Modelling the Determinants of House Prices Using Generalized Linear Models with Gamma Distribution and Log Link: A Case Study of Nigeria

Ajiboye Raimot Adenike, Oyebisi Oyetayo, Abdulrahman, Fatima Bukola

& Musa Yunus Olatunji

Department of Statistics, Kwara State Polytechnic, Ilorin, Kwara State, Nigeria

ajiboyera@gmail.com,+2348067971833; oyebisioyetayofrancis@gmail.com , +2347026922740

Abstract:
Housing is one of the most critical elements of economic and social development as both a fundamental human need and an important investment tool. The prices of houses differ significantly in Nigeria because of the differences in structural features, demand, and economic factors. The determinants of these price variations are essential to effective policymaking, investment choices, and regulation in housing markets. This study explores the determinants of house prices in Nigeria by employing a Generalized Linear Model (GLM) with a Gamma distribution and log link function because of the highly skewed house price data. This study uses a dataset of 24,326 properties across Nigeria's geopolitical zones. The research examines the influence of structural attributes bedrooms, bathrooms, toilets, and parking spaces, and regional variations. Findings reveal that bedrooms, parking spaces, and location are key drivers of house prices, while the number of toilets is statistically insignificant. The South West emerges as the most expensive region, with other zones exhibiting significantly lower prices.

Keywords: House Prices, Generalized Linear Model, Gamma Distribution, Log Link, Structural Attributes, Geopolitical Zones, Nigeria

1. Introduction

The real estate sector is a key driver of economic activity and investment in both developed and developing countries. Accurate valuation of residential properties is essential for buyers, sellers, investors, mortgage providers, and policymakers. Understanding the determinants of house prices enables stakeholders to make informed decisions about land use, property investment, housing policy, taxation, and urban development. However, property prices are influenced by a combination of structural characteristics, locational factors, market dynamics, and broader macroeconomic conditions. Capturing these relationships statistically presents a significant challenge, especially in contexts where housing markets are heterogeneous and data are heavily skewed.

In Nigeria, housing markets are diverse and fragmented due to regional disparities in infrastructure, economic opportunities, and urbanization. The demand for housing in urban centres, such as Lagos and Abuja, has driven up prices significantly, while rural and semi-urban areas often remain underdeveloped. Additionally, the housing market is influenced by varying levels of security,

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cultural preferences, and regional planning laws across Nigeria's six geopolitical zones: North Central, North East, North West, South East, South South, and South West.

The Ordinary Least Squares, which is a traditional regression technique, assumes normality and homoscedasticity of residuals, which are often violated in house price datasets and are typically right-skewed and heteroscedastic. Applying OLS to such data can lead to biased and inefficient parameter estimates, as well as a poor understanding of the relationships between predictors and outcomes. To overcome these limitations, more flexible modelling frameworks, such as Generalized Linear Models (GLMs), have been proposed.

This study adopts a Generalized Linear Model with a Gamma distribution and log link function to analyse house prices in Nigeria, considering both structural characteristics (e.g., number of bedrooms, bathrooms, toilets, and parking spaces) and geopolitical zones as categorical location variables. The Gamma distribution is particularly suitable for modelling continuous, positive, and right-skewed variables like house prices. The log link function ensures that predictions remain strictly positive and allows for multiplicative interpretations of the coefficients. By applying this robust statistical model to a large, nationally representative dataset of 24,326 observations, this study provides new insights into the drivers of house prices in Nigeria. This also shows the practical utility of the Gamma GLM in modelling skewed economic data of an area that remains underexplored in African housing markets.

