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Abstract

The aim of this paper is to compare various real estate valuation models and the manner in which they take into account environmental variables. The reference model is taken to be a standard linear regression model including ordinal variables to measure environmental quality. This type of model is widely used. It is first compared to linear models which incorporate environmental quality notes extracted from the urban habitat database of a Geographic Information System (GIS) which has been developed recently for Geneva, Switzerland. We also incorporate these quality notes in a single input parameter, a so-called geo-index. The price indices constructed in this way are quite similar to the more traditional hedonic model. We additionally find that Artificial Neural Network (ANN) models, which are non-linear per se, exhibit a similar general form of the price indices, but that the detailed price behaviours of different models feature notable differences depending on the input choice of environmental variables.

ENVIRONMENTAL VARIABLES AND REAL ESTATE PRICES

1. Introduction

The pricing of real estate has been studied extensively since the early eighties using a variety of methods. The research has focused on real estate valuation and the construction of real estate indices using mostly hedonic pricing models (Hoag, 1980; Miles *et al*., 1990; Webb *et al*., 1992; Fisher *et al*., 1994; Knight *et al*., 1995; Meese and Wallace, 1997; Kiel and Zabel, 1997). In Switzerland, such models have been developed for residential real estate prices in Geneva (Bender *et al*., 1994; Hoesli *et al*., 1997) and for residential rents in Lausanne and Geneva, respectively (Thalmann, 1980; Büchel and Hoesli, 1995). The models published by Bender *et al*. (1994) and Hoesli *et al*. (1997) have formed the basis for the models developed by the Informations- und Ausbildungs-Zentrum für Immobilien (IAZI) to value residential real estate and construct indices for the whole of Switzerland.

There is evidence indicating that both internal physical and external environmental characteristics impact on real estate prices. Among the most common physical attributes are the number of rooms, the number of bathrooms, the construction quality, the condition of the building, and whether parking facilities are available. Environmental parameters refer to the quality of the neighbourhood and the quality of the location within the neighbourhood and are commonly measured by ordinal variables. For example, Bender *et al*. (1994) use three levels for the quality of the neighbourhood and three levels for the quality of the location within the neighbourhood. Simons *et al*. (1997) and Brasington (1999) also use ordinal values to measure the impact of environmental variables on house values.

Extensive research has been conducted to substitute qualitative evaluation methods by quantitative decision support systems (Alberti, 1991; Dale, 1991; Densham, 1991; Parrott and Stutz, 1991; Fischer and Kijkamps, 1993; Whitley and Xiang, 1993; Rhind, 1997). In the context of real estate pricing, Geographic Information Systems (GIS) have made possible the development of databases which can be used to measure better the environmental characteristics of properties (Wyatt, 1996). In such a framework some qualitative variables may be replaced, for example, by distance variables such as distance to city centre or public transportation (Chen, 1994).

Environmental quality parameters, which may be quantified in a GIS framework, have been studied for Swiss residential real estate in Geneva, Zurich and Lugano (Bender *et al.*, 1997; Bender *et al.*, 2000) and for commercial real estate in the Geneva region (Bender *et al.*, 1999). An important objective of these studies was to establish the basis for evaluating the so-called geo-index defined as a weighted average of environmental quality notes extracted from a suitable GIS database on the urban habitat (Din, 1995b). The Analytical Hierarchy Process (AHP) offers a simple and effective methodology for determining the appropriate weighting of different environmental qualities (Saaty, 1980; Zahedi, 1986; Golden *et al.*, 1989). The AHP methodology has been applied to real estate in other contexts than environmental quality (Ball and Srinivasan, 1994), but appears to be particularly well suited in a GIS framework (Din, 1995a).

The purpose of this paper is to test the robustness of hedonic models when GIS measures of the environment are substituted for qualitative variables. We use the same database as that used by Bender *et al.* (1994) which contains 285 transactions on apartment buildings in Geneva for the period 1978-92[1]. The existence of a rather comprehensive set of precise input parameters from a GIS is also a motivation for investigating modelling approaches beyond the simple linear regression type of most hedonic models. It is likely that there are complex relationships between the input parameters and therefore a good price model should take into account certain non-linear effects. Non-linear models may be developed using parametric linear statistical techniques, but since they always involve some guesswork, we prefer to apply a non-parametric technique. Artificial neural networks (ANN) represent a relatively new approach to non-parametric and non-linear statistical modelling which has already been applied in a number of financial applications, particularly involving time series (Rummelhart *et al.*, 1986; Dayhoff,

[1] The number of properties used in this study is slightly lower than that used by Bender et al. (1994) due to missing addresses.

