A Neural Network Analysis of the Effect of Age on Housing Values

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Abstract. Empirical studies using multiple regression find the value of a residential property declines with its age. Because these results confirm the fact of physical deterioration of a house over time, little attention is paid to the statistical technique's inherent shortcomings. Accordingly, this paper uses a neural network, which is able to overcome multiple regression's methodological problems, to re-examine the effect of age on a house's value. We find that a negative relationship of value to age holds only for the first sixteen to twenty years of the life of a house. Then, not only does the decline in value stop, but a house actually starts to experience appreciation related, in part, to its lot size.

Introduction

An accurate assessment of the value of a house is important to its current owners, prospective suppliers of mortgage funds, and potential buyers of the house. Despite the vast amount of literature on housing prices, only Sabella's paper (1974) specifically examines the relationship between a property's age and its market value. Sabella argues that, over time, the combined effect of the decline in value of the structure along with an increase in value of its land component, will cause the total market value of a property first to fall and then to rise. Sabella (1975) examines empirically this relationship between the change in value and age of a property, and concludes that the older a home becomes the smaller the change (decrease) in its value.

Other empirical studies of housing prices incorporate age only as an explanatory control variable. Using statistical techniques, especially multiple regression, these studies find that the age of a property is negatively related to its value. While the change in value of a house with respect to its age seems to reflect the importance of a factor such as depreciation, it should be recognized that these valuations, because of the method used to generate them, may contain significant errors. Moreover, when multiple regression is used for valuation this inaccuracy is magnified by methodological problems, including functional form misspecification, interaction among variables, nonlinearity, multicollinearity, and heteroskedasticity (see, for example, Larsen and Peterson, 1988; Mark and Goldberg, 1988; Coleman and Larsen, 1991; Murphy, 1989; Weirick and Ingram, 1990; Ziemer, 1984; and Newsome and Zietz, 1992 for a discussion of some of these issues).

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Recently, neural network models inspired by the neural architecture of the brain have been developed and successfully applied across a variety of disciplines including psychology, genetics, linguistics, engineering, computer science, and economics. By learning through interaction with their environment, in a process that can be best characterized as recursive statistical estimation, neural networks have been shown to be particularly well suited to solving problems involving pattern recognition, classification, and nonlinear feature detection (White, in press). More specifically, substantial evidence indicates that neural networks possess the capability of providing accurate approximations to a very wide class of nonlinear functions[1] (see Hornik et al., 1989; Hornik et al., 1990; Stinchcombe and White, 1989; and Lee et al., forthcoming) and, because of this capability, can give us answers to several classes of problems that are difficult to resolve with classical statistical techniques (Eberhart and Dobbins, 1990).

Besides being proficient at finding accurate solutions in environments characterized by complex functional relationships, neural networks have the facility to minimize the consequences of several methodological problems (identified above) associated with multiple regression-based derivations of residential property values. The reason for the success of neural networks over multiple regression models stems from the difference in how their function form is specified. While traditional estimation methods must prespecify a functional form before fitting the data, neural networks self-determine their functional form based on tuning their estimation parameters to "best fit"[2] the data. What results is a superior modeling technique, which can approximate any functional form to any given degree of accuracy (see Hecht-Nielson, 1990 and Shadmehr and D'Argenio, 1990), to discover the relationship between the inherent characteristics of the residential asset and its estimated selling price.

Accordingly, this paper uses a neural network first to model residential property valuation based on single-family housing market transactions from a large city, and then to simulate how the derived values of these properties change as their age varies. Our purpose is to show that the negative monotonic relationship of value to age presumed to exist based on previous empirical studies is too general, and, for certain periods of the asset's age, incorrect.

The remainder of our paper is organized into three sections. The next section defines the valuation model adopted, describes the characteristics of the data used in the study, and identifies the procedures employed to analyze the data. In section three, the results of our study are given. The last section of the paper contains a summary of our investigation.

