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Determinants of Residential Property Value in Nigeria – A Neural Network Approach

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Abstract

This study investigated, by means of artificial intelligent system, the influence of residential real estate property characteristics on property values (prices) in Nigeria, using two major cities (Benin and Lagos) as examples. It revealed a high positive linear correlation between property characteristics and the property market values; an indication that these characteristics reasonably predict property market values. The study demonstrated that although several property characteristics can be identified with residential real estate properties, only are few important ones have significant impact on the market values of such properties. It identified nine (9) property characteristics that have relatively strong impact on market values (prices) and to that extent influence the sales and purchase decisions of sellers and buyers in Nigeria. The results of the study should enable Real Estate Professionals to make fair estimates of the market values of residential real estate properties given the

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features/characteristics of such housing units. This would aid rapid valuation, help to improve housing quality and make possible mass evaluation of properties. The study recommends to real estate practitioners and other professionals, amongst others, to use the knowledge of significant property features/characteristics for more efficient valuation, improved quality of their sales/purchase decisions and proper management of residential housing units.

Introduction

Hitherto, real estate property was generally seen as a legacy a parent bequeaths to the offspring. However, with the realization that real estate is a major source of capital appreciation and a good hedge against inflation, the real estate market is coming close in popularity and importance to the money and capital markets. In particular, as Nigeria stands on the threshold of establishing a secondary mortgage market to mobilize capital market finance for the primary market, the need to assist real estate professionals with information on the influence of property features/characteristics on residential property values cannot be over stressed. Although several studies have focused on investment in the money and capital markets in Nigeria, so much cannot be said of the real estate sector (Eriki & Udegbunam, 2008).

In the advanced economies however, the use of artificial neural networks (ANNs) in real estate valuation and other fields such as tax assessment, medical diagnosis, bank risk analysis, stock analysis & control, traffic control is now predominant (Moral- Esperanza, 2004). Indeed, artificial intelligent systems, particularly artificial neural networks have been shown to produce more accurate estimates of property values than the multiple regression analysis and other hedonic methods in many countries of the world – Australia (Kershaw & Rossini, 1999); U. K. (Wilson, et al, 2001); U.S.A. (Lokshina, et al, 2003); Spain (Mora-Esperanza, 2004); Finland (Taffese, 2007); Greece (Pagourtizi, et al. 2007); and Nigeria (Eriki & Udegbunam, (2008).

However, in the extant literature, only a few of the works have gone beyond mere demonstration of the use and capability of the ANNs to actual valuation of residential houses; and many of such works employed single city data. It is against this background, that this study examines the determinants of real property values using residential housing data from two major cities in Nigeria by means of artificial neural networks.

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The questions the study seeks to answer are: which property characteristics are important in the determination of the market value of a residential real estate? Can the artificial neural network be a practical model for the valuation of residential housing units in Nigerian property market given property characteristics/features? Arising there from, the primary objective of this paper is to identify property features/characteristics that have significant influence on property market values using artificial intelligent system. Other objectives of this work are to determine if the artificial neural network could be a practical model for real estate valuation in Nigerian property market, and to contribute to the development of knowledge in the field of real estate finance. The study is restricted to residential real property only and uses property transaction data from two major geographical locations in Nigeria - Benin and Lagos. Expectedly, the study should be of practical relevance to practicing real estate practitioners as well as academics.

Theoretical frame work and the relevant literature

Real estate refers to “land at, above and below the earth’s surface, plus all things permanently attached to it, whether natural [example, trees and minerals] or artificial [example, houses and roads]” (Galaty, Allaway, & Kyle, 2000, p. 14). On the other hand, real property (or realty) is a more encompassing term that refers to “the interests, benefits and rights that are automatically included in the ownership of land and real estate” (Galaty, Allaway, & Kyle, 2000, p. 15). It may also include appurtenance - a right or privilege often related to real estate but may not necessarily form part of the property. In this work, the terms - property, real estate and real property - shall be used interchangeably to convey the same ideas – land, improvements on land and the accompanying bundles of legal rights thereof. Although real estate can be classified into Residential, Commercial, Industrial, Agricultural and Special purpose (Corcoran, 1987; and Galaty, Allaway, & Kyle, 2000), the focus of this work is on residential real properties. This is the property type used for single or multi-family housing in urban, suburban or rural areas - the most popular type in this part of the world.

