

Modelling Coastal Externalities Effects on Residential Housing Values

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Abstract

Design/methodology/approach

A survey approach was adopted for the data collection process. For both models, property values were measured in proximity to coastline using 0–250m, 251-500m and 0-500m.

Purpose

This paper examines the impact of coastline on the rental value of residential property in proximity to the coastline, using the hedonic pricing model from two perspectives. First, model 1A-C accounted for estimating the influence of coastal amenities while controlling for other housing attributes influencing rent. Second, model 2A-C accounted for the interaction between coastal amenities/disamenities and other housing attributes influencing rent.

Findings

Findings revealed that property rental value increases as we move away from the coastline when disamenities are not controlled. The results suggested that for a mean-priced home (\frac{1}{2},941,029 or \frac{1}{2},170) at the mean distance from the coastline (301.83m), a 1% increase in distance from the coastline would result in a 0.001% or \frac{1}{2},977 (\frac{1}{2},0.03) increase in rental value.

Practical implications

The implication to real estate valuers is that varying premiums should be considered when valuing a property depending on the distance to the coastline while considering other housing attributes.

Originality/value

This research introduces a novel approach to the hedonic model for determining property values in proximity to coastal environment by estimating the influence of coastal amenities while controlling for other housing attributes influencing rent, on one hand, and accounting for the interaction between coastal amenities/disamenities and other housing attributes influencing rent on the other.

Keywords:

coastline; flood; housing; properties; rent

Introduction

Globally, the coastal area is a place of choice for many people for its diverse tangible and intangible amenities (Parker & Oates, 2016). Consequently, studies have revealed that values of residential properties in coastal areas have been worthwhile to investors across the globe, with the proximate properties to coastline outperforming those at rows behind as distance to the coastline increases (Bin & Kruse, 2006; Bin et al., 2009). However, in recent times, coastlines are vulnerable to disamenities such as the increased risk of flooding with various effects upon any development along its axis (Kalaugher, 2007; Urama & Ozor, 2010). Therefore, the trend of discourse in coastal hedonic price studies has been devoted to studying and evaluating the effect of coastal amenities and disamenities on property values. A tenable justification of the discourse trend is aptly rooted in Bin et al., (2008a) that biased inferences can result from not accounting for coastal amenities and disamenities.

Most coastal hedonic property studies were conducted in developed economies (Makinde & Tokunboh, 2013; Oladapo et al., 2019). To reflect the peculiarities of the developing countries, a study in African countries like Nigeria is necessary. Moreover, rental data are used in this study, which improves previous studies that rely on transaction-based or appraisal-based sale data. Rental data are more responsive to changes in the market while its analysis will allow for more sturdy models giving a better understanding of housing (Aliyu, 2010; Acheampong & Anokye, 2013; Famuyiwa, 2018). In addition, the rate of flood occurrence based on revealed preference techniques from tenants' percept was used to capture coastal disamenities, unlike previous studies that rely on historical floodplain maps. A dummy variable signalling the location of the floodplain in or outside of a floodplain could effectively underestimate the risk of flooding (Daniel et al, 2009).

In developing countries, there is sparse literature focusing on coastal amenities/disamenities impact on property values (Udechukwu & Johnson, 2010). Most property appraisers are faced with the problem of how to incorporate associated coastal amenities and disamenities when determining property market value (Kruger, 2015). Therefore, this paper examines the effect of coastline on residential property values along the coastline corridor in Victoria Island, a coastal community in a Mega city of a developing country in Nigeria.

In Victoria Island, a previous investigation by Udechukwu and Johnson (2010) for Victoria Garden City (VGC), Lagos, Nigeria, found that a home with a view commands a premium of

8% or N2.59 million naira more than homes without a view. In the same study area, Makinde and Tokunboh (2013) found that full view on average property increased the housing price by 47.9%. Each of these studies accounted for the effect of coastal amenity on residential property value while neglecting coastal disamenity. Unlike the generic definition of view utilised in the studies, this study employed the Euclidean distance of the property to the nearest coastline, a recent measure of coastal amenity. The generic definition of view measure is associated with the spatial dependency of observations, while view scape can change over time as structures adjoining a residential building are altered (Bin et al., 2008a; Walsh et al., 2015).

The study by Ajibola et al. (2017) was limited to identifying the climate-related threats affecting property values and benefits derived along the Coastline in Victoria Island, Lagos State, Nigeria, while also collecting rental values of commercial and residential properties. The study did considers the non-monetary properties values by evaluating the challenges and benefits as effects of coastline on property values while also collecting rental values of commercial and residential properties. The study failed to model or determine the influence of the coastline on proximate properties. This is a drawback in coastal housing economics and property value modelling literature. This present study estimate in real (monetary) term the marginal effects of the amenities and disamenities on house rent by emphasising distance to coastline and employing two model specifications concentrated on selected residential properties in the study area.

Literature review

Numerous contributions from coastal hedonic property studies have considered the extent to which coastal amenities and disamenities influence residential property values. Most studies investigating the property value effect of coastal amenities without controlling for coastal disamenities have focused on the value-added through the view of water and proximity to water. Jim and Chen (2006) employed a hedonic pricing model to examine the effect of environmental amenities on house prices in four residential precincts in Haizhu district, Guangzhou, China. The study found that environmental attributes such as green space view increase house prices by 7.1%, while proximity to water bodies could raise house prices by 13.2%. The authors found that traffic noise and proximity to woods were not significantly

significant in the house transaction prices. The authors concluded that proximity to water bodies has a more positive impact on house prices than other environmental amenities.

Baranzini and Schaerer (2011) analysed 12,932 rental data to examine the value of view and land uses close to buildings in Geneva-Switzerland rental market. The authors found that rent premium for a dwelling located in a neighbourhood with an extended surface of water can be as high as 3% and a maximal view of water-covered area can raise rent up to 57%. They also found that dwellings with a view of the famous Geneva water fountain generate an average 3.6% higher rents. The authors noted that while the size and the view of the natural environment raise rents, the view of built environments declines them.

Zhang et al. (2015) analysed the price-volume relationships in Chinese coastal and inland housing markets. Using panel data obtained from 35 Chinese metropolitans, findings show that relationship exists in coastal cities where house prices are high with speculation. This shows that strict market intervention could bring significant change but cannot radically change the driving mechanism. The study concentrated on Granger relationship of price to volume ratio which is not within the scope of this present study.

Dumm et al. (2016) examined price performance of the value of view across the boom, bust, and post-bust phases of the most recent real estate cycle using sales data from the Tampa Bay, Florida housing market for the 2000–2012 period. The authors found that the value of view for waterfront properties, as one category, commanded a price premium of 7.2% over non-waterfront properties for the period 2000 through 2012 while the average price premiums of view vary by type of waterfront across the 12-year time period and ranged from 3.1% for pond to 15% for lake, 61% for canal, 62% for river and 107% for bay respectively. They concluded that the performance of specific waterfront property types across the economic cycle shows that the premiums were highest at the end of the boom stage (2006–2007) and at the end of the recovery stage (2011–2012).

Each of the studies that examined the property value effect of water view has shown that water views increase property values. In addition, there are variations in the estimated amounts of the increase across different geographical areas. Intrigued by associated shortcomings of the generic definition of a view, Conroy and Milosch (2011) analysed 9,755 single-family home sales in 106 neighbourhoods of San Diego County. The study found that

a 1% increase in distance from the beach reduced house prices by 0.146%. The results of their study also revealed that coastal premium is approximately 101.9% for houses within 500 feet of the beach falling to 62.8% for homes between 500 and 1,000 feet, declining to about 3.3% for homes located between five and six miles of the beach, ultimately becoming insignificant beyond six miles from the beach.

Liu et al. (2019) analysed 14,789 apartment transactions to explore the interaction effects between landscape variables on house prices transacted between 1st quarter of 2015 and 4th quarter of 2017 in Chongquig, China. The authors found that people will pay 0.92% more money for a house 10% nearer to the urban river, while peninsula view and Mountain View could increase the total prices of houses by 6.82% and 14.33% respectively. They found an amenity premium of 5.67% on house price of the interaction of an urban river landscape and an urban mountain landscape but the coefficient of the interaction of river housing and peninsula landscape view on house price though positive was insignificant.

Later, studies began to account for more detailed estimates for the combined effect of coastal amenities and disamenities on property values. Bin and Kruse (2006) analysed differential flood risks associated with the location of homes within three significant flood categories zone in Outer Banks housing markets of Carteret County, North Carolina. The hedonic models revealed that moving away from the coastline at the mean distance of 220m has 14.3% (\$45,184) lower property values. The study found that location within the 500-year floodplains reduces a property value by 10.3% (\$32,519) while areas within the 100-year floodplains and 100-year floodplains with wave exposure raise property values by 10.0% (\$31,640) and 26.5% (\$83,580), respectively. The study concluded that while property values are lower if located within a flood zone not subject to wave action, flood location vulnerable to wave action is associated with higher property value.

Bin et al. (2008a) analysed a data set of 1,075 homes sold in four beach communities in New Hanover County, North Carolina, between 1995 and 2002. The authors found that decreasing the distance to the nearest beach by ten yards (approximately 9 metres) results in an \$854 increase in property value. They also found that the mean WTP for sound frontage and pier are \$141,022 and \$51,944, respectively. They submitted that the location within a Special

Flood Hazard Area (SFHA) zone lowers property values by approximately 11%, while the mean WTP to avoid site in SFHA is \$36,082.

Bakkensen & Barrage (2021) examined flood risk belief heterogeneity and coastal home price dynamics in Rhode Island. This was achieved by estimating how climate risk beliefs affect coastal housing markets. The study implements a door-to-door survey and provides theoretical and empirical evidence by building a dynamic housing market model, which shows that belief heterogeneity can reconcile the mixed empirical evidence on flood risk capitalization. Findings revealed significant flood risk underestimation and sorting based on flood risk beliefs and amenity values. The study focuses on flood risk belief which is outside the scope of this research.

The studies of Bin and Kruse (2006) and Bin et al. (2008a) investigated how floodplain location alters residential property value. It is observed that there are somewhat mixed results with the use of floodplain types. The conjecture that properties in flood location associated with wave action commands higher property values than those in flood zone not subjected to wave action appears counter intuitive. A similar study by Yi and Choi (2020) has explained that such a result is new information to the housing market and can be interpreted as the market response to the updated flood risk. However, Daniel et al. (2009) argued that the existence of water is associated with both negative and positive spatial amenities, so a floodplain location indicating a dummy variable may underestimate the value of the risk of flooding.

Consequently, studies began to use actual flood events as a proxy for flooding to account for disamenities in coastal hedonic price studies. Daniel et al. (2009) investigated 9,505 residential properties to detect the presence of ex-ante house price variations considering the perceived level of risk before the 1993 and 1995 river floods. It was observed that house prices before the 1993 flood were not different from those not subject to flood risk. However, between the two floods, the house value decreased by 4.6%. In contrast, the risk premium increased to about 9% after the second flood. In addition, within 500 metres of the river, they found that dwellings experience a positive effect of 2.7%. At the same time, houses affected by the flooding are 4.7% cheaper than other houses. The study concluded that local housing markets in the Netherlands are significantly sensitive to flood risk.

Atreya et al., (2013) utilised a difference-in-differences spatial hedonic model to investigate the sale of 8,042 homes in Dougherty County, Georgia, from 1985 to 2004 to capture the time trend in the flood risk discount before and after the 1994 flood event. The authors found that before the 1994 flood, property prices in the 100-year floodplain declined by 9%, but the costs of properties in the 500-year floodplain did not change significantly. They found that immediately after the 1994 flood event, there was a 32% (\$26,880) discount for the 100-year floodplain properties, discounted by \$24,100 the first year after the flood, by \$21,200 the second year, and flood risk discount becomes positive five years after the flood. Their findings also revealed that the prices of properties in the 500-year floodplain significantly weakly declined by 23% immediately after the surge, while the discount became insignificant after that. The authors also found that increasing the distance to Flint river (river associated with the 1994 flood event) by 1% results in an increase of the property values by 0.5% whereas increasing the distance to other rivers by 1% results in the decline of the property values by 0.4%.

Bekes et al. (2016) investigated 28,542 real estate transactions in the Hungarian housing market from 2012 to 2013. They found that properties by major river ways without accounting for inundation risk are an 18% increase in house prices. Regarding the interaction term, they found that a 10% higher inundation risk is associated with 2.1% lower house prices along major rivers. The authors concluded that while riverside areas have an overall price premium, risky areas lose this advantage to flood risk.

Daniel et al. (2009), Atreya et al. (2013), and Bekes et al. (2016) employed actual flood events as a proxy for flooding to account for coastal disamenities and amenities on property values and obtained a contradictory result. While Daniel et al. (2009) concluded that regional housing markets in the Netherlands are significantly susceptible to flood risk, Atreya et al. (2013) suggested that property prices in 100-year and 500-year floodplains after the 1994 flood event in Dougherty County, Georgia displayed a lower sensitivity to future flood risk. This conflicting opinion necessitate a study in developing countries like Nigeria to reflect the region's peculiarities.

This paper, like several studies in a large theoretical body of hedonic literature on residential property market (*see* Baranzini & Schaerer, 2011; Walsh et al., 2015; Yamagata et al., 2016;

Kahveci & Sabaj, 2017; Bedell, 2018; Beltrán et al., 2018; Du et al. 2018) is deeply rooted in Rosen (1974) work which provided a framework for hedonic analysis using a model of consumer bid and producer offer functions for determining the implicit price of the characteristics of a property for different consumers. The relationship between the price of housing units and housing attributes has been widely addressed in the coastal housing economics and property value modelling literature by the hedonic price models. From our extensive literature review, several empirical contributions from a large theoretical body of hedonic literature on residential property market suggest that house price is a function of packages of structural, location, neighbourhood and environmental attributes of the dwelling.