Methodology

From current empirical studies, the following traditional valuation model of residential housing prices is adopted:

$$SP_i = f(S_{ij}), \tag{1}$$

where SP_i is the selling price of house i as recorded at closing, and S_{ij} is the standard set of explanatory housing-price variables[3] with j being the explanatory variable for property i, which includes the following:

> AGE = the age of the structure in years,
> BR = the number of bedrooms,
> BA = the number of bathrooms in increments of 1/4 baths,
> SF = total square footage of the house,
> GA = the number of car-garages,
> FP = the number of fireplaces,
> ST = the number of stories, and
> LSZ = the lot size measured in square feet.

In the above valuation model, the expected influence of the explanatory variables on selling price are positive with the exception of the age of the structure.

Data

The data comes from information[4] provided by the San Diego Board of Realtors' Multiple Listing Service (MLS) to its member agents. Observations consist of 242 single-family homes sold during the period January 1991 through September 1991, in the southwestern part of San Diego, California county. The neighborhood from which the observations are drawn is somewhat uniform with respect to income, population density, access to major public facilities, and its residential-commercial composition.

The descriptive statistics of the sample are presented in Exhibit 1. The mean sales price for the houses in the sample is $169,927 with prices ranging from $105,000 to $400,000. The mean age of the properties is 27 years with a standard deviation of 12.8 years, and a range from 3 to 85 years. Exhibit 1 also provides descriptive statistics on

Exhibit 1
Descriptive Statistics of the Attributes of the Properties in the Sample

Attribute Abbreviation	Attribute Definition	Overall mean (Std Dev.)	Minimum (Maximum)
SP	Selling price ($)	169,927 (36,951)	105,000 (400,000)
AGE	Age (yrs.)	27.75 (12.76)	3 (85)
BR	Number of bedrooms	3.17 (.74)	1 (5)
BA	Number of bathrooms	1.87 (.54)	1 (3.5)
SF	Total square footage	1,474.14 (438.02)	650 (4,000)
GA	Number of car-garages	1.65 (.67)	0 (3)
FP	Number of fireplaces	.72 (.58)	0 (3)
ST	Number of stories	1.18 (.39)	1 (2)
LSZ	Lot size (sq. ft.)	7,625.43 (2,773.75)	2,943 (22,215)
	Sample size	242	

total square footage, the number of bathrooms, bedrooms, fireplaces, car-garages, stories, and lot size of the properties.

Procedures

In this investigation the neural network used to estimate the selling price of the sample properties is illustrated in Exhibit 2. Each node is represented by a circle, and each node interconnection, with its associated weight, by a line terminated by an arrow.

The neural network to value residential properties depicted in Exhibit 2 has an input layer i of eight nodes, each of which represents an attribute of a property; a hidden layer j of three nodes; and an output layer l, of one node, which represents the estimated selling price of the property. To facilitate training the network (discussed below), all inputs are normalized[5] to lie in the range 0 to 1.

Signals in the neural network feedforward from left to right. The signal presented to a hidden layer node in the network is the output value, o of the input node times the value of a hidden layer node's connection weight, w. The net input, i to the hidden node is equal to the sum of all connections into it. This value is described in equation 2.

$$i_j = \sum_i w_{ji} o_i. \tag{2}$$

The output of a hidden node is transformed according to a sigmoid function so that its value falls between 0 and 1. Equation 3 shows this transformation.