Although, there are many concepts of value, value as used in this work refers to a true market value. This may or may not be the same with a market price. A market price is the price a property actually sells for and could represent a true evidence of the current market value if the conditions for arriving at a market value exist. In this work, therefore, *a market value* is construed to

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mean a fair or true market value of a real estate property. That is, the most probable price that a real property should command in a fair sale.

Artificial neural networks (ANNs) and real estate valuation

A number of studies have investigated the application of neural networks to real estate valuation. Earlier studies were Borst (1992), who applied ANNs to some sets of residential accommodation in New England; Tay and Ho (1991, 1992) that investigated residential apartments in Singapore; DO and Grudnitiski (1992) and Evans, et al. (1993) who used residential data sets from California and U. K respectively. More recently, Wilson, Paris & Jenkins (2001) trained a neural network to forecast future trends in housing in the U.K. using national housing time series data. Pacharavanich, Wongpinunwatana & Rossini (2000) described the case-based reasoning system for valuation of town houses in Bangkok, while Lokshina, Hammerslag & Insinga (2003) demonstrated and compared the use of MRA, ANN and ANFIS Models in the pricing of real estate. Mora-Esperanza (2004) also demonstrated and applied artificial intelligence in the valuation of collective housing in the region of Madrid.

An ANN can also use as many variables as possible. On the average, an ANN for real estate valuation usually works with variables between 10 and 50 (Mora-Esperanza, 2004). However, the number of input neurons must correspond with the number of variables. Although the number of hidden layers and neurons can vary but the extant literature suggests that at least one hidden layer with the number of neurons correspondent to the model specification is effective (Lokshina, et. al., 2003). In the same vein, the following property characteristics and attributes have commonly been used by ANN experts as useful variables in real estate valuation. These are the number of bedrooms, building size, age of building, land size, location convenience (distance from main road or city centre) and quality of building materials. Other useful variables sometimes include road type, car park facility, number of bathrooms, number of toilets, number of floors in the building, neighbourhood attractiveness, physical condition, space arrangement, structural quality, house interior, and recreational facilities, among others (Paracharavanich et al, 2000; Lokshina et al, 2003).

An ANN must be trained and cross validated to correctly learn patterns in the training data to enable it perform well on other data. To train an ANN network, a group of samples containing all the variables including known market values are selected. To ensure good generalization, the standard

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practice is to divide the entire samples (total data set) into three sub-data sets - training, cross validation, and testing data. The training data set is used to train the network while the cross validation data set is used by the network during the training session to determine if and when the network is correctly trained. Cross validation is necessary to avoid over-training. The testing data set is used to test the performance of the network after successful training.

Hypotheses of the study

From the extant literature on property valuation, the most common property variables are: prices of comparable properties, cost of construction, property characteristics such as location, neighbourhood attractiveness, land size, number of bedrooms, and number of bathrooms, among many others. However, some of these variables and the approaches utilizing them have either been found to produce subjective results that do not lend themselves to empirical validation (Fan et. al., 2006) or do not provide satisfactory estimates of property values (Calhoun, 2001). Hence, this study uses artificial intelligence model developed herein to produce fair market values of residential real estate properties to test the validity of our proposed hypothesis.

In the real estate markets, customers (or their agents) look out for certain property features (characteristics) in their choice of residential properties, and these features which distinguish one property from the other, ultimately influence the value that is placed on the particular property. Thus, it is expected that a positive relationship would exist between these characteristics/features and individual property market value. Hence, the hypothesis below:

$H_{o:}$ *Real estate property characteristics do not directly predict property market value.*

