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Determinants of House Prices in Dublin: A Quantile Regression Approach

Master`s Degree in Corporate Finance

Carlos José Silva Sousa

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ABSTRACT

Today's property market is more competitive than ever, making accurate property valuation essential for ensuring fair transactions for both buyers and sellers. Historically, the Irish have shown a strong preference for homeownership over renting, with the homeownership rate reaching 69.4% in 2023 (Eurostat, 2023). This research underscores the significance of identifying key factors that influence housing prices in the Dublin market.

Over time, researchers have developed various methods to achieve the most rigorous results in real estate valuation. As in many previous studies, the hedonic price model was employed, as it is widely regarded as one of the most effective approaches for property valuation. To conduct the empirical analysis, different forms of the hedonic price model were tested on a sample of 5,091 houses in Dublin, with the double logarithmic form proving to yield the most accurate results. To enhance performance, the study applied quantile regression, a technique that provides a more comprehensive view of price variations across the housing market. This approach allowed for the identification of attributes that significantly influence price fluctuations in both lower- and higher-priced properties.

Our findings reveal that location and house size exert the strongest positive influence on property prices, consistently driving price variations across all market segments. Additionally, property type plays a crucial role in determining house values. However, factors such as usage status, the number of bedrooms, and the availability of gardens or terraces primarily impact lower- and mid-priced houses. Furthermore, Building Energy Rating (BER) significantly affects prices, but mainly in cases of lower ratings, which lead to price reductions, particularly in the lower-priced segment. Lastly, proximity to the sea enhances house values, especially for high-priced houses.

Keywords: Real Estate Valuation, House Prices, Hedonic Price Model, Quantile Regression, Dublin, House Market.

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LIST OF ACRONYMS AND ABREVIATIONS

AI - Artificial Intelligence

AIC - Akaike Information Criterion

ANNs - Artificial Neural Networks

ARIMA - Autoregressive Integrated Moving Average

AVM`s - Automated Valuation Models

BER - Building Energy Rating

BIC - Bayesian Information Criterion

CSO - Central Statistics Office, Ireland

ECB - European Central Bank

EPC - Energy Performance Certification

GIS - Geographic Information Systems

HP - Hedonic Price

HPM - Hedonic Price Model

MAE - Mean Absolute Error

LAD - Least Absolute Deviation

LASSO - Least Absolute Shrinkage and Selection Operator

MR – Multiple Regression

OLS - Ordinary Least Squares

PL - Pinball Loss

QR – Quantile Regression

QQ – Quantile-Quantile

1. INTRODUCTION

Purchasing a house is one of the most significant financial decisions for most families. In traditional accounting, a house is considered an asset. However, buying a home to live in differs from purchasing one as a rental investment. Kohl and Wood (2024) highlight that landlords seek to diversify their portfolios and generate additional income. While real estate development and sales can be highly profitable, market downturns pose the risk of financial loss. Regardless of the motivation, it is essential to carefully evaluate all factors before making a property investment.

Today's housing market is challenging. Unlike previous generations, when buying a home was more attainable, young adults today are finding it increasingly difficult to enter the property market. In summary, rising house prices and the increasing cost of living are having a significant impact on their lives.

House valuation is a subjective process, and it is essential to consider potential negotiating strategies. Sellers may inflate prices to maximise their profit or to create room for negotiation. This dissertation aims to explore which factors have the greatest impact on house price fluctuations. Consequently, the research identifies the key determinants that play a crucial role in determining prices within the housing market.

Following the studies by Abidoye (2018), Abidoye et al. (2018), Abidoye, Junge, et al. (2019), Bourassa and Hoesli (2022), Chan and Abidoye (2019), Gabrielli and French (2021) and Kanojia et al. (2016), we analyse what attributes influence the housing market, such as structural characteristics, neighbourhood quality, facilities near the house, and other factors that impact house prices. The housing market is influenced by structural characteristics and by attributes such as neighbourhood quality, facilities near the house, and others that affect prices.

According to data from the European Central Bank (ECB, 2024), which shows the change in residential property prices in Ireland over the years, the increase in prices has reached a record high. Kiley (2022) argued that the Irish housing market is facing several problems. There is too much demand for the available supply, and according to the law of supply and demand, when demand exceeds supply, prices rise. As in most countries, the most expensive properties are in the capital. Research by Corrigan et al. (2019) explains that the main issues contributing to these effects are low investment in property and rapid population growth. This has been the case in Dublin, which is why house prices are higher to rent or buy compared to other cities.

Therefore, the main objective of this research is to study the Dublin housing market and identify precisely which determinants drive the greatest price variation.

Moreover, this study uses the quantile regression approach to understand which determinants influence house prices the most. This method has been used to study the variation in house prices, but never in the Dublin housing market. It allows us to analyse the impact of different attributes on prices across the distribution. Rather than focusing solely on the mean of house prices, this method is used in housing markets where heterogeneity in prices and factors affects different market segments in different ways (Koenker & Hallock, 2001). Different quantiles were objectively studied to understand the impact of the determinants on different price levels, from the cheapest to the most expensive houses. The research focused on the 10th quantile, the quantile with the cheapest houses; the 25th quantile; the 50th quantile, which represents the median; the 75th quantile; and the 90th quantile, which represents the most expensive houses.

This dissertation is developed into five sections. The first section presents the literature review, which (1) explores various methods for evaluating house prices, (2) examines the differences between traditional and advanced approaches, and (3) focuses on empirical evidence using hedonic and quantile regression techniques. The second section outlines the methodology and the database used in the study. The third section evaluates the best hedonic price model to adopt in this research, also studies the outliers and residuals of the quantile regression. The fourth section discusses the research findings. Finally, the fourth section provides the conclusions and addresses the limitations of the study.

2. THEORETICAL FRAMEWORK

This section focuses on understanding and analysing the various traditional and advanced real estate valuation methods. The discussion covers the most widely accepted property valuation models and considers the limitations of each one, with a particular focus on hedonic price and quantile regression models. It also analyses the critical conclusions drawn from previous empirical studies using these models.

2.1. Characterization of the Housing Market in Dublin

The city of Dublin is a pillar in Ireland's economic landscape. As the capital of the country, it takes on the role of a thriving economic epicentre and contributes to the economic prosperity of Ireland in a number of important ways. First and foremost, it has become a centre of attraction for multinational companies. This concentration of corporate power enhances Dublin's economic standing and enriches Ireland's business ecosystem. This makes Dublin the city with the most expensive real estate in the country and the fourth most expensive city in Europe to build in, according to the report of International Construction Market Survey (2024), from global professional services company Turner & Townsend.

The report of the Central Statistics Office (CSO) from 2024 about the Dublin housing market highlights a 1.9% decline in house prices on the second semester of 2023, largely due to higher interest rates affecting buyer behaviour. This decline, the most pronounced since 2012, contrasts with a modest 1.4% annual increase in house prices countrywide. The ECB's sequential interest rate hikes have led to increased borrowing costs, slowing overall buying activity. In the context of a subdued national housing market following the financial crisis, the 7.2% decline in house purchases in September has a tangible impact. The CSO's report shows that the median price in Dublin is € 435,500 for 2023. Real estate agents in Ireland highlight continued demand despite economic challenges, often supported by intergenerational assistance (Burke-Kennedy, 2023).

Duffy (2022) closely examines the Dublin housing market from 1976 to 2000, with a particular focus on the late 1990s. The principal factors influencing house prices are economic growth, population growth, and demand, highlighting a significant drive to increase house prices. The research underscores a notable rise in both nominal and real house prices in Dublin, surpassing national averages and historical trends, with annual growth rates exceeding 20% in the late

1990s. This increase, possibly influenced by speculative behaviour, resulted in prices exceeding fundamental levels.

Duffy (2022) characterises the housing supply in Dublin as relatively inelastic, with a slow response to increasing demand due to factors such as land availability, planning regulations, construction costs and builder profits. Government interventions are recognised as important for improving the supply of affordable and social housing and reduce the demand for secondary homes. There is evidence of a significant affordability gap, particularly for first-time buyers and low-income households. Demographics and incomes are expected to continue driving demand, while supply is anticipated to grow gradually. The study concludes with a moderate outlook for house price inflation over the medium term, providing valuable insights into the unique dynamics shaping the Dublin housing market.

Breen and Reidy's (2021) study focuses on the factors that determine housing supply and demand, the rising cost of housing inputs, and the impacts on the affordability of home ownership and rental prices. The authors discuss the dependence of viable development in the home ownership and private rental sectors on affordable housing prices and rents for households.

Another study by Kiley (2022) provides an in-depth analysis of the Dublin housing market, focusing on the affordability crisis in Dublin. It applies urban spatial equilibrium and spatial misallocation theories to explain the high housing prices and their economic impact. In comparison with international examples, the article evaluates various policy interventions, including rent controls, vacancy taxes, and state-led development.

Kiley's (2022) study also advocates for a more comprehensive approach, simplifying development processes and reducing unnecessary regulations. This could potentially increase the supply of housing and reduce costs for both developers and tenants. Furthermore, the study proposes a counter-cyclical approach to housing development led by the state, which could provide more stable conditions for market activity and improve affordability.

Lastly, Kiley (2022) suggests a blend of private and public housing development, similar to the model employed in Vienna, as an efficient solution to increase supply and maintain affordable rents. The solutions proposed in the implemented model aim to address the unaffordability of the Dublin housing market by increasing supply and improving affordability through a combination of policy changes and development strategies.

2.2. State of Art in Housing Valuation

Investing in a home is a significant decision, and it is important to evaluate several factors before making a financial commitment. For this reason, valuation methods are essential for buyers to get an idea of the price. However, it is important to note that there are limitations, and calculating an accurate house value can be difficult.

The characteristics of real estate properties, such as environmental and structural features, affect their valuation. Moreover, macroeconomic factors may also be important to consider. Sandbhor and Chaphalkar (2016) studied both intrinsic and extrinsic factors and concluded that each has an impact on real estate prices.

As noted by Gilbertson and Preston (2005), the selection of property valuation methodologies employed within a nation has the potential to influence not only the domestic economy but also the economies of other countries. The valuation methodologies practised by real estate professionals within a specific country are intrinsically tied to their educational background, cultural environment, professional experience, and exposure to diverse perspectives (Mackmin, 1999). Property valuation methods have been categorised into traditional and advanced methods (Chan & Abidoye, 2019).

Traditional methods involve assessing market value by observing the market and usually include the cost, comparative sales, and income approaches. Typically, these methods require a small number of comparable properties for accurate application (Abidoye et al., 2018). Conversely, advanced methods generally require the decision-making processes of real estate players and demand a substantial amount of historical transaction data to accurately estimate property values (Pacharavanich et al., 2000).

2.2.1. Traditional Valuation Methods

A) Comparable Method

According to Mayer and Nothaft (2022), the comparable method estimates the value of a house by comparing similar properties that have recently been sold in the same market. The idea behind this method is that a buyer would not pay more for one house than for another with the same or similar characteristics.

To implement this method, the valuer must identify a group of comparable houses with the same characteristics (i.e., size, location, quality, condition, amenities, and other features that affect value) to compare with the house being valued. The valuer must then adjust the prices of the comparable properties to reflect the differences between them and the home being valued. The adjusted prices of the comparable houses are then used to estimate the value of the house under evaluation (Gilbert, 2017; Mayer & Nothaft, 2022).

As noted by Mayer and Nothaft (2022), the comparable method is one of the most common and widely used methods for valuing residential and commercial properties, especially when enough data is available for reliable comparisons. However, Gilbert (2017), as well as Yeh and Hsu (2018), argued that the method has some drawbacks and can be misleading due to the lack of comparable transactions or variations in property specifics (e.g., location factors). Additionally, the comparable method is more prone to subjectivity, which can lead to disputes during rent assessments.

B) Investment / Income Method

This investment or income method values the property based on the income it generates. According to Gabrielli and French (2021), income is derived by converting future cash flows into a single capital value by estimating the income that the property generates or could generate through real income (e.g., rent from tenants) or potential income. The tenant pays rent to the owner for the use of the property.

Moreover, this method is especially suitable for investment properties that generate stable and predictable cash flows (e.g., rental buildings, offices, shopping centres, and other income-producing assets). In the case of investment properties, this income often takes the form of rent, while for owner-occupied buildings, an assumed rent is used to estimate income (Abidoye, Junge, et al., 2019).

This method estimates the present value of future cash flows the property can produce, and discounts them at an appropriate capitalisation rate. The capitalisation rate (i.e., cap rate) reflects the risk and return of the real estate investment (i.e., yield). It is then compared to the market risk, which can be obtained from market data or asset pricing models (Gabrielli & French, 2021).

Gabrielli and French (2021) highlight the income method, which reflects the interaction between the occupational market (i.e., the properties available on the market) and the investment market (i.e., the demand for properties as investments). The market forces determine the rent level, which represents the economic rent of the property, while the value reflects the present value of these future cash flows.

C) Profit Method

According to Gilbert (2017), the profit method involves a detailed forensic analysis of a business's finances (i.e., sales, costs, and profits). The rent values are projected after an examination over a period. It also requires a deep understanding of a business's operational metrics, such as income and expenses, as well as external factors (e.g., location and marketing competition).