$$o_j = 1/(1 + \exp(-i_j)). \tag{3}$$

Exhibit 2
Structure of the Residential Valuation Neural Network
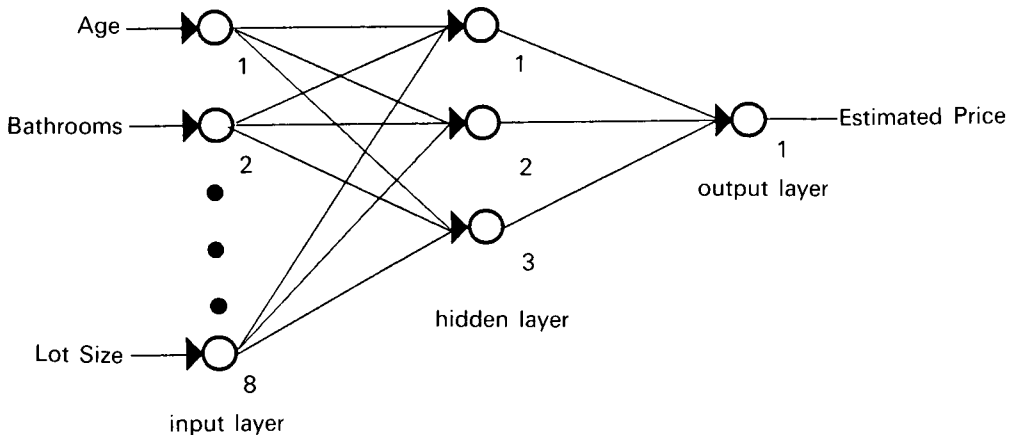
Once the outputs of all hidden layer nodes are calculated, the net input to the output layer node is calculated in an analogous manner, as described in equation 4. Similarly, the output of the output layer node (i.e., the estimated selling price of the property) is transformed according to equation 5.

$$i_l = \sum_i w_{lj} o_j, \tag{4}$$

$$o_l = 1/(1 + \exp(-i_l)). \tag{5}$$

To summarize, the feedforward process in the residential valuation neural network entails performing two operations per hidden and output layer node. The first operation sums the output of the previous layer nodes times the interconnecting weights, and the second operation functionally transforms the output.

Data on a residential property forms a pattern, p. Presenting each property's characteristics and actual selling price (i.e., the target value, t_l) over and over again to the network causes the network to adapt its weights so that the estimated price of the property mirrors its target value. The adaptation process, called training, is discussed next.

An error term measures how well our neural network is trained. The term represents the difference between the price estimated by the network and the property's actual value. The error term is summed over all patterns and then divided by the number of training patterns to give the following average sum-squared value:

$$E_p = (\sum (t_{pl} - o_{pl})^2)/l. \tag{6}$$

The goal of training is to minimize the error over all patterns. The process of adapting the weights of the network's nodes to achieve this objective is called back propagation.

Recall that by equation 5 the output of the node in the output layer indicating the property's estimated selling price is a function of its input, or $o_l = f(i_l)$. The first derivative of the function $f'(i_l)$ is called the error signal δ_l and is defined by equation 7 for the single output layer node.

$$\delta_l = f'(i_l)(t_l - o_l). \tag{7}$$

The first derivative of the sigmoid transfer function of equation 5 is $o_l(1 - o_l)$. Equation 8 represents the output layer error signal.

$$\delta_l = (t_l - o_l)o_l(1 - o_l). \tag{8}$$

The neural network propagates this error value back through the output layer node and performs appropriate adjustments to its weights. Specifically, using a coefficient η and a factor α, equation 9 describes how the weights feeding the output layer node of our valuation neural network are updated.

$$w_{lj}(new) = w_{lj}(old) + \eta \delta_l o_j + \alpha[\Delta w_{lj}(old)], \tag{9}$$

where $\Delta w(old)$ represents the weight change on the previous training iteration.

What is being applied here is weight adaptation according to the gradient descent method. The idea behind the method of gradient descent adaptation is to make changes in the network's weights that are proportional to the negative of the derivative of the error, as measured on the current training pattern, with respect to each weight.

For the hidden layer nodes of the network, the error term is calculated as,

$$\delta_j = f'(i_j)\sum w_{lj}\delta_l, \tag{10}$$

and equations 11 and 12 are equivalent to equations 8 and 9.

$$\delta_j = o_j(1 - o_j)\sum w_{lj}\delta_l, \tag{11}$$

$$w_{ji}(new) = w_{ji}(old) + \eta\delta_j o_i + \alpha[\Delta w_{ji}(old)]. \tag{12}$$

In summary, for each pattern the neural network calculates the error terms for its output layer node using equation 8, and then for each hidden layer node using equation 11. It then sums the error terms, and, after all patterns are presented once, adjusts the weights of its nodes according to equations 9 and 12. The neural network is considered to be trained, and its weights are not modified further, when the sum of its error terms approaches zero. This occurred after 3,000 iterations and resulted in a matrix of connecting weights (shown in Exhibit 3) as the input signals flowed from left to right through the network.[6]

