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Achieving property valuation accuracy in developing countries: The implication of data source

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Achieving property valuation accuracy in developing countries: The implication of data source

Abstract

Purpose

The demand for accurate property value estimation by valuation report end-users has led to a shift towards advanced property valuation modeling techniques in some property markets and they require a sizeable number of data set to function. In a situation where there is a lack of centralised transaction data bank, scholars and practitioners usually collect data from different sources for analysis, which could affect the accuracy of property valuation estimates. This study aims to establish the suitability of different data sources that are reliable for estimating accurate property values.

Design/methodology/approach

This study adopted the Lagos metropolis property market, Nigeria, as the study area. Transaction data of residential properties were collected from two sources i.e. from real estate firms (selling price) and listing prices from an online real estate company. A portion of the collected data was fitted into the artificial neural network (ANN) model which was used to predict the remaining property prices. The holdout sample data were predicted with the developed ANN models. Thereafter, the predicted prices and the actual prices were compared so as to establish which data set generates the most accurate property valuation estimates.

Findings

It was found that the listing data (listing prices) produced an encouraging mean absolute error (MAE), root means square error (RMSE) and mean absolute percentage error (MAPE) values compared with the firms' data (selling prices). An MAPE value of 26.93% and 29.96% were generated from the listing and firms' data, respectively. A larger proportion of the predicted listing prices had property valuation error of margin that is within the industry acceptable standard of between ± 0 to 10%, compared with predicted selling prices. Also, a higher valuation accuracy was recorded in properties with lower values, compared with expensive properties.

Practical implications

The opaqueness in real estate transactions consummated in developing nations could be attributed to why selling prices (data) could not produce more accurate valuation estimates in this study when compared with listing prices. Despite the encouraging results produced using listing prices, there is still an urgent need to maintain a robust and quality property data bank in developing nations, as obtainable in most developed nations, so as to achieve a sustainable global property valuation practice.

Originality/value

This study did not investigate the relationship between listing prices and selling price which has been conducted in previous studies but examined their suitability to improve property valuation accuracy in an emerging property market. The findings of this study would be useful in property markets where property transaction data bank is not available.

Keywords: property valuation accuracy, real estate, listing price, selling price, developing countries, data bank.
Paper type: Research paper

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Introduction

Real estate property is a form of long-term investment in which real estate investors usually invest in so as to recoup invested capital in the form of a capital return or regular flow of income in the future (Shapiro et al., 2012). Rational real estate investors occasionally or regularly, request to know the value of their investment for the purpose ranging from sales and purchase of interest, letting or leasing, real estate development feasibility and viability appraisal, alternative use, merger and acquisition, financial reporting and secured lending, among other purposes (Scarrett & Osborn, 2014).

The emergence of big data analysis has led to the improvements in the practice related to property valuation, investment analysis and portfolio management, among other aspects, of the real estate practice (Du et al., 2014). This advancement has resulted in the adoption of "advanced methods" of valuation such as hedonic pricing model (HPM), artificial neural network (ANN), fuzzy logic system (FLS), autoregressive integrated moving average (ARIMA) and spatial analysis method, among others (Pagourtzi et al., 2003). The advanced methods have been adopted both in real estate practice and research in different property markets around the world (Mora-Esperanza, 2004; Schwartz, 1995).

The outputs of the advanced valuation methods have been more accurate and reliable when compared with the traditional methods (Gilbertson & Preston, 2005; Paliwal & Kumar, 2009).

This could be attributed to the fact that most advanced valuation techniques emulate the thought process of the real estate stakeholders (Bagnoli & Smith, 1998) and they can also handle the non-linear relationship that exists between property values and its determinants (Mora-Esperanza, 2004). Whereas most traditional methods do not possess a methodological structure and they lack efficiency (Wiltshaw, 1991). Accuracy has been referred to here as the measure of the closeness or divergence of property valuation figures to the market value of the subject property (Waldy, 1997).