Gilbert (2017) argues that the profit method is one of the most accurate ways of assessing market rents, as it directly links business performance indicators to site characteristics. Another author, Jansen van Vuuren (2016), considers this method to be particularly suitable for projects involving risk and profit expectations, such as commercial or residential property development.

The profit method consists of estimating the final value of the project, calculating the total cost of the project, determining the present value of the total cost, and subtracting this from the final value to obtain the present value of the project's profit (Jansen van Vuuren, 2016).

Gilbert (2017) explains that the profit method provides more precise estimates when assessing rent for retail properties and takes into account the performance and profitability of businesses. This makes it particularly useful for valuing retail spaces, where performance between tenants can vary significantly.

D) Residual Method

Skarzyński (2006), as well as Bourassa and Hoesli (2022), argued that the residual method involves estimating the potential income from the property and subtracting the costs associated with completing or upgrading the property, leaving a residual value that represents the land or property value. In some cases, the values can be inaccurate or even negative.

The research by Bourassa and Hoesli (2022) compares the residual method with the hedonic price model and matching techniques. In conclusion, this model is less effective than the other approaches; the residual method is not usually used in mass appraisals due to its dependence on accurate data about the characteristics and depreciation of structures.

According to Skarzyński (2006), this method is typically used to determine the value of land or property that requires significant upgrading and is under development. Moreover, it is often used in risky development projects, so any errors in forecasting costs or final value can lead to substantial financial risk.

E) Contractor´s Method / Cost Method

The cost method, which is particularly used in cases where there is limited or no market data available, is another method of property valuation. Additionally, this method estimates the value of a property based on the costs of repairs, further subtracting depreciation to account for age, wear, and obsolescence (Camposinhos & Oliveira, 2019).

First, it is necessary to calculate the construction cost of a new property equivalent to the existing one. Next, the depreciation value must be determined based on the property's condition. Depreciation is calculated to reflect the loss in value over time due to deterioration and other factors. In addition to the building replacement cost, the value includes the market value of the land. The final property value results from adding the depreciated replacement cost (i.e., subtracting depreciation from replacement costs) to the value of the land. Therefore, this yields the property's capital value (Onyejiaka et al., 2015).

Camposinhos and Oliveira (2019) argued that this method is useful for newly constructed buildings or unique properties, even if there are no directly comparable constructions on the market. The authors presented a dynamic version, showing in their research that the cost method accurately estimates a property's market value.

F) Multiple Regression Methods

The Multiple Regression (MR) methods are key in the development of Automated Valuation Models (AVMs) to estimate property values, according to Doumpos et al. (2021). These methods involve estimating property prices based on a combination of several house characteristics or variable predictors.

Doumpos et al. (2021) analysed the main MR methods, including Ordinary Least Squares (OLS), Least Absolute Deviation (LAD), and Least Absolute Shrinkage and Selection Operator (LASSO) regression. OLS is a basic linear regression model that minimises the sum of the squared differences between the observed and predicted property values. On the other hand, LAD regression minimises the sum of the absolute differences, where the influence of outliers has less impact on the results compared to OLS. Meanwhile, LASSO is a method of regularised regression that adds a penalty. The main aim of LASSO is to reduce the complexity of the model, deal with multicollinearity, and shrink the coefficients of less important variables to zero, resulting in simpler models.

Benjamin et al. (2004) considered that MR methods reduce subjectivity by choosing comparable properties and allow the use of mass appraisals because they can be updated quickly and reduce costs in the long term. Another significant advantage is the adjustment of property characteristics.

However, Doumpos et al. (2021), Benjamin et al. (2004), and Geerts et al. (2023) argued that MR methods depend on the availability and accuracy of a large amount of data. Incomplete or inaccurate data can lead to unreliable valuations and results. Another major drawback is dealing with multicollinearity when two or more explanatory variables in the model are highly correlated, making it difficult to observe the individual effect of each variable on the dependent variable.

G) Stepwise Regression Method

Ruengvirayudh and Brooks (2016) explained that the stepwise method is a variable selection technique used in regression analysis, where variables are either added or removed from the model at each step, based on specific statistical criteria.

There are several methods of stepwise regression, differing in how the model is approached, either starting by adding or removing variables, and the two methods can also be combined. In forward selection, the model starts with no variables and then adds the most influential predictors one at a time based on their correlation with other variables (Ruengvirayudh & Brooks, 2016).

Yeh and Hsu (2018) stated that the method aims to eliminate the subjectivity of the model, creating a series of dimensionless adjustment models. The stepwise regression model adjusts the coefficients through several iterations of regression to maximise the accuracy of the results.

The research by Ruengvirayudh and Brooks (2016) considers the significance of each variable’s contribution to the overall model, clarifying that this methodology builds a model iteratively. However, it is primarily recommended for exploratory purposes rather than explanatory research, as it may not always identify the best set of predictors, particularly when multicollinearity is present.

Yeh and Hsu (2018) also argued that stepwise regression has some advantages, such as simplicity, automation, and computational efficiency. On the other hand, it also has drawbacks, including arbitrariness, instability, and potential bias.

2.2.2. Advanced Valuation Methods

A) Artificial Neural Networks (ANNs)

The origin of Artificial Neural Networks (ANN) is traced back to McCulloch and Pitts in 1943, as cited in Abidoye and Chan (2017), who modelled the neuron, demonstrating that neural networks can perform arithmetic and logical functions. Chan and Abidoye (2019) and Abidoye and Chan (2017) describe ANN as a computational model that uses Artificial Intelligence (AI) and is designed based on the human brain. It is composed of interconnected processors that mimic neural networks.

The neural structure is explained in terms of neurons (processing units) and layers. The neurons receive signals through dendrites, process them, and pass them to other neurons via axons. Additionally, the layers are organised into input layers (i.e., where the input variables and property attributes are fed into the model), hidden layers (i.e., where the computational processing occurs), and output layers, where the final prediction (property value) is produced (Abidoye & Chan, 2017).

Chan and Abidoye (2019) argued that ANN is particularly useful for property valuation because it can handle non-linear relationships between property attributes and values, which traditional methods like OLS struggle with. ANN is less reliant on human input, making it more objective than traditional methods, which often involve subjective judgments by valuers. ANN has been proven to provide accurate and reliable property valuation estimates in several studies. Additionally, the model has been praised for its ability to generalise across different types of data, producing robust and reliable results in many contexts. Despite this knowledge being available in academic circles, it has not been translated into practical application by professionals.

The ANN model has been widely adopted in real estate valuation due to its ability to learn from past data. This kind of model is suitable for mass appraisals and situations where traditional valuation techniques fail to handle complex non-linear relationships between variables (Chan & Abidoye, 2019).

Although ANN has shown better performance in property value estimation compared to traditional methods, Abidoye et al. (2018) found that traditional methods are preferred over advanced methods due to their simplicity and ease of interpreting results. In fact, one of the criticisms of ANN is that the model is not easily understood, making it difficult to interpret how the model arrives at its predictions. Moreover, it is also difficult to understand how this model makes decisions, unlike linear models where the effect of each variable is explicit. Additionally, ANN requires large amounts of historical transaction data for effective training, which can be a challenge, especially in markets where data is limited, affecting the performance of the model. Therefore, implementing and tuning an ANN model can be more complex compared to simpler regression models (Abidoye & Chan, 2017; Abidoye & Chan, 2018; Abidoye et al., 2018; Chan & Abidoye, 2019).

B) Autoregressive Integrated Moving Average (ARIMA)

Abidoye, Chan et al. (2019), Pagourtzi et al. (2003), and Tse (1997) highlighted that the Autoregressive Integrated Moving Average (ARIMA) model is unique as it is the only valuation method that depends on time variables. The model is designed for time series data. The process involves transforming the data into a stationary form (e.g., where statistical properties such as the mean and variance remain constant over time) by applying various techniques. In essence, the ARIMA model is an economic forecasting methodology that is fundamentally based on time series data.

Tse (1997) explained that the ARIMA model, with additional techniques, can enhance the precision of forecasts, helping investors with a stronger and more dependable instrument to navigate the real estate market.

The ARIMA model incorporates historical data and decomposes it into three components: (1) the autoregressive (AR) process, which takes into account the influence of past events with a decreasing lag (for example, the current house price is related to the previous month's price); (2) the integrated (I) process, which stabilizes the data for easier forecasting; (3) the moving average (MA) of forecast errors, which improves accuracy when more historical data is used. These three components are integrated and interact with each other to form the ARIMA model (Mukopi, 2012).

Jadevicius and Huston (2015) argue that despite their complexity, ARIMA models are relatively easy to implement and interpret. This makes them accessible for forecasting future trends in house prices. ARIMA is particularly suitable for univariate time series forecasting, which relies solely on past values of the data to make predictions. This approach is useful when other explanatory variables are unavailable or unreliable. ARIMA models can be used in volatile housing markets, such as the Lithuanian housing market.

However, Jadevicius and Huston (2015) point out that the model can experience structural breaks in the time series—periods of sudden changes in the data, such as economic shocks. These breaks can affect the predictive power of the model. ARIMA is more suitable for short-term forecasts. The article cautions against relying on ARIMA for long-term forecasts, as its accuracy declines over longer forecasting horizons. In addition, the effectiveness of the model depends on the choice of the appropriate combination of parameters. Including too many parameters can lead to overfitting. Furthermore, ARIMA models are univariate, meaning that they do not include external explanatory variables, such as economic indicators or demographic trends, which could provide more context or insight into the drivers of house price changes.

Abidoye, Chan et al. (2019) also compared ARIMA to ANN and concluded that ARIMA was the least accurate in predicting property prices. The article notes that ARIMA struggled with sudden changes in property prices and was less able to handle non-linear relationships, which are often present in housing markets. This limitation led to higher prediction errors, especially during periods of rapid price changes.

C) Spatial Analysis Methods

Spatial interpolation techniques use a data set derived from discrete points within sub-areas. These techniques then produce a function that optimally represents the entire surface, which can be used to predict values at different points or sub-areas (Geerts et al., 2023).

Can (1998) argues that the impact of neighbourhoods on mortgage and housing markets is most effectively studied in an advanced Geographic Information Systems (GIS) research computing environment. Researchers can take full advantage of the location information contained in these databases to support the application of spatial econometric and statistical methods, thanks to GIS capabilities that also facilitate the organisation and management of geographic data. Thus, the combination of GIS research infrastructure and spatial research offers excellent opportunities for the study of the neighbouring context in the field of mortgage and housing market research.

Morali and Yilmaz (2022) applied this particular method of analysis to the study of property prices and found that the location and surroundings of a property were important in determining its value. This is known as spatial dependence. The researchers found that by incorporating these spatial factors into their models, they were able to improve predictive accuracy, control for omitted variables correlated with location, and improve inference. This means that the way a property is built and the services it provides have a significant impact on its price, as well as the prices of nearby properties. Another interesting finding was the unique effect of high-rise apartment blocks on spatial autocorrelation. These buildings seem to create price anomalies in their surroundings, affecting the prices of nearby properties in a unique way.

Greenaway-McGrevy and Sorensen (2021) used spatial analysis methods to study the variation in transaction prices. They compared the spatial analysis method with OLS and concluded that the spatial method had more accurate results and better performance than the traditional method.

Dubin et al. (1999) and Geerts et al. (2023) analyse the model focusing on property valuation and emphasise the importance of incorporating spatial statistical methods to align theoretical considerations with empirical ones. They also discuss the potential of these techniques to improve predictive accuracy, control for omitted variables correlated with location, and improve inference.

The adoption of spatial statistical techniques, combined with GIS technology, provides unprecedented data availability with coordinated information, allowing for better empirical analysis in real estate. The findings also suggest that learning and using these techniques can provide new empirical opportunities in the field (Dubin et al., 1999).

D) Fuzzy Logic

The fuzzy logic model is a key advanced method used in real estate valuation, particularly when handling uncertain and ambiguous information. Unlike probabilistic methods, fuzzy logic models can mathematically represent judgements that lack a clear or unique definition. This approach assumes that uncertainty is possibilistic rather than probabilistic and relies more on the perceived likelihood of an event than on statistical confidence (Del Giudice et al., 2017).

Traditional techniques, such as multiple regression analysis, are commonly employed to predict house prices but often struggle to address issues like outliers, non-linearity, and non-normality in the data. To overcome these limitations, methods like artificial neural networks (ANN) and fuzzy logic models are used to more accurately model the complex relationships between house characteristics and prices (Sarip & Hafez, 2015).

In fuzzy logic, the most probable value is initially assigned to a variable. Other elements of the fuzzy set may include the highest or lowest possible values. If these values fall outside the variable's possible range, they are assigned a membership degree of 0 in the fuzzy set. The most probable value, however, may have a membership degree of 1, as it remains within the possible range of the variable. Any value the variable may take, between the highest and lowest, is included in the fuzzy set with a membership degree between 0 and 1. The variability of membership degrees for each possible value can be graphically represented in various ways, depending on the available knowledge of the probability of different values for the variable. This process is akin to allocating subjective probabilities to the values of a variable (Del Giudice et al., 2017).