Methodology

Study Area

Victoria Island is a Coastal Community of Eti-Osa Local Government Area (LGA) in Lagos State. Eti-Osa LGA borders Lagos Island and Ibeju-Lekki local government areas in the West and East. In contrast, the Lagos Lagoon and the Atlantic Ocean define its northern and southern borders. The Local Government Area covers land and water areas of 193,460 km² and 145 km², lying approximately between Latitude 60° 26′ 20" N to 60° 27′ 50" N and Longitudes 30° 24′ 10" E to 30° 40′ 10" E (National Population Commission, 2006; Lagos Bureau of Statistics, 2015; Agboola & Ayanlade, 2016). Fig 1 shows the map of the study area.

Insert Fig 1

Victoria Island is an attractive, densely built, and overpopulated area (Van-Bentum, 2012). It is an area desirable for people to reside in (Dada, 2009). Nevertheless, its axis has experienced consistent flooding due to sea-level rise over the years (Ajibola et al., 2012). This coastal disamenity amidst the tangible and intangible benefits associated with the research area makes the study area suited for this study.

Previous studies used a threshold of 500 metres to describe proximal environmental amenities to the apartments analysed (Jim & Chen, 2006; Daniel et al., 2009). The study covers residential buildings within the width of 500 metres from the Coastline inland, having a stretch of 1.2 kilometres along the Atlantic Ocean extending from after the east mole/Atlantic city through to Oniru beach and Vantage beach. The tenanted residential property types

considered are purposely built two and three-bedroom blocks of flats and bungalow respectively (See Fig 2).

Insert Fig 2

Segmented linear spline of the distance of 250 metres from coastline to the extent of 500 metres was constructed to capture the non-linear effect of coastline on house rent (Kriesel & Friedman, 2002; Conroy & Milosch, 2011; Atreya & Czaikowski, 2014; Bedell, 2018). Figure 3 shows the surveyed area at an incremental distance of 250m to the coastline the map of the study area showing residential properties at an incremental distance of 250m to the coastline.

Insert Fig 3

Sampling procedure

Taking a cue from Gopalakrishnan et al., (2009), the residential properties within 500m of the coastline was counted and the figures stands at 1,273. After ground-truthing, the physically identified single tenancy rented residential properties within 500 metres of the coastline in the study area amounted to 484, constituted the sample for the study.

Out of the residential properties sampled, 37.19% are within 250 metres of the coastline, while the remaining 62.81% are located between 251 and 500 metres of the coastline. The most equally distributed residential properties within 250 metres to the coastline and those between 251 and 500 metres of the coastline is associated with the 3 bedroom bungalow with a proportion of 11.27% for the former and 10.30% for the latter.

Insert Table 1

Method of data analysis

The choice of variables employed in this study was driven by a holistic review of the coastal property hedonic literature and the selection of relevant variables to the study area. The data extracted from the field survey of the properties pertain to house rent, frequently appearing structural attributes in literature namely building floor area, age of house, number of bathrooms, number of bedrooms, building condition, multistory or number of floors and presence of garage (Baranzini & Schaerer, 2011; Conroy & Milosch, 2011; Gordon et al.,

2013; Hansen & Benson, 2013; Makinde & Tokunboh, 2013; Atreya & Czajkowski, 2014; Wyman et al., 2014; Below et al., 2015; Walsh et al., 2015; Dumm et al., 2016) and locational characteristics including distance to workplace, distance to nearest public transport stop and distance to nearest school (Blackwell et al., 2010; Baranzini, & Schaerer, 2011; Conroy & Milosch, 2011; Makinde & Tokunboh, 2013; Atreya & Czajkowski, 2014; Dumm et al., 2016; Liu et al., 2019). Other frequently appearing attributes in literature related to neighbourhood is quality of neighbourhood landscaping (Bourassa et al., 2004; Bourassa et al., 2005; Des Rosiers et al., 2007; Jim & Chen, 2009; Du et al., 2018; Liu et al., 2019; Oyedeji, 2019) and the environmental variables of interest which are majorly distance to the nearest coastline and flood occurrence rate (Conroy & Milosch., 2011; Atreya & Czajkowski, 2014). Fig 4 depicts the rented properties from which the information used were extracted.

Insert Fig 4

As argued by Kriesel et al., (2000), hedonic regressions estimations ensure a more robust comparison as they allow the averages to be computed on a constant-quality basis. Data on the level of flood occurrence indicate that the preponderance of respondents' responses on the rate of flood occurrence oscillates between low and medium perceptual ratings in the study area in the last two years. The hedonic regression model was used to examine the influence of coastline while controlling for other housing attributes on the rental value of residential properties. Models were estimated with the log-log functional form in which all the variables, except dichotomous variables, are measured in logarithmic form. The natural log of distance to the coastline *log(DISCOAST)* was included to capture coastal amenities associated with the homes within 500 metres of the coastline. Model 1 is given as:

Where rent is expressed in its natural logarithm, β_0 is a constant term, the coefficients β_1 - β_6 is the percentage change in rent resulting from a unit change in age, building floor area, house-workplace distance, house-bus stop distance, house-school distance, and house-nearest Coastline distance (or interaction of distance to the coastline and flood occurrence) respectively. The coefficients β_7 - β_{13} reveal the percentage change in renting an additional

bedroom, bathroom, floor, garage, excellent building condition, and excellent landscape quality. The uncorrelated residual term is ε .

As it is logical that the effect of distance to the coastline will be non-linear, a segmented set of models (model 2) was estimated to incorporate flooding. To account for coastal disamenity as the distance to the coastline increases, the natural log of distance to coastline and rate of flood occurrence *log*(DISCOAST*FLODRATE) were interacted to account for the effect of coastal disamenity. Model 2 is given as:

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LogRENT = \beta_0 + \beta_1 logBLDAGE + \beta_2 logBFLOAREA + \beta_3 logDISTWORK + \beta_4 logDISBSTOP + \beta_5 logDISTSCH + \beta_6 log(DISCOAST*FLODRATE) + \beta_7 NBEDROOM + \beta_8 NBATROOM + \beta_9 NFLOORS + \beta_{10} GARAGE\_Yes + \beta_{11} BLDCOND\_Excellent + \beta_{12} LSCAPQUA\_Excellent + \varepsilon ------ (eq. 2)
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The multicollinearity and spatial autocorrelation tests were applied to the hedonic models to establish if some regression analysis assumptions were met. Following Rosiers et al. (1996), Menard (2002), Gujarati (2004), Glen (2015), McCormack (2015), Xiao (2017), and Senaviratna, and Cooray (2019), the tolerances for all the explanatory variables for the models which are close to 1 and all the VIF values which are less than 4, suggest that multicollinearity is not a concern (*see Appendix C*). Also, relying on Field (2009) and Glen (2016), the Durbin-Watson statistic values ranging from 1.647 to 2.226 (Tables 2 and 3) for all the regression models signify that there are no spatial correlations in the residuals of the estimated hedonic models. The empirical results are presented in the next section.

Results and Discussion

The results of the hedonic price models are presented in Tables 2 and 3. The models have a good predictive power for the explanatory variables, with *R*-squared statistics ranging from 0.55 to 0.64. The F-statistics in the range of 6.491 – 21.115 show that at 0.1% level, the models are statistically significant and explain between 55% and 64% of the variance of rents in the study area. The entire-sample models reveal that variables such as building age (LogBLDAGE), floor area (LogBFLOAREA), number of floors (NFLOORS), and Garage (GARAGE_YES) are significant determinants of rent of residential properties in the study area.

Insert Tables 2 & 3

Across all the models, the coefficients on building age imply that a 1% increase in the property's age decreases rent in a range of from 0.1% to 0.2%, or \$\frac{1}{2}6,581\$ (\$74) to \$\frac{1}{2}49,017\$ (\$136) at the mean. The coefficient on a floor area is significant at 0.1% across the models and imply that a 1% increase in a square metre of floor area increases house rent in a range of from 1.86% to 2.71% or \$\frac{1}{2}31,485\$ (\$88) to \$\frac{1}{2}46,573\$ (\$129). The estimated marginal effect for the number of floors variable in models 1A and 2A implies that for the whole houses within 500 metres of the coastline, properties with a higher number of floors increase rent by approximately 3% or \$\frac{1}{2}95,600\$ (\$266). Moving to the segmented models, a unit increase in the number of floors leads to a rise in house rent by as much as 5.7% or \$\frac{1}{2}167,095\$ (\$464) in model 1C and 5.4% or \$\frac{1}{2}160,857\$ (\$447) in model 6 for residential properties between 251 to 500 metres from the coastline, or as low as approximately 1% or \$\frac{1}{2}29,500\$ (\$82) in models 1B and 2B for homes within 250 metres of the coastline.

As displayed in models 1A and 2A, the significantly positive coefficient for the dummy variable, which captures the garage effect, increases rents for the whole houses within 500 metres of the coastline by approximately 16% or N483,000 (\$1,342). The impact is most significant in models (1C) and (2C), where the rent of a home having garage could increase by around 20% or N593,469 (\$1,649) and 22% or N647,102 (\$1,798), respectively. The results suggest that tenants attach importance to this attribute in the study area, but more weight is attached to the attribute in homes between 251 and 500 metres of the coastline. The insignificantly positive coefficient for the dummy variable that captures the garage effect implies that the garage increases house rents by approximately 6% or N178,000 (\$494) within 250 metres of the coastline (models 1B and 2B).

Moving on to the variables of interest, the signs (positive or negative) of the effects of the coastal amenity (LogDISCOAST) and disamenity {Log(DISCOAST*FLODRATE)} variables across the models are somewhat not consistent with expectation. The variable LogDISCOAST is positive but statistically insignificant in the model (1A). As the results show, a 1% increase in distance from the coastline leads to a rise in property values by 0.001%, which is equivalent to $\frac{1}{2}$ 9.77 (\$0.03) when evaluated at the average house rent among homes up to 500 metres of the coastline. The result implies that distance to the coastline has a weak effect on the rent of the properties with increasing returns. The coefficient on Log(DISCOAST*FLODRATE) in the model (2A) indicates that when flooding becomes an issue, increasing the distance to the coastline by 1%, there is an insignificant

discount of about 0.02% associated with properties up to 500 metres of the coastline, equivalent to №194.88 (\$0.54) when evaluated at the average house price. The result implies that when flooding is accounted for, increasing distance from the coastline has a weak negative impact on house rents.

Turning to the segmented models, without controlling for flood occurrence, in models 1B, the variable *LogDISCOAST* is positive but insignificant. The results imply that proximity to the coastline is somewhat undesirable and increasing distance from the coastline has a weak positive effect on the house rent. A 1% increase in distance from the coastline is associated with approximately 0.08% or ¥1,318 (\$3.66) increase in property rent within 250 metres of the coastline (model 2). The insignificant coefficient on *LogDISCOAST* in the model (1C) suggests that a 1% increase in distance from the coastline increases rents by 0.23% or ¥1,757.09 (\$4.88). When flood occurrence is accounted for within 250 metres of the coastline (model 2B), the result reveals that proximity to the coastline further dampens house rent though insignificant. The insignificant coefficient on *Log(DISCOAST*FLODRATE*) is 0.047, indicating that a 1% increase in distance from the coastline increases rent by approximately 0.05% or ¥805 (\$2.24). Contrarily, in the model (2C), a 1% increase in distance from the coastline decreases rent by approximately 0.09% or ¥641 (\$1.78) between 251 and 500 metres of the coastline.

The results reveal that proximity to Coastline (LogDISCOAST) has not enhanced residential property rental values in the study area. Without controlling for disamenities, proximity to coastline has a weak negative effect on rent for models 1A-C. The weak negative effect of coastline on rent means that the coastline is insignificantly undesirable for households in the research area. The previous ocean surges and flooding experience in Victoria Island could be the possible reason why families are not willing to pay a reasonable premium to have access to the coastline that lies within 500 metres of their homes (Awosika et al., 2002; Olaniyan & Afiesimama, 2003; Oyinloye, 2016). This finding differs from other coastal studies that found that proximity to the coastline has a robust positive effect on residential property prices (Bin & Kruse, 2006; Bin et al., 2008a, b; Samarasinghe & Sharp, 2008; Bin et al., 2009; Conroy & Milosch, 2011; Atreya & Czajkowski, 2014; Fu et al., 2016). While studies that found that proximity to the coastline has a robust positive effect on house prices are common, there is some evidence for similar findings that proximity to coastline negatively affects house prices (Bourassa et al., 2004; Atreya et al., 2013).

Moreover, when disamenities are controlled for, it is only in model (2B) that flooding lowers the rent with proximity to the coastline. The reverse is demonstrated in models (2A and 2C). This discrepancy can be explained by the fact that no substantial cost of flood occurs when the entire sample is considered (model 4) and in the location between 251 and 500 metres of the coastline (model 2C). In other words, the level of flood occurrences in the areas was relatively lower compared to locations within 250 metres of the coastline. The finding that flooding lowers residential property value with proximity to the coastline reaffirms the studies of Bin et al. (2008b), Daniel et al. (2009), and Bekes et al. (2016). On the other hand, the finding that signifies that in the phase of flooding, rent increases with proximity to the coastline (models 2A and 2C) somewhat agree with the study of Bin and Kruse (2006) and Atreya and Czajkowski (2014), which concluded that the associated positive amenity values of living in high-risk areas outweigh the flood risk.

Conclusion

This study estimated the price of proximity to the coastline, among other housing attributes. Without controlling for coastal disamenities, the results suggested that proximity to the coastline has an insignificant negative effect on property value in the research area. This finding indicates that values of proximate residential properties to the research area's coastline are somewhat associated with the risk of flooding. Moreover, controlling for disamenities, property values tend to increase with proximity to the shoreline in locations within 500 metres of the coastline and between 251m to 500m of the coastline, indicating that flood occurrence in the areas is low in the years between 2017 and 2018. Contrariwise, flooding further decreases rent with decreasing distance to the coastline within 250 metres of the coastline. Considerably, the findings are within the confine of results in the literature.