Advanced property valuation methods require more data set for their development when compared with traditional methods that can be applied with as few as two comparable properties (Jenkins, 2000). Undoubtedly, property sales and purchases transactions data is an essential pre-condition for the development of property price models, however, the robustness and quality of such data could improve the credibility of the models to produce estimates that could be a good representation of market prices (Gilbertson & Preston, 2005; Grover, 2016). In a matured and transparent property markets, property sales data banks are generally available and accessible by real estate scholars and valuers (Hofmann, 2003), whereas the opposite is the situation in the property markets of developing countries (Walters et al., 2011).

In situations where there is a lack of property sales data bank, scholars and valuers usually gather transaction data from different sources such as newspapers, online, real estate agents, and so on (Chin & Chau, 2002). The quality of the data sample used for property prices modeling could affect the accuracy and reliability of property valuation estimates which valuers report to valuation report end-users (Lenk et al., 1997), and such reports are relied on by real estate clients in making informed real estate investment decisions (Taffese, 2007). Property valuation inaccuracy has attracted the attention of scholars and valuers operating in different real estate markets around the world (Shapiro et al., 2012). The implications of property valuation inaccuracies could include job losses, investors' bankruptcy, loss of profits, economic slowdown and so on (Yalpir, 2014). This could be attributed to the link between the real estate sector and the personal wealth of individuals and national economic development (Chiang et al., 2015; Pietroforte et al., 2000).

Considering the aforementioned, the aim of this study will be achieved by (1) modeling property prices using listing prices collected from online property platform, (2) modeling property prices using selling prices collected from real estate firms, (3) Predicting the hold out samples from both the listing and selling prices using the developed models, and (4) comparing the accuracy of the valuation estimates from both models in order to establish the more suitable data set to achieve property valuation accuracy. The findings of this study would provide useful insights into the type of data to be used in arriving at accurate estimates, so as to reduce property valuation inaccuracy in property markets where there is no robust property data bank. At the same time, it would inform key real estate stakeholders on the kind of data to make available in both developed and developing property markets for property price modeling. The rest of this paper is divided into four sections. The next section presents a brief literature review, followed by the description of data and research methods adopted for this study. The third section presents the results and discussion of the data analysis, while the last section of this paper presents the conclusion of this study.

Literature Review

As generally referred to in the literature, listing price is the price of a property that is put up for sale by a property owner or the agent(s), while selling price is the amount a property is sold or purchased when been exchanged (see Knight, 2002; Yavas & Yang, 1995). The studies of Pozo (2009), Hayunga and Pace (2016) and Gordon and Winkler (2016), among other studies, used property listing prices collected from real estate companies in property price modeling. Also, information of sold and purchased properties collected from real estate companies were used for property price modeling by scholars including McGreal et al. (1998), Bourassa et al. (2006), Choy et al. (2007) and Owusu-Ansah (2012). In another context, some scholars have investigated the relationship between listing prices and selling prices (for instance, Anglin et al., 2003; Beracha & Seiler, 2014; Knight, 2002). However, Curto et al. (2015) mentioned that valuers use listing prices for property valuation in Italy, due to the lack of selling prices information. The empirical findings of Curto et al. (2015) revealed that the use of listing prices could not produce accurate property value estimates. This suggests that property data from other sources could be investigated, which is the focus of the present study.

Pagourtzi et al. (2003) documented a detailed review of both traditional and advanced valuation methods. In another vein, Paliwal and Kumar (2009) conducted a review of the performance of advanced valuation approaches from previous studies. The study reported that the ANN technique outperformed other advanced valuation methods in 56 out of the 96 articles reviewed, its performance was equal to other advanced methods in 23 out of the 96 articles, and other techniques outperformed it in 17 instances of the 96 articles. This was also corroborated by Abidoye and Chan (2016b) that reported that the ANN technique outperformed other advanced methods especially, the HPM approach in 82% of the total articles reviewed.