Exhibit 3
Connecting Weights of the Input Nodes to the Output Nodes

From/To	Hidden Node 1	Hidden Node 2	Hidden Node 3	Output Node
Age Node	2.2869	.440438	−11.3261	
BR Node	3.48725	−6.49039	1.86168	
BA Node	−.13048	−.33	1.18724	
SF Node	5.28212	3.09125	2.50608	
GA Node	2.23533	−1.15172	.974551	
FP Node	−5.65779	19.1808	−.90809	
ST Node	3.88156	−10.1494	−.7587	
LSZ Node	4.12753	−.83792	1.47675	
Hidden Node 1				1.67911
Hidden Node 2				1.26221
Hidden Node 3				1.58112
Constant	3.5355	−2.78259	−1.89762	−3.67173

Results

The effect of age on the value of a property is illustrated for five houses, which represent the spectrum of selling prices in our sample. The attributes of these houses are identified in Exhibit 4.
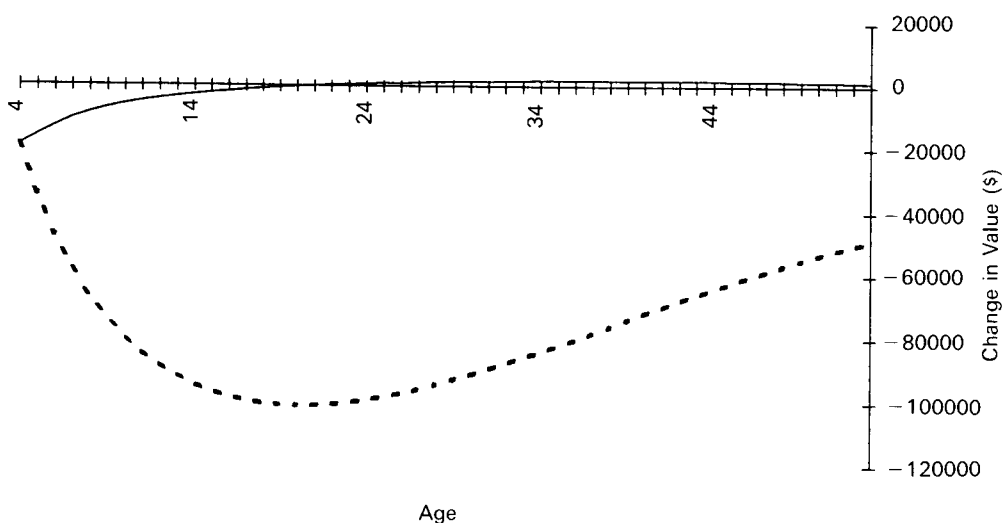
Exhibit 4
Attributes of the Sample Properties

| Attribute	Property 1	Property 2	Property 3	Property 4	Property 5
Selling Price	121,000	138,000	169,900	174,500	205,000
Age	21	26	36	38	23
Bedrooms	3	3	4	3	4
Bathrooms	1.75	1	2	1	1.75
Sq. Footage	1,234	1,072	1,715	1,690	2,205
Car-garages	1	1	0	2	3
Fireplaces	0	0	1	0	1
Lot Size	3,480	8,300	9,400	6,800	7,400
Stories	1	1	1	1	2

The changes in estimated value are computed by the neural network for simulated patterns of each of the five properties as their age is varied from three to fifty years.[7] The changes in estimated value for the five houses are graphed in Exhibits 5 through 9, where the yearly changes are depicted by the solid line and the cumulative changes are shown as a dashed line.