This research provides valuable insight to coastal managers, government, and real estate professionals. Findings suggest a reflection of flood risk in values of proximate residential properties to the coastline. The study recommends that government and coastal managers adopt proper protection measures of the coastline and ensure an integrated approach to flooding control to lessen the consequence of flooding in the research area. The implication to real estate valuers is that varying premiums should be considered when valuing a property depending on the distance to the coastline while considering other housing attributes in the

study area. The future research agenda could employ the concept of the submarket, which could involve the use of data for only a particular property type other than the amalgamation of the attributes of different residential property types utilised in this study. The approach will further enhance understanding the complex residents-environment behaviour within the various categories of residential properties with associated housing attributes.

Notes:

¹The coefficient of the predictor variable, when both response variable and predictor variable are log-transformed, is interpreted as the per cent increase in the dependent variable for every 1% increase in the independent variable (Ford, 2018).

²The equivalent actual term estimation of the marginal effect of the log-transformed continuous or distance-related explanatory variable on rent is calculated by $(\gamma *\beta \div \bar{y})$, where γ is the mean house rent, β is the coefficient of the continuous or distance-related variable, and \bar{y} is the mean value of the continuous or distance-related variable (Bin et al., 2008b).

³The percentage increase or decrease in rent resulting from a change in dummy or discrete explanatory variable is derived from the exponent of the coefficient of the variable, then one subtracted from this number and multiplied by 100: [exp (β) - 1]*100 (Halvorsen & Palmquist, 1980; Giles, 1982; Baranzini & Schaerer, 2011; Ford, 2018).

⁴The equivalent actual term estimation of the marginal effect of dummy or discrete explanatory variable on rent is calculated by $\gamma^*\{\exp(\beta) - 1\}$, where γ is the mean house rent and β is the coefficient of a dummy or discrete variable (Bin et al., 2008b).

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References

- Acheampong, R.A., & Anokye, P.A. (2013). Understanding households' residential location choice in Kumasi's Peri-urban settlements and the implications for sustainable urban growth. *Research on Humanities and Social Sciences*, *3*(9), 60-70.
- Agboola, A.M., & Ayanlade, A. (2016). Sea level rise and its potential impacts on coastal urban area: A case of Eti-Osa, Nigeria. *Analele Universității Din Oradea, Seria Geografie, 2,* 188-200.
- Ajibola, M. O., Izunwanne, E. M., & Ogungbemi A. O. (2012). Assessing the effects of flooding on residential property values in Lekki phase I, Lagos, Nigeria. *International Journal of Asian Social Science*, 2(3), 271-282.
- Ajibola, M.O., Owolabi D.R., & Ogungbemi, A. O. (2017). Examining the effects of coastline on property values in Victoria Island. *International Journal of Science, Environment and Technology*, (6)1, 958 970.
- Aliyu, M.A. (2010). *Microeconomic analysis of the residential location decision: The case of Kano, Nigeria*. (Doctoral dissertation). University of East Anglia, Norwich.
- Atreya, A., Ferreira, S., & Kriesel, W. (2013). Forgetting the flood? An analysis of the flood risk discount over time. *Land Economics*, 89(4), 577-596.
- Atreya, A., & Czajkowski, J. (2014). Housing price response to the interaction of positive coastal amenities and negative flood risks (Report No. 2014-09). Philadelphia, USA: Risk Management and Decision Processes Center, The Wharton School, University of Pennsylvania.
- Awosika, L., Dublin-Green, C.O., & Folorunsho, R. (2002). Bar beach Victoria Island erosion problem: A critical assessment as of 30th October, 2002 and need for urgent mitigating measures. Marine Geology/Geophysics Division, Nigerian Institute for Oceanography and Marine Research, Victoria Island, Lagos. Retrieved from https://aquadocs.org
- Bakkensen, L.A., & Barrage, L. (2021). Going underwater? Flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies*, 00, 1-44.
- Baranzini, A., & Schaerer, C. (2011). A sight for sore eyes: Assessing the value of view and land use in the housing market. *Journal of Housing Economics*, 20(3), 191-199.

- Bedell, W.B. (2018). Capitalisation of green space and water quality into residential housing values. *Theses and Dissertations Agricultural Economics*, 63. https://uknowledge.uky.edu/agecon_etds/63
- Bekes, G., Horvath, A., & Sapi, Z. (2016). Flood risk and housing prices: Evidence from Hungary. (IEHAS Discussion Papers, No. MT-DP 2016/20, ISBN 978-615-5594-56-4). Hungarian Academy of Sciences, Institute of Economics, Budapest.
- Below, S., Beracha, E., & Skiba, H. (2015). Land erosion and coastal home values. *Journal of Real Estate Research*, *37*(4), 499-535.
- Beltrán, A., Maddison, D., & Elliott, R.J.R (2018). Is flood risk capitalised into property values? *Ecological Economics*, *146*, 668-685.
- Bin, O., Crawford, T.W., Kruse, J.B., & Landry, C.E. (2008a). Viewscapes and flood hazard: Coastal housing market response to amenities and risk. *Land Economics*, 84(3), 434-448.
- Bin, O., & Kruse, J.B. (2006). Real estate market response to coastal flood hazards. *Natural Hazards Review*, 7(4). Retrieved from https://ascelibrary.org
- Bin, O., Kruse, J.B., & Landry, C.E. (2008b). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *The Journal of Risk and Insurance*, 75(1), 63-82.
- Bin, O., & Landry, C.E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management, 65*, 361–376.
- Bin, O., Poulter, B., Dumas, C.F., & Whitehead, J.C. (2009). Spatial hedonic models for measuring the impact of sea-level rise on coastal real estate. Retrieved from www.researchgate.net
- Blackwell, C., Sheldon, S., Lansbury, D., & Vaught, D. (2010). Beach renourishment and property value growth: The case of folly beach, South Carolina. *The Review of Regional Studies*, 40(3), 273-286.
- Bourassa, S.C., Hoesli, M., and Sun, J. (2004). What's in a view? *Environment and Planning A*, 36, 1427-1450.

- Bourassa, S.C., Hoesli, M., & Sun, J. (2005). The price of aesthetic externalities. *Journal of Real Estate Literature*. *13*(2), 167-187.
- Conroy, S.J., & Milosch, J.L. (2011). An estimation of the coastal premium for residential housing prices in San Diego County. *J Real Estate Finan Econ*, 42, 211–228.
- Dada, A. (2009, 28th December). Eko Atlantic City: Daring the waves. *Punch Newspaper*. Retrieved from http://www.ekoatlantic.com/category/latestnews/press-clipping/
- Daniel, V.E., Florax, R.J.G.M., & Rietveld, P. (2009). Floods and residential property values: A hedonic price analysis for the Netherlands. *Built Environment*, *35*(4), 563-576.
- Des Rosiers, F., Thériault, M., Kestens, Y., & Villeneuve, P. (2007). Landscaping attributes and property buyers' profiles: Their joint effect on house prices. *Housing Studies*, 22(6), 945-964.
- Du, Q., Wu, C., Ye, X., Ren, F., & Lin, Y. (2018). Evaluating the effects of landscape on housing prices in urban China. *Tijdschrift voor Economische en Sociale Geografie*, 109(4), 525–541.
- Dumm, R.E., Sirmans, G.S., & Smersh, G.T. (2016). Price variation in waterfront properties over the economic cycle. *Journal of Real Estate Research*, 38(1), 1-25.
- Famuyiwa, F. (2018). Natural environmental amenities and house prices A hedonic analysis for integrated planning. *Journal of African Real Estate Research*, 3(2), 44-62. DOI: 10.15641/jarer.v0i0.482
- Field, A.P. (2009). Discovering statistics using SPSS: (and sex and drugs and rock 'n' roll) (3rd Edn.) London: Sage.
- Ford, C. (2018). *Interpreting log transformations in a linear model*. Retrieved from https://data.library.virginia.edu/interpreting-log-transformations-in-a-linear-model/
- Fu, X., Song, J., Sun, B., & Peng, Z. (2016). "Living on the edge": Estimating the economic cost of sea level rise on coastal real estate in the Tampa bay region, Florida. *Ocean & Coastal Management 133*, 11-17.
- Giles, D.E.A. (1982). The interpretation of dummy variables in semilogarithmic equations unbiased estimation. *Economics Letters*, *10*, 77-79.
- Glen, S. (2015). *Variance inflation factor*. Retrieved from https://www.statisticshowto.com/variance-inflation-factor/
- Glen, S. (June 2016). *Durbin Watson test & test statistic*. Retrieved from http://www.statisticshowto.com/durbin-watson-test-coefficient/

- Gopalakrishnan, S., Smith, M.D., Slott, J.M., & Murray, A.B. (2009, July 26-29). *The value of disappearing beaches: A hedonic pricing model with endogenous beach width.* Paper presented at the AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin.
- Gordon, B.L., Winkler, D., Barrett, J.D., & Zumpano, L. (2013). The effect of elevation and corner location on oceanfront condominium value. *Journal of Real Estate Research*, 35(3).
- Gujarati, D.N. (2004). *Basic econometrics* (4th ed.). New York: The McGraw-Hill Companies.
- Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *The American Economic Review, 70*(3), 474-475.
- Hansen, J.L., & Benson, E.D. (2013). The value of a water view: Variability over 25 years in a coastal housing market. *The Coastal Business Journal*, 12(1), 76-99.
- Jim, C.Y., & Chen, W.Y. (2006). Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape and Urban Planning*, 78, 422–434.
- Jim, C.Y., & Chen, W.Y. (2009). Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landscape and Urban Planning*, 91(4), 226-234.
- Kahveci, M., & Sabaj, E. (2017). Determinant of housing rents in urban Albania: An empirical hedonic price application with NSA survey data. *Eurasian Journal of Economics and Finance*, 5(2), 51-65.
- Kalaugher, L. (2007). *Africa continent one of the most vulnerable to climate change*. Retrieved from http://www.environmentalresearchweb.org/cws/article/opinion/27558
- Kothari, C.R. (2004). *Research methodology: Methods and techniques* (2nd Revised ed.). New Delhi: New Age International Publishers.
- Kriesel, W., & Friedman, R. (2002). Coastal hazards and economic externality: Implications for beach management policies in the American southeast (A Heinz center discussion paper, May 2002). Retrieved from www.heinzctr.org
- Kriesel, W., Landry, C., & Keeler, A. (2000, July). *Costs of coastal hazards: Evidence from the property market*. Paper selected for presentation at the American Agricultural Economics Association Annual Meeting in Orlando, Florida.
- Kruger, A. (2015). The influence of climate change on the market value of coastal residential property in South Africa. *WIT Transactions on the Built Environment, 148*. Retrieved from https://www.researchgate.net/publication/290439884
- Lagos Bureau of Statistics [LBS] (2015). Digest of statistics. Ministry of economic planning and budget, Alausa, Ikeja, Lagos.

- Laverne, R.J., & Winson-Geideman, K. (2003). The influence of trees and landscaping on rental rates at office buildings. *Journal of Arboriculture*, 29(5), 281-290.
- Liu, G., Wang, X., Gu, J., Liu, Y., and Zhou, T. (2019). Temporal and spatial effects of a 'Shan Shui' landscape on housing price: A case study of Chongqing, China. *Habitat International*, 94, 1-11.
- Makinde, O.I., & Tokunboh, O.O. (2013). *Impact of water view on residential properties house pricing*. Paper presented at the American Real Estate Society Conference, Kigali, Rwanda.
- McCormack, K. (2015). Diagnostics for hedonic models using an example for cars (hedonic regression). *Biometrics & Biostatistics International Journal*, 2(1), 23-37.
- McKenzie, R., & Levendis, J. (2010). Flood hazards and urban housing markets: The effects of Katrina on New Orleans. *J Real Estate Finance Econ*, 40, 62–76.
- Menard, S. (2002). Applied logistic regression analysis (2nd ed.). A Sage University Paper.
- National Population Commission [NPC], (2006). Population and housing census of the federal republic of Nigeria, priority tables volume III.
- Oladapo, R.A., Ayoola A.B., Ojo B., and Olukolajo M.A. (2019). The effect of coastal environment on residential property values: A review of literature. In M.B. Nuhu and S. Kuma (Eds): *Land Policy Governance and Sustainable Development in Nigeria: A Book of Readings;* 140 152; Centre for Human Settlements and Urban Development (CHSUD) Federal University of Technology, Minna, Niger State, Nigeria.
- Olaniyan, E., & Afiesimama, E.A. (2003). Understanding ocean surges and possible signals over the Nigerian coast: A case study of the Victoria Island bar beach Lagos. Retrieved from https://www.researchgate.net
- Oyedeji, J.O. (2019). Impact of landscaping on residential property value in Lekki phase 1 Lagos. *UNIOSUN Journal of Engineering and Environmental Sciences*, *1*(1), 49-56.
- Oyinloye, M.A. (2016). Assessment of coastal flooding on Victoria Island in Eti-Osa Local Government Area, Lagos State, Nigeria. *Recent Advances in Energy, Environment and Financial Science*, 292-304, ISBN: 978-1-61804-361-0.
- Parker, H., & Oates, N. (2016). How do healthy rivers benefit society? A review of the evidence. Retrieved from http://www.odi.org
- Parsons, G.R., & Powel, M. (2001). Measuring the cost of beach retreat. *Coastal Management*, 29, 91–103.