1990; Kendall and Ord, 1993; Azoff, 1994; Taylor, 1994; Refenes, 1995). Such models have also been applied to real estate valuation (Worzala *et al.*, 1995; Lenk *et al.*, 1997; McGreal *et al.*, 1998) and to examine the impact of age on housing values (Do and Grudnitski, 1993), but have not been extended to the context of real estate price index construction.

This paper is organised in the following way. In section 2, we present the geocoding of the Geneva database of properties and the evaluation of some environmental quality notes using a GIS database for the urban habitat. In section 3, alternative sets of descriptive real estate parameters are proposed to define four different scenarios for the inputs to standard linear regression models. Some aspects related with the implementation of such pricing models in Switzerland are also presented in section 3. The alternative ANN methodology is applied in section 4. In section 5, we present some concluding remarks.

2. Real estate prices in a GIS framework

The common dictum that location is the most important parameter for real estate valuation can only be fully taken into account by using the descriptive framework of a Geographic Information System. The most basic advantage of a GIS is to position properties on a local map in terms of their geographic co-ordinates. This is the operation of geocoding which simply uses the street address input of the property to associate it with a map co-ordinate.

In many cities around the world, geocoding may only be done approximately in reference to the street segments of a more or less comprehensive street network. For the case of Geneva, however, it is possible to perform the geocoding almost exactly through the use of a point GIS database of all house entrances (i.e. street addresses). We use this approach to geocode the 285 apartment buildings of our sample. The number distribution of the 285 transactions during the period 1978-92 is shown in Figure 1.

In Figure 2, the point location of the 285 properties is indicated by a star on a map of the Geneva Canton. The map shows that most properties are located in the city of Geneva and relatively few in the peripheral communes of the Canton. Their geographic distribution reflects approximately the actual density of apartment buildings.

In a GIS, it is important that the locations be defined very precisely in order to constitute the database of all parameters which may have an impact on real estate quality and price estimation. A GIS could in principle provide a full quantitative description of the urban habitat quality if all relevant data layers, for example concerning road networks and public services, were available and had been transformed in a convenient way into quality note attributes. In practice, the relevant data is often not available or is incomplete over the considered geographic region. However, even if the existing GIS is incomplete, it could be an improvement over the more qualitative approaches which are generally used in real estate pricing models.

In this study, we use eight quality criteria as listed in table 1. The GIS provides a quantitative framework for attributing to each point of the region a quality note q in the range from 0 to 100. The constitution of the GIS database underlying the quality notes is carried out through a process which starts with assembling different basic geographic data layers involving street networks, transport networks and digital elevation models, for example. Subsequently the basic data is transformed with standard operations, such as buffering, to classify areas of the urban environment in a way which most appropriately reflects the chosen environmental criteria. The classification is done in terms of discrete categories, generally three to five for each criterion, which translate directly into quality notes for every location of interest.

The individual eight values may be used directly as input parameters in a real estate valuation model. Alternatively, we may propose as input parameter an aggregation of the quality notes, the so-called geo-index, which is a weighted average of the quality notes q_i using empirical preference weights w_i for each criterion:

$$\text{Geo-index} = \sum_i q_i * w_i$$

It is interesting to use the geo-index as a single environmental input parameter in valuation models when the data set of historical transactions is small, because it is desirable to reduce the total number of parameters in order to produce more robust models. Since all the quality notes q_i are found through a quantitative process using the GIS, the geo-index is a fully quantitative-empirical attribute to a real estate location.

In this study, we use the empirical weights discussed in Bender *et al*. (1997). As Figure 3 shows, their values (18%, 11%, 7%, 12%, 10%, 18%, 14%, 10%) lie in the interval 7% to 18%. The weights were found by processing 1,800 questionnaires containing pairwise comparisons using the methodology of the Analytical Hierarchy Process (AHP). The questionnaire was sent to single-family owners of the Geneva region, but *a priori* there is no reason to believe that the perception as regards the quality of the environment will substantially differ from that of apartment building owners.

In a certain sense, the weights w_i may be considered to provide a pricing of the environmental quality notes since they are a result of an empirical preference elicitation, ultimately concerning real estate value. More precisely, such a pricing interpretation of the weights might be possible if one assumes the existence of a linear pricing formula involving uncorrelated quality variables and that empirically weighted qualities are a direct measure of real estate prices. Therefore it might, in principle, be possible to recover the weights as coefficients in a linear regression model with the eight quality notes as input parameters. In this study, however, this is not possible given the limited size of the sample.