The plausible reasons for the performance of the ANN technique could be because the ANN technique is capable of addressing the shortcomings of other valuation methods (Amri & Tularam, 2012; Do & Grudnitski, 1992). This is demonstrated by its learning ability and functioning structure that mimics the human brain (Taffese, 2006). Also, it is objective in nature (Grover, 2016), hence the reduction of valuers interference in property valuation exercises (Tay & Ho, 1992). It should be noted that no property valuation approach can handle all property valuation problems (Pagourtzi et al., 2007; Tse, 1997). However, for this study, the ANN technique was adopted in the modeling of the property prices based on the discussions presented above.

The input data to be modeled using the ANN technique is feed into the network at the input layer. Weight summation and transformation function takes place in the hidden layer and it is during this processes that the model learns from the data. The summation values are then transformed (through the transformation function) in the hidden layer and then transferred to the output layer. Figure 1 shows a typical processing unit of an ANN model with the mathematical expression of the weighted summation and transformation function which takes place in the hidden layer.

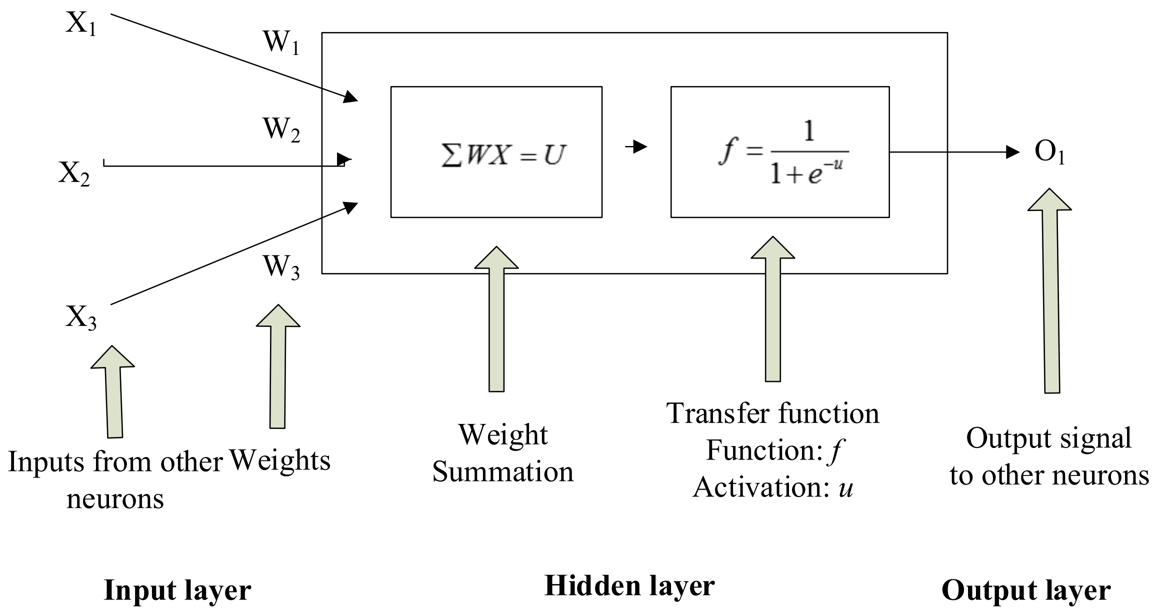

Figure 1: A typical ANN processing unit

Adopted from: Wong et al. (2002, p. 190) 190).

Where $X_{1\text{-}3}$ are the input value, $W_{1\text{-}3}$ are the assigned weights of the input values, U is the summation function, while f is the threshold value where output is determined.