- Posey, J., & Rogers, W.H. (2010). The impact of special flood hazard area designation on residential property values. *Public Works Management & Policy 15*(2), 81-90.
- Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82(1), 34-55.
- Rosiers, F.D., Lagana, A., Thériault, M., & Beaudoin, M. (1996). Shopping centres and house values: An empirical investigation. *Journal of Property Valuation & Investment, 14*(4), 1996, 41-62.
- Samarasinghe, O., & Sharp, B. (2008). Flood prone risk and amenity values: A spatial hedonic analysis. *The Australian Journal of Agricultural and Resource Economics*, *54*, 457–475.
- Senaviratna, N.A.M.R., & Cooray, T.M.J.A. (2019). Diagnosing multicollinearity of logistic regression model. *Asian Journal of Probability and Statistics*, *5*(2), 1-9.
- Udechukwu, C.E., & Johnson, O.O. (2010). The impact of lagoon water views on residential property values in Nigeria. *The Lagos Journal of Environmental Studies*, 7(2), 21-26.
- Urama, K.C., & Ozor, N. (2010). *Impact of climate change on water resources in Africa: The role of adaptation*. Retrieved from www.ourplanet.com
- Van-Bentum, K.M. (2012). *The Lagos coast: Investigation of the long-term morphological impact of the Eko Atlantic city project.* Dissertation submitted in partial fulfillment of the Master of Science in Civil Engineering requirements at the Delft University of Technology.
- Walsh, P., Griffiths, C., Guignet, D., & Klemick, H. (2015). Modeling the property price impact of water quality in 14 Chesapeake Bay counties (Report No.15-07).
 Washington, DC, USA: National Center for Environmental Economics, U.S. Environmental Protection Agency. Retrieved from http://www.epa.gov
- Wyman, D., Hutchison, N., & Tiwari, P. (2014). Testing the waters: A spatial econometric pricing model of different waterfront views. *Journal of Real Estate Research*, 36(3), 363-382.
- Xiao, Y. (2017). *Hedonic housing price theory review*. Retrieved from http://www.springer.com/978-981-10-2761-1
- Yamagata, Y., Murakami, D., Yoshida, T., Seya, H., & Kuroda, S. (2016). Value of urban views in a bay city: Hedonic analysis with the spatial multilevel additive regression (SMAR) model. *Landscape and Urban Planning*, 151, 89–102.
- Yi, D., & Choi, H. (2020). Housing market response to new flood risk information and the impact on poor tenant. *J Real Estate Finan Econ*, 61, 55 79.

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International, a. Zhang, L., Hui, E.C.M., & Wen, H. (2015). Housing price-volume dynamics under the

Appendix A

Rental Values of Residential Properties around the Coastline in the Study Area

esidential Property Type	Distance to			alue		Mean R	Rent	Standard	
'9/ ,	Coastline (m)	Min		Max				Deviation	
		(N)	\$	(N)	\$	(₩)	\$		
wo-bedroom block of flats	(0-500)	150000	417	5000000	13889	2470690	6863	1360509	
	(0-250)	1800000	5000	4000000	11111	2328571	6468	767494	
	(251-500)	600000	1667	5000000	13889	2577273	7159	1438561	
wo-bedroom bungalow	(0-500)	240000	667	3500000	9722	1923158	5342	934832	
	(0-250)	240000	667	2500000	6944	1748000	4856	939425	
	(251-500)	850000	2361	3500000	9722	1985714	5516	960454	
hree-bedroom block of flats	(0-500)	1000000	2778	6500000	18056	3236486	8990	1603419	
	(0-250)	1000000	2778	6500000	18056	3082927	8564	1436124	
	(251-500)	1000000	2778	6500000	18056	3326429	9240	1697285	
hree-bedroom bungalow	(0-500)	1500000	4167	5000000	13889		8365	898634	
	(0-250)	1500000	4167	4500000	12500	3113043	8647	823686	
	(251-500)	1600000	4444	5000000	13889	2900000	8056	982344	
				23					
									Sanorana,

Appendix B

Descriptive Statistics of the Independent Variables used

Variables	Description	Distance to Coastline (m)	Min	Max	Mean Value	Std.Dev
BLDAGE	Age of residential building (years)	(0-500)	1	49	9.78	5.99
		(0-250)	1	21	10.82	5.16
	0/,	(251-500)	1	49	9.17	6.37
BFLOAREA	Floor area of building (square metre)	(0-500)	57	308	177.32	37.63
	1/25.	(0-250)	129	308	173.00	9.78 5.99 10.82 5.16 9.17 6.37 177.32 37.63 173.00 40.07 172.09 35.23 2.76 0.44 3.00 0.37 2.70 0.48 3.06 1.02 3.00 0.93 2.99 1.06 2.64 1.60 2.00 1.73 2.69 1.52 0.86 0.34 0.91 0.29 0.84 0.37 0.29 0.46 0.26 0.44
	'0 /	(251-500)	57	296	172.09	
NBEDROOM	Number of bedrooms	(0-500)	1	3	2.76	0.44
	Ux,	(0-250)	2	3	3.00	9.78 5.99 10.82 5.16 9.17 6.37 177.32 37.63 173.00 40.07 172.09 35.23 2.76 0.44 3.00 0.37 2.70 0.48 3.06 1.02 3.00 0.93 2.99 1.06 2.64 1.60 2.00 1.73 2.69 1.52 0.86 0.34 0.91 0.29 0.84 0.37 0.29 0.46 0.26 0.44
	4 / / /	(251-500)	1	3	2.70	
NBATROOM	Number of bathrooms	(0-500)	1	5	3.06	6.37 37.63 40.07 35.23 0.44 0.37 0.48 1.02 0.93 1.06 1.60 1.73 1.52 0.34 0.29 0.37 0.46 0.44
	· U/.	(0-250)	1	4	3.00	0.93
		(251-500)	1	5	2.99	1.06
NFLOORS	Number of floors	(0-500)	1	7	2.64	1.60
		(0-250)	1	7	2.00	1.73
		(251-500)	1	6	2.69	1.52
GARAGE_YES	1 if property has a garage, otherwise 0	(0-500)	0	1	0.86	0.34
		(0-250)	0	1	0.91	0.29
		(251-500)	0	1	0.84	0.37
BLDCOND_Excellent	1 if the condition of building is rated excellent,	(0-500)	0	1	0.29	0.46
	otherwise 0	(0-250)	0	1_	0.26	0.44
		(251-500)	0	1	0.31	0.47
	24					

Variables	Description	Distance to Coastline	Min	Max	Mean Value	Std.Dev
LSCAPQUA_Excellent	1 if neigbourhood landscape quality is	(0-500)	0	1	0.21	0.41
4/	rated excellent, otherwise 0	(0-250)	0	1	0.24	0.43
		(251-500)	0	1	0.20	0.40
DISTWORK	Distance to workplace (metre)	(0-500)	0	150000	18156.90	23971.76
	<i>Y</i> _L .	(0-250)	1000	50000	11250.00	11473.01
	'//	(251-500)	0	150000	22257.80	28200.98
DISBSTOP	Distance to nearest public transport stop	(0-500)	608	1254	988.06	144.40
	(metre)	(0-250)	1010	1254	1146.50	65.87
	(0)	(251-500)	608	1154	904.53	109.04
DISTSCH	Distance to nearest school (metre)	(0-500)	19	698	271.84	127.22
		(0-250)	36	698	347.00	115.15
		(251-500)	19	490	226.48	111.69
DISCOAST	Distance from property to the Coastline*	(0-500)	72.22	500	301.83	131.64
	(metre)	(0-250)	72.22	200	171.46	42.92
		(251-500)	250.31	500	391.89	68.33
FLODRATE	Rate of flood occurrence in the last two	(0-500)	1	3	1.00	0.47
	years**	(0-250)	1	3	1.10	0.38
		(251-500)	1	3	1.06	0.30

^{*}Coastal amenity was measured by Euclidian distances from each sampled rented property to the nearest coastline. **An index was derived for · low (between 0-2 ... the rate of flood occurrence to measure the level and severity of flood risk and ranked as 1= low (between 0-2 times); 2= medium (between 3-4 times); and 3= high (more than four times).

Appendix C

TOL and VIF Statistics of the Explanatory Variables in Victoria Island

797	Non Flood Effect							Flood Effect						
Variables		Model 1		Model 2		Model 3		Model 4		Model 5		del 6		
<u> </u>	TOL	VIF	TOL	VIF	TOL	VIF	TOL	VIF	TOL	VIF	TOL	VIF		
LogBLDAGE	0.748	1.337	0.697	1.435	0.710	1.409	0.753	1.328	0.681	1.468	0.708	1.413		
NBEDROOM	0.698	1.432	0.636	1.571	0.563	1.777	0.710	1.408	0.648	1.544	0.612	1.633		
NFLOORS	0.951	1.051	0.786	1.272	0.821	1.218	0.946	1.057	0.776	1.288	0.846	1.182		
GARAGE_YES	0.680	1.471	0.769	1.300	0.587	1.704	0.681	1.468	0.779	1.283	0.616	1.624		
BLDCOND_Excellent	0.720	1.389	0.786	1.272	0.656	1.524	0.720	1.389	0.786	1.272	0.652	1.535		
LSCAPQUA_Excellent	0.653	1.532	0.630	1.588	0.589	1.697	0.671	1.490	0.659	1.519	0.610	1.639		
LogDISCOAST	0.270	3.709	0.348	2.871	0.409	2.448								
Log(DISCOAST*FLODRATE)							0.369	2.711	0.517	1.936	0.496	2.015		
LogDISTWORK	0.662	1.512	0.540	1.852	0.576	1.735	0.674	1.484	0.536	1.866	0.606	1.651		
LogDISBSTOP	0.269	3.716	0.373	2.684	0.395	2.529	0.337	2.964	0.510	1.959	0.453	2.210		
LogDISTSCH	0.639	1.565	0.710	1.408	0.681	1.467	0.647	1.545	0.814	1.228	0.691	1.447		
Distance Bands about the Coastline	0-50	00m	0-25	50m	251-	500m	0-50	00m	0-2	50m	251-	500m		
				26			0.647							

Modelling Coastal Externalities Effects on Residential Housing Values

Abstract

Design/methodology/approach

A survey approach was adopted for the data collection process. For both models, property values were measured in proximity to coastline using 0–250m, 251-500m and 0-500m.

Purpose

This paper examines the impact of coastline on the rental value of residential property in proximity to the coastline, using the hedonic pricing model from two perspectives. First, model 1A-C accounted for estimating the influence of coastal amenities while controlling for other housing attributes influencing rent. Second, model 2A-C accounted for the interaction between coastal amenities/disamenities and other housing attributes influencing rent.

Findings

Findings revealed that property rental value increases as we move away from the coastline when disamenities are not controlled. The results suggested that for a mean-priced home (\frac{1}{2},941,029 or \frac{1}{2},170) at the mean distance from the coastline (301.83m), a 1% increase in distance from the coastline would result in a 0.001% or \frac{1}{2},977 (\frac{1}{2},0.03) increase in rental value.

Practical implications

The implication to real estate valuers is that varying premiums should be considered when valuing a property depending on the distance to the coastline while considering other housing attributes.

Originality/value

This research introduces a novel approach to the hedonic model for determining property values in proximity to coastal environment by estimating the influence of coastal amenities while controlling for other housing attributes influencing rent, on one hand, and accounting for the interaction between coastal amenities/disamenities and other housing attributes influencing rent on the other.

Keywords:

coastline; flood; housing; properties; rent

Introduction

Globally, the coastal area is a place of choice for many people for its diverse tangible and intangible amenities (Parker & Oates, 2016). Consequently, studies have revealed that values of residential properties in coastal areas have been worthwhile to investors across the globe, with the proximate properties to coastline outperforming those at rows behind as distance to the coastline increases (Bin & Kruse, 2006; Bin et al., 2009). However, in recent times, coastlines are vulnerable to disamenities such as the increased risk of flooding with various effects upon any development along its axis (Kalaugher, 2007; Urama & Ozor, 2010). Therefore, the trend of discourse in coastal hedonic price studies has been devoted to studying and evaluating the effect of coastal amenities and disamenities on property values. A tenable justification of the discourse trend is aptly rooted in Bin et al., (2008a) that biased inferences can result from not accounting for coastal amenities and disamenities.

Most coastal hedonic property studies were conducted in developed economies (Makinde & Tokunboh, 2013; Oladapo et al., 2019). To reflect the peculiarities of the developing countries, a study in African countries like Nigeria is necessary. Moreover, rental data are used in this study, which improves previous studies that rely on transaction-based or appraisal-based sale data. Rental data are more responsive to changes in the market while its analysis will allow for more sturdy models giving a better understanding of housing (Aliyu, 2010; Acheampong & Anokye, 2013; Famuyiwa, 2018). In addition, the rate of flood occurrence based on revealed preference techniques from tenants' percept was used to capture coastal disamenities, unlike previous studies that rely on historical floodplain maps. A dummy variable signalling the location of the floodplain in or outside of a floodplain could effectively underestimate the risk of flooding (Daniel et al, 2009).

In developing countries, there is sparse literature focusing on coastal amenities/disamenities impact on property values (Udechukwu & Johnson, 2010). Most property appraisers are faced with the problem of how to incorporate associated coastal amenities and disamenities when determining property market value (Kruger, 2015). Therefore, this paper examines the effect of coastline on residential property values along the coastline corridor in Victoria Island, a coastal community in a Mega city of a developing country in Nigeria.

In Victoria Island, a previous investigation by Udechukwu and Johnson (2010) for Victoria Garden City (VGC), Lagos, Nigeria, found that a home with a view commands a premium of

8% or N2.59 million naira more than homes without a view. In the same study area, Makinde and Tokunboh (2013) found that full view on average property increased the housing price by 47.9%. Each of these studies accounted for the effect of coastal amenity on residential property value while neglecting coastal disamenity. Unlike the generic definition of view utilised in the studies, this study employed the Euclidean distance of the property to the nearest coastline, a recent measure of coastal amenity. The generic definition of view measure is associated with the spatial dependency of observations, while view scape can change over time as structures adjoining a residential building are altered (Bin et al., 2008a; Walsh et al., 2015).

The study by Ajibola et al. (2017) was limited to identifying the climate-related threats affecting property values and benefits derived along the Coastline in Victoria Island, Lagos State, Nigeria, while also collecting rental values of commercial and residential properties. The study did considers the non-monetary properties values by evaluating the challenges and benefits as effects of coastline on property values while also collecting rental values of commercial and residential properties. The study failed to model or determine the influence of the coastline on proximate properties. This is a drawback in coastal housing economics and property value modelling literature. This present study estimate in real (monetary) term the marginal effects of the amenities and disamenities on house rent by emphasising distance to coastline and employing two model specifications concentrated on selected residential properties in the study area.

