Air Pollution and the Housing Market: A Neural Network Approach

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ABSTRACT

Using the neural network method, this research explores the impact of total suspended particulate (TSP) and sulfur dioxide (SO_2), two major air pollutants, and of air pollution controls on the median real price of housing in Jacksonville, Florida. The results of this case study confirm the adverse effect of air pollution on the price of housing. The simulation of the model further suggests that pollution control measures improve property values. The findings imply that, in addition to other measures influencing the price of housing, property owners and buyers take air pollution and pollution controls into account. (JEL Q25)

INTRODUCTION

According to U.S. government reports, millions of Americans face adverse health risks as a result of exposure to airborne pollutants. For example, a recent General Accounting Office's report [1993, p. 8] to Congress concluded that, "Even though air pollution has been reduced since the passage of the Clean Air Act in 1970, commercial and industrial facilities in the U.S. continue to emit millions of tons of pollutants into the air annually. Air pollution brings about or aggravates health problems ranging from eye, nose, and throat irritation to bronchitis, emphysema, and other serious lung diseases. Air pollution also causes environmental problems ranging from impaired visibility in many areas of the country to damaged crops, forests, and lakes."

Specifically, there are reports revealing that total suspended particulate (TSP) and sulfur dioxide (SO_2), the two major air pollutants, are responsible for most of the damaging effects on human health in the U.S. [Seaton et al. 1995, p. 176; U.S. General Accounting Office, 1994, p. 3]. In 1981, Winchester et al. claimed that "mortality in many counties of the southeastern United States are greater than the U.S. average. The rate in Jacksonville and Duval County, northeastern Florida, is especially high." These authors further claimed that, in addition to the local factor, SO_2 is imported to Jacksonville by winds from the northeastern part of the U.S. This SO_2 pollution leads to the formation of aerosol [H_2SO_2] in the humid South Atlantic coastal climate, proportionately increasing the risk of lung cancer.

The measurement of the benefits of air pollution control, as a public good, is very difficult without direct transaction. As a result, researchers have necessarily resorted to an indirect market method. The different prices of real property that have different levels of air pollution, but are otherwise similar, can be attributed to losses from increased maintenance, adverse

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health effects, and damage to aesthetic values. Property values are affected if property owners and buyers perceive adverse health effects from air pollution. To the extent that some of these damages are not perceived, the pollution price differentials may understate the true effects. Thus, the property value approach may measure only a portion of the total benefits of improved air quality.

Investigators mostly have used Hedonic price analysis, a factorial survey method such as contingent valuation, and cost-benefit analysis to evaluate the benefits from proposed pollution control measures. Nearly all comprehensive studies which incorporated numerous variables influencing housing prices used the Hedonic approach. This method uses housing demand functions and estimates the parameters of the variables, including the pollutants components. Based on an estimated function, the partial derivative of the function with respect to the pollutant variables represented their impact. Hedonic approach may require additional information function originated from factor survey.

Using the Hedonic method, Ridker and Henning [1967] presented the first major empirical work on the impact of air-pollution on the price of real property. Other researchers expanded or adjusted the model. These Hedonic studies for a large number of cities used different specification functions (which require different transformations to estimate the parameters), different measures of air pollution (with varying degree of precision), and varying precision of estimation of the parameters. The findings of these studies confirmed the positive impact of air-quality improvement on the price of housing, although the results of some of the studies are not consistent with *a priori* expectations.[1]

The theoretical and empirical approaches of the Hedonic estimation have been criticized. One of the criticisms concerns the violation of the normality assumption of error distribution. Critics argue that the normal distribution has little weight in its tails, so that great importance is placed on outlying observations.[2] There have been some attempts to remedy this problem by different methods such as nonparametric maximum likelihood estimation [Cosslett, 1983].