2. Literature Review

The modelling of house prices has been a major focus of housing economics and urban analysis because it is crucial as a factor in policy development, investment decision-making and housing affordability analysis and application. Conventional methods in the modelling of housing prices have been mainly based on Multiple Linear Regression (MLR) models that assume linear relationships, constant variance, and normally distributed errors. Based on the simplicity and interpretability of MLR models have led to their popularity but typically fail to satisfy their underlying assumptions with real-world data, particularly when the price distributions are highly skewed and heteroscedastic (Bax et al., 2019; Li, 2022). Since housing prices are continuous and strictly positive, they often have skewed distributions to the right causing classical OLS estimators to be inefficient and prone to bias (Hardin and Hilbe, 2012). Researchers have therefore, increasingly shifted to more flexible statistical methods that can deal with such anomalies in data.

2.1 Some Sophisticated Statistical Modelling of Houses.

Other studies have used quantile regression to Seoul (Heeho et al., 2015) and Istanbul (Ebru and Eban, 2011), respectively, indicating that the effect of structural features (bedrooms, bathrooms, location) is not consistent across price quantiles. Other models, such as spatial lag and spatial error models, are used to correct spatial dependence and thus bias regression estimates. A series of extensions was created to address regional differences in housing determinants, including Geographically Weighted Regression (GWR) and spatial quantile models (Berberoglu, 2023). But

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these spatial techniques tend to be data-intensive and computationally time-consuming, an issue in developing-country settings where geospatial information can be sparse or unavailable.

2.2 The Emergence of Generalized Linear Models (GLMs).

Generalized Linear Models (GLM) have become predominant in applied fields, such as real estate, insurance, and healthcare, to deal with non-normal data overcoming the shortcomings of linear and spatial models (Hardin and Hilbe, 2012). GLMs build on classical linear model, but instead of the mean of the dependent variable, they associate it with a linear predictor using a given link function and permit a flexible distributional assumption. The Gamma distribution with a log link is especially beneficial in the context of house price modelling, allowing one to work with positive, continuous, and right skewed data and at the same time, retain multiplicative relationships between variables (Bax et al., 2019).

Real estate applications of Gamma GLMs have performed better than conventional log-linear models. In fact, in the South African housing market, it was shown that a Gamma GLM outperforms a classic log-linear OLS model by offering a superior fit and generalization (Bax et al., 2019). Likewise, Li (2022) used a generalized linear regression model to estimate housing prices in China and concluded that the heteroscedasticity and skewness were well explained, and their estimates are reliable and interpretable. These results indicate that the Gamma GLM is not only statistically sound, but it also has interpretive power because coefficients could be interpreted as elasticities in the log link.

2.3 Empirical Data on Nigeria and Developing Economies.

In spite of these methodological innovations, the use of GLMs and particularly the Gamma variant in developing countries is not wide-spread. Empirical research on determinants of house prices has focused on single cities or states in Nigeria mainly using multiple regression or machine-learning methods. Auwal et al. (2018) used multiple regression analysis to estimate the price of houses in Kaduna North, where the model found location and building materials to be important factors. Nwankwo et al. (2023) utilised ML algorithms for the prediction of housing prices in Lagos and prioritized the predictive accuracy of nonlinear models over interpretability and statistical diagnostics.

At macro level, Okey (2025) used long-run and short-run causes of real house prices using the vector autoregression (VAR) model, which found the importance of income and inflation, but failed to measure the skewness of data and regional structural variations. In the same fashion, Oluyele (2024) modelled the dynamics of rental prices in Lagos by applying the conventional regression methods but failed to consider the non-normality of the housing data. All the studies point to one thing and that is, there is a gap in the literature regarding the housing market of Nigeria, most of the empirical research is geographically limited or methodologically restricted. The reality is that

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strong models are required to identify the asymmetric price distribution and still take into consideration both structural and regional variables within the six geopolitical zones of the country.

2.4 Summary and Research Gaps

Three major gaps arise out of the reviewed literature. First, the majority of Nigerian house prices studies still use the linear regression with its premises of normality and homoscedasticity even though the premises of highly skewed and non-normally distributed house prices have been observed. Second, whereas GLMs, especially the Gamma GLM using a log link, are well adapted to the analysis of positive, continuous data, they have not yet been applied in housing market research in third world economies. Third, geopolitical zones have not been systematically included in past studies as categorical variables to compare spatial variation in pricing patterns on a national level.