Literature review

Numerous contributions from coastal hedonic property studies have considered the extent to which coastal amenities and disamenities influence residential property values. Most studies investigating the property value effect of coastal amenities without controlling for coastal disamenities have focused on the value-added through the view of water and proximity to water. Jim and Chen (2006) employed a hedonic pricing model to examine the effect of environmental amenities on house prices in four residential precincts in Haizhu district, Guangzhou, China. The study found that environmental attributes such as green space view increase house prices by 7.1%, while proximity to water bodies could raise house prices by 13.2%. The authors found that traffic noise and proximity to woods were not significantly

significant in the house transaction prices. The authors concluded that proximity to water bodies has a more positive impact on house prices than other environmental amenities.

Baranzini and Schaerer (2011) analysed 12,932 rental data to examine the value of view and land uses close to buildings in Geneva-Switzerland rental market. The authors found that rent premium for a dwelling located in a neighbourhood with an extended surface of water can be as high as 3% and a maximal view of water-covered area can raise rent up to 57%. They also found that dwellings with a view of the famous Geneva water fountain generate an average 3.6% higher rents. The authors noted that while the size and the view of the natural environment raise rents, the view of built environments declines them.

Zhang et al. (2015) analysed the price-volume relationships in Chinese coastal and inland housing markets. Using panel data obtained from 35 Chinese metropolitans, findings show that relationship exists in coastal cities where house prices are high with speculation. This shows that strict market intervention could bring significant change but cannot radically change the driving mechanism. The study concentrated on Granger relationship of price to volume ratio which is not within the scope of this present study.

Dumm et al. (2016) examined price performance of the value of view across the boom, bust, and post-bust phases of the most recent real estate cycle using sales data from the Tampa Bay, Florida housing market for the 2000–2012 period. The authors found that the value of view for waterfront properties, as one category, commanded a price premium of 7.2% over non-waterfront properties for the period 2000 through 2012 while the average price premiums of view vary by type of waterfront across the 12-year time period and ranged from 3.1% for pond to 15% for lake, 61% for canal, 62% for river and 107% for bay respectively. They concluded that the performance of specific waterfront property types across the economic cycle shows that the premiums were highest at the end of the boom stage (2006–2007) and at the end of the recovery stage (2011–2012).

Each of the studies that examined the property value effect of water view has shown that water views increase property values. In addition, there are variations in the estimated amounts of the increase across different geographical areas. Intrigued by associated shortcomings of the generic definition of a view, Conroy and Milosch (2011) analysed 9,755 single-family home sales in 106 neighbourhoods of San Diego County. The study found that

a 1% increase in distance from the beach reduced house prices by 0.146%. The results of their study also revealed that coastal premium is approximately 101.9% for houses within 500 feet of the beach falling to 62.8% for homes between 500 and 1,000 feet, declining to about 3.3% for homes located between five and six miles of the beach, ultimately becoming insignificant beyond six miles from the beach.

Liu et al. (2019) analysed 14,789 apartment transactions to explore the interaction effects between landscape variables on house prices transacted between 1st quarter of 2015 and 4th quarter of 2017 in Chongquig, China. The authors found that people will pay 0.92% more money for a house 10% nearer to the urban river, while peninsula view and Mountain View could increase the total prices of houses by 6.82% and 14.33% respectively. They found an amenity premium of 5.67% on house price of the interaction of an urban river landscape and an urban mountain landscape but the coefficient of the interaction of river housing and peninsula landscape view on house price though positive was insignificant.

Later, studies began to account for more detailed estimates for the combined effect of coastal amenities and disamenities on property values. Bin and Kruse (2006) analysed differential flood risks associated with the location of homes within three significant flood categories zone in Outer Banks housing markets of Carteret County, North Carolina. The hedonic models revealed that moving away from the coastline at the mean distance of 220m has 14.3% (\$45,184) lower property values. The study found that location within the 500-year floodplains reduces a property value by 10.3% (\$32,519) while areas within the 100-year floodplains and 100-year floodplains with wave exposure raise property values by 10.0% (\$31,640) and 26.5% (\$83,580), respectively. The study concluded that while property values are lower if located within a flood zone not subject to wave action, flood location vulnerable to wave action is associated with higher property value.

Bin et al. (2008a) analysed a data set of 1,075 homes sold in four beach communities in New Hanover County, North Carolina, between 1995 and 2002. The authors found that decreasing the distance to the nearest beach by ten yards (approximately 9 metres) results in an \$854 increase in property value. They also found that the mean WTP for sound frontage and pier are \$141,022 and \$51,944, respectively. They submitted that the location within a Special

Flood Hazard Area (SFHA) zone lowers property values by approximately 11%, while the mean WTP to avoid site in SFHA is \$36,082.

Bakkensen & Barrage (2021) examined flood risk belief heterogeneity and coastal home price dynamics in Rhode Island. This was achieved by estimating how climate risk beliefs affect coastal housing markets. The study implements a door-to-door survey and provides theoretical and empirical evidence by building a dynamic housing market model, which shows that belief heterogeneity can reconcile the mixed empirical evidence on flood risk capitalization. Findings revealed significant flood risk underestimation and sorting based on flood risk beliefs and amenity values. The study focuses on flood risk belief which is outside the scope of this research.

The studies of Bin and Kruse (2006) and Bin et al. (2008a) investigated how floodplain location alters residential property value. It is observed that there are somewhat mixed results with the use of floodplain types. The conjecture that properties in flood location associated with wave action commands higher property values than those in flood zone not subjected to wave action appears counter intuitive. A similar study by Yi and Choi (2020) has explained that such a result is new information to the housing market and can be interpreted as the market response to the updated flood risk. However, Daniel et al. (2009) argued that the existence of water is associated with both negative and positive spatial amenities, so a floodplain location indicating a dummy variable may underestimate the value of the risk of flooding.

Consequently, studies began to use actual flood events as a proxy for flooding to account for disamenities in coastal hedonic price studies. Daniel et al. (2009) investigated 9,505 residential properties to detect the presence of ex-ante house price variations considering the perceived level of risk before the 1993 and 1995 river floods. It was observed that house prices before the 1993 flood were not different from those not subject to flood risk. However, between the two floods, the house value decreased by 4.6%. In contrast, the risk premium increased to about 9% after the second flood. In addition, within 500 metres of the river, they found that dwellings experience a positive effect of 2.7%. At the same time, houses affected by the flooding are 4.7% cheaper than other houses. The study concluded that local housing markets in the Netherlands are significantly sensitive to flood risk.

Atreya et al., (2013) utilised a difference-in-differences spatial hedonic model to investigate the sale of 8,042 homes in Dougherty County, Georgia, from 1985 to 2004 to capture the time trend in the flood risk discount before and after the 1994 flood event. The authors found that before the 1994 flood, property prices in the 100-year floodplain declined by 9%, but the costs of properties in the 500-year floodplain did not change significantly. They found that immediately after the 1994 flood event, there was a 32% (\$26,880) discount for the 100-year floodplain properties, discounted by \$24,100 the first year after the flood, by \$21,200 the second year, and flood risk discount becomes positive five years after the flood. Their findings also revealed that the prices of properties in the 500-year floodplain significantly weakly declined by 23% immediately after the surge, while the discount became insignificant after that. The authors also found that increasing the distance to Flint river (river associated with the 1994 flood event) by 1% results in an increase of the property values by 0.5% whereas increasing the distance to other rivers by 1% results in the decline of the property values by 0.4%.

Bekes et al. (2016) investigated 28,542 real estate transactions in the Hungarian housing market from 2012 to 2013. They found that properties by major river ways without accounting for inundation risk are an 18% increase in house prices. Regarding the interaction term, they found that a 10% higher inundation risk is associated with 2.1% lower house prices along major rivers. The authors concluded that while riverside areas have an overall price premium, risky areas lose this advantage to flood risk.

Daniel et al. (2009), Atreya et al. (2013), and Bekes et al. (2016) employed actual flood events as a proxy for flooding to account for coastal disamenities and amenities on property values and obtained a contradictory result. While Daniel et al. (2009) concluded that regional housing markets in the Netherlands are significantly susceptible to flood risk, Atreya et al. (2013) suggested that property prices in 100-year and 500-year floodplains after the 1994 flood event in Dougherty County, Georgia displayed a lower sensitivity to future flood risk. This conflicting opinion necessitate a study in developing countries like Nigeria to reflect the region's peculiarities.

This paper, like several studies in a large theoretical body of hedonic literature on residential property market (*see* Baranzini & Schaerer, 2011; Walsh et al., 2015; Yamagata et al., 2016;

Kahveci & Sabaj, 2017; Bedell, 2018; Beltrán et al., 2018; Du et al. 2018) is deeply rooted in Rosen (1974) work which provided a framework for hedonic analysis using a model of consumer bid and producer offer functions for determining the implicit price of the characteristics of a property for different consumers. The relationship between the price of housing units and housing attributes has been widely addressed in the coastal housing economics and property value modelling literature by the hedonic price models. From our extensive literature review, several empirical contributions from a large theoretical body of hedonic literature on residential property market suggest that house price is a function of packages of structural, location, neighbourhood and environmental attributes of the dwelling.

Methodology

Study Area

Victoria Island is a Coastal Community of Eti-Osa Local Government Area (LGA) in Lagos State. Eti-Osa LGA borders Lagos Island and Ibeju-Lekki local government areas in the West and East. In contrast, the Lagos Lagoon and the Atlantic Ocean define its northern and southern borders. The Local Government Area covers land and water areas of 193,460 km² and 145 km², lying approximately between Latitude 60° 26′ 20" N to 60° 27′ 50" N and Longitudes 30° 24′ 10" E to 30° 40′ 10" E (National Population Commission, 2006; Lagos Bureau of Statistics, 2015; Agboola & Ayanlade, 2016). Fig 1 shows the map of the study area.

Insert Fig 1

Victoria Island is an attractive, densely built, and overpopulated area (Van-Bentum, 2012). It is an area desirable for people to reside in (Dada, 2009). Nevertheless, its axis has experienced consistent flooding due to sea-level rise over the years (Ajibola et al., 2012). This coastal disamenity amidst the tangible and intangible benefits associated with the research area makes the study area suited for this study.

Previous studies used a threshold of 500 metres to describe proximal environmental amenities to the apartments analysed (Jim & Chen, 2006; Daniel et al., 2009). The study covers residential buildings within the width of 500 metres from the Coastline inland, having a stretch of 1.2 kilometres along the Atlantic Ocean extending from after the east mole/Atlantic city through to Oniru beach and Vantage beach. The tenanted residential property types

considered are purposely built two and three-bedroom blocks of flats and bungalow respectively (See Fig 2).

Insert Fig 2

Segmented linear spline of the distance of 250 metres from coastline to the extent of 500 metres was constructed to capture the non-linear effect of coastline on house rent (Kriesel & Friedman, 2002; Conroy & Milosch, 2011; Atreya & Czaikowski, 2014; Bedell, 2018). Figure 3 shows the surveyed area at an incremental distance of 250m to the coastline the map of the study area showing residential properties at an incremental distance of 250m to the coastline.

Insert Fig 3

Sampling procedure

Taking a cue from Gopalakrishnan et al., (2009), the residential properties within 500m of the coastline was counted and the figures stands at 1,273. After ground-truthing, the physically identified single tenancy rented residential properties within 500 metres of the coastline in the study area amounted to 484, constituted the sample for the study.

Out of the residential properties sampled, 37.19% are within 250 metres of the coastline, while the remaining 62.81% are located between 251 and 500 metres of the coastline. The most equally distributed residential properties within 250 metres to the coastline and those between 251 and 500 metres of the coastline is associated with the 3 bedroom bungalow with a proportion of 11.27% for the former and 10.30% for the latter.

Insert Table 1

Method of data analysis

The choice of variables employed in this study was driven by a holistic review of the coastal property hedonic literature and the selection of relevant variables to the study area. The data extracted from the field survey of the properties pertain to house rent, frequently appearing structural attributes in literature namely building floor area, age of house, number of bathrooms, number of bedrooms, building condition, multistory or number of floors and presence of garage (Baranzini & Schaerer, 2011; Conroy & Milosch, 2011; Gordon et al.,

Insert Fig 4

2013; Hansen & Benson, 2013; Makinde & Tokunboh, 2013; Atreya & Czajkowski, 2014; Wyman et al., 2014; Below et al., 2015; Walsh et al., 2015; Dumm et al., 2016) and locational characteristics including distance to workplace, distance to nearest public transport stop and distance to nearest school (Blackwell et al., 2010; Baranzini, & Schaerer, 2011; Conroy & Milosch, 2011; Makinde & Tokunboh, 2013; Atreya & Czajkowski, 2014; Dumm et al., 2016; Liu et al., 2019). Other frequently appearing attributes in literature related to neighbourhood is quality of neighbourhood landscaping (Bourassa et al., 2004; Bourassa et al., 2005; Des Rosiers et al., 2007; Jim & Chen, 2009; Du et al., 2018; Liu et al., 2019; Oyedeji, 2019) and the environmental variables of interest which are majorly distance to the nearest coastline and flood occurrence rate (Conroy & Milosch., 2011; Atreya & Czajkowski, 2014). Fig 4 depicts the rented properties from which the information used were extracted.