Data and research method

The data used in this study were collected from the Nigerian property market, being a developing real estate market where a property data bank does not exist (Adegoke et al., 2013; Ashaolu & Olaniran, 2016). This choice depicts a scenario of the lack of data bank needed for property price modeling and there are demands for the state-of-the-art property valuation services by both the local and the international property valuation clients. The data were gathered from two sources. Firstly, the listing prices of residential property (henceforth, online data) were collected from an online real estate platform, i.e. Nigeria Property Center (https://www.nigeriapropertycentre.com/for-sale/flats-apartments/lagos/lekki/showtype). The property prices collected here are asking prices and not values exchanged between a willing buyer and a willing seller in arms-length transactions. Secondly, information of sold and purchased residential properties (henceforth, firms' data) were collected from registered real estate firms operating in the Lagos metropolis property market in Nigeria. The choice of the Lagos metropolis property market is due to the fact that it is the most active property market in Nigeria (Dugeri, 2011), and it records a high number of property transactions in Nigeria, due to the high number of sophisticated stakeholders that interact in the property market (Oni, 2010).

In order to have a common and objective basis for the comparison of both data set, the same parameters were set for the development of the models in terms of (1) the properties considered in this study are residential properties in the Lagos Island property market in Lagos, Nigeria, which are properties in the Lekki Peninsular residential axis, (2) the period considered is 2016, i.e. properties listed online in 2016 and those sold or purchased in 2016, and (3) the same number of independent variables (10) and sample size (155) was collected during the data collection process. This sample size of 155 used in this study is in the range of what has been used in previous studies. For instance, Mora-Esperanza (2004) (100), Pagourtzi et al. (2007) (141) and Morano and Tajani (2013) (85), amongst others. This is because a small sample size can be used to efficiently develop an ANN model (Zhang et al., 1998).

The independent variables considered in this study are property structural attributes because these are the kind of variables that can be obtained online in such developing property market.

Moreover, studies have shown that structural variables contribute significantly to property value formation (Abidoye & Chan, 2016a; Wen et al., 2005). In addition, these class of property attributes have been widely adopted in the literature (for instance, Do & Grudnitski, 1992; Thanasi, 2016). The property structural attributes considered in this study are property number of bedrooms, number of toilets, number of bathrooms, property type, number of boy's quarters (BQ) room, number of parking space, age of property, number of floors and availability of security fence. The availability of security fence was added as a dummy variable among the considered variables. The property location was added as a locational variable. It is worth to note that the properties used in this study are located in the same area where factors such as population density, income level, availability of infrastructure and access to central business district, among others, are the same. The location variable distinguish the geographical position of each property as the valuers could not provide the house address of each property, and in the same vein, this information was not provided online (for the listed properties). The dependent variable considered in this study is property price. The summary of the descriptive statistics of the online data and firms' data used in this study are presented in Table 1 and Table 2, respectively. While the definitions and measurements of the variables are provided in Table 3.

Table 1: Descriptive statistics of online data

Variables	Mean	Standard Deviation	Minimum	Maximum
Price	76,448,387.10	46,687,764.12	22,000,000	350,000,000
Property location	2.613	.7845	1.0	4.0
Number of bedrooms	4.348	.7779	2.0	7.0
Number of toilets	5.381	.8699	3.0	8.0
Number of bathrooms	4.574	.9255	2.0	7.0
Property Type	1.852	1.0243	1.0	5.0
Number of BQ	.890	.5874	.0	3.0
Number of parking space	4.897	1.7252	2.0	10.0
Age of property	1.677	1.0626	1.0	10.0
Number of floors	2.232	.5323	2.0	5.0
Availability of security fence	1.000	.0000	.0	1.0

Sample size=155, US$1 = N282.5 (Source: Central Bank of Nigeria, as at 30/06/2016)

Table 2: Descriptive statistics of firms' data

Variables	Mean	Standard Deviation	Minimum	Maximum
Price	98,064,516.13	83,144,407.89	10,000,000.00	330,000,000.00
Property location	2.819	1.3116	1.0	4.0
Number of bedrooms	3.168	1.2578	1.0	10.0
Number of toilets	3.832	1.3949	1.0	6.0
Number of bathrooms	2.968	1.1589	1.0	5.0
Property Type	4.484	1.3011	1.0	6.0
Number of BQ	.626	.5827	.0	2.0
Number of parking space	2.342	1.4614	1.0	6.0
Age of property	2.187	4.4383	.0	37.0
Number of floors	3.135	1.9072	1.0	14.0
Availability of security fence	.994	.0803	.0	1.0

