer distances.

Maintaining older or taller stands may expand the contribution of forest amenity to farther properties. The neighboring homeowners do not seem to distinguish the uneven-aged old growth stands from the shelterwood stands with taller trees. Agricultural pastures and meadows in the forest are not preferred by neighboring homeowners. The neighboring homeowners also seem to prefer a forest stand with 85% or more conifers.

These results may be used to create a market for forest quality around residential properties. In 1995, the harvesting of the Cameron Tract along Soap Creek road brought a public dispute over McDonald Forest management (Corvallis Gazette-Times, 1995). The timber sale raised about 1 million dollars for the university, while many neighbors complained their property values would be affected. Even though the forest managers left a wider buffer between the clearcut sites and neighboring properties than the state regulation, the neighbors felt frustrated that they were unable to influence the forest management decision. If there were a mechanism where they could pay for a certain neighboring forest quality, it could improve benefits of both parties. For example, if a homeowner knows that her property is worth more in the neighborhood of pure conifer stands with no visible clearcuts, she can offer to pay the forest managers to keep that forest condition. In a previous study (Johnson et al., 1992), slightly less than half of interviewed adjacent homeowners around McDonald Forest were willing to pay up to $350 (1992 dollars) per year to avoid clearcuts in their backyard, which would be 2 or 3% of the annual payment of a typical home in this area. In this study, the negative contribution of visible clearcuts to the property price is about $12,391 per property in 1987 dollars, which is about 10% of the average property price, but this relationship also depends on other neighboring forest characteristics around the property.

For the case of the 1995 clearcut, the 200 acre parcel was donated to Oregon State University to provide money for the library renovation, as well as the fund for teaching and research into private forest management. Gift conditions maintained that the OSU harvest must raise 1 million dollars for the library and 62 acres was clearcut for that. If the neighboring homeowners in the area wanted to avoid the clearcut, they would have needed to bring together this sum of money to pay off the forest manager not to clearcut. This payment can be spread out over 60 years, which is roughly the rotation age of Douglas Fir. The annual payment is about $44,204 with 4% annual interest rate. If one hundred neighboring homeowners evenly participated on this payment, the annual payment to avoid any logging in their neighborhood is $442 per year per household. Using the results from the hedonic model, the decrease in the property value by visible clearcut is about $16,381 in 1995 dollars per property, which is about $724 per year with the same interest rate over 60 years. Therefore, homeowners have a financial incentive to compensate the forest managers not to clearcut.

The other possibility is that the Research Forest could use a harvest method like a selective cut, instead of a clearcut. The harvest would be more costly and the net revenue would be smaller, but the neighboring homeowners could be asked to compensate for the difference. In that case, the payment for having a selective cut instead of a clearcut will get even smaller than $442 per year. However, the coefficient of the visibility variable should be interpreted with caution. When I interpreted the negative impact of visible clearcut, all of the other explanatory variables in the hedonic model were assumed to be the same. In reality, that won't be true and the neighboring homeowners may not want to share the payment evenly.

Surrounding forest conditions can affect many neighboring properties. When a homeowner in the area buys a certain forest quality near her home, her neighbors can enjoy the same quality for free. As Johnson et al. noted, creating a market for a certain forest quality between forest owners and neighbors would be problematic. However, if we can accurately measure the contribution of the forest to each property according to distance and other locational differences, it may be possible to reach a consensus for the fair price of forest quality among the neighbors and with forest owners. Market solutions have the potential to reduce conflict between forest managers and neighboring homeowners.

6.3 Future Research Needs

To investigate the contribution of forest amenities to neighboring property values more carefully, we need to abstract various forest characteristics into a few variables for the hedonic price model. Since most forest characteristics are correlated among one another and with the distance from the forest, a comprehensive measure of forest characteristics is most needed, yet problematic. This study explored the possible application of GIS to develop extensive measures of locational amenities. The visual quality measure is one of the built-in functions of ArcView and ArcInfo. This can generate a visual quality score for each observation point by counting visible amenities and disamenities in the area. When there are numbers of observations and locational amenities, this can be very time consuming with a personal computer. The visual quality analysis is also limited because it may not be very clear which locational amenities should get higher points and also the pattern of surroundings can be more important than individual point locations.

A possible solution is applying the landscape indices determined by landscape experts. It is possible to include condensed information of surrounding landscape characteristics to the hedonic price regression. We may be able to compare ecosystem health of the area with perceived human values in this way. However, the judgements of landscape experts may not accurately represent the preferences of lay people. A social survey can also be used to measure actual preferences of neighboring homeowners for forest quality. The contribution of the forest to neighboring property values is mostly from scenic quality or recreational opportunity, but there may be some other concerns for being close to the forest, such as fire hazard or land development restrictions. By applying a social survey, we can also identify specific amenities or disamenities in the area. The differences among these measures should be compared systematically in the hedonic price model estimation. These steps would be helpful to improve the methodology of the hedonic price model in natural resource management.

This study also addressed some problems in the regression estimation of the hedonic price model for forest attributes. In this field, there are few cases of hedonic studies incorporating economic theory and the choice of functional forms. For the application of the hedonic price model in natural resource management, we need more cases of systematic comparisons of estimated hedonic price models, especially in non-metropolitan areas. In these cases, the observations are spatially spread out and show autocorrelation over distance like in time series, but we need to start from an a priori functional form to correct this spatial correlation. However, the linear model is violating economic tenets with constant marginal price. The log or double log functional form, which are widely used, may not be appropriate for a certain locational amenity, since this assumes a concave hedonic price model as the quantity increases.

The user cost of capital was introduced to the hedonic price model in this study. When market transactions are slow and data over time are aggregated, the user cost of capital is different for the observations of each year. The factors influencing a person's decision among buying, renting or improving a property should be included in the formal analysis of the hedonic price model. In this study, I just considered the utility function at a time period, but the differences in discounted future utility and budget constraint with respect to the choices need more theoretical investigation.

This study applied the hedonic price model to the near urban forest area and expanded the possibility of GIS application in measuring locational amenities. The theoretical problems were addressed to apply the hedonic price model in natural resource management, as well as the questions of choosing a proper functional form and measuring the focus variables. The results of this study will help further investigations to develop a new methodology of the hedonic price model.

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