As argued by Kriesel et al., (2000), hedonic regressions estimations ensure a more robust comparison as they allow the averages to be computed on a constant-quality basis. Data on the level of flood occurrence indicate that the preponderance of respondents' responses on the rate of flood occurrence oscillates between low and medium perceptual ratings in the study area in the last two years. The hedonic regression model was used to examine the influence of coastline while controlling for other housing attributes on the rental value of residential properties. Models were estimated with the log-log functional form in which all the variables, except dichotomous variables, are measured in logarithmic form. The natural log of distance to the coastline *log(DISCOAST)* was included to capture coastal amenities associated with the homes within 500 metres of the coastline. Model 1 is given as:

Where rent is expressed in its natural logarithm, β_0 is a constant term, the coefficients β_1 - β_6 is the percentage change in rent resulting from a unit change in age, building floor area, house-workplace distance, house-bus stop distance, house-school distance, and house-nearest Coastline distance (or interaction of distance to the coastline and flood occurrence) respectively. The coefficients β_7 - β_{13} reveal the percentage change in renting an additional

bedroom, bathroom, floor, garage, excellent building condition, and excellent landscape quality. The uncorrelated residual term is ε .

As it is logical that the effect of distance to the coastline will be non-linear, a segmented set of models (model 2) was estimated to incorporate flooding. To account for coastal disamenity as the distance to the coastline increases, the natural log of distance to coastline and rate of flood occurrence *log*(DISCOAST*FLODRATE) were interacted to account for the effect of coastal disamenity. Model 2 is given as:

```
LogRENT = \beta_0 + \beta_1 logBLDAGE + \beta_2 logBFLOAREA + \beta_3 logDISTWORK + \beta_4 logDISBSTOP + \beta_5 logDISTSCH + \beta_6 log(DISCOAST*FLODRATE) + \beta_7 NBEDROOM + \beta_8 NBATROOM + \beta_9 NFLOORS + \beta_{10} GARAGE\_Yes + \beta_{11} BLDCOND\_Excellent + \beta_{12} LSCAPQUA\_Excellent + \varepsilon ------ (eq. 2)
```

The multicollinearity and spatial autocorrelation tests were applied to the hedonic models to establish if some regression analysis assumptions were met. Following Rosiers et al. (1996), Menard (2002), Gujarati (2004), Glen (2015), McCormack (2015), Xiao (2017), and Senaviratna, and Cooray (2019), the tolerances for all the explanatory variables for the models which are close to 1 and all the VIF values which are less than 4, suggest that multicollinearity is not a concern (*see Appendix C*). Also, relying on Field (2009) and Glen (2016), the Durbin-Watson statistic values ranging from 1.647 to 2.226 (Tables 2 and 3) for all the regression models signify that there are no spatial correlations in the residuals of the estimated hedonic models. The empirical results are presented in the next section.

Results and Discussion

The results of the hedonic price models are presented in Tables 2 and 3. The models have a good predictive power for the explanatory variables, with *R*-squared statistics ranging from 0.55 to 0.64. The F-statistics in the range of 6.491 – 21.115 show that at 0.1% level, the models are statistically significant and explain between 55% and 64% of the variance of rents in the study area. The entire-sample models reveal that variables such as building age (LogBLDAGE), floor area (LogBFLOAREA), number of floors (NFLOORS), and Garage (GARAGE_YES) are significant determinants of rent of residential properties in the study area.

Insert Tables 2 & 3

Across all the models, the coefficients on building age imply that a 1% increase in the property's age decreases rent in a range of from 0.1% to 0.2%, or \$\frac{1}{2}6,581\$ (\$74) to \$\frac{1}{2}49,017\$ (\$136) at the mean. The coefficient on a floor area is significant at 0.1% across the models and imply that a 1% increase in a square metre of floor area increases house rent in a range of from 1.86% to 2.71% or \$\frac{1}{2}31,485\$ (\$88) to \$\frac{1}{2}46,573\$ (\$129). The estimated marginal effect for the number of floors variable in models 1A and 2A implies that for the whole houses within 500 metres of the coastline, properties with a higher number of floors increase rent by approximately 3% or \$\frac{1}{2}95,600\$ (\$266). Moving to the segmented models, a unit increase in the number of floors leads to a rise in house rent by as much as 5.7% or \$\frac{1}{2}167,095\$ (\$464) in model 1C and 5.4% or \$\frac{1}{2}160,857\$ (\$447) in model 6 for residential properties between 251 to 500 metres from the coastline, or as low as approximately 1% or \$\frac{1}{2}29,500\$ (\$82) in models 1B and 2B for homes within 250 metres of the coastline.

As displayed in models 1A and 2A, the significantly positive coefficient for the dummy variable, which captures the garage effect, increases rents for the whole houses within 500 metres of the coastline by approximately 16% or N483,000 (\$1,342). The impact is most significant in models (1C) and (2C), where the rent of a home having garage could increase by around 20% or N593,469 (\$1,649) and 22% or N647,102 (\$1,798), respectively. The results suggest that tenants attach importance to this attribute in the study area, but more weight is attached to the attribute in homes between 251 and 500 metres of the coastline. The insignificantly positive coefficient for the dummy variable that captures the garage effect implies that the garage increases house rents by approximately 6% or N178,000 (\$494) within 250 metres of the coastline (models 1B and 2B).

Moving on to the variables of interest, the signs (positive or negative) of the effects of the coastal amenity (LogDISCOAST) and disamenity {Log(DISCOAST*FLODRATE)} variables across the models are somewhat not consistent with expectation. The variable LogDISCOAST is positive but statistically insignificant in the model (1A). As the results show, a 1% increase in distance from the coastline leads to a rise in property values by 0.001%, which is equivalent to $\frac{1}{2}$ 9.77 (\$0.03) when evaluated at the average house rent among homes up to 500 metres of the coastline. The result implies that distance to the coastline has a weak effect on the rent of the properties with increasing returns. The coefficient on Log(DISCOAST*FLODRATE) in the model (2A) indicates that when flooding becomes an issue, increasing the distance to the coastline by 1%, there is an insignificant

discount of about 0.02% associated with properties up to 500 metres of the coastline, equivalent to №194.88 (\$0.54) when evaluated at the average house price. The result implies that when flooding is accounted for, increasing distance from the coastline has a weak negative impact on house rents.

Turning to the segmented models, without controlling for flood occurrence, in models 1B, the variable *LogDISCOAST* is positive but insignificant. The results imply that proximity to the coastline is somewhat undesirable and increasing distance from the coastline has a weak positive effect on the house rent. A 1% increase in distance from the coastline is associated with approximately 0.08% or ¥1,318 (\$3.66) increase in property rent within 250 metres of the coastline (model 2). The insignificant coefficient on *LogDISCOAST* in the model (1C) suggests that a 1% increase in distance from the coastline increases rents by 0.23% or ¥1,757.09 (\$4.88). When flood occurrence is accounted for within 250 metres of the coastline (model 2B), the result reveals that proximity to the coastline further dampens house rent though insignificant. The insignificant coefficient on *Log(DISCOAST*FLODRATE*) is 0.047, indicating that a 1% increase in distance from the coastline increases rent by approximately 0.05% or ¥805 (\$2.24). Contrarily, in the model (2C), a 1% increase in distance from the coastline decreases rent by approximately 0.09% or ¥641 (\$1.78) between 251 and 500 metres of the coastline.

The results reveal that proximity to Coastline (LogDISCOAST) has not enhanced residential property rental values in the study area. Without controlling for disamenities, proximity to coastline has a weak negative effect on rent for models 1A-C. The weak negative effect of coastline on rent means that the coastline is insignificantly undesirable for households in the research area. The previous ocean surges and flooding experience in Victoria Island could be the possible reason why families are not willing to pay a reasonable premium to have access to the coastline that lies within 500 metres of their homes (Awosika et al., 2002; Olaniyan & Afiesimama, 2003; Oyinloye, 2016). This finding differs from other coastal studies that found that proximity to the coastline has a robust positive effect on residential property prices (Bin & Kruse, 2006; Bin et al., 2008a, b; Samarasinghe & Sharp, 2008; Bin et al., 2009; Conroy & Milosch, 2011; Atreya & Czajkowski, 2014; Fu et al., 2016). While studies that found that proximity to the coastline has a robust positive effect on house prices are common, there is some evidence for similar findings that proximity to coastline negatively affects house prices (Bourassa et al., 2004; Atreya et al., 2013).

Moreover, when disamenities are controlled for, it is only in model (2B) that flooding lowers the rent with proximity to the coastline. The reverse is demonstrated in models (2A and 2C). This discrepancy can be explained by the fact that no substantial cost of flood occurs when the entire sample is considered (model 4) and in the location between 251 and 500 metres of the coastline (model 2C). In other words, the level of flood occurrences in the areas was relatively lower compared to locations within 250 metres of the coastline. The finding that flooding lowers residential property value with proximity to the coastline reaffirms the studies of Bin et al. (2008b), Daniel et al. (2009), and Bekes et al. (2016). On the other hand, the finding that signifies that in the phase of flooding, rent increases with proximity to the coastline (models 2A and 2C) somewhat agree with the study of Bin and Kruse (2006) and Atreya and Czajkowski (2014), which concluded that the associated positive amenity values of living in high-risk areas outweigh the flood risk.

Conclusion

This study estimated the price of proximity to the coastline, among other housing attributes. Without controlling for coastal disamenities, the results suggested that proximity to the coastline has an insignificant negative effect on property value in the research area. This finding indicates that values of proximate residential properties to the research area's coastline are somewhat associated with the risk of flooding. Moreover, controlling for disamenities, property values tend to increase with proximity to the shoreline in locations within 500 metres of the coastline and between 251m to 500m of the coastline, indicating that flood occurrence in the areas is low in the years between 2017 and 2018. Contrariwise, flooding further decreases rent with decreasing distance to the coastline within 250 metres of the coastline. Considerably, the findings are within the confine of results in the literature.

This research provides valuable insight to coastal managers, government, and real estate professionals. Findings suggest a reflection of flood risk in values of proximate residential properties to the coastline. The study recommends that government and coastal managers adopt proper protection measures of the coastline and ensure an integrated approach to flooding control to lessen the consequence of flooding in the research area. The implication to real estate valuers is that varying premiums should be considered when valuing a property depending on the distance to the coastline while considering other housing attributes in the

study area. The future research agenda could employ the concept of the submarket, which could involve the use of data for only a particular property type other than the amalgamation of the attributes of different residential property types utilised in this study. The approach will further enhance understanding the complex residents-environment behaviour within the various categories of residential properties with associated housing attributes.

Notes:

¹The coefficient of the predictor variable, when both response variable and predictor variable are log-transformed, is interpreted as the per cent increase in the dependent variable for every 1% increase in the independent variable (Ford, 2018).

²The equivalent actual term estimation of the marginal effect of the log-transformed continuous or distance-related explanatory variable on rent is calculated by $(\gamma *\beta \div \bar{y})$, where γ is the mean house rent, β is the coefficient of the continuous or distance-related variable, and \bar{y} is the mean value of the continuous or distance-related variable (Bin et al., 2008b).

³The percentage increase or decrease in rent resulting from a change in dummy or discrete explanatory variable is derived from the exponent of the coefficient of the variable, then one subtracted from this number and multiplied by 100: [exp (β) - 1]*100 (Halvorsen & Palmquist, 1980; Giles, 1982; Baranzini & Schaerer, 2011; Ford, 2018).

⁴The equivalent actual term estimation of the marginal effect of dummy or discrete explanatory variable on rent is calculated by $\gamma^*\{\exp(\beta) - 1\}$, where γ is the mean house rent and β is the coefficient of a dummy or discrete variable (Bin et al., 2008b).

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References

- Acheampong, R.A., & Anokye, P.A. (2013). Understanding households' residential location choice in Kumasi's Peri-urban settlements and the implications for sustainable urban growth. *Research on Humanities and Social Sciences*, *3*(9), 60-70.
- Agboola, A.M., & Ayanlade, A. (2016). Sea level rise and its potential impacts on coastal urban area: A case of Eti-Osa, Nigeria. *Analele Universității Din Oradea, Seria Geografie, 2,* 188-200.
- Ajibola, M. O., Izunwanne, E. M., & Ogungbemi A. O. (2012). Assessing the effects of flooding on residential property values in Lekki phase I, Lagos, Nigeria. *International Journal of Asian Social Science*, 2(3), 271-282.
- Ajibola, M.O., Owolabi D.R., & Ogungbemi, A. O. (2017). Examining the effects of coastline on property values in Victoria Island. *International Journal of Science, Environment and Technology*, (6)1, 958 970.
- Aliyu, M.A. (2010). *Microeconomic analysis of the residential location decision: The case of Kano, Nigeria*. (Doctoral dissertation). University of East Anglia, Norwich.
- Atreya, A., Ferreira, S., & Kriesel, W. (2013). Forgetting the flood? An analysis of the flood risk discount over time. *Land Economics*, 89(4), 577-596.
- Atreya, A., & Czajkowski, J. (2014). Housing price response to the interaction of positive coastal amenities and negative flood risks (Report No. 2014-09). Philadelphia, USA: Risk Management and Decision Processes Center, The Wharton School, University of Pennsylvania.
- Awosika, L., Dublin-Green, C.O., & Folorunsho, R. (2002). Bar beach Victoria Island erosion problem: A critical assessment as of 30th October, 2002 and need for urgent mitigating measures. Marine Geology/Geophysics Division, Nigerian Institute for Oceanography and Marine Research, Victoria Island, Lagos. Retrieved from https://aquadocs.org
- Bakkensen, L.A., & Barrage, L. (2021). Going underwater? Flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies*, 00, 1-44.
- Baranzini, A., & Schaerer, C. (2011). A sight for sore eyes: Assessing the value of view and land use in the housing market. *Journal of Housing Economics*, 20(3), 191-199.