3. Hedonic models using a GIS

The standard approach to constructing real estate price models is based on linear regression. Traditionally, environmental factors are measured by means of ordinal variables. In this section, we compare such an approach to one using GIS data. Four models are considered (see Table 2). The first one (scenario 1) is that constructed by Bender *et al*. (1994). Besides four standard internal variables (number of bathrooms per apartment, number of garages per apartment, building quality, purely residential building or building with commercial real estate also), it uses two qualitative, ordinal variables, commonly referred to as dummy variables, to measure the quality of the neighbourhood and the quality of the location within the neighbourhood. Three levels of neighbourhood quality and three levels of quality of location within the neighbourhood are used. These qualitative environmental variables are not directly related to the quantitative variables associated with Table 1 but are found by an on-site estimation.

The second scenario uses the eight environmental parameters described above as variables in the regression. Out of these eight parameters, five do not exhibit much variability over the considered apartment locations, and therefore the third scenario only considers the three variables which exhibit most variability. These variables are "Level of quietness", "Distance to city centre" and "Distance to nature". Finally, the fourth scenario uses the geo-index constructed with the eight variables and the preference weights for these variables. The fact that five variables show low variability (or multi-collinearity) is not a serious problem for a global pricing model as used in this work, as it would be the case for a more detailed explanatory incremental model.

All four models use the same internal physical variables (see Table 3). These variables are the same as those used by Bender *et al*. (1994). Therefore, the four scenarios differ only in the way we measure the environmental parameters.

The regression results are contained in Table 4. The models include annual time dummy variables. The linear regression models assume that there is a linear relationship between the price and the input parameters. Actually, the linearity assumption is commonly supposed to hold for the logarithm of the price, ln(P), as a function of the inputs. This implies that the price factorises as a function of the inputs.

We find that the linear regression models for ln(P) show a multiple correlation coefficient R = 0.84 for scenario 1 and R = 0.83 for scenarios 2, 3 and 4, respectively. Thus, the explanatory power of the four models is approximately the same. The coefficients of the physical characteristics of the buildings exhibit the expected sign and are highly significant in all four models. Not surprisingly for indices that exhibit a bullish trend during the period, the coefficients of the time dummy variables are usually negative in the first years of the sample period and positive in the latter years. This indicates that price levels first lie below the period average and then above average prices. In model 1, both the quality of the neighbourhood and quality of location variables are highly significant. In the other models, only the standing variable in model 2 is significant at the 1% level. This indicates that ordinal variables are a good measure of the quality of the environment. Such variables, however, are in most cases not available and the measurement of these variables is onerous and prone to measurement error. Despite differences in the significance levels of the environmental variables across models, the models' fit is the same.

Figure 4 contains the hedonic price indices for the four scenarios for the period 1978-92 and an index of the annual average price per square meter. The price indices for the four scenarios are quite similar. This result suggests that the linear price models are quite robust in the sense of being relatively insensitive to the precise choice of input parameters, i.e. qualitative and/or quantitative ones from a GIS. From a practical point of view, it is nevertheless important to make an appropriate choice of input variables, because it is possible to construct real estate price indices with substantial time savings using a GIS if such a system exists for a given city or region.

Not surprisingly the index of averages of prices per square meter (i.e. the year average in Figure 4) shows a completely different pattern. This results from the heterogeneity of property: the characteristics of the properties that are sold in any given period will in most instances differ from those of buildings sold in another period (Crone and Voith, 1992; Hoesli and MacGregor, 2000). When the real estate market is bearish, for example, few transactions occur and may involve buildings that are in poor condition. If this is true, a decline in the value of the index from period t-1 to period t could reflect a decline in property prices and/or the fact that the buildings that are sold in period t are of poorer quality than the buildings sold during period t-1. A similar explanation holds in bullish markets.

4. Neural network models

It is quite easy to identify non-linear price relationships for which the linear regression models fail badly both in terms of individual real estate price estimations and the price index. Price is not linearly related for instance to age, distance from the city center and the number of bathrooms. We are led therefore to investigate alternative non-linear models. In this paper, we study the possibility of using artificial neural networks to construct real estate pricing models.

In order to make the comparison easy with the linear regression models, the starting point for our neural network models is also the logarithmic price as a function of the input parameters of the various scenarios. In principle, though, ANN models are non-linear and non-parametric and therefore do not require any particular assumptions about the functional form of the price relationship. The ANN models use the same input and output parameters as in the linear models; in the ANN framework, they are called nodes and are supplemented by so-called hidden nodes which define the model in mathematically quite a precise way once an activation function has been selected.