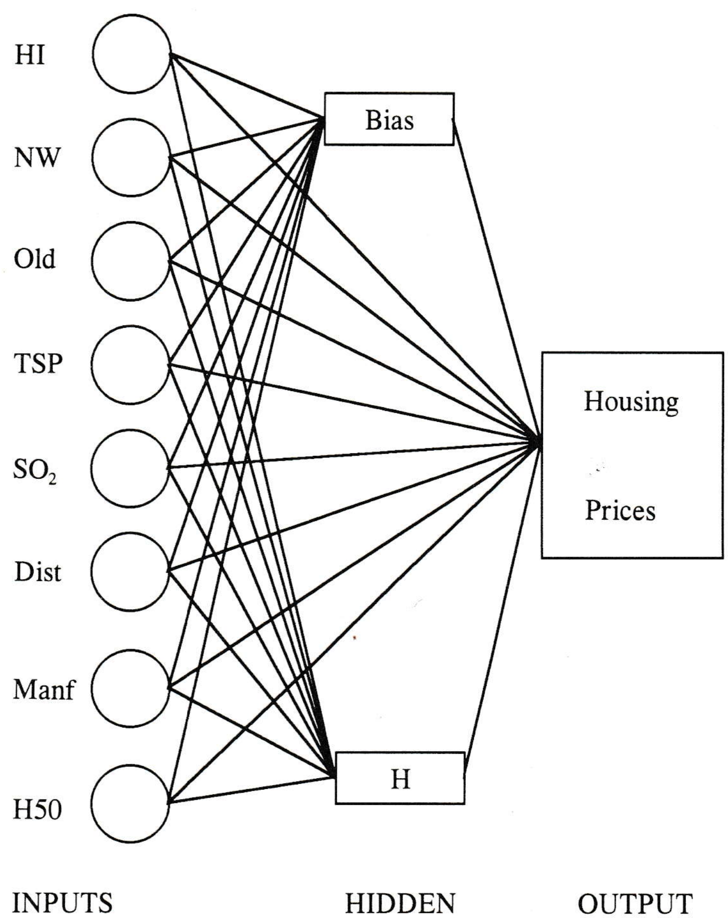
Using a neural network, a branch of artificial intelligence and a new approach, the purpose of this research is to measure the impact of TSP and SO_2 air pollution on housing prices in Jacksonville, Florida as a case study. Neural networks, unlike econometric models which have to pass some degree of assumptions and therefore become parametric, are nonparametric. Thus, neural networks can resolve the error distribution critique associated with econometric approach. Neural networks, in contrast to being programmed which requires an algorithm, are trained with some learning rule. Furthermore, while pollution levels in Jacksonville are high for Florida, they are relatively low compared to other cities in the U.S. and especially to national and state ambient air quality standards. Therefore, this is a good test case to examine the impact of relatively low levels of pollution on property values.[3]

The cross-sectional indices of TSP and SO_2 of the 1978 census track of Jacksonville, Florida and other related variables influencing the price of housing are incorporated in the model and used for estimation.[4] The findings suggest that lower air pollution in Jacksonville has resulted in a higher average price of housing. Furthermore, the findings of the simulation of the neural network suggest that the Clean Air Act Amendments of 1970 which resulted in lower levels of TSP and SO_2 by 1980 added to the prices of low-price housing. After describing the neural network model used in this research, we present the results of the model and those of the simulation of the network. In the last section, we present our summary and conclusions.

NEURAL NETWORKS

The study of neural networks is one of the branches of the field of artificial intelligence. Like the structure of the brain, neural networks are multiple-layer configurations consisting of simple processing elements (PEs) that interact with each other through weighted connection in the system. A typical neural network consists of one input layer, one or more intermediate or hidden layers, and one output layer. The design of an artificial neural network which is used in this study with one output, eight inputs, a bias, and a hidden layer is shown in Figure 1.

FIGURE 1
A Neural Network of Housing Prices



Each connection in the network has a weight, and each element computes a weighted sum of the incoming values and passes this sum through a nonlinear or linear function as output. The role of the hidden layer(s) is a processor and a mathematical-function bridge between the inputs and output(s). The mathematical function of the hidden layers are in different forms.

Notice that inputs of this network are not only connected indirectly through the hidden layer, but also connected directly to the output. Furthermore, there is a bias PE that is connected to the output. The bias PE is similar to that intercept concept in equations of econometric models, and it absorbs noises of other contributors to the output in the system. Compared to the econometric models, which are parametric and are required to pass some degree of assumption, neural networks are nonparametric in nature, even though the weights of connections are parametrized.

The three main phases in the operation of a network are learning, recall, and testing. In the learning phase, the neural network recognizes a pattern between inputs and output(s) and estimates final output(s) called actual, A. Subsequently, this output(s) is compared with the desired output, D, and errors are calculated. The errors become a factor to adjust the weights and subsequently to reduce the errors and readjust the weights of the connections. This process continues further until the errors decline to an acceptable level, if possible. Through this process, the neural network learns the rules and adapting patterns for processing the knowledge. The resulting pattern of linking the inputs to the output(s) in the learning process can be used for testing the accuracy of the networks. In addition, the pattern can be used for prediction of the output(s), given the inputs.