- Bedell, W.B. (2018). Capitalisation of green space and water quality into residential housing values. *Theses and Dissertations Agricultural Economics*, 63. https://uknowledge.uky.edu/agecon_etds/63
- Bekes, G., Horvath, A., & Sapi, Z. (2016). Flood risk and housing prices: Evidence from Hungary. (IEHAS Discussion Papers, No. MT-DP 2016/20, ISBN 978-615-5594-56-4). Hungarian Academy of Sciences, Institute of Economics, Budapest.
- Below, S., Beracha, E., & Skiba, H. (2015). Land erosion and coastal home values. *Journal of Real Estate Research*, *37*(4), 499-535.
- Beltrán, A., Maddison, D., & Elliott, R.J.R (2018). Is flood risk capitalised into property values? *Ecological Economics*, *146*, 668-685.
- Bin, O., Crawford, T.W., Kruse, J.B., & Landry, C.E. (2008a). Viewscapes and flood hazard: Coastal housing market response to amenities and risk. *Land Economics*, 84(3), 434-448.
- Bin, O., & Kruse, J.B. (2006). Real estate market response to coastal flood hazards. *Natural Hazards Review*, 7(4). Retrieved from https://ascelibrary.org
- Bin, O., Kruse, J.B., & Landry, C.E. (2008b). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *The Journal of Risk and Insurance*, 75(1), 63-82.
- Bin, O., & Landry, C.E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management, 65*, 361–376.
- Bin, O., Poulter, B., Dumas, C.F., & Whitehead, J.C. (2009). Spatial hedonic models for measuring the impact of sea-level rise on coastal real estate. Retrieved from www.researchgate.net
- Blackwell, C., Sheldon, S., Lansbury, D., & Vaught, D. (2010). Beach renourishment and property value growth: The case of folly beach, South Carolina. *The Review of Regional Studies*, 40(3), 273-286.
- Bourassa, S.C., Hoesli, M., and Sun, J. (2004). What's in a view? *Environment and Planning A*, 36, 1427-1450.

- Bourassa, S.C., Hoesli, M., & Sun, J. (2005). The price of aesthetic externalities. *Journal of Real Estate Literature*. *13*(2), 167-187.
- Conroy, S.J., & Milosch, J.L. (2011). An estimation of the coastal premium for residential housing prices in San Diego County. *J Real Estate Finan Econ*, 42, 211–228.
- Dada, A. (2009, 28th December). Eko Atlantic City: Daring the waves. *Punch Newspaper*. Retrieved from http://www.ekoatlantic.com/category/latestnews/press-clipping/
- Daniel, V.E., Florax, R.J.G.M., & Rietveld, P. (2009). Floods and residential property values: A hedonic price analysis for the Netherlands. *Built Environment*, *35*(4), 563-576.
- Des Rosiers, F., Thériault, M., Kestens, Y., & Villeneuve, P. (2007). Landscaping attributes and property buyers' profiles: Their joint effect on house prices. *Housing Studies*, 22(6), 945-964.
- Du, Q., Wu, C., Ye, X., Ren, F., & Lin, Y. (2018). Evaluating the effects of landscape on housing prices in urban China. *Tijdschrift voor Economische en Sociale Geografie*, 109(4), 525–541.
- Dumm, R.E., Sirmans, G.S., & Smersh, G.T. (2016). Price variation in waterfront properties over the economic cycle. *Journal of Real Estate Research*, 38(1), 1-25.
- Famuyiwa, F. (2018). Natural environmental amenities and house prices A hedonic analysis for integrated planning. *Journal of African Real Estate Research*, 3(2), 44-62. DOI: 10.15641/jarer.v0i0.482
- Field, A.P. (2009). Discovering statistics using SPSS: (and sex and drugs and rock 'n' roll) (3rd Edn.) London: Sage.
- Ford, C. (2018). *Interpreting log transformations in a linear model*. Retrieved from https://data.library.virginia.edu/interpreting-log-transformations-in-a-linear-model/
- Fu, X., Song, J., Sun, B., & Peng, Z. (2016). "Living on the edge": Estimating the economic cost of sea level rise on coastal real estate in the Tampa bay region, Florida. *Ocean & Coastal Management 133*, 11-17.
- Giles, D.E.A. (1982). The interpretation of dummy variables in semilogarithmic equations unbiased estimation. *Economics Letters*, 10, 77-79.
- Glen, S. (2015). *Variance inflation factor*. Retrieved from https://www.statisticshowto.com/variance-inflation-factor/
- Glen, S. (June 2016). *Durbin Watson test & test statistic*. Retrieved from http://www.statisticshowto.com/durbin-watson-test-coefficient/

- Gopalakrishnan, S., Smith, M.D., Slott, J.M., & Murray, A.B. (2009, July 26-29). *The value of disappearing beaches: A hedonic pricing model with endogenous beach width.* Paper presented at the AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin.
- Gordon, B.L., Winkler, D., Barrett, J.D., & Zumpano, L. (2013). The effect of elevation and corner location on oceanfront condominium value. *Journal of Real Estate Research*, 35(3).
- Gujarati, D.N. (2004). *Basic econometrics* (4th ed.). New York: The McGraw-Hill Companies.
- Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *The American Economic Review*, 70(3), 474-475.
- Hansen, J.L., & Benson, E.D. (2013). The value of a water view: Variability over 25 years in a coastal housing market. *The Coastal Business Journal*, 12(1), 76-99.
- Jim, C.Y., & Chen, W.Y. (2006). Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape and Urban Planning*, 78, 422–434.
- Jim, C.Y., & Chen, W.Y. (2009). Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landscape and Urban Planning*, 91(4), 226-234.
- Kahveci, M., & Sabaj, E. (2017). Determinant of housing rents in urban Albania: An empirical hedonic price application with NSA survey data. *Eurasian Journal of Economics and Finance*, *5*(2), 51-65.
- Kalaugher, L. (2007). *Africa continent one of the most vulnerable to climate change*. Retrieved from http://www.environmentalresearchweb.org/cws/article/opinion/27558
- Kothari, C.R. (2004). *Research methodology: Methods and techniques* (2nd Revised ed.). New Delhi: New Age International Publishers.
- Kriesel, W., & Friedman, R. (2002). Coastal hazards and economic externality: Implications for beach management policies in the American southeast (A Heinz center discussion paper, May 2002). Retrieved from www.heinzctr.org
- Kriesel, W., Landry, C., & Keeler, A. (2000, July). *Costs of coastal hazards: Evidence from the property market*. Paper selected for presentation at the American Agricultural Economics Association Annual Meeting in Orlando, Florida.
- Kruger, A. (2015). The influence of climate change on the market value of coastal residential property in South Africa. *WIT Transactions on the Built Environment, 148*. Retrieved from https://www.researchgate.net/publication/290439884
- Lagos Bureau of Statistics [LBS] (2015). Digest of statistics. Ministry of economic planning and budget, Alausa, Ikeja, Lagos.

- Laverne, R.J., & Winson-Geideman, K. (2003). The influence of trees and landscaping on rental rates at office buildings. *Journal of Arboriculture*, 29(5), 281-290.
- Liu, G., Wang, X., Gu, J., Liu, Y., and Zhou, T. (2019). Temporal and spatial effects of a 'Shan Shui' landscape on housing price: A case study of Chongqing, China. *Habitat International*, 94, 1-11.
- Makinde, O.I., & Tokunboh, O.O. (2013). *Impact of water view on residential properties house pricing*. Paper presented at the American Real Estate Society Conference, Kigali, Rwanda.
- McCormack, K. (2015). Diagnostics for hedonic models using an example for cars (hedonic regression). *Biometrics & Biostatistics International Journal*, 2(1), 23-37.
- McKenzie, R., & Levendis, J. (2010). Flood hazards and urban housing markets: The effects of Katrina on New Orleans. *J Real Estate Finance Econ*, 40, 62–76.
- Menard, S. (2002). Applied logistic regression analysis (2nd ed.). A Sage University Paper.
- National Population Commission [NPC], (2006). Population and housing census of the federal republic of Nigeria, priority tables volume III.
- Oladapo, R.A., Ayoola A.B., Ojo B., and Olukolajo M.A. (2019). The effect of coastal environment on residential property values: A review of literature. In M.B. Nuhu and S. Kuma (Eds): *Land Policy Governance and Sustainable Development in Nigeria: A Book of Readings;* 140 152; Centre for Human Settlements and Urban Development (CHSUD) Federal University of Technology, Minna, Niger State, Nigeria.
- Olaniyan, E., & Afiesimama, E.A. (2003). Understanding ocean surges and possible signals over the Nigerian coast: A case study of the Victoria Island bar beach Lagos. Retrieved from https://www.researchgate.net
- Oyedeji, J.O. (2019). Impact of landscaping on residential property value in Lekki phase 1 Lagos. *UNIOSUN Journal of Engineering and Environmental Sciences*, *1*(1), 49-56.
- Oyinloye, M.A. (2016). Assessment of coastal flooding on Victoria Island in Eti-Osa Local Government Area, Lagos State, Nigeria. *Recent Advances in Energy, Environment and Financial Science*, 292-304, ISBN: 978-1-61804-361-0.
- Parker, H., & Oates, N. (2016). How do healthy rivers benefit society? A review of the evidence. Retrieved from http://www.odi.org
- Parsons, G.R., & Powel, M. (2001). Measuring the cost of beach retreat. *Coastal Management*, 29, 91–103.

- Posey, J., & Rogers, W.H. (2010). The impact of special flood hazard area designation on residential property values. *Public Works Management & Policy 15*(2), 81-90.
- Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82(1), 34-55.
- Rosiers, F.D., Lagana, A., Thériault, M., & Beaudoin, M. (1996). Shopping centres and house values: An empirical investigation. *Journal of Property Valuation & Investment*, 14(4), 1996, 41-62.
- Samarasinghe, O., & Sharp, B. (2008). Flood prone risk and amenity values: A spatial hedonic analysis. *The Australian Journal of Agricultural and Resource Economics*, *54*, 457–475.
- Senaviratna, N.A.M.R., & Cooray, T.M.J.A. (2019). Diagnosing multicollinearity of logistic regression model. *Asian Journal of Probability and Statistics*, *5*(2), 1-9.
- Udechukwu, C.E., & Johnson, O.O. (2010). The impact of lagoon water views on residential property values in Nigeria. *The Lagos Journal of Environmental Studies*, 7(2), 21-26.
- Urama, K.C., & Ozor, N. (2010). *Impact of climate change on water resources in Africa: The role of adaptation*. Retrieved from www.ourplanet.com
- Van-Bentum, K.M. (2012). *The Lagos coast: Investigation of the long-term morphological impact of the Eko Atlantic city project.* Dissertation submitted in partial fulfillment of the Master of Science in Civil Engineering requirements at the Delft University of Technology.
- Walsh, P., Griffiths, C., Guignet, D., & Klemick, H. (2015). Modeling the property price impact of water quality in 14 Chesapeake Bay counties (Report No.15-07).
 Washington, DC, USA: National Center for Environmental Economics, U.S. Environmental Protection Agency. Retrieved from http://www.epa.gov
- Wyman, D., Hutchison, N., & Tiwari, P. (2014). Testing the waters: A spatial econometric pricing model of different waterfront views. *Journal of Real Estate Research*, 36(3), 363-382.
- Xiao, Y. (2017). *Hedonic housing price theory review*. Retrieved from http://www.springer.com/978-981-10-2761-1
- Yamagata, Y., Murakami, D., Yoshida, T., Seya, H., & Kuroda, S. (2016). Value of urban views in a bay city: Hedonic analysis with the spatial multilevel additive regression (SMAR) model. *Landscape and Urban Planning*, 151, 89–102.
- Yi, D., & Choi, H. (2020). Housing market response to new flood risk information and the impact on poor tenant. *J Real Estate Finan Econ*, 61, 55 79.

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International, Zhang, L., Hui, E.C.M., & Wen, H. (2015). Housing price-volume dynamics under the regulation policy: Difference between Chinese coastal and inland cities. Habitat

Appendix A

Rental Values of Residential Properties around the Coastline in the Study Area

Residential Property Type	Distance to			alue		Mean F	Rent	Standard	
'9/ ,	Coastline (m)	Min		Ma				Deviation	
		(₩)	\$	(N)	\$	(₩)	\$		
Two-bedroom block of flats	(0-500)	150000	417	5000000	13889	2470690	6863	1360509	
	(0-250)	1800000	5000	4000000		2328571	6468	767494	
	(251-500)	600000	1667	5000000		2577273	7159	1438561	
Swo-bedroom bungalow	(0-500)	240000	667	3500000	9722	1923158	5342	934832	
	(0-250)	240000	667	2500000	6944	1748000	4856	939425	
	(251-500)	850000	2361	3500000	9722	1985714	5516	960454	
Three-bedroom block of flats	(0-500)	1000000	2778	6500000	18056	3236486	8990	1603419	
	(0-250)	1000000	2778	6500000	18056	3082927	8564	1436124	
	(251-500)	1000000	2778	6500000	18056	3326429	9240	1697285	
Three-bedroom bungalow	(0-500)	1500000	4167	5000000		3011364	8365	898634	
	(0-250)	1500000	4167	4500000	12500	3113043	8647	823686	
	(251-500)	1600000	4444	5000000	13889	2900000	8056	982344	
									Sandanan
				23					

Appendix B

Descriptive Statistics of the Independent Variables used

Variables	Description	Distance to Coastline (m)	Min	Max	Mean Value	Std.Dev
BLDAGE	Age of residential building (years)	(0-500)	1	49	9.78	5.99
		(0-250)	1	21	10.82	5.16
	0/,	(251-500)	1	49	9.17	6.37
BFLOAREA	Floor area of building (square metre)	(0-500)	57	308	177.32	37.63
	1/) > .	(0-250)	129	308	173.00	40.07
	'0'/	(251-500)	57	296	172.09	35.23
NBEDROOM	Number of bedrooms	(0-500)	1	3	2.76	0.44
	UX,	(0-250)	2	3	3.00	0.37
		(251-500)	1	3	2.70	0.48
NBATROOM	Number of bathrooms	(0-500)	1	5	3.06	1.02
	· 0/.	(0-250)	1	4	3.00	0.93
	9	(251-500)	1	5	2.99	1.06
NFLOORS	Number of floors	(0-500)	1	7	2.64	1.60
		(0-250)	1	7	2.00	1.73
		(251-500)	1	6	2.69	1.52
GARAGE_YES	1 if property has a garage, otherwise 0	(0-500)	0	1	0.86	0.34
		(0-250)	0	1	0.91	0.29
		(251-500)	0	1	0.84	0.37
BLDCOND_Excellent	1 if the condition of building is rated excellent,	(0-500)	0	_1	0.29	0.46
	otherwise 0	(0-250)	0	1_	0.26	0.44
		(251-500)	0	1	0.31	0.47
	24				0.31	