The objective of the ANN model construction is to develop models which are as simple as possible and show some robustness when validated with out-of-sample data. Unfortunately the small size of our data set does not allow for a complete training, testing and validation procedure. Using back propagation techniques for optimising the correlation with the target prices, we arrive at models for each of the four scenarios which feature only two to four hidden nodes. The procedure followed consists in separating the sample in training, test and validation sets and to select models with the lowest possible number of hidden nodes which show a good and robust out-of-sample price behaviour.

The back propagation perceptron model with a sigmoid activation function was implemented using the Neuralware software within Excel. Typically the dataset was divided with 60% of observations for training, 30% for testing, and 10% for validation. The model using two to four hidden nodes appeared to offer rather similar results with relatively robust behaviour considering the small dataset.

Our ANN models (using two hidden nodes) feature a correlation coefficient for scenario 1 of R = 0.87, R = 0.89 for scenario 2, R = 0.86 for scenario 3, and R = 0.85 for scenario 4, respectively, which is somewhat higher than for the regression models. This indicates that the ANN models have a potential for more realistic pricing of individual properties. This result is in line with the conclusions contained in Tay and Ho (1991) and Evans *et al*. (1992), but in contrast with those contained in Worzala *et al*. (1995) and McGreal *et al*. (1998).

The construction of ANN models is more complicated than is the case of linear regressions (see also Lenk *et al*., 1997). In particular, the additivity structure in the logarithmic price function makes the construction particularly simple. The most logical generalisation of the price index construction to the general situation of a non-linear relationship of the inputs with ln(P) is as follows. For a particular non-linear ANN model and for each year during the 1978-92 period, we take the average of the predicted ln(P) over all the 285 objects, and this value becomes our estimated overall ln(P) for that year. This means that we operate as if all objects were undergoing transactions every year and not just during one year. In this way, we treat the market globally and avoid the shortcoming of a simple average of the transactions during one year. It is easy to see that this approach applied to the trivial case of linear regression leads to the same price index as already discussed above. The resulting ANN price indices for the four scenarios compared to the average price index are displayed in Figure 5.

Contrary to what is the case for the linear models, we observe notable differences in price behaviour between the various scenarios. This is understandable since the construction of price indices may be interpreted as defining interpolation models in a complex multi-dimensional input parameter space. Clearly, interpolation using linear regression can only capture some gross average features of this space.

In a certain way, it might appear as a virtue that the linear models seem to be so robust so as to give almost identical results for the different input scenarios. The drawback, however, is that the linear models are constructed so globally that they are unable to capture more extreme market conditions with sufficient precision and/or anticipation. The ANN models are likely to be more promising in this respect because of their ability, as confirmed when applied to various classification problems where linear methods fail, to spatially disentangle different regions of a complex input parameter space.

Finally, we compare the linear model to the ANN model. Figure 6 contains that comparison for scenario 4. As can be seen, the hedonic and ANN indices behave in quite a similar fashion.

5. Conclusion

The first objective of this paper was to analyse whether the use of GIS data would lead to different real estate price indices in a linear framework. The results show clearly that the differences are relatively small. This is an interesting result as one criticism of the standard hedonic approach relates to the measurement of the subjective ordinal variables. Obviously, when GIS data are available, they should be used. As GIS databases are developed for more cities, it would be highly desirable to further investigate this issue.

Since the relationship between real estate prices and several independent variables is likely to be non-linear, the second aim of the paper was to devise a non-linear procedure for constructing price indices using Artificial Neural Networks (ANN). This analysis leads to two conclusions. First, the general shape of the linear and ANN price indices is similar. Second, the differences across scenarios are much more pronounced when using ANN models than with hedonic linear models.

At this stage it is not possible to give a definite answer to the question of whether these differences are significant. It could be that the linear models do not capture very precisely the impact of environmental factors on real estate values. However, it could also be that the ANN models are not sufficiently robust. In order to improve our analysis, further research is required involving larger data sets which will enable a more systematic out-of-sample testing.