Methodology

Data were obtained for this study from both primary and secondary sources. First, real estate transaction data were obtained primarily from registered real estate valuers, property agents, and developers operating in Lagos and Benin City by four properly trained and experienced research assistants and this researcher, using semi-structured questionnaire. Secondly, relevant data were also retrieved from the database of some property agents/managers including that of Crown properties (@ http://www.ip4properties.com/). For both sources, details of real estate transactions (sales or purchases) undertaken by respondents in the last six years preceding the study date were elicited. A total of 3034 real estate transactions made up of 856 for Benin and 2,178 for Lagos were used as the samples for this work. This gave an aggregate sample size of 3,034 real estate transactions. 70% (2124) of the data were set aside as training data set and 15% (455) as the corresponding cross validation data set. The complementary data set of 455 representing 15% of the total data was proposed as the testing data set. The property input variables of the ANN model were: property type, property category, number of units of property sold, neighbourhood group, land size, neighbourhood category, and neighbourhood attractiveness. Other property variables were number of boys' quarter/chalet rooms, number of bedrooms, number of rooms ensuite (rooms with bathrooms and toilets attached), number of rooms fitted with Jacuzzi, total number of bathrooms/toilets, year property was sold, month property was sold, number of penthouse rooms, availability of recreational facilities, and lastly, other facilities available. The sales price (in million naira) was the desired output variable. These characteristics were classified and appropriately coded to make them readable by the ANN network.

With the network parameters specified and data pre-processed and tagged, we built a customized ANN (breadboard) using the neuralBuilder software (a component package of NeuralSolutions). The network training and cross validation was executed using NeuralSolutions for Excel (based on Microsoft Excel 2007), another component of NeuralSolutions version 5.0. The recurrent back propagation learning method was adopted in the training. Successful training was achieved when the learning curves (the graph of the output versus iteration) decreased exponentially towards zero, and the cross validation data curve fell below the training data curve. The best weights of the training epochs were automatically saved when the cross validation error reached the minimum point. The breadboard (network) was manually saved after a successful training.

To assess the performance of the trained network, the testing data set was fed into the network. Using three important ANN performance measures (MSE, NMSE and regression coefficient), the null hypothesis was tested based on the performance of the testing data set on the ANN model. The final test was a sensitivity analysis conducted to determine the impact of property characteristics/features on property market values.

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Result

The Artificial Neural Network developed in pursuit of the study's objective was trained, cross-validated and tested with a total of 3034 real estate transactions' data from Benin and Lagos. From sixteen initial variables in the sample data, only twelve were used as input to the network. Four property variables (Master bed rooms with Jacuzzi, Number of penthouse rooms, Availability of recreation facilities, and Availability of other facilities) that contributed less than 0.1% to market value were considered redundant and were eliminated with their respective values from the sample.

The results of the networks' training and cross validation are presented in the sub-sections below:

The network training results

The ANN Neural Network which was trained with 2124 real estate property data (70% of sample) and cross – validated with 455 real estate properties (15% of sample data set), produced the best network training weights after 1200 epochs (see table 1). The minimum/final mean square error (MSE) was 0.0048 and 0.0058 for training and cross validation data respectively. These represent training and validation errors of 0.48% and 0.58% respectively for both the training and validation data sets.

Depicting successful training, the learning curves decreased exponentially towards zero with the cross validation data curve falling within the training data curve. Figure 1 below shows the learning curves of the Benin-Lagos Breadboard portraying a successful training.

Following successful training and cross-validation of the Neural Network, an evaluation test to determine the performance of the data set on the network vis-à-vis the actual market prices in the sample was conducted using 455 transaction data (15% of sample data set) previously set aside as testing data set. The generated property market values were used to verify the hypothesis of the study. The null hypothesis (H_o) is: real estate property characteristics do not directly predict property market values while the alternate (H_1) is: real estate property characteristics directly predict property market values.