Variables	Description	Distance to Coastline	Min	Max	Mean Value	Std.Dev
LSCAPQUA_Excellent	1 if neigbourhood landscape quality is	(0-500)	0	1	0.21	0.41
4/	rated excellent, otherwise 0	(0-250)	0	1	0.24	0.43
		(251-500)	0	1	0.20	0.40
DISTWORK	Distance to workplace (metre)	(0-500)	0	150000	18156.90	23971.76
	<i>Y</i> _L .	(0-250)	1000	50000	11250.00	11473.01
	'//	(251-500)	0	150000	22257.80	28200.98
DISBSTOP	Distance to nearest public transport stop	(0-500)	608	1254	988.06	144.40
	(metre)	(0-250)	1010	1254	1146.50	65.87
	(0)	(251-500)	608	1154	904.53	109.04
DISTSCH	Distance to nearest school (metre)	(0-500)	19	698	271.84	127.22
		(0-250)	36	698	347.00	115.15
		(251-500)	19	490	226.48	111.69
DISCOAST	Distance from property to the Coastline*	(0-500)	72.22	500	301.83	131.64
	(metre)	(0-250)	72.22	200	171.46	42.92
		(251-500)	250.31	500	391.89	68.33
FLODRATE	Rate of flood occurrence in the last two	(0-500)	1	3	1.00	0.47
	years**	(0-250)	1	3	1.10	0.38
		(251-500)	1	3	1.06	0.30

^{*}Coastal amenity was measured by Euclidian distances from each sampled rented property to the nearest coastline. **An index was derived for low (between 0-2 ... the rate of flood occurrence to measure the level and severity of flood risk and ranked as 1= low (between 0-2 times); 2= medium (between 3-4 times); and 3= high (more than four times).

Appendix C

TOL and VIF Statistics of the Explanatory Variables in Victoria Island

TOL and VIF Staustics of the Explanator	•		Non Floo		t				Flood	Effect		
Variables	Mod	lel 1	Mod	lel 2	Mod	del 3	Mod	del 4	Mod	del 5	Mo	del 6
70 ,	TOL	VIF	TOL	VIF	TOL	VIF	TOL	VIF	TOL	VIF	TOL	VIF
LogBLDAGE	0.748	1.337	0.697	1.435	0.710	1.409	0.753	1.328	0.681	1.468	0.708	1.413
NBEDROOM	0.698	1.432	0.636	1.571	0.563	1.777	0.710	1.408	0.648	1.544	0.612	1.633
NFLOORS	0.951	1.051	0.786	1.272	0.821	1.218	0.946	1.057	0.776	1.288	0.846	1.182
GARAGE_YES	0.680	1.471	0.769	1.300	0.587	1.704	0.681	1.468	0.779	1.283	0.616	1.624
BLDCOND_Excellent	0.720	1.389	0.786	1.272	0.656	1.524	0.720	1.389	0.786	1.272	0.652	1.535
LSCAPQUA_Excellent	0.653	1.532	0.630	1.588	0.589	1.697	0.671	1.490	0.659	1.519	0.610	1.639
LogDISCOAST	0.270	3.709	0.348	2.871	0.409	2.448						
Log(DISCOAST*FLODRATE)							0.369	2.711	0.517	1.936	0.496	2.015
LogDISTWORK	0.662	1.512	0.540	1.852	0.576	1.735	0.674	1.484	0.536	1.866	0.606	1.651
LogDISBSTOP	0.269	3.716	0.373	2.684	0.395	2.529	0.337	2.964	0.510	1.959	0.453	2.210
LogDISTSCH	0.639	1.565	0.710	1.408	0.681	1.467	0.647	1.545	0.814	1.228	0.691	1.447
Distance Bands about the Coastline	0-50	00m	0-25	50m	251-:	500m	0-50	00m	0-2	50m	251-	500m
				26			0.647					

Table 1: Questionnaire administration

Distance to Coastline	Coastline Stretch	Ques	tionnaire	
		Administered	Retrieved	Valid
Within 250m	Residential buildings behind	180	147	118
Between 251m-500m	Oniru beach Resort to Vantage Beach Resort/Lekki	304	239	200
Total	Leisure Lake	484	386	318

Table 2: Log-log Hedonic Price Models of Coastline and Housing Characteristics for Victoria Island (Non Flood Effect)

			Model	1		
VARIABLES	A (0-500	Om)	В (0-250	m)	C (251-50	00m)
	coeff	t-stat	coeff	t-stat	coeff	t-stat
Constant	2.408	1.828	-1.091	-0.282	1.043	0.500
LogBLDAGE	**-0.163	-3.454	-0.098	-1.300	***-0.235	-3.775
LogBFLOAREA	***2.381	10.627	***1.856	6.040	***2.672	8.368
NBEDROOM	0.025	0.576	0.071	1.083	0.029	0.489
NBATROOM	-0.114	-0.953	0.105	0.624	-0.252	-1.471
NFLOORS	***0.031	3.966	0.010	0.803	***0.055	4.682
GARAGE_YES	**0.152	3.468	0.059	0.851	**0.183	3.124
BLDCOND_Excellent	0.028	0.892	-0.007	-0.162	0.020	0.460
LSCAPQUA_Excellent	0.028	0.817	0.039	0.743	-0.031	-0.679
LogDISCOAST	0.001	0.009	0.077	0.359	0.233	0.763
LogDISTWORK	-0.029	-0.932	-0.048	-0.852	-0.065	-1.510
LogDISBSTOP	-0.437	-1.220	1.074	0.952	-0.345	-0.718
LogDISTSCH	-0.002	-0.040	-0.073	-0.653	0.023	0.301
R ²	0.571		0.553		0.637	
Adjusted R ²	0.544		0.468		0.599	
Standard Error (SE)	0.17254401		0.150936371		0.17801468	
Durbin-Watson	2.116		1.649		2.226	
F-Statistic	21.104		6.491		16.657	
p-Value	0.000		0.000		0.000	
Observations	318		118		200	

Dependent variable: LogRENT, *** indicates sig @ 0.1% (p<0.001) level, ** indicates sig, @ 1% (p<0.01) level, *indicates sig, @ 5% (p<0.05) level

Table 3: Log-log Hedonic Price Models of Coastline and Housing Characteristics for Victoria Island (Flood Effect)

| Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE **-0.162 -3.44 -0.101 -1.318 ***-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ***0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES **0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 LogOISCOAST*FLODRAT -0.020 -0.239 0.047 0.387 -0.085 -0.319 LogDISBSTOP -0.494 -1.545 1.004 1.049 -0.687 -1.52
 | Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ***-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ****0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.004 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052 <t< th=""><th>Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ***-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ***0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT 0.028 0.891 -0.004 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052 -1</th><th>Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ****-0.237 -3.78 LogBFLOAREA ****2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ****0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.044 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052</th><th>Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ***-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.004 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052</th><th>Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE **-0.162 -3.44 -0.101 -1.318 ***-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.004 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052 -</th><th>Coeff t-stat coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ****-0.237 -3.78 LogBFLOAREA ****2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ****0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT 0.028 0.891 -0.004 0.044 0.859 -0.085 -0.319 Log(DISTWORK -0.028 -0.898 <</th><th>Coeff t-stat coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ****-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ****0.053 4.602 GARAGE YES ***0.152 3.484 0.058
0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.004 0.044 0.859 -0.085 -0.319 Log(DISTWORK -0.028 -0.898 <</th><th>Coeff t-stat coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ****-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.004 -0.859 -0.051 -0.91 -0.052 -1.241 LogDISTWORK -0.028 <td< th=""><th>Coeff t-stat coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ****-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ***0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.898 -0.051 -0.91 -0.052 -1.241 LogDISTWORK -0.028 -0.898 -0.051 <td< th=""><th>V/ABV ABV 55</th><th>1 (0 =0</th><th>0)</th><th>Model</th><th></th><th>C (5=1 =</th><th>'00 ·</th></td<></th></td<></th></t<> | Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ***-0.237 -3.78 LogBFLOAREA ***2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ***0.032 3.975 0.009 0.75 ***0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT 0.028 0.891 -0.004 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052 -1
 | Coeff t-stat coeff t-stat coeff t-stat Constant 2.619 2.285 -0.806 -0.254 2.796 1.518 LogBLDAGE ***-0.162 -3.44 -0.101 -1.318 ****-0.237 -3.78 LogBFLOAREA ****2.385 10.622 ***1.863 6.147 ***2.712 8.395 NBEDROOM 0.025 0.569 0.073 1.116 0.017 0.294 NBATROOM -0.117 -0.986 0.103 0.612 -0.293 -1.696 NFLOORS ****0.032 3.975 0.009 0.75 ****0.053 4.602 GARAGE YES ***0.152 3.484 0.058 0.833 **0.198 3.478 BLDCOND Excellent 0.028 0.891 -0.006 -0.14 0.022 0.517 Log(DISCOAST*FLODRAT -0.028 0.891 -0.044 0.859 -0.085 -0.319 LogDISTWORK -0.028 -0.898 -0.051 -0.91 -0.052
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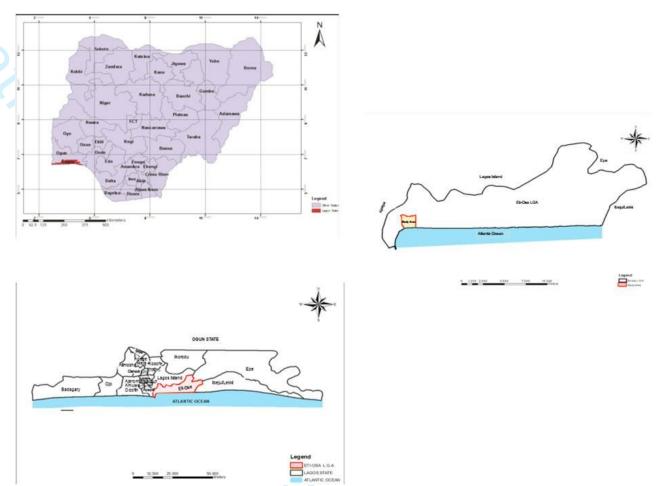


Fig. 1: Map of the Nigeria showing the study area

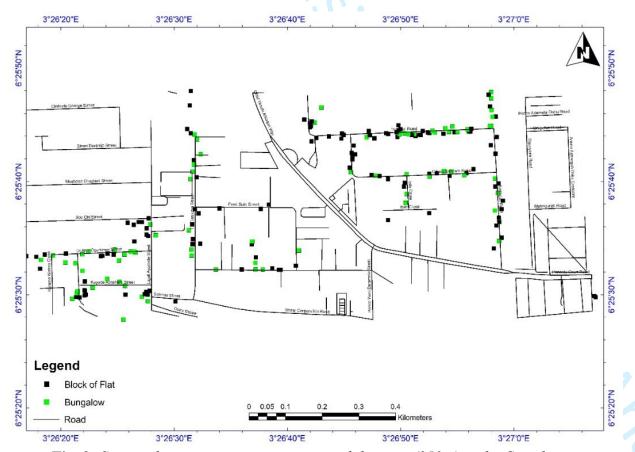


Fig. 2: Surveyed property types at incremental distance (250m) to the Coastline

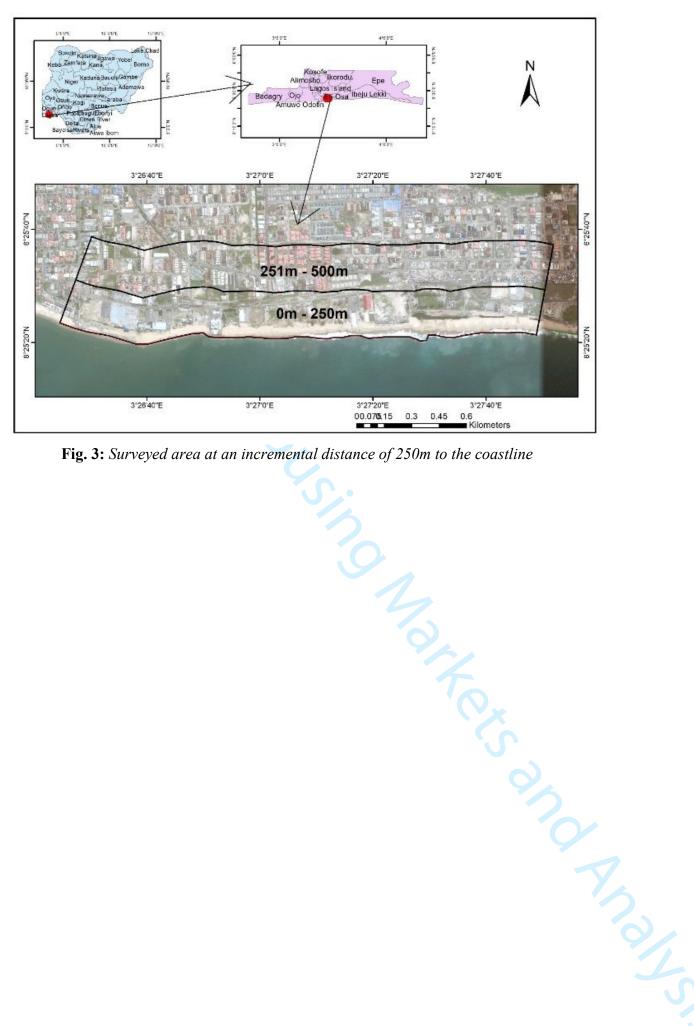


Fig. 3: Surveyed area at an incremental distance of 250m to the coastline



Fig. 4: Rented residential property at incremental distance (250m) to the Coastline