The most widely used neural network model is back propagation, which is an algorithm for adjusting connection weights in multiple layer network. Back propagation is a learning design by which the multi-layer network is set for pattern recognition utilizing actual cross-section or time-series data as the external teacher. It calculates the summation of multiplication of inputs by their corresponding weights as follows:[5]

$$X_J^{[s]} = f\left[\sum_i \left(X_i^{[s]} * W_{ji}^{[s-1]}\right)\right] = f\left(I_J^{[s]}\right), \tag{1}$$

where: $X_i^{[s]}$ is the current output state of ith neuron in layer s; $Wji^{[s]}$ is the weight on connection joining ith neuron in layer $[s - 1]$ to jth neuron in layer s; and $I_j^{[s]}$ is weighted summation of inputs to jth neuron in layer s. This weighted summation is then transformed by a transfer function to the hidden layer. Three common nonlinear transfer functions used in artificial neural networks are the Sigmoid, hyperbolic tangent, and sine functions. The Sigmoid transfer function used in this study is a continuous monotonic mapping of the input into a value between zero and one. The Sigmoid function for the local error, e, is a smooth version of $\{0,1\}$ step function and is defined as:

$$f(z) = (1 + e^{-z})^{-1} \tag{2}$$

and the local error at processing element j in level s is back propagated and determined by:

$$e_j^{[s]} = -\frac{\delta E}{\delta\left(I_J^{[s]}\right)}. \tag{3}$$

Here E is the global error function which is differentiable of all the connection weights in the network. The chain rule twice in succession of (3) gives a relationship between the local errors at a particular processing element at level s and at the level $s + 1$ as:

$$e_j^{[s]} = f'(I_J^{[s]}) * \sum_j (e_k^{[s+1]} * W_{kj}^{[s+1]}) . \tag{4}$$

Since $f'(z) = f(z) * [1.0 - f(z)]$ from (1), (4) can be rewritten as:

$$e_j^{[s]} = (x_J^{[s]}) * (1.0 - x_J^{[s]}) * \sum_j (e_k^{[s+1]} * W_{kj}^{[s+1]}) . \tag{5}$$

The summation term in (5) is analogous to the one in (1) which is used to forward propagate the input through the network. To increment or decrement the weights in order to decrease the global error, a gradient descent rule is used as follows:

$$\Delta W_{ji}^{[s]} = -lcoef * (\frac{\delta E}{\delta w_{Ji}^{[s]}}) , \tag{6}$$

where *lcoef* is a learning coefficient, and the partial derivative in (6) is:

$$\frac{\delta E}{\delta w_{Ji}^{[s]}} = (\frac{\delta E}{\delta I_J^{[s]}}) * (\frac{\delta I_J^{[s]}}{\delta w_{Ji}^{[s]}}) = -e_J^{[s]} * x_i^{[s-1]} , \tag{7}$$

and combining (6) and (7) together gives:

$$\Delta W_{ji}^{[s]} = lcoef * e_j^{[s]} * x_i^{[s-1]} . \tag{8}$$

Suppose the desired output, D, is specified by a teacher, and the actual output, A, produced by the network with its current set of weights. Then the global error function, E, is the square of the Euclidean distance between the desired output and the actual output of the network for a particular input pattern, and is given by:

$$E = 0.5 * \Sigma (D_k - A_k)^2 , \tag{9}$$

where $(D_k - A_k)$ is the raw local error. From (3), the scaled local error at each processing element of the output layer is determined by:

$$e_k^{(0)} = \frac{-\delta E}{\delta I_k^{(0)}} = (-\frac{\delta E}{\delta A_k}) * (\frac{\delta A_k}{\delta I_k^{(0)}}) = (D_k - A_k) * f'(I_k) . \tag{10}$$

The sum of all pattern specific error function is the overall global error function. The back-propagation algorithm modifies the weights to reduce the particular component of the overall error function. One way to adjust the weights is by the Delta rule, which incorporates the learning coefficients, *lcoef,* and another parameter called momentum (M) as follows:

$$\Delta W_{ji}^{[s]} = lcoef * e_j^{[s]} * x_i^{[s-1]} + M * \Delta W_{jI} \ . \qquad (11)$$

The momentum (M) is a parameter which is used to smooth learning. Its function as a low-pass filter is to set an appropriate learning rate and convergence speed for the network. The explain command in the neural network reveals the information about the causes and the magnitudes of contributions of inputs on the output(s). This information is somewhat similar to the measure of elasticity of output(s) for each input in the econometric approach.