Overall, there is general agreement as to the shape of the function depicting the yearly and cumulative change in the estimated value of a house and its age. Studying the exhibits we see that for about the first fifteen years of a property's life, its value decline is consistent with a depreciable asset experiencing physical deterioration.
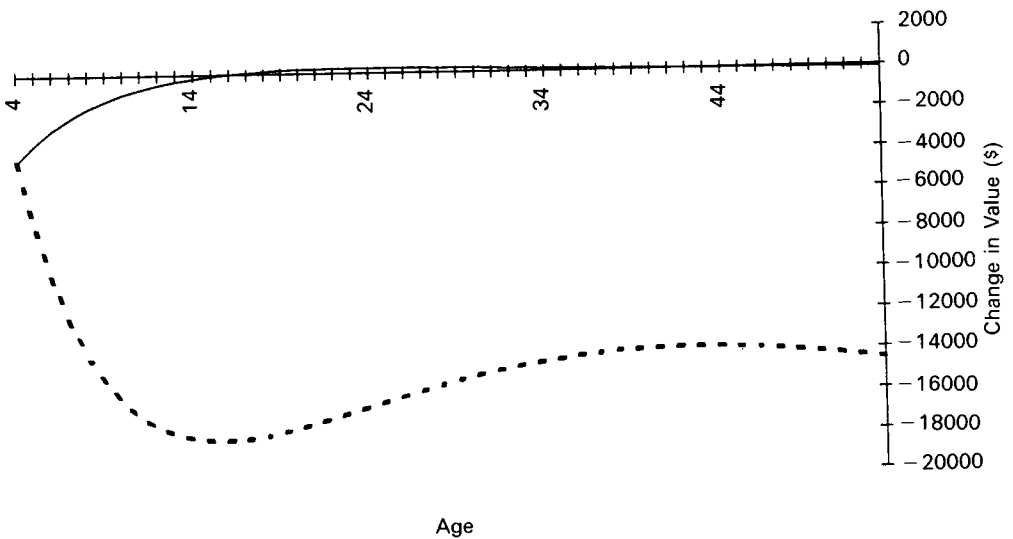
Exhibit 5
Change in Value Relative to Age of Sample Property 1

Age

Exhibit 6
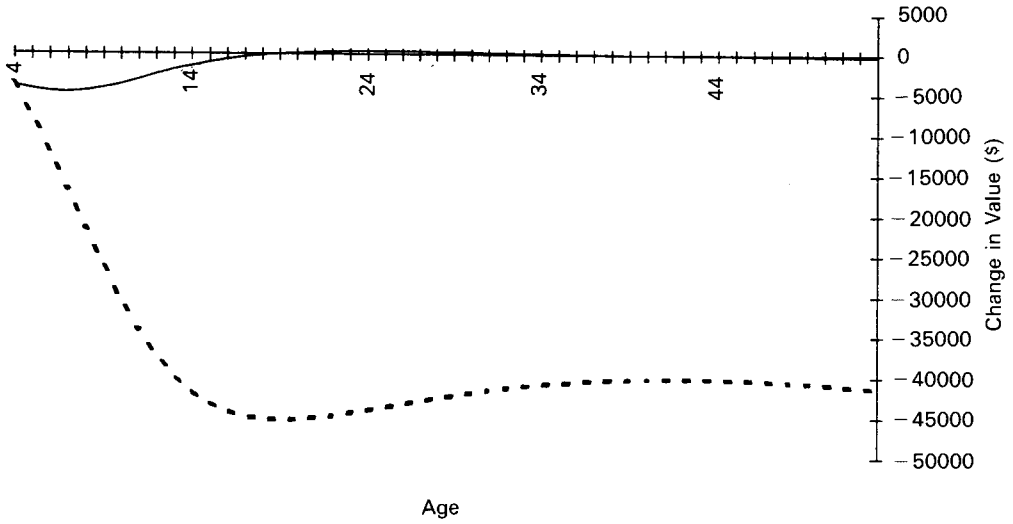**Change in Value Relative to Age of Sample Property 2**