Zadeh (1973) defined fuzzy logic as a system of reasoning where the primary components are not numerical values, but descriptive labels assigned to fuzzy sets. These sets represent categories of things where the transition from belonging to not belonging is gradual rather than abrupt. The widespread occurrence of fuzziness in human thought suggests that much human reasoning operates on a logic that is neither conventional two-valued nor even multivalued logic. Instead, it operates on a logic that involves fuzzy facts, fuzzy connectives, and fuzzy inference rules.

Fuzzy logic systems have proven especially useful in property and stock price valuation, as well as in the fields of information technology and artificial intelligence. In property investment, fuzzy logic is employed to assess the confidence level in taking a particular action based on specific evidence (Hui et al., 2009). The authors explain that their model demonstrates a strong correlation between confidence levels and the house price index. By analysing the evolution of confidence levels, investors can gain valuable insights to inform their real estate investment decisions. This research highlights the potential of fuzzy logic systems to convert complex raw data from multiple indicators into a unified sequence that can be easily interpreted and managed.

There are various AI techniques for making predictions. In comparison, fuzzy logic offers several advantages, such as its simplicity and adaptability. It excels in handling imprecise statements and data. To achieve more precise results, fuzzy logic relies on human knowledge and experience. Since fuzzy logic is based on a common language, it offers distinct advantages over other techniques. Fuzzy logic is employed to build models using the selected data sets (Kamire et al., 2021).

Sarip and Hafez (2015) explored how fuzzy logic performs better in situations where information is incomplete or uncertain, enabling predictions and decisions even when not all data points are clearly defined or measurable.

E) Hedonic Price Method

Pagourtzi et al. (2003) introduced the Hedonic Pricing Model (HPM) as an advanced method, which is further discussed in the following section.

2.3. The Classic Estimation of House Price with Hedonic Value Model

The first applications of the Hedonic Price Model were in the automotive industry. Court (1939), one of the pioneers of the model, focused his study on the car price index. The author defined the model as a measure whose main objective is to explain which characteristics most influence the price. In his article, he discusses the shortcomings of previous models that focused solely on physical characteristics. One example he gives is the effect of brand names on price. Other methods did not focus on external factors. His research aimed to find a more complete model that would yield more accurate results. He also highlighted the need to choose the right characteristics to obtain precise results.

Lancaster (1966), in an attempt to establish a new valuation method that could understand consumer behaviour and decision-making, analysed how consumers choose different goods from various combinations based on specific attributes of these goods. He argues that any good can be described by a vector of characteristics or attributes. For example, a car is valued based on its attributes such as speed, fuel consumption, comfort, etc. The consumer's utility function is defined based on the characteristics of the goods, so different combinations of goods could provide the same level of utility if the goods share the same combination of characteristics.

Lancaster's (1966) research introduced the concept of the efficiency frontier, which represents all combinations of attributes that maximise consumer utility within a given budget. The author challenged traditional valuation methods, which focused specifically on goods as indivisible units, and proposed an analysis that offers richer insights and more detail about consumer behaviour.

The hedonic model estimates the relationship between prices and attributes and is used in various markets, such as real estate. This model allows for the isolation of the implicit value of each attribute. It is used to compare different attributes and understand the impact of changes in these attributes on overall prices. Rosen (1974) developed this theory in the context of competitive markets, arguing that in a market in equilibrium, observed prices reflect the interaction between consumers' preferences and producers' costs of production.

Additionally, in the implicit market, each product attribute can be negotiated, and the prices are determined by the buyer's disposition to purchase the products, as well as the producer's willingness to accept the seller’s terms. Rosen (1974) concluded that the model is a powerful tool for understanding the structure of prices in markets with different products and provides important insights for both the economy and public policy.

Houses are complex goods, meaning they have many characteristics, which makes it difficult to calculate an exact price. Each unit or model of a house differs qualitatively and quantitatively, forming a specific set of multiple characteristics. Consequently, changes in these specifications alter the price. The hedonic price model measures the influence of the characteristics of the model on the price of houses, considering that a good is a package of characteristics (Paixão, 2023).

Goodman and Thibodeau (1998) played a pivotal role in advancing the hedonic price methodology, arguing that it is a crucial tool for analysing the segmentation of the housing market. The hedonic price model is founded on the premise that property prices can be broken down into various characteristics that collectively determine their value. These characteristics include internal factors, such as square footage, number of rooms, and the age of the house, as well as external factors, such as location, neighbourhood quality, and proximity to public transport or schools. The authors used a sample of housing data from the Dallas-Fort Worth metropolitan area in Texas, USA, to explore the relationship between property characteristics and prices. By applying the hedonic price model, they were able to identify groups of properties with similar characteristics that exhibited comparable pricing trends, indicating the presence of distinct submarkets.

The model, therefore, helps to understand how market segmentation takes place. For example, in some urban areas, the value of properties may increase because they are close to good schools, commercial areas, or public transport stations. Although the methodology has its limitations, Goodman and Thibodeau (1998) explain that the model assumes that all relevant characteristics are observable and measurable. One limitation is that the accuracy of the model depends on the quality of the available data and the correct specification of the econometric model.

The hedonic price model is extended to account for consumer heterogeneity, which indicates that different consumers may assign different values to certain characteristics. Bajari et al. (2005) estimated product demand in markets where consumers have heterogeneous preferences (i.e., some consumers prefer to buy a house because of its location, while others value different characteristics) and where some characteristics are not directly observable (e.g., quality, manufacturer's reputation, etc.). The authors concluded that the hedonic model is effective in estimating market demand when consumers have heterogeneous preferences and some product characteristics are unobserved, which is crucial for obtaining accurate results.

The Hedonic Price Model (HPM) has been employed to estimate economic values for ecosystem or environmental services that directly impact market prices. Kanojia et al. (2016) used a sample of residential property data from the Delhi National Capital Region (NCR) in India to examine the relationship between property prices and various environmental factors. In their model, the price reflects the characteristics of the houses (e.g., plot size, age, number of bathrooms and bedrooms) and the local environment (e.g., environmental quality, air pollution, noise, etc.). The authors make it clear that it is possible to place a value on certain characteristics, but the real aim is to focus on what people value more. The findings are summarised in Table 1.

Epple (1987) studied the hedonic price model, focusing on demand and supply in the real estate market. The author concluded that the house's characteristics influence the demand and supply functions. Consequently, depending on consumers' choices, demand for properties on the market either increases or decreases, influencing the price.

The study by Mayor et al. (2012) uses a dataset of house sales between 2001 and 2006 and incorporates Geographical Information System (GIS) data on train and tram lines in Dublin. It concludes that train stations have a positive effect on house prices, while houses near train lines have the opposite effect. The authors also found that other variables affect house prices, such as the number of rooms and bathrooms. Additionally, houses close to beaches and coastlines have a positive effect on house prices, but properties close to beaches do not have the same effect. The authors conclude that the South Zone has the most expensive houses in Dublin, and it was found that detached houses and older properties are the most sought-after.

Moro et al. (2013), in their study, were interested in finding out the impact of the distance from heritage sites on the housing market. The authors used a sample of 6,956 houses in the city of Dublin, Ireland. The study shows that the distance from historic buildings to the houses had a significant impact on house prices. Moro et al. (2013) also concluded that house prices do not increase when properties are located near the sea but when the houses are close to facilities such as public transport, parks.

Ozalp and Akinci (2017) made a valuable contribution to the field of house valuation by applying HPM. Their study aimed to identify which factors, including structural and environmental features, had the most influence on the selling price of homes. The research focused on properties in the Orta neighbourhood of Artvin, which recorded the highest number of sales in 2015. As shown in Table 1, the authors found that structural factors had a more significant impact on property prices than environmental and accessibility factors. The most influential characteristics were proximity to the city centre, distance to primary schools, floor area, and the age of the property, while the number of rooms was found to have a negative effect on prices.

Zakaria and Fatine (2021), focus their study on the Rabat region of Morocco, they used a comprehensive dataset from Morocco's official land registry from 2014, covering a total of 43,552 real estate properties located in three major urban areas of the Rabat-Temara region, Rabat Centre, Hay Riad-Agdal and Temara. The sample predominantly includes apartments, but also includes several property types such as independent houses, villas, land plots, duplexes, and buildings. This extensive and diverse sample enabled the authors to robustly analyse the determinants of property prices. They found that both the surrounding area and the location of properties have a significant influence on property prices. The authors highlight those external factors, such as the country's economic situation, affect the property market and the supply and demand within it. They also note the substantial influence of the government on the real estate market in Morocco. As shown in Table 1, the study further concludes that the size of the houses and the neighbourhood have a statistically significant impact on property prices. However, the floor level was found to have no statistically significant effect. Additionally, within a specific area, the structural characteristics of properties, such as the presence of a garage or balcony and the age of the house, also play a role in determining price.

Zilisteanu et al. (2019), with their research, reinforce the confirmation that the structural characteristics of houses (number of rooms, bathrooms, parking, balconies and comfort) have a statistically significant impact on house prices. The authors studied housing prices in Bucharest, the capital of Romania, employing a sample of 765 properties, applying a hedonic price model estimated using OLS.

Sirmans et al. (2006) utilised a sample of residential property data from various metropolitan areas across the United States to explore the relationship between property characteristics and housing prices. The study employed several specifications of the Hedonic Price Model (HPM). The authors focused on a range of structural house characteristics, including: (1) house size, (2) age of the house, (3) number of rooms, (4) number of bathrooms, (5) garage, (6) pool, (7) fireplace, (8) air conditioning, and (9) lot size. As shown in Table 1, the authors found that the age of the property had a significant negative impact on price, although this effect varied by location. In contrast, variables such as house size and the number of bathrooms had a positive and statistically significant effect on price.

Cheshire and Sheppard (1995) used a sample of residential property data from the Oxford and Milton Keynes areas in the United Kingdom. The study aimed to analyse the relationship between house prices and the value of urban amenities. The urban amenities considered in the study included the quality of schools, public transportation, proximity to parks and green spaces, area security, and more. The authors concluded that urban amenities positively influence house prices and are crucial in explaining price variation. Furthermore, they noted that land near industrial zones or polluted areas, as well as zones with high crime rates and lacking essential infrastructure (e.g., commercial establishments, hospitals, schools, etc.) or green spaces, have a negative impact on land prices. Concluding neighbourhood quality has a positive correlation with house prices.

Aziz et al. (2023) investigated the influence of nearby services on property values, employing the Hedonic Price Model (HPM) to examine how various factors—such as socioeconomics (including neighbourhood rent levels and population density), the environment (e.g., air quality, green spaces, and proximity to industrial zones), and urban structure (such as proximity to schools, parks, commercial areas, and public transportation)—affect property values. The study was conducted in the densely populated urban area of Children Park Town, located in Gujrat, Pakistan. The authors collected primary data through a questionnaire and secondary data related to property transactions. Their findings highlighted that the availability of services and the overall quality of the neighbourhood significantly influence property prices in urban areas. Moreover, they found that areas with high crime rates, proximity to industrial zones, or excessive population density tend to have a negative impact on property values.

Goodman and Thibodeau (1998) found that property location is the most significant factor in determining property values, with structural characteristics also playing an important role. Additionally, they noted that higher rents and better socioeconomic indicators contributed to the formation of a submarket for the most highly valued properties.

Bin and Polasky (2003) also conducted a study to assess the impact of environmental amenities on property values using the HPM. The sample used in their study included residential property data from the Minneapolis-St. Paul metropolitan area in the United States. The authors focused on evaluating the effects of natural disasters and examined properties before and after Hurricane Floyd. They concluded that locations prone to natural disasters face a considerable risk of property depreciation. Additionally, they noted that structural property characteristics (such as property age, number of bedrooms, number of bathrooms, property size, and lot size) positively affect prices. Socioeconomic and demographic variables (such as rent levels and population density) also have a significant impact. However, properties near airports and areas with heavy traffic tend to decrease in value, while houses near business centres increase in value.

Gyourko and Tracy (1991) identified that factors such as location, neighbourhood quality, and housing characteristics play a crucial role in determining property prices. Their analysis, which utilised data from the New York metropolitan area, revealed a strong correlation between property values and variables like proximity to employment centres, crime rates, and education levels. As demonstrated in Table 1, the researchers emphasised that improvements in neighbourhood amenities, such as enhanced safety (linked to a reduction in crime rates), have a significant positive impact on house values.

Palmquist (1984) also made significant contributions to the formulation HPM. The author used a sample of residential property data from the Twin Cities metropolitan area (Minneapolis and St. Paul) in Minnesota, USA, to explore the relationship between property prices and various environmental elements such as air quality, proximity to amenities, and other locational characteristics. According to their findings, proximity to the urban centre, well-rated schools, and larger house sizes had a positive impact on house prices. In contrast, factors such as proximity to busy roads, industrial zones, and areas with higher levels of pollution or noise had a negative effect on property values.

In Table 1 we can observe the summary of the prediction highlighted in the majority of previous research exhibited.