EMPIRICAL RESULTS

The back propagation technique, a normal cumulative Delta rule, and a Sigmoid transfer function were considered appropriate for the learning and pattern recognition. Cross-sectional data of the 1978 census tracts of Jacksonville, Florida were utilized to evaluate the impact of air pollution (TSP and SO_2) on the median price of housing (as output) in 1979 dollar.

A higher cross-section index of TSP and SO_2 air pollution[6] (1972 level) combined with 1980 data of median family income, percent of nonwhite population, percent of population 65 and over, indices of distance from the central business district (as a measure of accessibility to the business area), percent of total manufacturing employment (as a measure of neighborhood quality), and percent of housing units built before 1950 are used. It is hypothesized that the impact of a higher TSP level alone or with a higher SO_2 level on the price of housing will be negative. In addition, it is also expected that the signs of the weights of nonwhite population, percent of population 65 and over, percentage of housing units built before 1950, and percent of total manufacturing employment will be negative. On the other hand, the influence of family income and the distance from the central business district on the housing are expected to be positive.

Table 1 presents the results of the learning of the neural network for each of the eight inputs influencing housing value (output). The input value column represents the results of price of housing as output of the PE where the connection originates. The estimated weights of the connection between the inputs PE and the output are also shown in the table. In this study, variable weight with relative scope connection are used. The delta weight is the result of the last change in the connection weight.

According to the results of Table 1, the signs of the weights of all inputs are as expected. The weights of TSP and SO_2 are both negative, which suggests that discounting for other variables, a higher TSP alone or with a higher SO_2 (1972 level) results in a lower price of housing. The resulted signs of the weights further suggest that the median household income (*HI*) and the distance between houses and the central business district (*Dist*) have positive impacts on the price of houses. On the other hand, the percent of nonwhite population (*NW*), the percent of total manufacturing employment (*Manf*), and the percent of housing units built before 1950 (*H50*) have negative impact on the price of housing in Jacksonville, Florida. The distance from the central business district (*Dist*) and household income (*HI*) captured the highest input value. The household income and percent of the nonwhite population captured the highest weights.

TABLE 1
Neural Networks' Estimated Results of Input Values, Input Weights, Delta Value, and Delta Weight of Housing Prices as Output PE*

Input PE	Input Value	Input Weight	Delta Value	Delta Weight	Elasticity *AV*	Elasticity *SD*
Bias	+1.0000	-0.2913	-0.0019	-0.0014		
HI	+0.5344	+0.6491	-0.0008	+0.0007	15.59	1.111
NW	+0.1150	-0.5736	-0.0003	-0.0003	-13.65	0.973
Old	+0.0377	-0.0707	-0.0002	-0.0001	-1.62	0.115
TSP	+0.5281	-0.0513	-0.0010	+0.0000	1.16	0.082
SO_2	+0.0475	-0.2509	-0.0002	-0.0002	-5.87	0.418
Dist	+0.6667	+0.2040	-0.0010	+0.0008	4.9	0.35
Manf	+0.3178	-0.1477	-0.0006	-0.0001	-3.64	0.26
H50	+0.0476	-0.2802	-0.0003	-0.0005	-6.67	0.476
Hidden	+0.4939	-0.2508	-0.0009	-0.0007		

Notes: *AV* = Average; *SD* = Standard deviation; and *Old* = Percent of population 65 and older.