Age
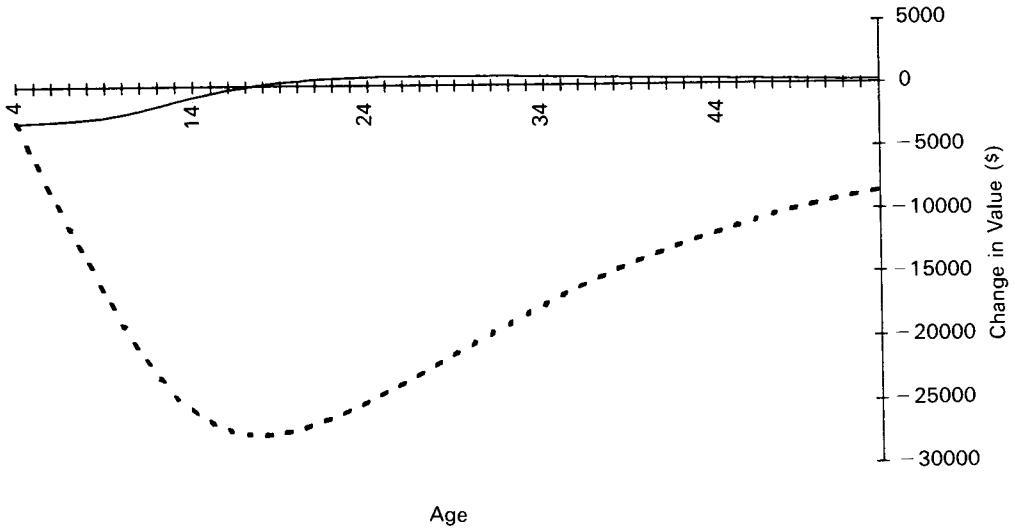
Exhibit 7
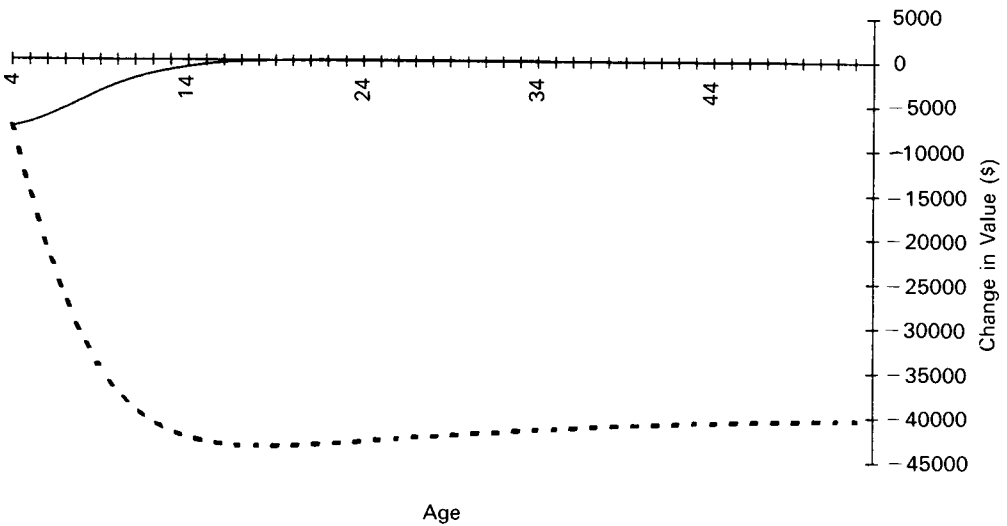**Change in Value Relative to Age of Sample Property 3**

Age

Exhibit 8
Change in Value Relative to Age of Sample Property 4

Age

Exhibit 9
Change in Value Relative to Age of Sample Property 5

Age

Exhibit 10
Average Yearly Change in Value During Years 4–15 of the Sample Properties

Age of the Property	Property 1	Property 2	Property 3	Property 4	Property 5
4–7 years	−14,560	−2,837	−3,124	−4,232	−6,623
8–11 years	−6,528	−2,458	−1,145	−4,363	−4,263
12–15 years	−3,098	−1,370	−276	−2,276	−939
Ratio*	1:2.82	1:7.74	1:5.48	1:4.02	1:3.36

*ratio of the square footage of a house to its lot size

Because this decline is logarithmic rather than linear, it approximates a form of accelerated versus straight-line depreciation. We also notice from Exhibit 10 that the average yearly changes in the value of these houses during this maturation period appear unrelated to their selling price. However, the decline in property values appear to be correlated, at least in years four to seven, to the ratio of the square footage of the structure and its lot size. This result is consistent with Sabella's (1974) notion of a fall and then a rise in the total value of a property with its age, due primarily to an increase in the land value of the property.