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Figure 1: Distribution of the number of real estate transactions

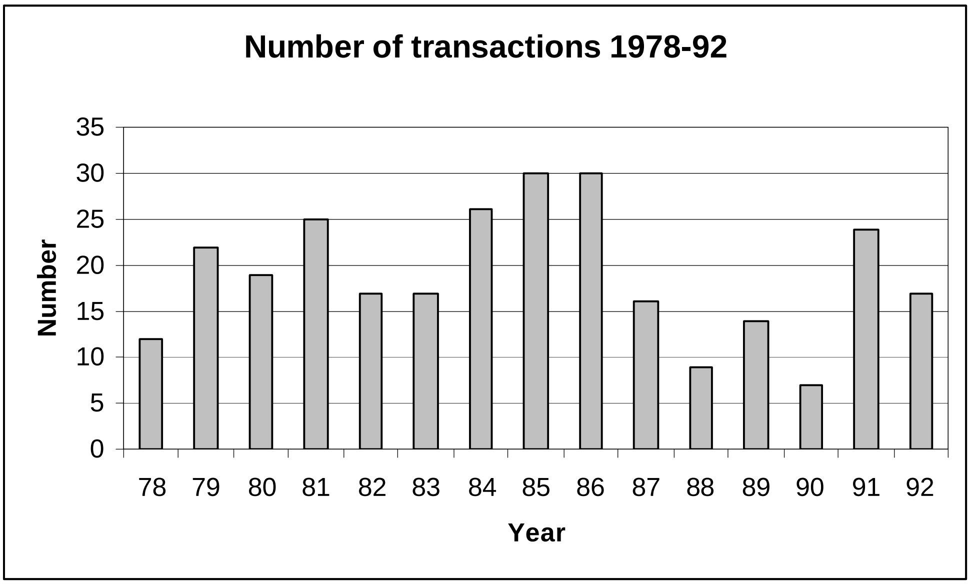

Figure 2: Geographic distribution of the 285 apartment buildings in the Geneva Canton