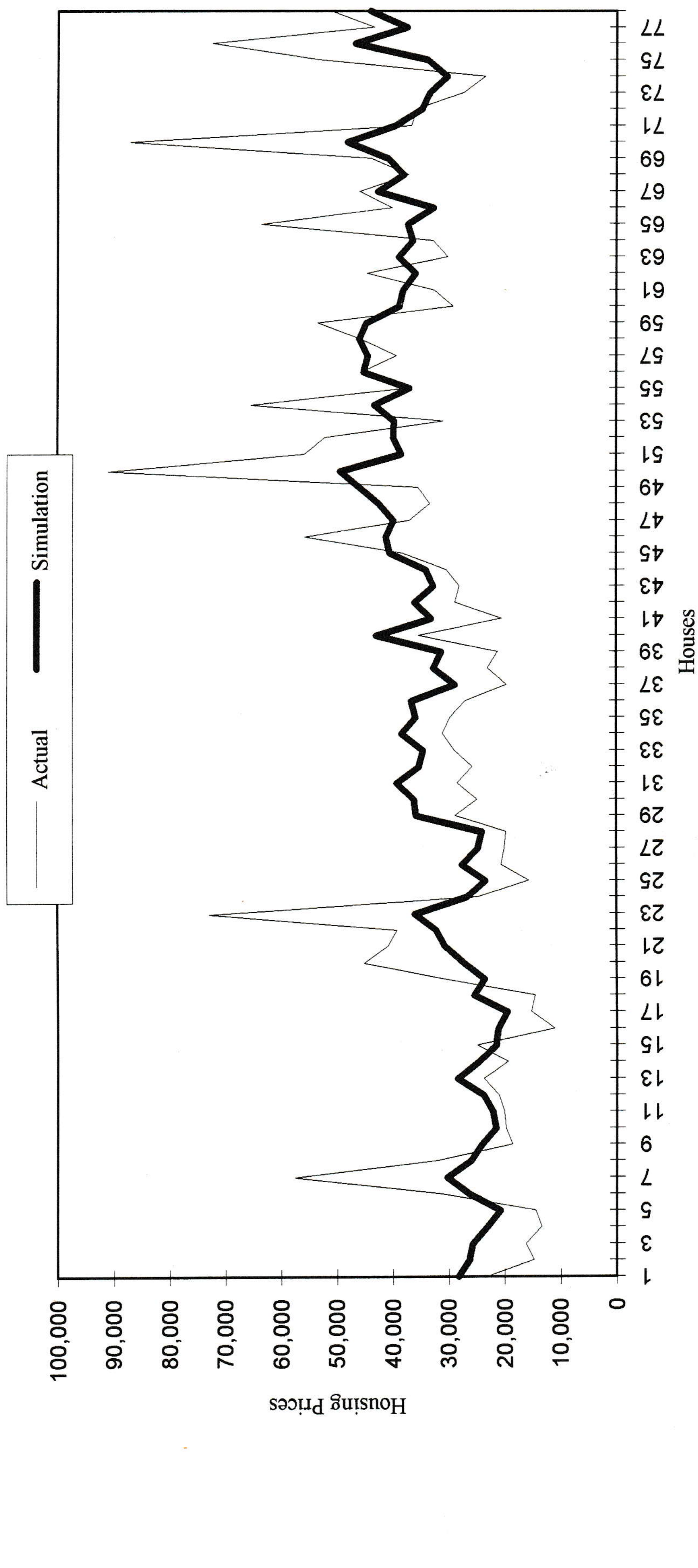
The neural network also estimated the elasticity (sensitivity) of housing values for each variable. Table 1 also shows the resulted average (*AV*) and standard deviations (*SD*) of percentage changes of housing prices as a result of a 5 percent change (dithering) in each of the eight variables.[7] Accordingly, a 5 percent increase in mean concentration levels of TSP and mean concentration levels of SO_2 resulted, respectively, in a decrease of housing prices of 1.15 percent (inelastic) and of 5.8 percent (slightly elastic). Similarly, a 5 percent increase in *HI*, *NW*, *Old*, *Dist*, *Manf*, or *H50* changes the price of housing by 15.99, -13,65, -1.62, 4.9, -3.64, or -6.67 percent, respectively.

In sum, a higher index of TSP or of SO_2 results in a lower price of housing. While the input value of TSP is higher, its resulted weight (as a measure of the degree of the influence) is lower than those of the SO_2.

SIMULATION AND THE IMPACT OF THE CLEAN AIR ACT

To test the impact of reduction of air pollution that occurred due to the Pollution Act of 1970, the network was simulated (tested) with the 1980 levels of SO_2 and TSP (as a lower level of pollution) instead of those of the 1972. The results of the simulated prices of houses are compared with those of the actual and are shown in Figure 2 and Table 2. The difference

FIGURE 2
Housing Prices: Actual and Simulation (with High Pollution)



between the simulated and actual price of housing (the error of the simulation) are also calculated and shown in Table 2.