Sample size=155, US$1 = N282.5 (Source: Central Bank of Nigeria, as at 30/06/2016)

Table 3: Definition and measurement of the variables

Table 3: Definitions and measurements of the variables

Variables	Definition	Measurement
Price	Sale price of a property	Naira (₦), Nigerian currency
Property location	Location of the property in the neighbourhood	North, South, East or West of the neighbourhood
Number of bedrooms	Number of bedrooms in a property	Numeric (0,1,2,3…)
Number of toilets	Number of toilets in a property	Numeric (0,1,2,3…)
Number of bathrooms	Number of bathrooms in a property	Numeric (0,1,2,3…)
Property type	Construction style of a property	Numeric (1,2…6)
Number of boy's quarters	Number of BQ rooms in a property	Numeric (0,1,2,3…)
Number of parking space	Number of parking lots in a property	Numeric (0,1,2,3…)
Age of property	Property age	Numeric in years (0,1,2,3…)
Number of floors	Number of floors of a property	Numeric (0,1,2,3…...)
Availability of security fence	Availability of security fence	1 if available, and 0 otherwise

Note: Property type includes: flat, terrace, semi-detached house, detached house, duplex and others.
BQ means Boy's quarters which is called servants' quarters in some other countries

The ANN model is designed to function like the human brain's learning process (Mora-Esperanza, 2004). The ANN models presented in this study were developed using the Waikato Environment for Knowledge Analysis (WEKA) software. WEKA "provides a uniform interface to many different learning algorithms, along with methods for pre and post processing and for evaluating the result of learning schemes on any given dataset" (Witten & Frank, 2005, p. 366). It has been applied successfully in ANN studies and has produced excellent results, see, for example, Al Jarullah (2011); Lam et al. (2008); Olson et al. (2012), among others.

A three-layer feedforward ANN network was developed. That is a network which consists of the input layer, one hidden layer and one output layer. This is because one hidden layer is sufficient to handle complex real-world problems such as property valuation (McCluskey et al., 2012). The number of neurons in the input layer is 10, which represent the number of explanatory variables included in the models. Also, the output layer had one neuron which represents the property price to be predicted. The number of hidden neurons was determined automatically by the software by optimizing the network architecture that best fit the data using default parameters.

Each set of the data used in this study were divided into two parts for the training and testing of the developed models. This was done by splitting them in the ratio of 80:20, for training and testing the models, respectively, which is a common approach in the literature (Morano et al., 2015). That is, 124 observations were used for estimating the models, while 31 were used as the holdout samples for the evaluation and validation of the models. The suitability of both sets of data examined in this study was established by evaluating their predictive accuracy through the ANN models developed. This was achieved by predicting the hold-out-sample data with the developed models and comparing the actual property values with the predicted property values generated by the ANN models. Their predictive accuracy of the models was measured by adopting accuracy metrics commonly used in the literature namely the mean absolute percentage error (MAPE), mean absolute error (MAE) and the root mean squared error (RMSE). The values generated by these metrics should be close to 0 for the model to be assumed to be fit to produce accurate estimates. The mathematical expressions of these metrics are presented in Equations 1 to 3.

$$\text{MAPE} = \frac{\sum_{i=1}^{n}\left(\frac{\text{P}_\text{i} - \hat{\text{P}}_\text{i}}{\hat{\text{P}}_\text{i}}\right)}{\text{n}} \quad (1)$$

$$\text{MAE} = \frac{1}{\text{n}}\sum_{\text{i}=1}\left(\text{P}_\text{i} - \hat{\text{P}}_\text{i}\right) \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\text{P}_\text{i} - \hat{\text{P}}_\text{i}\right)^2} \quad (3)$$

Where P_i is the actual property value, $\hat{\text{P}}_\text{i}$ is estimated/predicted property value from the model, $\overline{\text{P}}$ is the sample mean of the property values and n is the number of observations.