Table 1

A Summary of the Empirical Evidence from Studies that Employed the Hedonic Price Model

Variables Predicted	Expected Sign	Research Results
Structural Characteristics		
Type of House		
The house price increases or decreases depending on the type of house.	Positive (+) / Negative (-)	**Yes:** Mayor et al. (2012), Cheshire and Sheppard (1995), Palmquist (1984).
Usage Status		
The house price increases or decreases depending on the usage status of the house.	Positive (+) / Negative (-)	**Yes:** Mayor et al. (2012), Bin and Polasky (2003). **No:** Cheshire and Sheppard (1995), Palmquist (1984).
Number of Bedrooms		
The house price increases when the number of bedrooms increases.	Positive (+)	**Yes:** Zilisteanu et al. (2019), Mayor et al. (2012); Bin and Polasky (2003), Cheshire and Sheppard (1995), Aziz et al. (2023), Sirmans et al. (2006), Kanojia et al. (2016), Palmquist (1984). **No evidence:** Ozalp and Akinci (2017).
Number of Bathrooms		
The house price increases when the number of bathrooms increases.	Positive (+)	**Yes:** Goodman and Thibodeau (1998), Bin and Polasky (2003), Cheshire and Sheppard (1995), Sirmans et al. (2006); Palmquist (1984).
House Size		
The house price increases when the house size increases.	Positive (+)	**Yes:** Goodman and Thibodeau (1998), Zilisteanu et al. (2019), Ozalp and Akinci (2017), Bin and Polasky (2003), Paixão (2023), Cheshire and Sheppard (1995), Aziz et al. (2023), Zakaria and Fatine (2021), Sirmans et al. (2006), Kanojia et al. (2016), Palmquist (1984).
House Age		
The house price decreases over age.	Negative (-)	**Yes:** Goodman and Thibodeau (1998), Zilisteanu et al. (2019), Ozalp and Akinci (2017), Mayor et al. (2012), Bin and Polasky (2003), Paixão (2023), Sirmans et al. (2006); Kanojia et al. (2016).

Note. Continues

Table 1 (Continued)

Variables Predicted	Expected Sign	Research Results
Structural Characteristics		
Terrace / Balcony		
The house price increases when the house has a terrace or balcony.	Positive (+)	**Yes:** Zilisteanu et al. (2019); Zakaria and Fatine (2021). **No evidence:** Ozalp and Akinci (2017).
Garage or Parking		
The house price increases when the house has a garage or parking.	Positive (+)	**Yes:** Goodman and Thibodeau (1998); Zilisteanu et al. (2019); Mayor et al. (2012); Zakaria and Fatine (2021); Sirmans et al. (2006); Kanojia et al. (2016).
Electricity		
The house price increases when the rating of energy efficiency increases.	Positive (+)	**No evidence:** Ozalp and Akinci (2017).
Pool		
The house price increases when the house has a pool.	Positive (+)	**Yes:** Goodman and Thibodeau (1998); Sirmans et al. (2006).
Garden		
The house price increases when the house has a garden.	Positive (+)	**Yes:** Mayor et al. (2012).
Elevator		
The house price increases when the house has an elevator.	Positive (+)	**No evidence:** Ozalp and Akinci (2017).
Air Conditioning / Fireplace / Heating System		
The house price increases when the house has air conditioning/fireplace or a particular heating system.	Positive (+)	**Yes:** Goodman and Thibodeau (1998); Bin and Polasky (2003); Cheshire and Sheppard (1995); Sirmans et al. (2006).
Floor Levels		
The house price increases when the floor level is higher.	Positive (+)	**Yes:** Palmquist (1984). **No:** Zilisteanu et al. (2019); Zakaria and Fatine (2021).
House View		
The house price increases when the house has a particular house view (e.g., sea view)	Positive (+)	**No evidence:** Zilisteanu et al. (2019).

Note. Continues

Table 1 (Continued)

Variables Predicted	Expected Sign	Research Results
Structural Characteristics		
Special Material Construction		
The house price increases when it was constructed with a specific material or has a particular decoration.	Positive (+)	**Yes:** Zilisteanu et al. (2019); Bin and Polasky (2003); Paixão (2023); Cheshire and Sheppard (1995).
Location Characteristics		
Distance from Downtown		
The house price increases when the house is near downtown.	Positive (+)	**Yes:** Ozalp and Akinci (2017); Bin and Polasky (2003); Paixão (2023); Cheshire and Sheppard (1995). **No:** Aziz et al. (2023); Zakaria and Fatine (2021); Palmquist (1984).
Housing in a particularly District or Area		
The house price increases or depreciates when the house is in a specific zone.	Positive (+) / Negative (-)	**Yes:** Paixão (2023); Zakaria and Fatine (2021). **No:** Kanojia et al. (2016). **No evidence:** Ozalp and Akinci (2017); Bin and Polasky (2003).
Near Urban Green Space		
The house price increases when the house is near green spaces.	Positive (+)	**Yes:** Zilisteanu et al. (2019); Mayor et al. (2012); Aziz et al. (2023); Palmquist, (1984).
Near the Sea / River / Lake		
The house price increases when the house is near the sea, lake or river.	Positive (+)	**Yes:** Mayor et al. (2012). **No:** Moro et al. (2013).
Neighbourhood Characteristics		
Crime Rate		
The house price increases when the neighbourhood safety increases.	Positive (+)	**Yes:** Gyourko and Tracy (1991); Kanojia et al. (2016).

Note. Continues

Table 1 (Continued)

Variables Predicted	Expected Sign	Research Results
Neighbourhood Characteristics		
Neighbourhood quality The house price increases when the quality of the neighbourhood increases.	Positive (+)	**Yes:** Gyourko and Tracy (1991); Cheshire and Sheppard (1995); Aziz et al. (2023); Palmquist (1984).
Near Public Transport Stations The house price increases when the house is near public transport stations.	Positive (+)	**Yes:** Mayor et al. (2012). **No evidence:** Zilisteanu et al. (2019).
Near Public Services (Bank, Hospital, Schools, Post-Offices, University, etc) The house price increases when the house is near public services.	Positive (+)	**Yes:** Goodman and Thibodeau (1998); Ozalp and Akinci (2017); Moro et al. (2013); Gyourko and Tracy (1991); Kanojia et al. (2016). **No evidence:** Zilisteanu et al. (2019); Bin and Polasky (2003); Aziz et al. (2023).

Note. The table provides a concise summary of all the studies discussed in the literature review. These studies examine multiple factors influencing property prices, including structural house characteristics, location attributes, and neighbourhood features that affect property values. Furthermore, the table explains the impact of various variables on house prices and presents the findings of different studies. It indicates whether the predicted effect of each variable was positive (+) or negative (-) on house prices. Additionally, it shows whether the studies found that a particular variable influenced house prices ("Yes"), concluded the opposite ("No"), or found insufficient evidence to determine its effect ("No Evidence").

Despite the importance of the findings from previous research, Freeman's (1979) considerations should also be taken into account. Without focusing on a specific dataset or geographic region, the author explained that the hedonic price model can be used to estimate the monetary value associated with various environmental attributes (e.g., improving air quality can lead to a significant increase in property prices). The study discusses the theoretical framework and emphasises that the accuracy of the results depends on the quality and availability of data, the correct specification of econometric models, the careful selection of variables, and, most importantly, addressing the potential multicollinearity between attributes and property heterogeneity.

2.4.Hedonic Price Model Functional Form

After thoroughly reviewing existing frameworks related to HPM, it is evident that the model can be implemented in several different forms, including linear, semi-logarithmic, quadratic, double logarithmic, and cubic. These variations have been tested and applied in previous research. For the empirical analysis in this study, the focus will be on the linear, semi-logarithmic, and double-logarithmic models.

Goodman and Thibodeau (1998) examined house prices using a semi-logarithmic hedonic pricing model, highlighting several advantages of this approach. These include: (1) the ability to interpret coefficients as percentage changes in the dependent variable, (2) the handling of skewed data, which helps make the data more normally distributed, (3) its capacity to capture non-linear relationships by addressing diminishing or increasing marginal effects, and (4) providing efficient estimation.

According to Ozalp and Akinci (2017), the semi-logarithmic model helps mitigate issues like heteroscedasticity, where error terms have non-constant variances. This model is particularly useful in explaining how small changes in the explanatory variable lead to proportional changes in prices. Additionally, it is commonly used when the dependent variable covers a broad range of values, as it simplifies the analysis of non-linear relationships.

Moro et al. (2013) tested various forms of HPM. While they utilised the semi-logarithmic model in their study and discussed the double-log form, they noted that the coefficients of the independent variables could be interpreted as elasticities, meaning percentage changes in the explanatory variables correspond to changes in house prices. The double-log model, according to their analysis, is particularly useful when variables are measured on different scales.

Similarly, Ozalp and Akinci (2017) highlighted that the double-log model is especially advantageous when the relationships between the dependent and independent variables are expected to be multiplicative rather than additive. This model is more effective than the semi-log in addressing skewed data and, in some cases, provides a more accurate interpretation of elasticity.

Epple (1987) and Kanojia et al. (2016) discuss the linear form of the HPM as the most straightforward approach, offering direct interpretation and helping to understand the relationships between variables. The coefficients in this model represent the marginal impact of each characteristic on price. Epple (1987) also highlights the usefulness of linear models in addressing identification issues and enhancing the ability to predict property prices by considering a variety of factors, including (1) location characteristics, (2) structural characteristics, and (3) environmental characteristics.

2.5. The Use of Quantile Regression-Based Models for House Pricing

Koenker and Bassett (1978) introduced the Quantile Regression (QR) model, extending the concept of quantiles from univariate analysis to regression settings. This approach offers a more robust method of statistical estimation, particularly when dealing with heteroscedasticity or outliers. While classical linear regression estimates the conditional mean of the dependent variable based on independent variables, it is sensitive to outliers and does not account for the behaviour of the distribution's tails, such as the lower or upper extremes.

In contrast, quantile regression allows for the estimation of various conditional quantiles of the dependent variable, such as the median or the 10th and 90th percentiles. This enables the analysis of the full distribution of the dependent variable in relation to the independent variables, rather than focusing solely on the mean. For instance, the 0.5 quantile represents the median regression, which minimises the sum of absolute deviations and is less sensitive to outliers than traditional least squares estimation.

Further, Koenker and Bassett (1978) demonstrated a practical application of quantile regression to model salary data. The authors showed how different quantiles of salary distributions could be estimated as functions of covariates, providing insights into wage dispersion and inequality that cannot be captured by mean regression alone.

Koenker and Bassett (1978) argued that quantile regression provided more robust estimators than ordinary least squares (OLS) in the presence of outliers. Since quantile regression minimises a weighted sum of absolute residuals rather than squared residuals, it is less influenced by extreme values. Additionally, its ability to model heteroscedasticity, where the variability of the dependent variable differs across the range of independent variables, is an advantage. Unlike OLS, which assumes constant variance, quantile regression can estimate the conditional distribution at various points, allowing for a more nuanced understanding of the data's spread.

Quantile regression is a generalisation of classical linear regression, which focuses on modelling the conditional mean of the data. Although linear regression refers to the conditional mean E(Y|X), regression quantiles focus on modelling the conditional quantiles of the outcome variable Y given the vector of explanatory variables X. This model allows the study of different parts of the conditional distribution of Y, such as the median (quantile 0.50) or other quantiles (e.g. 0.25 or 0.90). Yu and Moyeed (2001) explained that the regression quantile for the p-th quantile of the outcome variable Y is a linear function of the covariates X. The p-th quantile, the regression quantile problem, can be formulated as follows:

$$q_p(Y \mid X) = X'\beta(p) \tag{2.1}$$

where $\beta(p)$ is a vector of specific coefficients for the quantile p.

The central problem of quantile regression is to solve the following minimisation:

$$\min t\sum \rho_p(Y_t - X_t'\beta) \tag{2.2}$$

where $\rho_p(u)$ is the function of quantile loss defined by:

$$\rho_p(u) = u\big(p - I(u < 0)\big) \tag{2.3}$$

The loss function differs from the quadratic loss function used in traditional linear regression, resulting in more accurate results with outliers, especially when researchers focus on extreme quantiles.

Zietz et al. (2008) use data consisting of 1,366 home sales from mid-1999 to mid-2000 in the Orem/Provo, Utah area. The authors argue that the quantile regression model offers a better understanding of how the effects of housing characteristics vary across the price distribution, which traditional OLS regression may not accurately capture. Additionally, the model accounts for spatial autocorrelation, a phenomenon where houses tend to have similar prices. The regression quantile minimises the absolute differences of the weighted sum between observed and predicted values, enabling the modulation of the median or other distribution quantiles instead of the mean, as in OLS regression. According to Zietz et al. (2008), quantile regression provides a more complete and accurate picture of consumer preferences.

In brief, the authors concluded that characteristics, such as house square footage and the number of bathrooms, significantly impact higher-priced houses more than lower-priced ones. The buyers of higher-valued houses look for more of these characteristics. Also, the model minimises a sum of asymmetrically weighted absolute residuals for quantiles other than the median. This weighting allows the model to focus on different parts of the distribution.

Koenker and Hallock (2001) developed a traditional linear regression to explain how quantile regression works but focused on the estimation of conditional quantiles, studying the results of the variables instead of the mean. The paper discusses the advantages of quantile regression, especially in situations where the data exhibits heteroscedasticity, outliers, or non-normality.