Table 2 shows the results of the Benin-Lagos data performance test on the ANN. The results show a Mean Squared Error (MSE) of 0.0137, that is, about 1.37% Mean Square Error between the actual sales prices and the desired network generated market values (desired output). The normalized MSE is 0.2796, while the regression coefficient is 0.85. Other measures, the

AIC and the MDL which are -1478 and -1226 respectively, are at very low levels, thus portraying a good generalization (predictive) capacity of the Benin-Lagos ANN model. These network performance test results are reasonably good indications of high input –output mapping of property features and market value outputs. Specifically, the mean squared errors of the testing data set on the ANN network is below 1.4%, far below the error limit of 5%. What this means is that the squared mean difference between the actual market prices of the data sets and the network generated market values is just below 1.4%. By itself and when compared with the error limit of 5%, it is a strong indication of the high ability of the property input characteristics of the data to predict the property market values using the neural network. Similarly, the normalized MSE of the data set is just below 0.3. Also, the regression coefficient is 0.85, an indication of a reasonably high positive linear correlation between the property inputs characteristics and the network generated property market value outputs. Based on these high performance measures, we can reasonably conclude that the input property characteristics/features significantly predict the property market values. Thus, we reject the null hypothesis, and conclude that real estate property characteristics/features directly predict property market values. The implication of this is that some real estate property characteristics or features can be used to predict the market values of residential housing units.

To conduct the sensitivity analysis, the total sample (3034 real estate transactions) was fed into the artificial neural network. Table 3 below contains the sensitivity analysis result of the Benin-Lagos data set on the ANN.

The table shows that Neighbourhood attractiveness (NEGHATTRA), size of land on which property was built (LANDSIZE), year property was sold (YEARSOLD) and number of bathrooms/toilets (NABATHRMS) were the four most important property input factors (in that order) that impacted significantly on prices of property. Other property input factors in order of importance were Type of property (PROTYPE), neighbourhood category (NEGHCATG), number of bedrooms attached with a bathroom (NENSUIT) and property category (PROCATG). The four least important property features were number of units of property sold (NOUNITS), the month of the year property was sold (MONSOLD), number of bedrooms (NBEDRMS), and lastly, the number of boys' quarter rooms/chalets (NBQRMS). The above information is diagrammatically represented in the histogram in Figure 2.

Thus, in general, the most significant input factors, and to that extent, the property characteristics or features that influence the prices of residential properties in Benin and Lagos, and by extension most cities in Nigeria, are: Neighbourhood attractiveness, size of the land on which the property is built, the year a property is sold (the time element which is indicative of the time value of money/level of inflation), number of bathrooms, and the type of property on offer. Contrariwise, the number of units of property sold, number of boy's quarter rooms/chalets and month of sales of property do not appear to be very significant factors in the valuation (pricing) of residential real estate properties in Lagos and Benin, and perhaps other cities in Nigeria.

Discussions

This study sets out primarily to identify residential real estate property characteristics that have significant influence on property values (prices) in Nigeria using artificial intelligent system. The study revealed a high positive linear correlation between property characteristics and the property market values; an indication that these characteristics reasonably predict property market values. The import of this is that property characteristics or features do not only distinguish a particular property from the other but they are also major determinants of their market values. This finding is significant in two ways. First, property valuers and other real estate property professionals would be enabled to make fair estimates of the market values of residential real estate properties given the features/characteristics of such housing units. Secondly, real estate valuers and others professionals would, ipso facto, want to know and indeed be keenly interested in those property features that have significant influence on the market values of residential properties.

Thus, as a corollary to the above, the study further revealed that some property characteristics have greater impact on property market values than others. The significance of this finding is twofold. One, it would provide a useful knowledge of the property features that buyers, sellers and realtors should look out for when they make 'buy or sell' decisions in respect of residential properties in Benin and Lagos. Two, such knowledge of significant real estate features would enable valuers and others professionals to adequately focus on such features in assessing, maintaining and enhancing the market values of the properties they manage. In this regard, the study successfully identified nine (9) property characteristics that have relatively

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strong impact on market values (prices) and to that extent influence the sales and purchase decisions of sellers and buyers in Lagos and Benin, and by extension Nigeria. These characteristics or features are: the attractiveness of the property neighbourhood, the size of the land (in square meters) on which the property is built, the year the property is sold or being sold, the number of bathrooms/toilets that the property has, and the type of property under consideration. Other property variables that have impact on market values are the neighbourhood category (in terms of population density), the number of bedrooms attached with bathrooms/toilets, the property category (in terms of whether the property is detached, semi-detached, a flat or blocks of flat), and lastly the number of units of the property being evaluated. However, other property characteristics like number of bedrooms, number of boy’s quarter room and month of sale of property did not make as much impact on property market values as the nine features identified above.