This research paper addresses these lapses by considering a Gamma GLM with a log link to portray the determinants of house prices using a massive sample of more than 24000 houses in the geopolitical regions in Nigeria. This study can be seen as a methodologically and empirical contribution to the housing economics literature by combining model performance based on information-theoretic measures (AIC, BIC and likelihood ratio tests) with structural characteristics (bedrooms, bathrooms, toilets and parking spaces) along with regional indicators. It shows that flexible GLM structures are applicable to models that capture skewed property data and augments insights into interactions between structural and locational factors to form house prices in Nigeria.

3. Methodology

3.1 Study Design and Data Source

This study adopts a **quantitative cross-sectional design** to analyze the influence of housing characteristics on residential property values in Nigeria. Data were obtained from a combination of structured field surveys and secondary data from real estate transaction records. The dataset includes information on key structural and locational attributes of residential properties.

3.2 Variable Description

Let Y denote the **residential property value** (dependent variable), and the independent variables (housing characteristics) include:

X_1: Number of bedrooms

X_2: Number of bathrooms

X_3: Property size in square meters

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X_4: Parking space ($1 = \text{Yes}, 0 = \text{No}$)

X_5: Distance to the central business district (in kilometers)

X_6: Age of property (in years)

X_7: Property type (categorical: apartment, duplex, etc.)

3.3 Model Specification

3.3.1 Multiple Linear Regression Model (MLR)

To investigate the linear effect of housing features on property values, we use the following multiple linear regression model:

$$Y_i: \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + \varepsilon_i$$

Where:

Y_i: Property value of observation ii

β_0: Intercept

β_j: Coefficient for each explanatory variable Xji

ε_i : Error term, assumed $\varepsilon_i \sim N(0, \sigma 2)$

3.3.2 Log-Linear Hedonic Pricing Model

Due to the typically skewed distribution of property values, a logarithmic transformation of the dependent variable is used to linearize relationships and stabilize variance:

$$\boldsymbol{L_n}\ (\boldsymbol{Y_i}) = \boldsymbol{\beta_0} + \sum_{j=1}^{k} \boldsymbol{\beta_0}\ \mathbf{X_{ji}} + \boldsymbol{\varepsilon}_i$$

This hedonic pricing model treats housing as a bundle of characteristics, each contributing additively to the logarithm of its market value.

4.0 Data Analysis

Introduction

House prices are influenced by a variety of factors, including structural attributes, location, and regional economic conditions. Understanding these determinants is crucial for real estate investors, policymakers, and property developers to make informed decisions. Traditional linear regression models often struggle with the skewed nature of house price distributions, making alternative modeling techniques more suitable. This study employs a Generalized Linear Model (GLM) with a Gamma distribution and log link function to better capture the relationship between house prices and their key predictors. By incorporating structural variables such as the number of bedrooms, bathrooms, parking spaces, and regional variations across Nigeria's geopolitical zones

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4.1 Model Information

Dependent Variable	price
Probability Distribution	Gamma
Link Function	Log

Categorical Variable Information

			N	Percent
Factor	Geopolitical_Zone	North Central	3553	14.6%
		North East	2	0.01%
		North West	27	0.1%
		South East	528	2.2%
		South South	636	2.6%
		South West	19580	80.5%
		Total	24326	100.0%

The **Geopolitical_Zone** variable in the **Gamma GLM (log link)** model represents regional differences in the dataset, with a total of **24,326 observations**. The data is highly skewed, with the **South West (80.5%)** being the most dominant group, while the **North East (0.01%)** and **North West (0.1%)** have extremely low representation. The **North Central (14.6%)**, **South East (2.2%)**, and **South South (2.6%)** have moderate representation, allowing for more stable estimates. Since the **Gamma GLM with a log link** models a **positive, right-skewed dependent variable**, the estimated coefficients for each region reflect their multiplicative effect on the outcome variable relative to the reference category. Given the severe class imbalance, model estimates will be primarily driven by the **South West.**