Koenker and Hallock (2001) conducted an empirical case comparing the CEO's salary to the company size. One notable example they use is wage data from EXECCOMP (1999), which provides a rich dataset for illustrating how quantile regression can be applied to study income distributions and the effects of covariates.

Instead of modelling the mean salary, the authors estimated the wage distribution across different quantiles, allowing them to capture variations in the distribution that a simple mean regression might miss. As a result, it was observed that the dispersion of CEO salaries tends to increase with firm size, especially in the tails of the distribution. The authors argued that quantile regression problems are solved using linear programming techniques. The model minimises the weighted sum of residuals, where the weight corresponds to the estimated quantile.

Linear programming makes estimation efficient even for large datasets. Additionally, by estimating different quantiles, the model provides a comprehensive understanding of the distribution of the corresponding variable, not just the centre (mean or median). The model can reveal how the relationships between covariates and the response variable differ across various points in the distribution. For example, a covariate's effect on lower-income households may differ significantly from its impact on higher-income households.

Hassan (2018) employed ANN and QR models to analyse residential properties sold in Dublin between 2010 and 2018. The study explored the relationship between house prices and proximity to primary schools, finding a positive correlation. It also considered structural features such as the number of rooms and bathrooms, reaching similar conclusions regarding their effect on property prices.

Akay and Eban (2011) analysed the factors influencing house prices in Istanbul using a quantile regression approach, based on a sample of 992 residential property transactions that took place in Istanbul, Turkey, between 2006 and 2007. The authors argued that this method is robust to heteroscedasticity and outliers. Furthermore, they employed the hedonic price model to investigate how various characteristics of a house—such as the number of rooms, bathrooms, heating systems, and location—affect its price. Unlike traditional regression models, which focus on dependent variables, quantile regression enables a more detailed analysis by estimating the effects of covariates across the entire distribution of house prices.

Akay and Eban (2011) in their research found that structural house characteristics, such as the number of rooms, larger kitchens, houses with garages, heating systems, cable TV, and others, increase house prices. Contrary to other studies, this research found that the age of the properties positively affects property prices in Istanbul. Additionally, the study highlights the characteristics that influence house prices, which can vary significantly depending on the city, region, and country.

Kim, Hung, and Park (2015) use property transaction data of condominium units from Taikoo Shing, one of the largest real estate properties in Hong Kong. The authors argue that the relationship between housing prices and their characteristics is nonlinear and varies across different quantiles of the price distribution. One example is that the impact of the size of the gross area is more pronounced for the higher quantiles (i.e., expensive properties). Furthermore, different housing characteristics, such as floor level, age, sea view, and proximity to transport services and shopping centres, affect housing prices differently across the price spectrum. The analysis also suggests that the housing market for high-priced units in specific zones is tighter than for lower-priced units, indicating higher demand for housing in the higher-price segments. The empirical results show that using a simple linear model is insufficient to capture the heterogeneous behaviour of housing prices, which vary significantly across different price levels.

Amédée-Manesme et al. (2017) focused on understanding the complexities of the apartment market in Paris, employing a quantile regression approach. The authors noted that the Paris apartment market is highly heterogeneous, with apartments differing in characteristics such as price, size, location, and more. Traditional hedonic models assume homogeneity across the market, which may not be realistic in settings like Paris. The study used quantile regression to examine how housing price attributes vary across different market segments. Unlike traditional methods, the quantile regression approach allows for the analysis of price variations within specific market segments, providing a more accurate understanding.

Amédée-Manesme et al. (2017) analysed approximately 156,000 transactions from 2000 to 2006. The key variables included apartment structural characteristics (e.g., size, floor level, number of rooms, construction period) and neighbourhood characteristics. Essentially, the research concluded that the price elasticity of apartment size decreases as the unit price increases. As a result, a 10% increase in size leads to a more significant percentage increase in the price of cheaper apartments than in more expensive ones. Additionally, lower-priced apartments tend to appreciate more rapidly over time than higher-priced ones, indicating a catch-up effect in more affordable neighbourhoods. Furthermore, attributes such as the presence of a parking space, floor level, and construction period have varying impacts on price across different market segments. For example, higher floors are generally associated with higher prices, but the premium decreases for more expensive apartments.

McCord et al. (2020) investigated the relationship between Energy Performance Certification (EPC) and property prices, focusing on the Belfast housing market. The study used a sample of 1,478 residential property transactions in Belfast, Northern Ireland, between 2018 and 2019. The EPC system is designed to assess the energy efficiency of a building and influence future investments in energy improvements, with ratings ranging from A (most energy-efficient) to G (least energy-efficient). However, the study analysed only properties rated from B to G. A quantile regression model was used to estimate how EPC ratings affect house prices across the price spectrum. The results showed that higher EPC ratings are associated with price premiums in the upper quantiles, while properties with lower EPC ratings experienced a negative impact on prices due to their lower environmental performance.

Evangelista et al. (2022) investigated the impact of energy efficiency levels on house prices in the Portuguese real estate market. The study used a sample of over 256,000 residential property transactions in Portugal, covering the period from 2009 to 2013. The authors found that the effect of EPC levels on house prices varied significantly, depending on the property type. The positive influence of energy efficiency was more pronounced for lower-priced apartments, while it had a greater impact on higher-valued homes. Additionally, the authors explored the effects of the economic crisis, revealing that high-priced properties were more resilient to external economic shocks than low-priced ones.

Zhang and Yi (2017) analysed the house prices in Beijing, the study focused on the prices between 2013 and 2015. The author used quantile regression to estimate the determinants of house prices. In this research, the model follows below:

$$\mathrm{p}_{\tau} = \alpha_{\tau} + \beta_{\tau}\mathrm{U} + \gamma_{\tau}\mathrm{C} + \phi_{\tau}\mathrm{G} + \delta_{\tau}\mathrm{M} + \epsilon_{\tau} \quad (2.4)$$

where:

- p_{τ}: house prices at a given quantile τ.
- *U:* Vector of unit-level attributes (e.g., number of bedrooms, size of the living area).
- *C:* Vector of complex-level characteristics (e.g., greening rate, lake view).
- *G:* Geographic attributes (e.g., proximity to subway stations, parks).
- *M:* Monthly dummy variables capturing temporal patterns.
- ϵ_{τ}: Error term.

The model was estimated also by Kim, Park et al. (2015) across multiple quantiles (e.g., 0.1, 0.2, ..., 0.9) to examine how various determinants of house prices affect different points in the price distribution. The results reveal significant variation in the influence of housing attributes across different quantiles of house prices. Specifically, the number of bedrooms and living rooms had a greater impact on lower-priced homes than on higher-priced ones. In contrast, higher-priced houses tended to benefit more from larger living areas and higher greening rates.

It is also noted that higher floor areas had a negative effect on higher-priced homes but a positive effect on lower-priced homes. The authors included the proximity to subway stations in the model, finding it to be more valuable for lower-priced homes. In contrast, proximity to parks and ring roads contributed significantly to house price appreciation across all price levels, although the impact of ring roads slightly diminished for higher-priced homes. Lower-priced properties benefited more from specific unit-level characteristics, such as the number of bedrooms and proximity to subways (Kim, Park et al., 2015).

At the same time, higher-priced homes experience a greater benefit from greening rates and overall living areas. The findings suggest that policymakers should take into account the heterogeneity in house price dynamics across the price distribution. A one-size-fits-all policy may prove ineffective, as the factors influencing house prices vary across price levels. For example, enhancing public amenities such as parks and subways may be more beneficial to lower-income households, while higher-income households may place greater value on environmental quality and larger living spaces (Kim, Park et al., 2015).

Zhang and Yi (2017) examined the impact of house characteristics, such as the number of bedrooms, living area size, and proximity to green spaces, on variations in house prices. The study focused on the Beijing housing market, explaining the observed variations as “quantile effects.” As a result, lower-priced homes (at lower quantiles) tend to place more value on characteristics like the number of bedrooms and living rooms. In contrast, higher-priced homes (at higher quantiles) prioritise larger living areas and environmental factors such as green spaces.

The authors explained that buyers in various price segments prioritise different housing attributes, highlighting the segmentation of the housing market based on buyers' preferences. As a result, lower-priced homes are more sensitive to market dynamics, experiencing faster appreciation rates during booms and steeper declines during downturns. In contrast, higher-priced homes show greater stability, with smaller fluctuations in both upward and downward directions.

Mathur (2020) used a dataset that included sales transactions of single-family homes from January 2000 to April 2018, located within eight kilometres (five miles) of the Warm Springs station of the San Francisco Bay Area Rapid Transit (BART) system. The study employed quantile regression, enabling an analysis of how the proximity to train stations influences house prices across the entire price spectrum, rather than focusing solely on average-priced homes. This approach contrasts with traditional OLS regression, which is often used in previous studies and mainly examines the conditional mean of house prices. However, OLS does not account for how the impact of specific factors might vary across different segments of the housing market.

By applying quantile regression, Mathur (2020) was able to estimate the effect of being near the Warm Springs BART station on house prices at various price points, offering a more nuanced understanding of the relationship between transit stations and housing prices. His findings revealed that the proximity to the train station had a greater impact on lower-priced homes compared to higher-priced ones.

McMillen (2008) explored house prices in Chicago. The study focused on the entire distribution of house prices rather than just the mean or median price trends. The author used hedonic price quantiles, which measured how different variables explained several points of the house price distribution.

McMillen (2008) research divided the distribution changes into two parts: variations due to explanatory variables and changes resulting from the regression coefficients over time. This paper found that, over time, high-priced houses were valued more highly than low-priced properties. As a result, the disparity of house prices increased at the top of the distribution. In previous studies, price increases were attributed to location or house characteristics (e.g., number of rooms or square metres). However, the variations in the coefficients on hedonic functions had a more significant impact on the prices. Indeed, buyers' preferences for specific characteristics changed over time. For example, the effect of a larger house or one in a particular location had more influence in 1995 than in 2005 due to the increased price of properties that were valued more highly.

Gao and Asami (2001) concluded that green spaces have a greater impact on smaller houses. Furthermore, their research empirically demonstrated that sunlight has a positive effect on property prices. In addition, other factors influencing house prices include the quality of the apartments and neighbourhood conditions, such as the quality and width of the roads. The author analysed 190 land lots with detached houses located in Tokyo, Japan.

In Table 2 we can observe the summary of the prediction highlighted in the majority of previous research exhibited.

Table 2

A Summary of the Empirical Evidence from Studies that Employed the Quantile Regression

Variables Predicted	Expected Sign	Research Results
House Price		
Structural Characteristics		
Type of House		
The house price increases or decreases depending on the type of house.	Positive (+) / Negative (-)	**Yes:** McCord et al. (2020); Amédée-Manesme et al. (2017).
Number of Bedrooms		
The house price increases when the number of bedrooms increases.	Positive (+)	**Yes:** Akay and Eban (2011); Evangelista et al. (2022); McMillen (2008); Zhang et al. (2017). **No evidence:** Zietz et al. (2008); Mathur (2020).
Number of Bathrooms		
The house price increases when the number of bathrooms increases.	Positive (+)	**Yes:** Zietz et al. (2008); McMillen (2008). **No:** Akay and Eban (2011); Mathur (2020).
House Size		
The house price increases when the house size increases.	Positive (+)	**Yes:** Zietz et al. (2008); Akay and Eban, (2011); Kim, Park et al. (2015); McMillen (2008); Kim, Hung et al. (2015); Gao and Asami (2001); Evangelista et al. (2022); Mathur (2020); Zhang et al. (2017); Amédée-Manesme et al. (2017).
House Age		
The house price increases when the age increase	Negative (-)	**Yes:** Zietz et al. (2008); Akay and Eban (2011); McMillen (2008); Kim, Park et al. (2015); Gao and Asami (2001); Evangelista et al. (2022); Mathur (2020). **No:** McCord et al. (2020).
Terrace		
The house price increases when the house has a terrace.	Positive (+)	**Yes:** Kim, Hung et al. (2015). **No evidence:** Zietz et al. (2008).

Note. Continues

Table 2 (Continued)

Variables Predicted	Expected Sign	Research Results
House Price		
Structural Characteristics		
Garage or Parking		
The house price increases when the house has a garage or parking.	Positive (+)	**Yes:** Zietz et al. (2008); Akay and Eban, (2011); McMillen (2008); Gao and Asami (2001); Amédée-Manesme et al. (2017).
Electricity		
The house price increases when the level of electricity increases or is controversial.	Positive (+) / Negative (-)	**Yes:** Evangelista et al. (2022); McCord et al. (2020).
Pool		
The house price increases when the house has a pool.	Positive (+)	**Yes:** Zietz et al. (2008). **No:** Kim, Hung, Park (2015).
Garden		
The house price increases when the house has a garden.	Positive (+)	**Yes:** Amédée-Manesme et al. (2017).
Elevator		
The house price increases when the house has an elevator.	Positive (+)	**No evidence:** Amédée-Manesme et al. (2017).
Air Conditioning / Heating System / Fireplace		
The house price increaseswhen the house has air conditioning, a heating system or a fireplace.	Positive (+)	**Yes:** Akay and Eban (2011); McCord et al. (2020). **No evidence:** Zietz et al. (2008); McMillen (2008).
Floor Levels		
The house price increases when the floor level is higher or controversial.	Positive (+) / Negative (-)	**Yes:** Kim, Hung et al. (2015); Kim, Park et al. (2015). **No:** Zhang et al. (2017).
House View		
The house price increases when a house has a particular view (e.g., sea view)	Positive (+)	**Yes:** Zietz et al. (2008); Kim, Hung et al. (2015); Kim, Park et al. (2015). **No:** Zhang et al. (2017). **No evidence:** Amédée-Manesme et al. (2017).