Results and discussion

The predictive accuracy measures produced from both data sources are presented in Table 4. The fitness of the models was tested based on the coefficient of determination (r^2). Considering the r^2 generated from both online data and firm data, the online data set produced a higher value of 0.75 which suggests that the data set fit the model well and that the independent variables included in the model could explain about 75% of the variations in the prices of properties (online prices) in the study area. This value is higher compared with the one generated by firms' data which is 0.69. This indicates that the variables included in the model developed using firms data could explain 69% of the changes in such prices (sales prices).

The suitability of both data set was established by comparing their predictive accuracy generated using both data set to model the property values. The figures shown in Table 4 shows that the online data generated lower MAE and RMSE values of 28,243,269.45 and 50,102,468.93, respectively, compared to the same values of firms' data of 34,844,776 and 54,161,657.68. This suggests that the error that could be generated when using online data for property valuation is minimal when compared with using selling prices retrieved from real estate firms. On the MAPE values of both data sources, the MAPE value of 26.93% was recorded for online data. This is also lower than the MAPE value of firms' data which is 29.96%. This depicts that when firms' data are used for property valuation, a variation of ± 30% of the property value could be recorded.

Table 4: Predictive accuracy of the models

Accuracy measure	Data source	
	Online data	Firms' data
r^2	0.75	0.69
MAE	28,243,269.45	34,844,776
RMSE	50,102,468.93	54,161,657.68
MAPE (%)	26.93	29.96

Previous studies (Hutchinson et al., 1996; Brown et al., 1998) have argued that a margin of error of between ± 0 and 10% of the actual property price is generally acceptable for a real estate valuation, and that an error beyond ± 10% that could be attributed to negligence. In addition, previous studies have used this margin in evaluating the predictive accuracy of property valuation models (see Amri & Tularam, 2012; McCluskey et al., 2012; Peterson & Flanagan, 2009). Following this rule, the percentage of the predicted prices of both online data and firm's data that fell within this bracket and above it were established. Table 5 shows that a larger percentage (45.16%) of the online data had an error of margin of between ± 0 and 10%, compared with that of the firm's data where only 19.35% had the same margin of error. It may be safe to conclude that the probability of estimating an acceptable/accurate property values is higher when online data are used for property valuation, while it could be lower when firms' data are used. On the extreme accuracy range of ± 20% and above, a lower percentage (45.16%) of online data fell within this margin, whereas a higher percentage (58.06%) fell within this margin as well. This also suggests that there is a high chance of estimating property values accurately when online data are used for property value modeling.

Table 5: Valuation accuracy of the online and firms' data

Accuracy range	Online data		Firms' data	
	Frequency	Percentage	Frequency	Percentage
± 0 - 10%	14	45.16	6	19.35
± 11 - 19%	3	9.68	7	22.59
± 20% and above	14	45.16	18	58.06

Figures 2 and 3 shows the plot of the actual property prices and the predicted property prices using online data and firms' data, respectively. Although in both cases the actual values and predicted values are close, but it is closer in the case of online data compared with firms' data, which conforms to the information in Table 4. From Figures 2 and 3, it is observed that the values (actual and predicted) were closer for properties with smaller values (i.e. for properties with values below ₦100,000,000.00) than for properties with higher values. This could be attributed to the immature nature of the Nigerian property market (Akinbogun et al., 2014). The situation in Nigeria is that there is a high level of secrecy in real estate transactions being consummated in the property market (Olaleye, 2008), and clients could influence the valuers' opinion of value during a property valuation exercise (Nwuba et al., 2015). The high inaccuracy recorded in expensive properties could be justified by the findings of Amidu and Aluko (2007) that found that the size of a client is a significant factor that could influence the pressure on a valuer during a property valuation exercise. This suggests that high net worth clients could find a way around to increase the value of their properties in order to derive a higher value when the property is to be sold or to be used as a collateral for a bank loan. All these corroborate the findings of Ogunba (2004) that reported that the level of valuation inaccuracy in Nigeria could be as high as between 22.73 and 67.91%.