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Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	price	24326	90000.0	1800000000000.0	301380208.472	12204027269.3809
Covariate	bedrooms	24326	1.0	9.0	4.339	1.1385
	bathrooms	24326	1.0	9.0	4.601	1.1632
	toilets	24326	1.0	9.0	5.176	1.2263
	parking_space	24326	1.0	9.0	4.042	1.3999

The Continuous Variable Information provides insights into the distribution of house prices and key structural property attributes. The dependent variable (price) exhibits extreme variation, ranging from ₦90,000 to ₦1.8 trillion, with a mean price of ₦301,380,208.47 and a very high standard deviation of ₦12,204,027,269.38, indicating significant price dispersion and a highly skewed distribution. Among the covariates, the number of bedrooms, bathrooms, toilets, and parking spaces ranges from 1 to 9, with mean values of 4.34, 4.60, 5.18, and 4.04, respectively. The relatively small standard deviations suggest that most properties have similar structural characteristics, though variations exist. These findings support the use of the Gamma distribution, which is suitable for modeling positively skewed data like house prices.

4.3 Model Estimation

MODEL 1

Goodness of Fit[a]

	Value	df	Value/df
Deviance	41013.108	24316	1.687
Scaled Deviance	29317.057	24316	
Pearson Chi-Square	8985751.192	24316	369.541
Scaled Pearson Chi-Square	6423209.315	24316	
Log Likelihood	-490201.365		
Akaike's Information Criterion (AIC)	980424.730		

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Finite Sample Corrected AIC (AICC)	980424.741		
Bayesian Information Criterion (BIC)	980513.823		
Consistent AIC (CAIC)	980524.823		

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	12105.508	1	.000
Geopolitical_Zone	520.514	5	.000
bedrooms	1820.547	1	.000
bathrooms	7.211	1	.007
toilets	.028	1	.868
parking_space	692.243	1	.000

MODEL 2

Goodness of Fit[a]

	Value	df	Value/df
Deviance	66051.419	24303	2.718
Scaled Deviance	86682.228	24303	
Pearson Chi-Square	50933832.611	24303	2095.784
Scaled Pearson Chi-Square	66842743.673	24303	
Log Likelihood[b]	-510310.407		
Akaike's Information Criterion (AIC)	1020668.813		
Finite Sample Corrected AIC (AICC)	1020668.863		
Bayesian Information Criterion (BIC)	1020863.197		
Consistent AIC (CAIC)	1020887.197		

Tests of Model Effects

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Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	.[a]	.	.
Geopolitical_Zone	189.170	4	.000
bedrooms	65.510	1	.000
bathrooms	7.512	1	.006
toilets	759.869	1	.000
parking_space	.955	1	.329
Geopolitical_Zone * bedrooms	93.454	4	.000
Geopolitical_Zone * bathrooms	15.950	4	.003
Geopolitical_Zone * parking_space	88.401	4	.000

Model 3

Goodness of Fit[a]

	Value	df	Value/df
Deviance	64741.817	24295	2.665
Scaled Deviance	85191.404	24295	
Pearson Chi-Square	47966304.43	24295	1974.328
Scaled Pearson Chi-Square	63117116.42	24295	
Log Likelihood[b]	-509528.488		
Akaike's Information Criterion (AIC)	1019120.976		
Finite Sample Corrected AIC (AICC)	1019121.063		
Bayesian Information Criterion (BIC)	1019380.153		
Consistent AIC (CAIC)	1019412.153		

Dependent Variable: price
Model: (Intercept), Geopolitical_Zone, bedrooms, bathrooms, toilets, parking_space, Geopolitical_Zone * bedrooms, Geopolitical_Zone * bathrooms, Geopolitical_Zone * parking_space, bedrooms * bathrooms, Geopolitical_Zone * bedrooms * bathrooms * parking_space, bedrooms * parking_space, bathrooms * parking_space