Note. Continues

Table 2 (Continued)

Variables Predicted	Expected Sign	Research Results
	House Price	
	Structural Characteristics	
Special Construction		
The house price increases when it has constructed with a specific material or has a specific decoration.	Positive (+)	**Yes:** Zietz et al. (2008); McMillen (2008); McCord et al. (2020); Amédée-Manesme et al. (2017).
	Location Characteristics	
Distance from Downtown		
The house price increases when the house is near downtown.	Positive (+)	**No:** Zietz et al. (2008).
Housing in a particular District or Area		
The house price increases when the house is in a specific zone.	Positive (+) / Negative (-)	**Yes:** Akay and Eban (2011); Kim, Park et al. (2015); Evangelista et al. (2022); Amédée-Manesme et al. (2017).
Near Urban Green Space		
The house price increases when the house is near green spaces.	Positive (+)	**Yes:** Gao and Asami (2001); Zhang et al. (2017). **No evidence:** Mathur (2020).
	Neighbourhood Characteristics	
Neighbourhood quality		
The house price increases when the quality of the neighbourhood increases.	Positive (+)	**Yes:** Zietz et al. (2008).
Near Public Transport Stations		
The house price increases when the house is near public transport stations.	Positive (+)	**Yes:** Kim, Hung, Park (2015); Zhang et al. (2017). **No:** Kim, Park et al. (2015); Gao and Asami (2001).

Note: (Continues)

Table 2 (Continued)

Near Public Services and Facilities		
House prices tend to increase when the property is located near public services and facilities, such as hospitals, police stations, shopping malls, supermarkets, and so on.	Positive (+)	**Yes:** Zietz et al. (2008); Kim, Hung and Park (2015); Kim, Park et al. (2015); Mathur (2020).

Note. The table provides a concise summary of all the studies discussed in the literature review. These studies examine multiple factors influencing property prices, including structural house characteristics, location attributes, and neighbourhood features that affect property values. Furthermore, the table explains the impact of various variables on house prices and presents the findings of different studies. It indicates whether the predicted effect of each variable was positive (+) or negative (-) on house prices. Additionally, it shows whether the studies found that a particular variable influenced house prices ("Yes"), concluded the opposite ("No"), or found insufficient evidence to determine its effect ("No Evidence").

2.6.Problems Associated with the Quantile Regression Method

Evaluating the influence of house characteristics on prices is not a uniform process. The QR model was chosen for its ability to handle such analysis, although, like all methods, it has its limitations and challenges.

Zietz et al. (2008) explained that in every regression model, the results depend on the variables included in the correct specification. The results can be skewed or improved if essential variables are omitted or poorly specified, which could lead to biased estimates.

Zietz et al. (2008), Kim, Park et al. (2015), and Akay and Eban (2011) observed that one of the advantages of using the QR method is its ability to analyse how the impact of different housing attributes varies across the distribution of house prices (i.e., examining the different quantiles). However, the results vary significantly between lower and higher quantiles, making it more complex to provide a general interpretation. A variable that strongly influences prices at lower quantiles might have a weaker or opposite effect at higher quantiles, complicating the overall understanding of the housing market.

Additionally, the QR model has considerable computational complexity; in large datasets, it is challenging to analyse the results as being evident and direct. As Kim, Hung and Park (2015) argued in their research, the QR model can be inefficient in possible spatial correlations, an essential characteristic in the housing market (i.e., the location of the house can impact its price).

McMillen (2008) concluded that, besides the model that uses community area fixed effects to control neighbourhood characteristics, the analysis shows that neighbourhood fixed effects had relatively little impact on changes in house prices across the distribution. This suggests that the model may not fully capture neighbourhood-specific factors, and the impact of location on house prices might be understated.

Akay and Eban (2011) analysed the housing market in Istanbul. They explained that the city is unique because it spans two continents (i.e., one part in Asia and the other in Europe), which significantly impacts house prices. Furthermore, the authors acknowledge that while their model captures this specific factor for Istanbul, the generalisation of the model to other cities or regions with different characteristics could be limited.

Kim, Hung, and Park (2015) also argued that while QR captures the heterogeneity of housing prices across different quantiles, it does not fully account for the complexity of non-linear relationships between prices and house attributes. Another limitation, as noted by Koenker and Hallock (2001), is multicollinearity among independent variables (i.e., high correlation between covariates), which can inflate standard errors and lead to unreliable estimates, particularly in small sample sizes. This issue affects not only OLS but also QR.

2.7.Conclusion of the Section

This literature review has provided a comprehensive examination of existing studies that applied HPM and QR methods, focusing on the housing market. The review highlights key factors influencing house prices, including locational and property-specific characteristics, and underscores the potential of QR to capture heterogeneity across different segments of the housing market. It also identifies gaps and limitations in prior research that used other methodologies, establishing a clear foundation for the present study in selecting the appropriate methods.

The findings suggest that investigating the determinants of price variation in the Dublin housing market using a QR approach is feasible, as this method offers unique insights into price dynamics across various market conditions. The next chapter will detail the methodology employed in this study, outlining the data sources, variables, and analytical framework used to explore these relationships comprehensively.

3. METHODOLOGY

This section presents the methodology and data utilised in this research. It offers a comprehensive overview of all variables incorporated in the HPM, along with the three variations of the model that were tested. Furthermore, it details the procedures followed in the subsequent section and the tests conducted to ensure the research produced the most accurate results.

3.1. Sample Selection

Gathering data is a crucial step in conducting this empirical study. However, obtaining comprehensive information on house prices in Dublin presents a challenge. Significant efforts were made to collect as much relevant data as possible regarding residential properties and their key characteristics.

The initial dataset was sourced from the Property Price Register (PPR) website, which records all property transactions in Ireland. Transactions from 11 July 2023 to 31 December 2023 within Dublin County were selected, resulting in a total sample of 10,000 transactions. This database included information on transaction prices, property addresses, and whether the house was newly built or second-hand.

To enhance the dataset, additional variables were created to provide more comprehensive insights. Structural property characteristics were extracted from the MyHome.ie website, allowing for the inclusion of the following variables:

- *SIZE* – the size of the house in square metres.
- *BED* – the number of bedrooms in the house.
- *BATH* – the number of bathrooms in the house.
- *GDT* – whether the house has a terrace or garden.
- *CAR* – whether the house has parking space or a garage.
- *USTAT* – the condition of the house, classified into different levels of usage status.
- *BER* – the Building Energy Rating of the property.

Additionally, locational variables were generated based on the district in which each house was located. These include:

- *SEA* – whether the house is near the sea.

- *GRN* – whether the house is close to one of Dublin's 46 main parks and green spaces.
- *DWTN* – whether the house is located in the city centre.

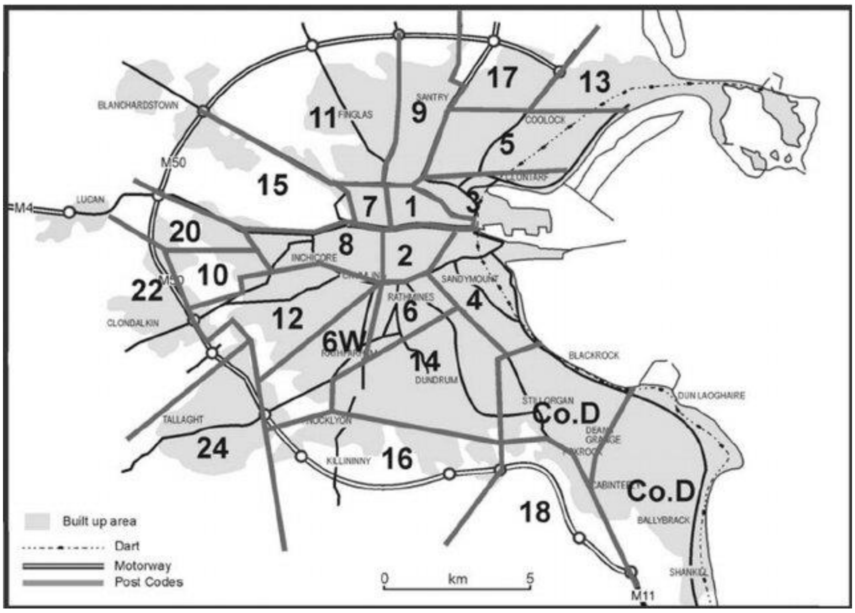
These enhancements ensured a richer dataset, allowing for a more detailed analysis of the factors influencing property prices in Dublin.

As a result, the final dataset comprises information on 5,091 houses. Due to incomplete data for some transactions from the Property Price Register (PPR) website, it was not possible to include all original records in the dataset. Additionally, duplicate transactions were identified and removed to ensure data accuracy.

Dublin City is divided into various districts, as shown in Figure 1. The sample includes houses from these districts, including areas in the north of Dublin and the Lucan region, with the postcode K78, which has recently been incorporated into the Dublin metropolitan area (List of Dublin Postal Districts, 2024).

Figure 1

Districts in Dublin

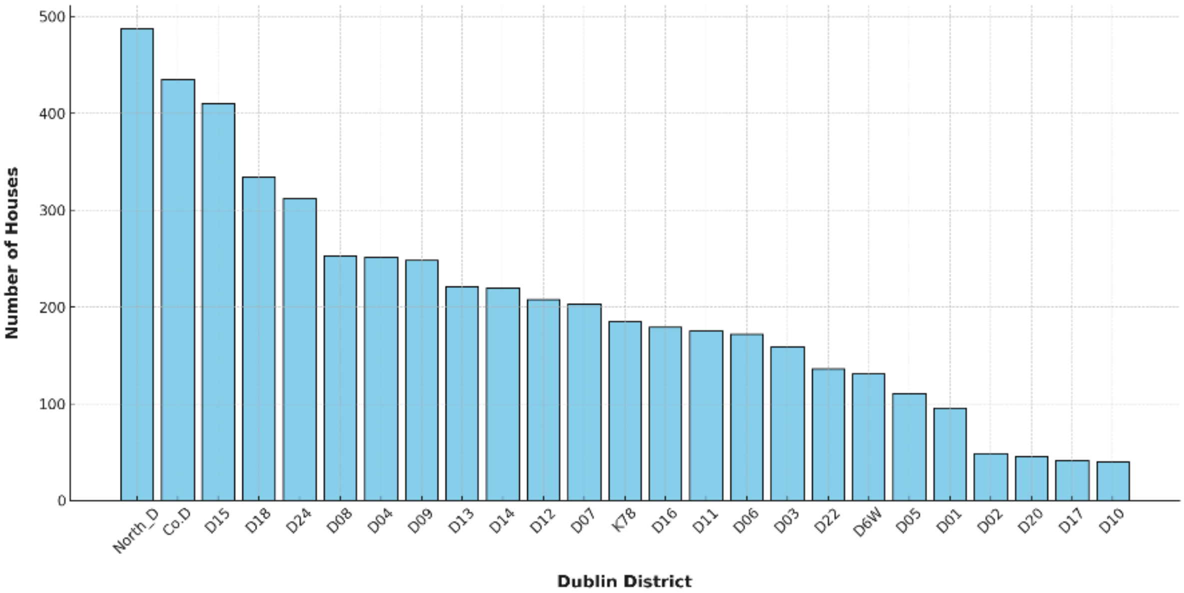


Note. The figure represents a map of the Dublin City metropolitan area, showing the various districts of the city. It was sourced from the research conducted by Ghahramani et al. (2021).

Figure 2 illustrates the number of houses per district in the study sample. It is evident that the areas with the highest number of houses in Dublin are located in the north (North_D), as well as parts of the city encompassing Killiney, Dalkey, and Dun Laoghaire (Co. D), and district 15 (D15). In contrast, district 10 (D10) contains only 40 houses in the sample, primarily due to its smaller size and the relatively low number of transactions in that area.

Figure 2

Distribution of Houses Across Districts



Note. The figure was created using R Studio. The districts are represented by abbreviations, which are detailed in Table 3.

The variable Region groups the various districts into zones of the city. This variable was created to address multicollinearity with other variables and to provide clearer results. Table 3 summarises the composition of the Region variable. The region with the highest number of houses is in the western districts, accounting for 24% of the Dublin districts.

Table 3

Region Variable Summary

Region	Districts	N	%
North Districts	D9, D5, D17, D13	4	16%
North of Dublin	North_D	1	4%
North Central Districts	D1, D7, D3	3	12%
South Districts	D12, D24, D16, D6W, D6	5	20%
South Central Districts	D4, D2, D8	3	12%
East Districts	Co. Dublin, D14, D18	3	12%
West Districts	D11, D15, D22, D10, D20, K78	6	24%

Note. This table summarises the Region variables, illustrating how the different districts were grouped. It also shows the number of districts included in each region of Dublin, along with their corresponding percentages relative to the total number of districts analysed.