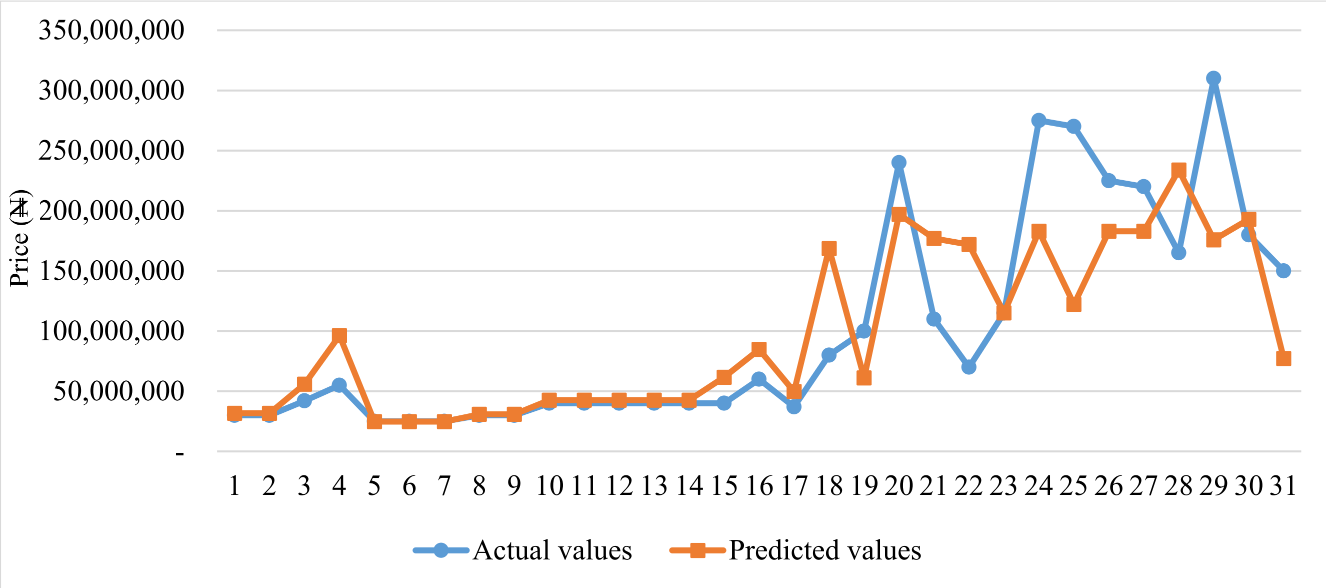

Figure 2: The actual prices versus predicted prices from online data

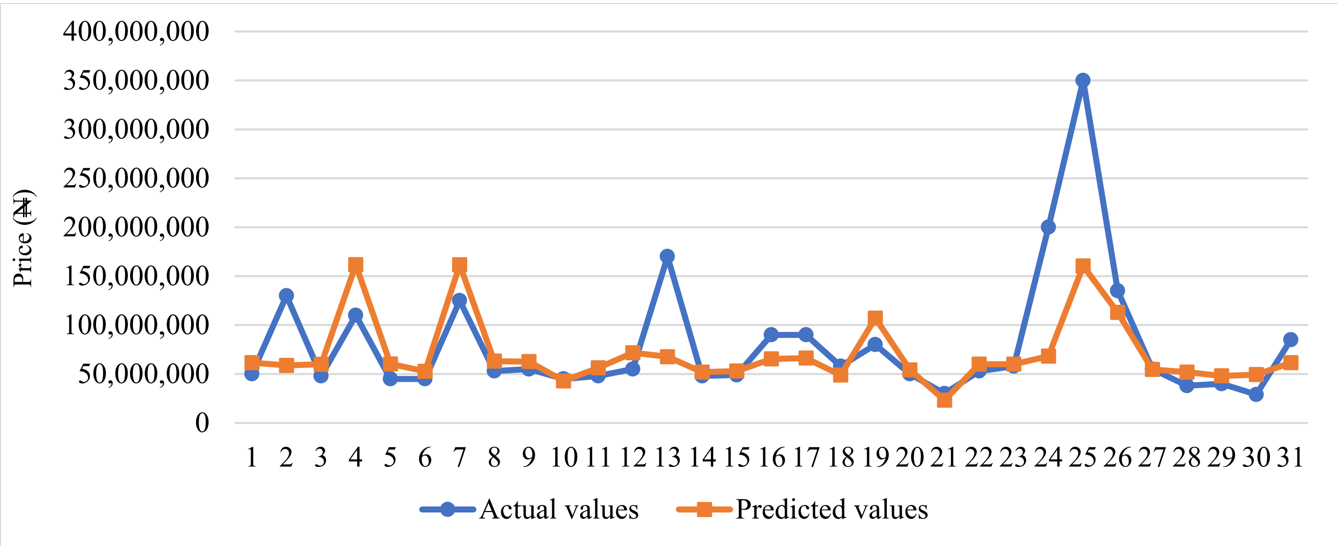

Figure 3: The actual prices versus predicted prices from firms' data

On the suitability of data to be used for property valuation in a market where there is a lack of centralised data bank, it could be suggested from the results of this study that listing prices could produce more accurate results. This corroborates the findings of Han and Strange (2016) that reported that listing prices plays a significant role in property value formation. This is also in line with results of Olaleye et al. (2015) that found that property listing price could predict property values with an accuracy of up to 84%. It can be concluded that property listing prices (online data) are a good data source for achieving property valuation accuracy, unlike selling prices (firms' data) that might have been achieved under different confidential (opaque) situations, especially in developing countries (Walters et al., 2011).

Conclusions

The need to achieve property valuation accuracy in any property market cannot be overemphasized due to the importance of the real estate section to the economic and household development of any nation. The centralised property data bank that is needed for modeling property values towards accuracy is mostly unavailable in developing countries. This study investigated the suitability of the available data in achieving property valuation accuracy in a developing nation with special emphasis on the Nigerian property market. Property information i.e. listing prices and selling prices were collected from online and real estate firms, respectively, in Nigeria. The data were fitted into an ANN model to predict the hold out sample so as to establish the suitability of both data sources to produce accurate property valuation estimates. It was revealed that online data produced more accurate estimates compared with firms' data. A more accurate property valuation was also recorded with less expensive properties, higher differences between actual property prices and predicted property prices were recorded for expensive properties. In a situation where property data bank is not existing, valuer could rely on listing prices for property valuation exercises. This conforms to the existing findings from previous studies. As scholars have argued that a quality and robust property data bank is highly necessary for estimating accurate and reliable property values, it is pertinent for all real estate stakeholders in countries where there is a lack of such information to put in place a centralised property transactions data bank in order to improve the quality of property valuations provided to valuation report end-users. Small data sets were used for this study and this is due to the limitations of garnering a large data set from different real estate firms in the Lagos metropolis property market. However, the data set is within the range that has been adopted successfully in previous studies and moreover, the ANN model does not need more data than usually required by linear models for it to function excellently. This study only focused on highbrow areas of the Lagos metropolis property market, however, data from other property markets could produce a different result. Also, a different result could be generated when more data are available for analysis. In order to achieve a global sustainable property valuation practice, studies of this nature could and should be replicated in property markets where quality and robust property data bank is lacking.

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