The low ranking or low level of contribution of certain property characteristics such as number of bedrooms, numbers of boy’s quarter room and month of sale of property, to market values deserve some clarifications. Generally, a property characteristic like number of bedrooms in a flat, duplex or bungalow should be the first consideration in the purchase of a property. However, this result is neither contradictory nor surprising. One reason for this outcome is that a high proportion of the number of properties in the sample was mostly three and four bedroom properties (as it is generally the case in Nigeria). Thus, the preponderance of three and four bedroom properties in the two cities covered reduced the relative influence of this particular factor (number of bedrooms) on market value in the study. This does not imply generally that the number of bedrooms in residential properties has no influence in property valuation.

Similarly, the number of boy’s quarter room had little impact on market price. One possible explanation for this could either be buyers/valuers indifference to such feature or the relatively low level of importance of this characteristic compared to others in the estimation of buyers/valuers. Also, the month of sale of the property was of little importance. This is understandably so in the short run except when there is an occurrence of a major intervening event during the year that will make prices to change substantially. However, unlike the month of sale, the year of sale of a property was an important variable that impacted highly on property values in this study. This variable was very significant because of the combined

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effects of inflation and the appreciation of property values over time. This is more so because the data sets were for a six-year period (2003 to 2008, both years inclusive). Thus, the year a property is sold or being evaluated would remain an important and relevant factor in the determination of property values.

The sensitivity analysis results led to two important conclusions. First, the study successfully identified the real estate property characteristics that have significant impact on property market values (prices). Secondly, it rightly observed that some property characteristics contribute more significantly to market values than others. Furthermore, the study notes that the performance of an ANN model on real estate data can be enhanced by eliminating insignificant input variables to reduce its size and complexity.

Conclusion and recommendation

The study developed an artificial neural network model for Benin- Lagos on the basis of which property features and characteristics that have significant impact on market values of real estate properties from the markets were identified. Arising therefrom, the study gave a strong indication of a high level of approximation of input property characteristics/features to property market values. Thus, property features or characteristics such as property category (detached or semi-detached house, block of flats or conversion property), Neighbourhood attractiveness (highly, fairly or poorly attractive neighbourhood), number of bathrooms (in the house or flat), the dimension of land (in square meters), the year property is or to be sold or evaluated, the number of bathrooms, the property type (mansion, tenant house, storey building or flat), and the neighbourhood category (suburban, exclusive, low density or slum) that have significant influence on property values (prices) can be identified and used to assess, maintain and/or improve the true market value of a residential real estate property by realtors, property valuers and other professionals. This study has further shown that although several property characteristics can be identified with residential real estate properties, only are few important ones have significant impact on the market values of such properties. Thus, nine important property features or characteristics in the Nigerian real estate market were identified. Other conclusions of this study are that the elimination of insignificant property input factors would improve neural network performance and results, and that artificial neural networks could, indeed, become a practical and dynamic model for fair valuation of residential housing units in Nigerian property market.

We believe strongly that the knowledge of property features that significantly influence property market values of residential properties would, no doubt, aid rapid valuation, help to improve housing quality and make possible mass evaluation of properties. Therefore, we recommend to real estate practitioners and other professionals to focus more attention on property features/characteristics that have greater impact on market values for more efficient valuation, improved quality of their sales/purchase decisions and proper management of residential housing units.

In the light of the above, and due to the expensive nature of this venture, we also recommend that the Institution of Estate Surveyors and the Board of real estate Valuers of Nigeria should, in collaboration with Government, make funding available for further research in this area of advanced property valuation to keep pace with developments in the field of Real Estate Finance in the developed economies.