Based on these findings, a lower pollution level caused only the prices of low-priced houses to increase, while the prices of high-priced houses decreased. This can be visualized easily in Figure 2. This suggests that low-priced housing is located in areas with higher pollution levels, and that high-price housing is located in the area with lower pollution levels. The negative (error difference) signs confirm even a stronger case for the impact of the air pollution on the prices of houses.

TABLE 2
Actual and Simulation Prices of Housing, Their Differences (Errors), Averages, and Standard Deviations

No.	Actual	Simulation	Difference	No.	Actual	Simulation	Difference
1	23,080	30,446	7,366	40	35,385	46,764	11,379
2	14,827	18,949	4,122	41	20,561	37,345	16,784
3	16,235	26,503	10,268	42	28,809	40,805	11,996
4	13,496	16,683	3,187	43	28,043	37,972	9,929
5	14,541	17,697	3,156	44	30,374	39,280	8,906
6	31,144	30,410	-734	45	38,276	44,501	6,225
7	57,609	35,164	-22,445	46	55,768	46,123	-9,645
8	31,899	31,523	-376	47	37,038	41,582	4,544
9	18,660	25,491	6,831	48	33,411	45,782	12,371
10	19,836	19,993	157	49	35,542	51,326	15,784
11	20,141	21,446	1,305	50	90,979	56,141	34,838
12	21,115	18,786	-2,329	51	55,903	43,184	12,719
13	23,799	26,659	2,860	52	52,248	44,038	-8,210
14	19,436	16,595	-2,841	53	30,992	44,444	13,452
15	24,938	14,391	-10,547	54	65,419	47,568	17,851
16	11,137	14,417	3,280	55	37,377	40,149	2,772
17	15,329	12,807	-2,522	56	45,603	49,264	3,661
18	14,634	24,101	9,467	57	39,377	48,343	8,966
19	30,816	27,165	-3,651	58	45,809	49,219	3,410
20	45,194	32,971	-12,223	59	53,425	47,953	-5,472
21	40,938	37,138	-3,800	60	29,220	42,174	12,954
22	39,310	38,144	-1,166	61	32,560	42,191	9,631
23	72,895	42,494	-30,401	62	44,660	41,150	-3,510
24	24,787	30,977	6,190	63	30,229	43,126	12,897
25	15,685	18,759	3,074	64	32,803	39,922	7,119
26	20,663	28,073	7,410	65	63,599	43,901	19,698
27	20,016	16,488	-3,528	66	40,140	37,500	-2,640

TABLE 2 (CONT.)
Actual and Simulation Prices of Housing, Their Differences (Errors), Averages, and Standard Deviations

No.	Actual	Simulation	Difference	No.	Actual	Simulation	Difference
28	19,769	15,967	-3,802	67	46,015	46,673	658
29	28,876	27,308	-1,568	68	37,264	38,650	1,386
30	24,898	26,954	2,056	69	44,038	42,905	-1,133
31	28,430	32,492	4,062	70	87,134	52,544	34,590
32	25,698	38,064	12,366	71	36,757	44,217	7,460
33	28,958	37,758	8,800	72	35,791	40,871	5,080
34	31,085	30,443	-642	73	27,416	40,423	13,007
35	29,674	26,117	-3,557	74	23,556	29,430	5,874
36	26,969	26,972	3	75	53,306	38,807	14,499
37	19,675	20,736	1,061	76	72,442	53,448	18,994
38	23,025	23,528	503	77	43,462	42,670	-792
39	21,171	36,338	15,167	78	51,277	51,058	-219
T^1	2,702,396	2,730,388	27,992	*AV*	34,646	35,005	359*
T+	2,702,396	2,730,388	316,077	*AV+*	34,646	35,005	4,052**
SD	16,576	11,177	10,826				

Notes: T^1 = Total; *T+* = Total positive values; *AV* = Average; *AV+* = Average positive values; and *SD* = Standard deviation. * = 1 percent. ** = 11.7 percent.