Moreover, at an age of approximately sixteen to twenty years, the exhibits show that not only does the decline in value stop, but that a house actually starts to experience appreciation. While this convex value function may be in part due to the appreciation in land consistent with Sabella's theory, it may also be caused by the initiation of major repairs being made to a house. For instance, a house in Southern California after twenty years needs its roof replaced. It may also require replacement of its heating and cooling systems, modernization of its major appliances, and an overhaul of its plumbing system. Moreover, at this age many houses are completely remodeled to reflect the tastes of a new generation of homebuyers. These major repairs and remodeling efforts, which entail expenditures far in excess of routine maintenance expenses, contribute to an increase in a house's value each year. We believe what is happening to houses of this vintage, therefore, is that the effect on value caused by physical deterioration is being more than offset by both an increase in land value and the capital appreciation from major repair expenditures.

Summary

This paper investigates the relationship between age and selling price of single-detached dwellings using a neural network to analyze transaction data from a large city. Our results indicate that a negative relationship between age and value occurs only during the first sixteen to twenty years of the life of the house. Subsequently, the relationship between age and value becomes positive, and appreciation in housing values is found. This reversal in the relationship of age and value is consistent with

Sabella (1974), who theorizes that the value of a property rises in later years due in part to the increase in value of the land portion of a home. Further, we think that major repair and remodeling efforts are being made, which result in expenditures far in excess of normal maintenance expenses, and thereby contribute to an additional increase in an older house's value.

Notes

[1]This capability comes from the functional form produced by the hidden layer nodes of a neural network. This functional form may be viewed as belonging to a family of flexible functions, which are indexed by the number of hidden layers in the neural network and by an activation function that gives a nonlinear mapping of input to output for each node. (For a more thorough discussion of this capability, see White, 1989a and White, 1989b).

[2]The term "best fit" is meant to represent the minimum difference between the actual value and the value estimated by the neural network over all observations used to derive the parameters of the neural network.

[3]These standard explanatory variables are consistent with previous studies on housing price determinants (see, for example, Sirmans, Sirmans and Benjamin, 1990 and Sirmans and Sirmans, 1991). Time variables are not included in the model because it is observed that selling prices remained stable during the sample period.

[4]The sample data set contains information about each sold property in San Diego and vicinity, which includes the following: (1) physical characteristics of the house, such as the total square footage of the house, the age of the property, the number of fireplaces and number of car-garages; (2) lot sizes; and (3) the actual selling prices and date of sale as recorded by the real estate firm.

[5]Normalization of an individual attribute value is accomplished by subtracting the minimum value of the attribute from the attribute's value, and then dividing the result by the attribute's range.

[6]Once trained, our neural network accounted for 99% of the total variance in the selling price of houses in our sample. Comparatively, the following multiple regression model, which contained a quadratic term for age, was able to account for only 74% of the total variance in selling prices:

$$SP = 91160.96 - 1772.59AGE + 23.62AGE^2 - 3672.19BR - 894.09BA$$
$$\quad (10048.59)^* \quad (317.84)^* \quad (4.72)^* \quad (2378.79) \quad (3559.59)$$

$$+ 56.28SF + 6572.04GA - 1613.03FP + 5079.47ST + 2.67LSZ,$$
$$\quad (5.30)^* \quad (2115.17)^* \quad (2666.91) \quad (4200.52) \quad (0.47)^*$$

where the standard errors are in parentheses, and an asterisk denotes significance of a regression coefficient at the .01 level. The F-statistic for the equation is 76.4.

[7]Our sample contains no houses newer than three years old, and relatively few houses older than fifty years of age (i.e., only 5 out of 242). Therefore, we feel it is appropriate to limit our simulation to the age range on which the neural network is trained.

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