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)			

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Geopolitical_Zone	52.293	4	.000
bedrooms	10.645	1	.001
bathrooms	6.928	1	.008
toilets	534.463	1	.000
parking_space	13.031	1	.000
Geopolitical_Zone * bedrooms	53.438	4	.000
Geopolitical_Zone * bathrooms	9.758	4	.045
Geopolitical_Zone * parking_space	25.358	4	.000
bedrooms * bathrooms	2.032	1	.154
Geopolitical_Zone * bedrooms * bathrooms * parking_space	6.732	5	.241
bedrooms * parking_space	9.872	1	.002
bathrooms * parking_space	10.868	1	.001

MODEL SELECTION

Model	AIC	AICc	BIC
Model 1	**980424.730**	**980424.741**	**980513.823**
Model 2	1020668.813	1020668.863	1020863.197
Model 3	1019120.976	1019121.063	1019380.153

The **model table** compares three models using **AIC, AICc, and BIC**, where lower values indicate a better balance between model fit and complexity. **Model 1 has the lowest AIC (980,424.730), AICc (980,424.741), and BIC (980,513.823), making it the most optimal model** compared to Model 2 and Model 3, which have significantly higher values. Since both **AIC and BIC are low Model 1**, it suggests that this model provides the best trade-off between explanatory power and simplicity. Therefore, **Model 1 is the best**

Omnibus Test

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
9889.735	9	<0.0001

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The **Omnibus Test** evaluates the overall significance of the model by comparing it to a null model (a model with no predictors). The **Likelihood Ratio Chi-Square value of 9889.735** with **9 degrees of freedom (df)** and a **p-value (Sig.) of <0.001** indicates that the model is **highly significant**. This means that at least one of the predictor variables in the model contributes significantly to explaining variations in the dependent variable. Therefore, the model provides a significantly better fit to the data.

Model Effect Test

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	12105.508	1	.000
bedrooms	1820.547	1	.000
bathrooms	7.211	1	.007
toilets	.028	1	.868
parking_space	692.243	1	.000
Geopolitical_Zone	520.514	5	.000

The Tests of Model Effects table shows that the intercept ($\chi^2 = 12{,}105.508$, $p = 0.000$) is highly significant, confirming a meaningful baseline prediction. Among the predictors, bedrooms ($\chi^2 = 1{,}820.547$, $p = 0.000$), bathrooms ($\chi^2 = 7.211$, $p = 0.007$), parking space ($\chi^2 = 692.243$, $p = 0.000$), and geopolitical zone ($\chi^2 = 520.514$, $p = 0.000$) significantly influence the house price. However, toilets ($\chi^2 = 0.028$, $p = 0.868$) is not significant, indicating it does not meaningfully impact the outcome. This suggests that bedrooms, bathrooms, parking space, and location are key determinants, while the number of toilets does not contribute significantly to the model.

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	16.760	.0297	16.702	16.818	317817.640	1	<0.0001
Bedrooms	.406	.0095	.387	.425	1820.547	1	<0.0001
Bathrooms	.028	.0105	.008	.049	7.211	1	0.007
Toilets	.001	.0074	-.013	.016	.028	1	0.868
Parking space	.138	.0052	.128	.148	692.243	1	<0.0001
North Central	.112	.0224	.068	.156	24.941	1	<0.0001
North East	-.585	.8364	-2.224	1.055	.489	1	0.485
North West	-1.524	.2279	-1.971	-1.077	44.697	1	<0.0001
South East	-.773	.0527	-.877	-.670	215.484	1	<0.0001
South South	-.707	.0478	-.801	-.614	218.928	1	<0.0001
South West	0^a	.	.	.	.	.	.
(Scale)	1.399^b	.0108	1.378	1.420			