3.2. Empirical Model Specification

The literature review section explains several characteristics that influence house prices. These characteristics are grouped according to different aspects: structural characteristics, location and neighbourhood attributes. They were selected based on the works of Aziz et al. (2023), Evangelista et al. (2022), Mathur (2020), Mayor et al. (2012), McMillen (2008), Ozalp and Akinci (2017), Paixão (2023), Zakaria and Fatine (2021), and Zilisteanu et al. (2019).

The equation below represents the HPM used in the research by Zietz et al. (2008) and outlines the different groups of characteristics that influence house prices.

$$P_i = f\ (H_i, L_i, N_i) \tag{3.1}$$

Table 4

Characterisation of Hedonic Price Formula

Symbols	House Characteristics	Explanation
P	House Prices	Transaction value of properties.
H	Structural	Each structural characteristic of the properties, that is, their physical attributes.

Note: Continues

Table 4 (Continued)

L	Locational	The variables associated with the house's location (e.g., district, area).
N	Neighbourhood	All the variables related to and attributes of the neighbourhood (e.g., crime, near facilities).

Note. This table displays the groups of variables included in the hedonic price formula used in this study.

3.2.1. General HPM Model

In this research, the HPM will be used to investigate how various property characteristics influence house prices. The model will break down house prices into their contributing factors, providing a comprehensive understanding of how individual attributes impact the overall price. As previously discussed, hedonic price models offer a well-established framework for capturing the influence of different property attributes in the study of house prices.

Moreover, QR is a robust statistical technique that provides a nuanced approach to understanding the relationship between house prices and their attributes by analysing various points of the conditional distribution of the dependent variable, as demonstrated in prior research (e.g., Evangelista et al., 2022; Koenker & Hallock, 2001; McCord et al., 2020; Zietz et al., 2008).

As noted by Mathur (2020), OLS models fail to capture the variability and heterogeneity across the distribution of house prices. QR overcomes this limitation by estimating relationships at specific quantiles of the price distribution, providing a more comprehensive view of the underlying dynamics.

In this research, we use QR to analyse relationships across five quantiles: 0.10, 0.25, 0.50, 0.75, and 0.90. These quantiles represent different segments of the housing market. The lower quantiles, 0.10 and 0.25, correspond to low-priced houses, which are typically more affordable properties characterized by smaller sizes, less desirable locations, or fewer amenities. Analysing these quantiles helps to understand the factors influencing the prices of the least expensive properties. The median quantile, 0.50, represents the central tendency of the housing market and reflects attributes associated with mid-range properties. Lastly, the upper quantiles, 0.75 and 0.90, represent higher-priced properties, often linked to premium features, prime locations, and larger sizes (Kim, Park et al., 2015; Zhang & Yi, 2017).

3.2.2. Variable Definition

3.2.2.1 Dependent Variable

According to previous studies by Kim, Park et al. (2015), Koenker and Hallock (2001), Akay and Eban (2011), and Moro et al. (2013), the price of properties sold is the dependent variable and serves as the primary variable in the model. This variable was obtained from the Irish Property Price Register (PPR) website.

3.2.2.2 Independent Variables

The independent variables, or hedonic variables, explain the variations in the dependent variable and are sourced from the Irish Property Price Register (PPR) website and the MyHome.ie website. Our purpose is to analyse the impact of the hedonic variables on house value and price variation, with the variables being selected based on previous studies, as evidenced in Table 5.

Table 5

Description of the Selected Hedonic Variables

Variable	Definition	Description	Reference support	Expected effect on price
Structural Characteristics				
SIZE	Size	The floor area of the house in square meters.	Mathur (2020)	Positive (+)
BED	Number of bedrooms	The number of bedrooms in the house.	Evangelista et al. (2022)	Positive (+)
BATH	Number of bathrooms	The number of bathrooms in the house.	McMillen (2008)	Positive (+)
USTAT	Usage status	Property's interior condition or state of maintenance. The variable includes five dummy variables related with usage status: new, old, renovated, semi-new, to recover, and used.	Mayor et al. (2012)	Positive (+) / Negative (-)
BER	BER code	Energy efficiency rating. The variable includes seven dummy variables related to energy efficiency rating: rating A, B, C, D, E, F, G, and property exempt.	Ozalp and Akinci (2017)	Positive (+) / Negative (-)
TH	Type of house	Classification of a house by structure. The variable includes four dummy variables: apartment, semi-detached house, detached house, end-of-terrace house, and terrace house.	McCord et al. (2020)	Positive (+) / Negative (-)

Note: (Continues)

Table 5: (Continued)

GDT	Garden or terrace	A dummy variable that takes the value of 1 if the house has a garden or terrace, and 0 otherwise.	Mayor et al. (2012)	Positive (+)
CAR	Parking or garage	A dummy variable that takes the value of 1 if the house has a parking of garage, and 0 otherwise.	Zilisteanu et al. (2019)	Positive (+)
Locational Attributes				
DWTN	Districts in downtown	Dummy variable taking the value 1 if the house is in Dublin city centre and 0 otherwise.	Paixão (2023)	Positive (+)
REGION	Region of Dublin	The districts are group by regions (see Table 3). The variable includes six dummy variables.	Zakaria and Fatine (2021)	Positive (+) / Negative (-)
Neighbourhood Attributes				
GRN	Green spaces	Dummy variable taking the value 1 if the house near green spaces and 0 otherwise.	Aziz et al. (2023)	Positive (+)
SEA	Near sea	Dummy variable taking the value 1 if the house near the sea and 0 otherwise.	Mayor et al. (2012)	Positive (+)

Note. The table presents a summary of the variables included in the hedonic price model, along with their descriptions, explaining how each was measured. Additionally, it references the authors who support the selection of each variable and the expected effect of the independent variables on price. Some variables are expected to have both types of effects due to the inclusion of multiple dummy variables.

The research focuses on examining the impact of independent variables on price. For this reason, an analysis will be carried out to determine whether there is sufficient statistical evidence to support the hypothesis outlined below.

Hypothesis 1: An increase in property size leads to a positive variation in price.

Hypothesis 2: An increase in the number of bedrooms leads to a positive variation in price.

Hypothesis 3: An increase in the number of bathrooms leads to a positive variation in price.

Hypothesis 4: The price of a property varies positively or negatively depending on its usage status.

Hypothesis 5: The price of a property varies positively or negatively depending on its type.

Hypothesis 6: Properties with a car park or garage experience a positive variation in price.

Hypothesis 7: Properties with a garden or terrace experience a positive variation in price..

Hypothesis 8: The price of a property varies positively or negatively depending on its BER (Building Energy Rating) code.

Hypothesis 9: Properties located in Dublin city center experience a positive variation in price.

Hypothesis 10: The price of a property varies positively or negatively depending on its location.

Hypothesis 11: Properties near green spaces experience a positive variation in price.

Hypothesis 12: Properties near the sea and beach experience a positive variation in price.

3.2.3. Functional Form of the Model

In the present research, three distinct forms of the HPM were employed: linear, logarithmic, and double logarithmic. These specific forms were selected based on their theoretical and empirical suitability for analysing the relationship between the dependent and independent variables in the context of the data.

As previously discussed in the literature review, the HPM linear model assumes a direct, linear relationship between the variables, providing a straightforward interpretation of the estimated coefficients. In contrast, the HPM logarithmic model accounts for diminishing marginal effects by modelling the independent variables in their logarithmic form. Finally, the HPM double logarithmic model applies logarithmic transformations to both the dependent and independent variables, yielding elasticity estimates. These elasticity estimates facilitate the interpretation of the percentage change in the dependent variable resulting from a percentage change in the explanatory variables, a common approach in econometric modelling (Goodman & Thibodeau, 1998; Mayor et al., 2012; Moro et al., 2013; Paixão, 2023; Zakaria & Fatine, 2021).

To ensure the robustness and accuracy of the models and to select the HPM with the most precise results, a series of tests were conducted to assess their predictive performance: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), cross-validation using Mean Absolute Error (MAE), and pseudo R-squared. These tests were applied to all quantiles of the data to evaluate model consistency and reliability across different segments of the distribution (Koenker & Bassett, 1978; Koenker & Hallock, 2001; Yu & Moyeed, 2001).

The AIC and BIC tests were used to compare the relative fit of the models. Both criteria penalise model complexity to prevent overfitting while rewarding goodness-of-fit. A lower AIC or BIC value indicates a more parsimonious model that achieves an optimal balance between explanatory power and complexity.

The cross-validation method was chosen to assess the out-of-sample predictive accuracy of the models. Using the Mean Absolute Error (MAE) as the evaluation metric, it provides a clear and interpretable measure of the average magnitude of the prediction errors. This metric was useful for evaluating model performance in terms of its robustness across varying data subsets. Lastly, the pseudo R-squared was computed as an additional measure of the model's explanatory power. This statistic indicates the proportion of variance in the dependent variable explained by the independent variables, serving as an indicator of how well the models fit the data overall (Koenker & Bassett, 1978; Koenker & Hallock, 2001; Yu & Moyeed, 2001).

A) Hedonic Price Model Linear

$$\begin{aligned} Y_i = {} & \beta_0 + \beta_1 \cdot SIZE_i + \beta_2 \cdot BED_i + \beta_3 \cdot BATH_i + \beta_4 \cdot CAR_i + \beta_5 \cdot SEA_i \\ & + \beta_6 \cdot DWTN_i + \sum_{j=1}^{7} \beta_{6+j} \cdot BER_{j,i} + \sum_{j=1}^{4} \beta_{13+j} \cdot TH_{j,i} + \sum_{j=1}^{6} \beta_{17+j} \cdot REGION_{j,i} \\ & + \sum_{j=1}^{5} \beta_{23+j} \cdot USTAT_{j,i} + \beta_{29} \cdot GDT_i + \beta_{30} \cdot GRN_i + \varepsilon_i \end{aligned} \tag{3.2}$$

where:

SIZE represents the area of the house; *BED* represents the number of bedrooms in the house; *BATH* represents the number of bathrooms in the house; *CAR* indicates whether the house has a garage or parking space; *SEA* indicates whether the house is near the sea or ocean; *DWTN* indicates whether the house is located in a downtown area; *BER* represents the energy efficiency rating; *TH* represents the construction type of the house; *REGION* represents the location of the house; *USTAT* represents the usage condition of the house; *GDT* indicates whether the house has a garden or terrace, and *GRN* indicates whether the house is near green spaces.

B) Hedonic Price Model Semi-Logarithmic

$$\log(Y_i) = \beta_0 + \beta_1 \cdot SIZE_i + \beta_2 \cdot BED_i + \beta_3 \cdot BATH_i + \beta_4 \cdot CAR_i + \beta_5 \cdot SEA_i + \beta_6 \cdot DWTN_i + \sum_{j=1}^{7} \beta_{6+j} \cdot BER_{j,i} + \sum_{j=1}^{4} \beta_{13+j} \cdot TH_{j,i} + \sum_{j=1}^{6} \beta_{17+j} \cdot REGION_{j,i} + \sum_{j=1}^{5} \beta_{23+j} \cdot USTAT_{j,i} + \beta_{29} \cdot GDT_i + \beta_{30} \cdot GRN_i + \varepsilon_i \quad (3.3)$$

C) Hedonic Price Model Double Logarithmic

$$\log(Y_i) = \beta_0 + \beta_1 \cdot \log(SIZE_i) + \beta_2 \cdot BED_i + \beta_3 \cdot BATH_i + \beta_4 \cdot CAR_i + \beta_5 \cdot SEA_i + \beta_6 \cdot DWTN_i + \sum_{j=1}^{7} \beta_{6+j} \cdot BER_{j,i} + \sum_{j=1}^{4} \beta_{13+j} \cdot TH_{j,i} + \sum_{j=1}^{6} \beta_{17+j} \cdot REGION_{j,i} + \sum_{j=1}^{5} \beta_{23+j} \cdot USTAT_{j,i} + \beta_{29} \cdot GDT_i + \beta_{30} \cdot GRN_i + \varepsilon_i \quad (3.4)$$

4. PRESENTATION AND DISCUSSION OF THE RESULTS

In this section, the descriptive analysis has been outlined. Furthermore, the empirical research was conducted using HPM and QR methods, and the results are discussed.

4.1. Descriptive Statistics

In the housing market, several factors influence property prices, as previously mentioned. This research examines the key elements driving the price variation of houses. These characteristics are categorised, and their combination contributes to the overall property value. Each category has a unique specification, and it is crucial to understand how these attributes influence the price. As outlined earlier, the key characteristics this study focuses on are location, structural, and neighbourhood factors.

The following Tables 6 and 7 provide a statistical summary of each hedonic price variable. Additionally, Table 8 presents the specifications of each dummy variable included in the HPM

Table 6 presents a summary of the dependent variable - house price (*PRICE*) - and the independent continuous variable *SIZE*.