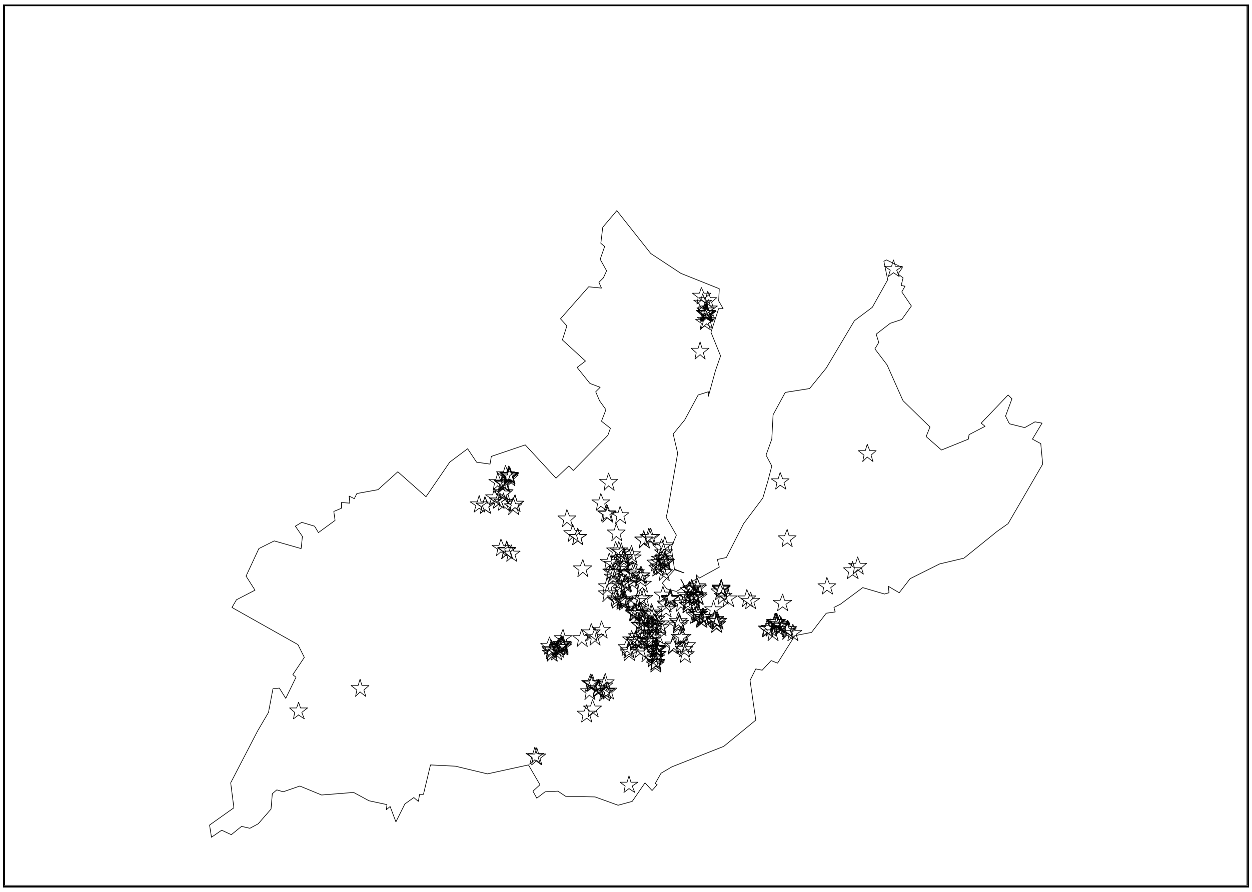

Figure 3: Preferences weights for environmental quality

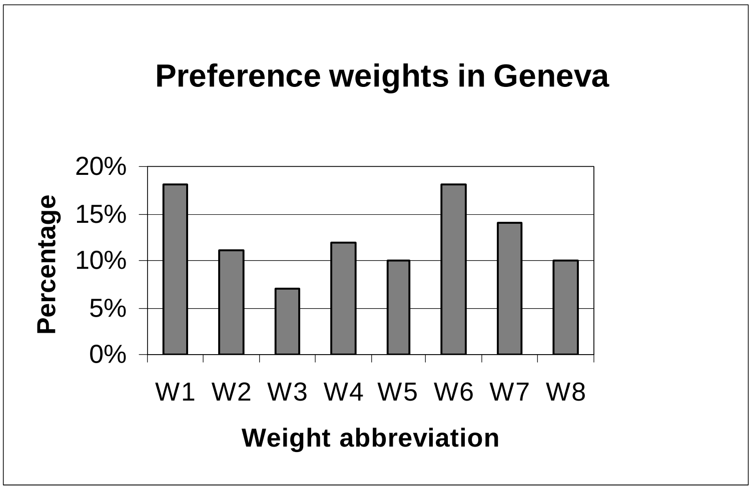

Figure 4: Price index models for different regression scenarios

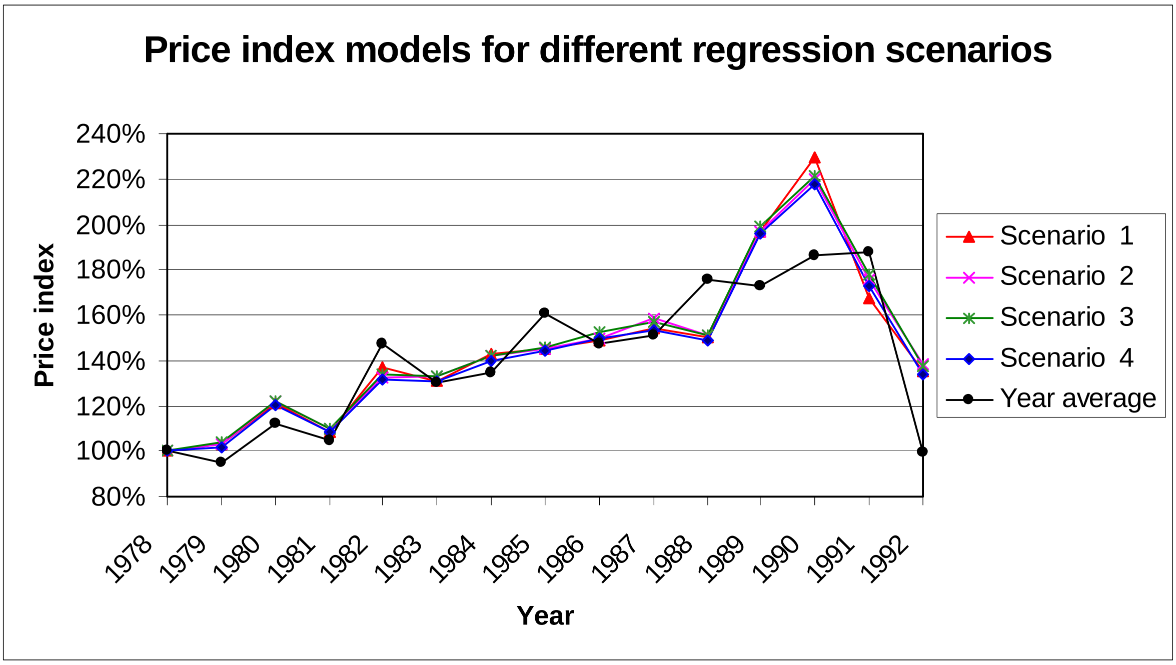

Figure 5: Price indices for neural network model

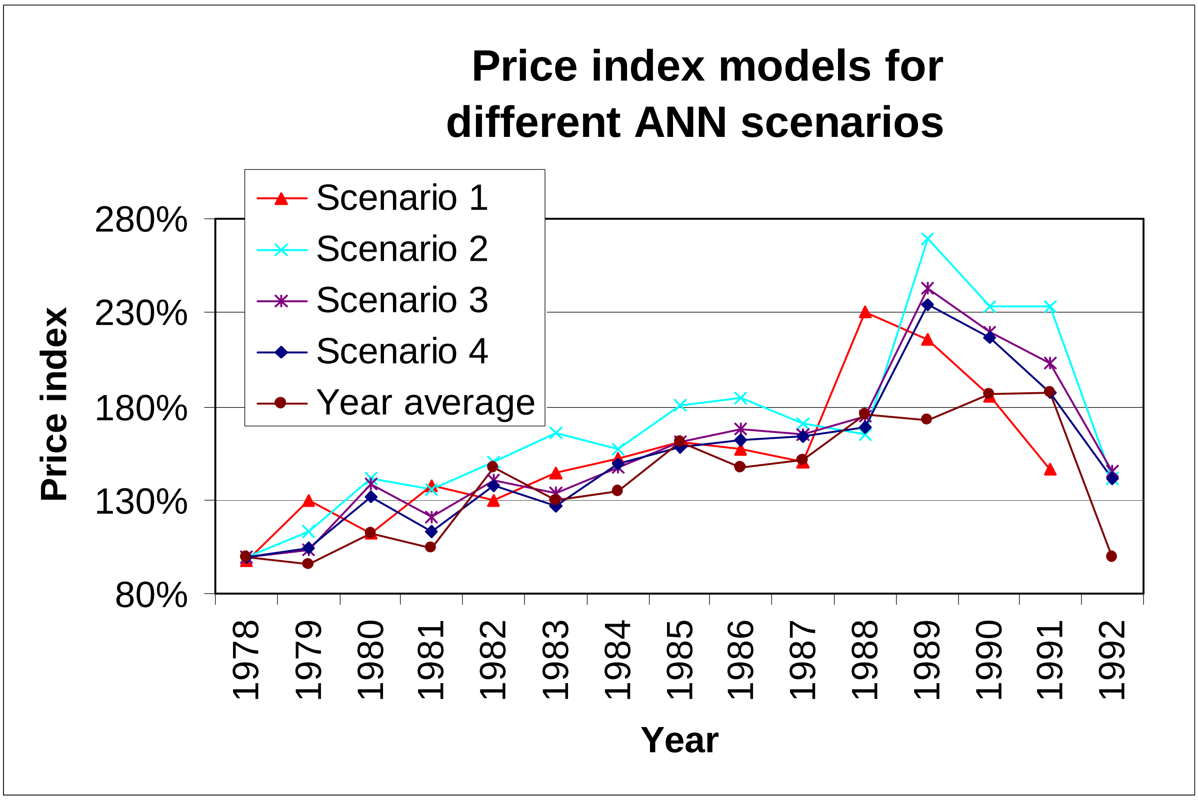

Figure 6: Model comparison for scenario 4

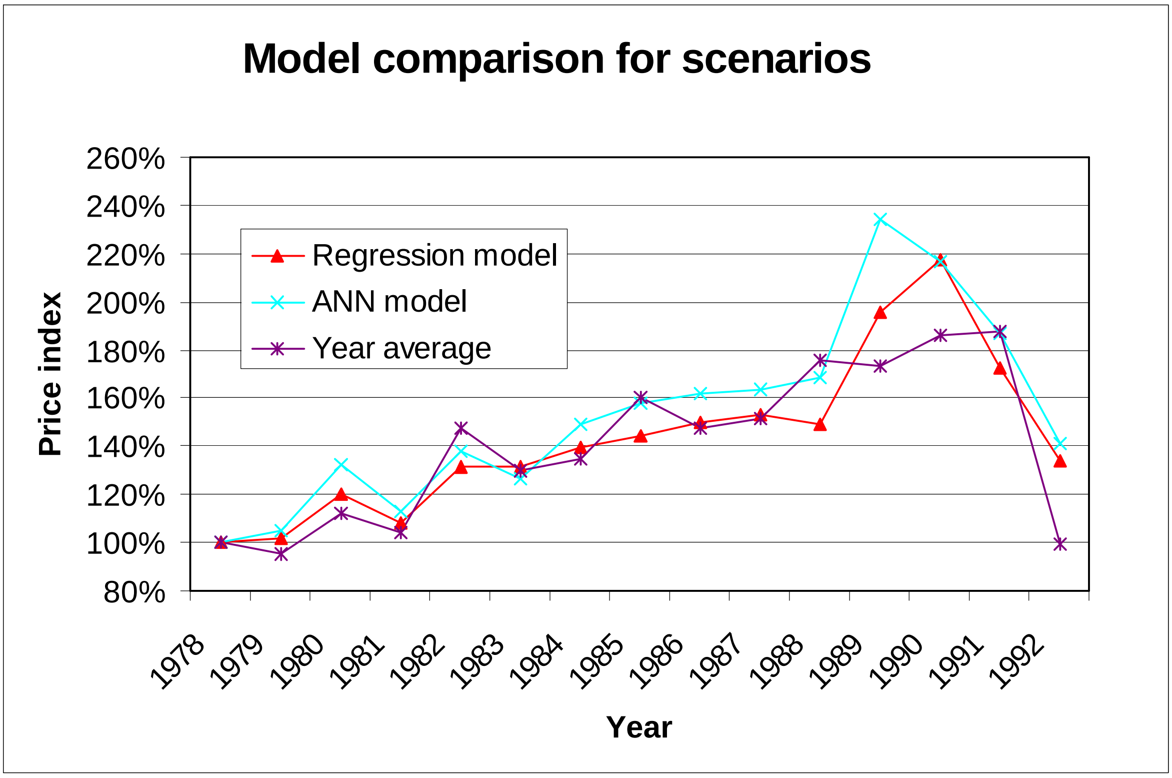

Table 1: Environmental criteria definition

Environmental criterion	Definition
1. Level of quietness	Absence of noise from road traffic, railways or airport
2. Distance to public transportation	Distance to stops for bus, tram, or train
3. Distance to city center	Distance to the bona-fide city center
4. Quality of view	General unobstructed view to surroundings
5. Distance to shopping facilities	Distance to shopping streets and centers
6. Distance to nature	Closeness to forest, open areas, or lake
7. Distance to schools	Distance to primary and secondary schools