The findings further suggest that, due to pollution reduction, the total median value of the 1978 census track houses increased from $2,702,396 to $2,730,388, an increase of $27,992 in 1979 dollars. These results are also shown in Table 2. On the average, the price of each house increased from $34,646 to $35,005, an increase of $359 per house or 1.04 percent. However, the total positive-value (*TOT+*) of the simulation error is $316,077 and that of the average positive value (*AV+*) is $4,052, or 11.7 percent. According to this measure, the average price of housing increased by $4,052, instead of $359. Probably the positive-value approach is a more appropriate estimate of the impact of air pollution than the algebraic measure. In the positive-value approach, only the positive errors are added. With either measure, the median housing-price increases, due to pollution control measures, should account for only those property owners and buyers who had valued air-quality improvement.[8] Thus, the findings of the simulation of the network suggest that the Pollution Control Act of 1970 which resulted in lower levels of TSP and SO_2, on average, increased housing prices in Jacksonville, Florida.

SUMMARY AND CONCLUSIONS

The intent of this research was to investigate the impact of air pollution on the price of housing. One of the criticisms of earlier studies has been the violation of the normality assumption of the error of the econometric models. To remedy this problem, artificial neural networks, a nonparametric approach, was used. Cross-section data of the 1978 census tracts of Jacksonville, Florida for 1980 were used. This was a good case study because Jacksonville had simultaneously a high mortality rate and a low pollution rate.

The output used for the study was the median price of housing, and the inputs were TSP, $S0_2$ (two pollutants), median family income, percent of nonwhite population, percent of population 65 and over, indices of distance from the central business district (as a measure of accessibility to the business area), percent of total manufacturing employment (a measure of neighborhood quality), and percent of housing units built before 1950.

The results confirm the findings of earlier econometric studies that an increase (decrease) in the level of air pollution of TSP and $S0_2$ results in a lower (higher) price of housing. The findings also suggest that housing prices are not as sensitive to the level of TSP (inelastic) as they are to the level of $S0_2$ (barely elastic). In addition, the simulation of the model suggests that the lower air pollution which resulted from the 1970 Clean Air Act, as perceived by home buyers and owners, is reflected in housing prices by at least an average of $359 (in 1979 dollars) per house (1 percent of the total price) in Jacksonville, Florida.

FOOTNOTES

[1] The literature on environmental issues is beyond the scope of this paper. For a summary of the past studies and comparison of their results, see Smith and Huang [1995], Cummings et al. [1986], Freeman [1979], and Gregory [1986].

[2] For example, see Belsley et al. [1980]. Other criticisms are related to variable selection and treatment, functional form of the models, and pollution-measurement error. For example, see Graves et al. [1988], Atkinson and Crocker [1987], Bartick and Smith [1984], Cummings et al. [1986], Freeman [1979], and Gregory [1986].

[3] The 1972 $S0_2$ data for Jacksonville had a mean of 19 ug/m^3 with a range of 7 to 64 ug/m^3. The federal standard for SO_2 is 80 ug/m^3 and the state standard is 60 ug/m^3. The 1972 TSP data had a mean of 58 ug/m^3 with a range of 44 to 81 ug/m^3. The federal standard is 75 and the state standard is 60 ug/m^3.

[4] To avoid difficulties encountered in analyzing differences in interurban property values, the model is designed for intraurban analysis and applied to Jacksonville's census tracts.

[5] For more detail about an artificial neural network, see NeuralWare, Inc. [1991].

[6] Since there are no monitoring stations within the tracts' boundaries (38 census tracts), an interpolation model was used. This model was applied by a computer mapping program called the Synagraphic Mapping System (SYMAP). SYMAP calculates the weighted average of slopes from values of nearby data points (monitoring stations) by a gravity-type model and by considering distance and direction. SYMAP is based on the x-y coordinate system. Once x-y coordinates and their corresponding TSP and SO_2 readings are given to monitoring stations in Jacksonville, the data are referred into the computer. The computer program interpolates the values at intervening locations, basing the interpolated values on the values of and the distances to the other data points. By plotting these interpolated values on a map of Jacksonville, the average annual values of TSP and SO_2 for each census tract were estimated. See Dougenik and Sheehan [1975] for more detail.

[7] This elasticity concept of the neural network is not linear. That is, if the price of housing changes by X percent as a result of a 1 percent change in $S0_2$, it would not imply that the price changes would be five times X as a result of a 5 percent change in $S0_2$.

[8] See Smith and Huang [1995] for the comparison of the dollar value of the air quality improvement of the past studies.

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