Illustrations

Table 1: Training Result of the Benin – Lagos Neural Network Showing the Least Network Training Error:

Best Networks	*Training*	*Cross Validation*
Epoch #	1200	1200
Minimum MSE	0.004826678	0.005842643
Final MSE	0.004826678	0.005842643

Source: Benin-Lagos ANN Training Result, July 2009

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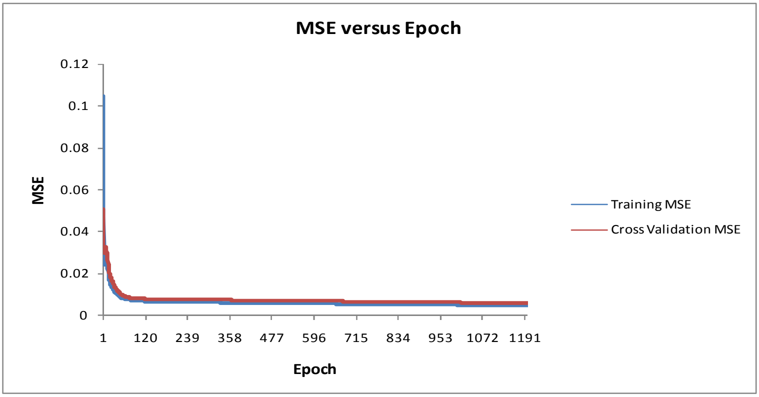
Figure 1: Final Training Result of the Benin-Lagos Neural Network Showing the Learning Curves:



Source: Benin-Lagos ANN Training Result, July 2009

Table 2: Active Performance Measures of the Testing Data Set on the Artificial Neural Network

	BENIN-LAGOS ANN
MSE	0.01372
NMSE	0.27956
R	0.85135
% Error	273.86240
AIC	- 1477.60302
MDL	- 1226.34778

Source: Real Estate Data Performance Test Results, July 2009

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Table 3: benin-Lagos Data Sensitivity Analysis Result Showing Property Features in order of Importance

SENSITIVITY FACTOR	SALES PRICE SENSITIVITY
NEGH. ATTRACTIVENESS	14.3527
LAND SIZE	13.4545
YEARS SOLD	12.9015
NO. OF BATH ROOMS	9.5902
PROPERTY TYPE	7.5583
NEGH. CATEGORY	7.2946
NO. B/ROOMS ENSUITE	6.4353
PROPERTY CATEGORY	4.9903
NO. OF UNITS	3.5126
MONTH SOLD	2.9675
NO. OF BEDROOMS	1.9410
NO. OF BOYS Q/ROOMS	0.6102

Source: Benin-Lagos data sensitivity result, July 2009

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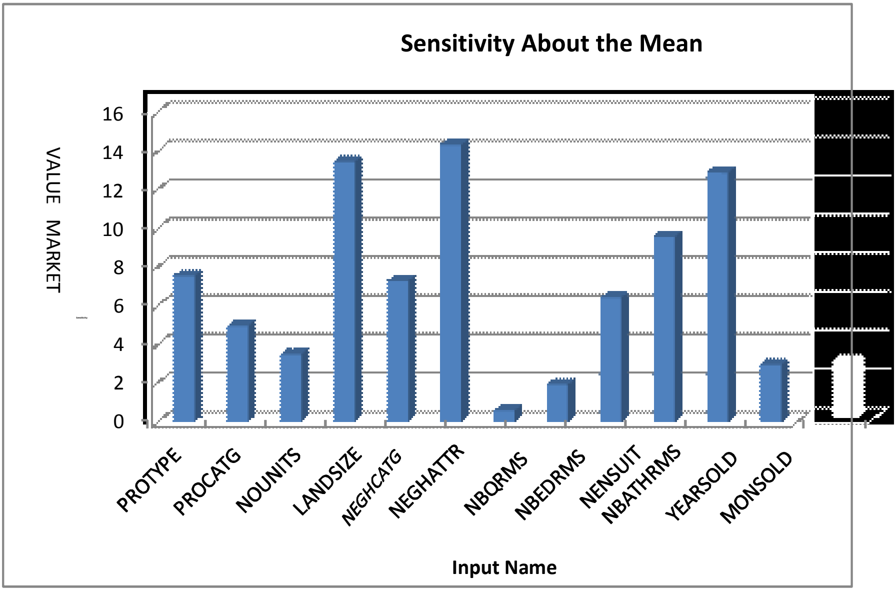
Figure 2: Benin-Lagos Data Sensitivity Analysis Chart



Source: Data analysis by the researcher, July 2009

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