8. Social standing of the area	General living quality of the local area

Table 2: Scenarios for real estate input parameters

Scenario number	Selection of input parameters
1	4 internal + 2 qualitative environmental
2	4 internal + 8 quantitative environmental
3	4 internal + 3 quantitative environmental
4	4 internal + geo-index

Table 3: Physical real estate parameters

Internal parameter	Definition	Possible values
Bathrooms	Number of bathrooms per apartment	1 to 2
Parking	Number of garages per apartment	0 to 1.2
Building quality	Building quality index	0, 1 or 2
Type	Purely residential or mixed with commercial	0 or 1

Table 4: Regression results

VARIABLE	COEFFICIENT			
	Model 1	Model 2	Model 3	Model 4
Intercept	6.286***	6.667***	6.414***	6.359***
Number of bathrooms	0.230***	0.226***	0.228***	0.234***
Number of Garages	0.149***	0.144***	0.132***	0.136***
Building quality	0.360***	0.362***	0.363***	0.361***
Mixed-use property	0.089***	0.094***	0.091***	0.101***
1978	-0.323***	-0.330***	-0.335***	-0.317***
1979	-0.290***	-0.297***	-0.294***	-0.300***
1980	-0.134*	-0.130	-0.137*	-0.131*
1981	-0.241***	-0.233***	-0.140***	-0.238***
1982	-0.010	-0.052	-0.043	-0.042
1983	-0.053	-0.044	-0.050	-0.047
1984	0.035	0.020	0.014	0.017
1985	0.048	0.040	0.042	0.051
1986	0.072	0.072	0.088	0.085
1987	0.109	0.130	0.118	0.109
1988	0.084	0.083	0.076	0.081
1989	0.355***	0.345***	0.354***	0.353***
1990	0.509***	0.458***	0.459***	0.460***
1991	0.191***	0.236***	0.242***	0.229***
1992	-0.020	-0.006	-0.017	-0.024
Neighbourhood quality	0.080***	-	-	-
Location quality	0.077***	-	-	-
Quietness	-	0.405E-03	0.550E-03	-
Public transportation	-	-0.261E-02	-	-
City centre	-	0.127E-02	0.792E-03	-
View	-	0.193E-02	-	-
Shopping facilities	-	-0.440E-03	-	-

Nature	-	-0.432E-03	-0.576E-03	-
Schools	-	-0.215E-03	-	-
Standing	-	0.150E-02**	-	-
Geo-index	-	-	-	0.172E-02

* indicates significance at the 10% level

** indicates significance at the 5% level

*** indicates significance at the 1% level