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The **GLM (Gamma with Log Link) model equation,** based on the parameter estimates, is:
log(Price)=16.760 + 0.406*Bedrooms + 0.028*Bathrooms + 0.138*Parking Space + 0.112*North Central −1.524 *North West −0.773*South East −0.707* South South.
Since the **South West** region serves as the reference category, its coefficient is **0** and is excluded from the equation.
The negative coefficients (**North East, North West, South East, South West**) indicate that **houses in these regions are generally cheaper** than in the South West.
The GLM (Gamma with Log Link) parameter estimates provide insights into how various factors influence house prices, with the dependent variable modeled in a multiplicative (log) fashion. The intercept (B = 16.760, p = 0.000) is highly significant, representing the baseline log-transformed house price when all predictors are zero. Among the property features, bedrooms (B = 0.406, p = 0.000) and parking space (B = 0.138, p = 0.000) significantly increase house prices, meaning each additional bedroom or parking space is associated with a multiplicative increase in price. Bathrooms (B = 0.028, p = 0.007) also have a positive but weaker effect, while toilets (B = 0.001, p = 0.868) are insignificant, indicating they do not meaningfully impact pricing. The South West is the reference category, and all other geopolitical zones except the North East (p = 0.485, not significant) have significantly lower house prices. The North West (B = -1.524, p = 0.000), South East (B = -0.773, p = 0.000), and South South (B = -0.707, p = 0.000) have notably lower prices compared to the South West, while North Central (B = 0.112, p = 0.000) has a slight positive effect. Overall, bedrooms, parking spaces, and location are strong determinants of house prices, while toilets have no significant effect.

5. Discussion of Findings

The analysis of house prices using a Generalized Linear Model (GLM) with a Gamma distribution and log link function provides valuable insights into the key determinants of property pricing. The model selection criteria confirmed that Model 1 is the most optimal model, indicating a strong balance between goodness-of-fit and model complexity.

The Omnibus Test demonstrated that the model is statistically significant (χ^2 = 9889.735, p = 0.000), meaning that the predictors collectively contribute significantly to explaining variations in house prices. The Wald Chi-Square tests further confirmed the significance of individual predictors, with bedrooms, bathrooms, parking spaces, and geopolitical zones playing crucial roles in determining house prices.

From the parameter estimates, the intercept (B = 16.760, p = 0.000) was highly significant, representing the baseline log-transformed house price. Among the property features, bedrooms (B = 0.406, p = 0.000) and parking space (B = 0.138, p = 0.000) had the strongest positive impact on prices, meaning that each additional bedroom or parking space leads to a multiplicative increase in house price. Bathrooms (B = 0.028, p = 0.007) had a weaker but significant positive effect, while toilets (B = 0.001, p = 0.868) were not statistically significant, indicating that the number of toilets does not meaningfully influence pricing.

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The effect of geopolitical zones was also substantial, with the South West serving as the reference category. Compared to the South West, house prices were significantly lower in the North West (B = -1.524, p = 0.000), South East (B = -0.773, p = 0.000), and South South (B = -0.707, p = 0.000). North Central (B = 0.112, p = 0.000) was the only zone with a slight positive effect, while North East (B = -0.585, p = 0.485) was not significant, suggesting that house prices in this region are highly variable and possibly influenced by other external factors.

The extreme variation in house prices, ranging from ₦90,000 to ₦1.8 trillion, suggests a highly heterogeneous property market, where regional and structural factors drive substantial pricing differences.

6. Conclusion

The findings from the GLM (Gamma Log) analysis highlight the key determinants of house prices, showing that bedrooms, parking spaces, and geopolitical location are the most influential factors. The study confirms that house prices vary significantly across geopolitical zones, with the South West being the most expensive region and the North West, South East, and South South having significantly lower prices. The number of bedrooms and parking spaces substantially increases property value, while the number of toilets does not have a meaningful impact. Okey (2023).

7. Recommendations

1. **Policy Action:** Encourage infrastructure investment in underperforming zones to reduce regional disparities.
2. **Real Estate Planning:** Developers should prioritize the inclusion of more bedrooms and parking spaces.

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