Table 6

Statistical Summary – Dependent Variable and Continuous Independent Variable

Description	N	Mean	Median	Standard Deviation	Minimum	Maximum
Dependent Variable						
PRICE	5,091	526,690.42	435,000	307,162.74	90,000	2,500,000
Independent Variable						
SIZE	5,091	101.3	91	46.72	25	488

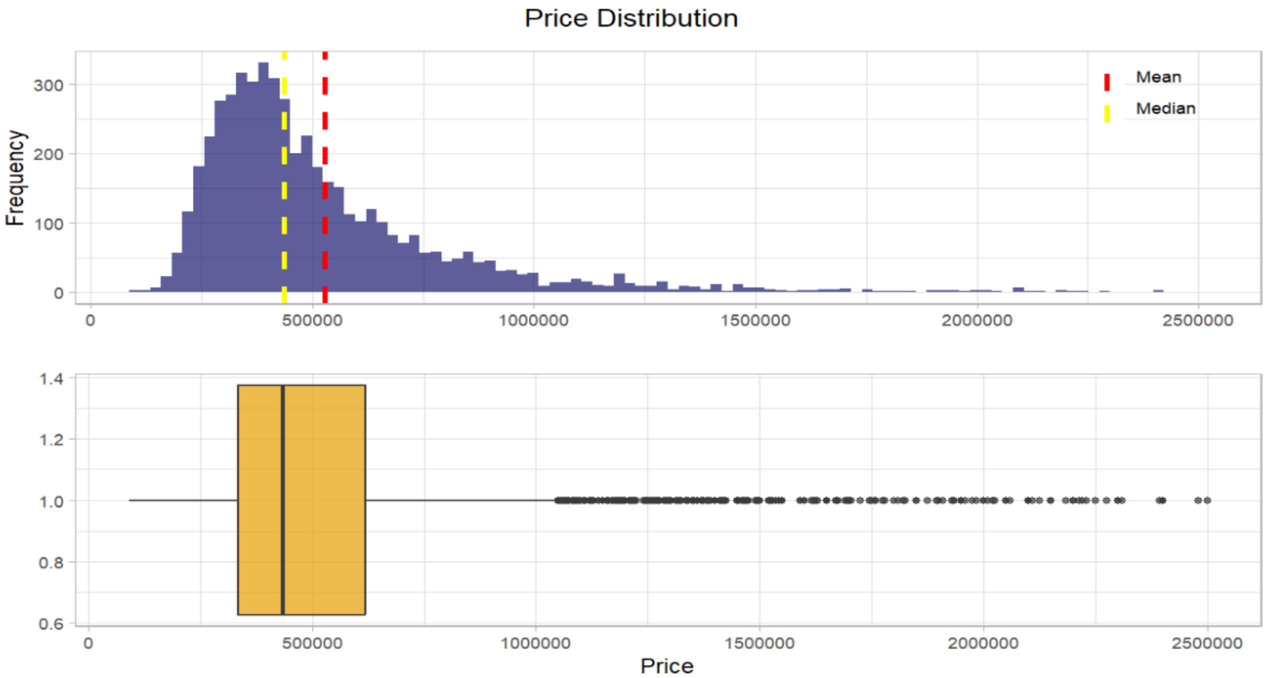
Note. The units of the variable PRICE are in Euros, representing the price of the houses. The N represents the number of houses included in the dataset, and the independent variable SIZE represents the floor area of the house in square metres.

The mean house price in the study sample, which contains 5,091 properties located in Dublin, is approximately €526,690. There is considerable variation, as indicated by the standard deviation of €307,163. This suggests that house prices vary across the distribution, surrounding both lower-cost and higher-priced properties. Moreover, the size of the houses ranges from 25 to 488 square metres, indicating a broad diversity in property sizes. The standard deviation is 46.72 square metres, suggesting significant variation in property sizes around the mean of 101.33 square metres, which reflects a wide range of house dimensions.

Figure 3 presents the price distribution in two ways. It shows that there are many high-priced properties and the difference between the mean and median prices. Additionally, these values are represented in Table 5. There are numerous outliers, with the majority of prices concentrated well below the highest house price. It is essential to test the results both with and without outliers to assess their impact and ensure accuracy.

Figure 3

Price Distribution



Note. The price distribution is illustrated in the figure using two graphs. In the first graph, the mean is represented by the red line, while the median house price is shown in yellow. These results are based on the 5,091 elements in the sample.

Figure 4 illustrates the various property sizes in relation to house prices. The plot demonstrates a positive correlation between price and property size, with a correlation coefficient of 0.79, indicating that as house prices increase, property size also tends to increase. It is observed that in some houses included in the sample, the price is not directly related to the house size.

Figure 4

Comparing House Size to Price

Note. The blue points in the graph represent the houses in the sample, varying according to price and size. The red line in the graph corresponds to the bisector of the odd quadrants (line y=x), it represents the ideal alignment between the sample quantiles of the residuals and the theoretical quantiles of a normal distribution.

Table 7 summarizes the variables of the bedrooms and bathrooms number (*BED* and *BATH*) in each house, considered as numerical variables.

Table 7

Statistical Summary – Numerical Variables

Numerical Variables	N	%
Number of Bedrooms		
Houses with 1 bedroom	394	7.74%
Houses with 2 bedrooms	1603	31.49%
Houses with 3 bedrooms	1991	39.11%
Houses with 4 bedrooms	878	17.25%
Houses with 5 bedrooms	189	3.71%
Houses with 6 bedrooms	36	0.70%
Number of Bathrooms		
Houses with 1 bathroom	1941	38.13%
Houses with 2 bathrooms	1890	37.12%

Note: (Continues)

Table 7: (Continued)

Houses with 3 bathrooms	1045	20.52%
Houses with 4 bathrooms	177	3.48%
Houses with 5 bathrooms	32	0.63%
Houses with 6 bathrooms	5	0.10%
Houses with 7 bathrooms	1	0.02%

Note. This table presents the number of houses in the study sample with a specific number of bedrooms (*BED*) or bathrooms (*BATH*), along with the percentages that compare the number of houses with each characteristic to the total number of houses analysed.

Table 7 notes that 39.11% of the houses in the sample have 3 bedrooms, followed by 2 bedrooms with a percentage of 31.49%. Additionally, most of the houses have 1 and 2 bathrooms.

Table 8 shows the specifications of the remaining variables, which are classified as qualitative or dummy variables. It also presents the composition of the REGION variable, which is grouped by districts.

Table 8

Statistical Summary – Qualitative Independent Variables and Dummy Variables

Variables	N	%
Property Structural Characteristics		
Energy Rating (BER)		
Rating A	324	6.36%
Rating B	738	14.50%
Rating C	1788	35.12%
Rating D	1125	22.10%
Rating E	608	11.94%
Rating F	237	4.66%
Rating G	182	3.57%
Property exempt	89	1.75%
Usage Status		
New	120	2.36%
Old	242	4.75%
Renovated	1004	19.72%
Semi-new	1370	26.91%
To recover	43	0.84%

Note: (Continues)

Table 8: (Continued)

Used	2312	45.41%
Type of House		
Apartment	1612	31.66%
Semi-detached house	1620	31.82%
Detached house	393	7.72%
End-of-terrace house	200	3.93%
Terrace house	1266	24.87%
Garage / Parking		
Yes	4387	86.17%
No	704	13.83%
Garden / Terrace		
Yes	3456	67.88%
No	1635	32.12%
Property Location Characteristics		
Located in downtown		
Yes	142	2.79%
No	4949	97.21%
Districts		
District 1 (D01)	96	1.89%
District 2 (D02)	48	0.94%
District 3 (D03)	158	3.10%
District 4 (D04)	250	4.91%
District 5 (D05)	111	2.18%
District 6 (D06)	172	3.38%
District 7 (D07)	203	3.99%
District 8 (D08)	251	4.93%
District 9 (D09)	248	4.87%
District 10 (D10)	40	0.79%
District 11 (D11)	175	3.44%
District 12 (D12)	208	4.09%
District 13 (D13)	221	4.34%
District 14 (D14)	220	4.32%
District 15 (D15)	410	8.05%
District 16 (D16)	179	3.52%
District 17 (D17)	42	0.82%
District 18 (D18)	334	6.56%
District 20 (D20)	46	0.90%
District 22 (D22)	135	2.65%

Note: (Continues)

Table 8: (Continued)

District 24 (D24)	310	6.09%
North (North_D)	485	9.53%
Lucan (K78)	184	3.61%
District 6W (D6W)	131	2.57%
Killiney / Dalkey / Dun Laoghaire (Co. D)	434	8.52%
Region		
North Districts (North)	622	12.22%
North Central Districts (North_Cent)	457	8.98%
North of Dublin (North County)	485	9.53%
South Central Districts (South_Cent)	549	10.78%
South Districts	1000	19.64%
East Districts	988	19.41%
West Districts	990	19.45%
Neighbourhood Characteristics		
Located near the sea		
Yes	2086	40.97%
No	3005	59.03%
Located near green spaces		
Yes	4326	84.97%
No	765	15.03%

Note. This table shows the number of houses in the study sample analysed for each characteristic, together with the percentages comparing the number of houses with each characteristic to the total number of houses analysed.

Table 8 provides a comprehensive summary of the qualitative independent variables related to property characteristics, location, and neighbourhood attributes. It reveals that 35.12% of houses in the sample have a BER energy rating of C, while only a small proportion, 6.36%, are rated A. The majority of properties are used, accounting for 45.41%, or semi-new, and approximately two-thirds have a garden or terrace. Most houses also have a parking space or garage.

In terms of location, only a small percentage (2.79%) are situated in the city centre, but a significant number are near green spaces and the sea. The northern area contains around one-tenth of the houses in the sample, while the district with the highest number of houses is District 15, with 410 properties.

4.2.Hedonic Price Model Specification

In this section, the research focuses on identifying the most accurate and effective form of the HPM to ensure clear and reliable results. The study will evaluate the linear, semi-log, and double-log models.

4.2.1. Testing the models

The pseudo-R squared, cross-validation test, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) are employed to assess the model. Additionally, the Variance Inflation Factor (VIF) is evaluated based on the variable values and model outcomes.

4.2.1.1. Pseudo-R^2

As shown in Table 9, in an HPM using QR, the pseudo-R squared helps assess the model's explanatory power across different quantiles of the house price distribution, allowing for a more detailed analysis of the impact of price determinants (Koenker & Bassett, 1978; Koenker & Hallock, 2001).

Table 9

Pseudo-R^2 – Hedonic Price Model using QR

Model	Quantiles				
	.10	.25	.50	.75	.90
Hedonic Price Linear	0.19	0.37	0.47	0.34	-0.02
Hedonic Price Semi-Logarithmic	0.20	0.39	0.47	0.31	-0.11
Hedonic Price Double Logarithmic	0.21	0.40	0.49	0.38	0.042

Note. The pseudo-R squared values range from 0 to 1, with values closer to 1 indicating that the model explains the variation more effectively.

The results for the linear HPM pseudo-R squared range from 0.185 at the 0.10 quantile to 0.47 at the 0.50 quantile, indicating that the linear model fits reasonably well for houses priced around the median. In contrast, the semi-log HPM performs better in explaining price variation for the lower quantiles up to the median.

The HPM double-log shows the best overall performance, with the pseudo-R squared rising to 0.49 at the 0.50 quantile and 0.376 at the 0.75 quantile. These results effectively capture house price variability, particularly for middle to high-priced homes. At the 0.90 quantile, the HPM double-log is the only model to show a positive pseudo-R squared value (0.0416) compared to the linear and semi-log models. This indicates that the HPM double-log better fits high-priced properties.

In conclusion, the results using the pseudo-R squared measure suggest that the HPM double-log is the best choice. While the linear and semi-log models perform well for median-priced homes, they fail to capture the variability in higher-priced properties, as evidenced by the negative pseudo-R squared values in the upper quantiles.

4.2.2.2. Cross-Validation Using Mean Absolute Error (MAE)

The cross-validation test is a statistical method used to assess the performance of a model by partitioning the data into subsets for testing. The primary objective is to evaluate how well the model generalises to unseen data, helping to prevent overfitting and providing a more reliable estimate of the model's predictive performance. The Mean Absolute Error (MAE) measures the average magnitude of predictive errors. Calculating the MAE using the cross-validation method directly demonstrates its robustness as a metric (Koenker & Bassett, 1978; Yu & Moyeed, 2001).

Table 10

Cross-validation – Mean Absolute Error (MAE)

Model	Quantiles				
	.10	.25	.50	.75	.90
Hedonic Price Linear	161,647.9	124,275.6	105,368.3	130,391.5	200,084.4
Hedonic Price Semi-Logarithmic	159,197.6	121,414.8	105,500.9	135,701.6	219,739.7
Hedonic Price Double Logarithmic	156,119.5	120,645.5	101,150.7	123,495.4	191,367.2

Note. The values in the table are expressed in Euros.

Table 10 presents the MAE results of the HPMs across the quantiles. The HPM linear model exhibits the highest prediction error at the extreme quantiles, 0.10 and 0.90. The median (0.50 quantile) shows the lowest error of € 105,368.3, suggesting that the model performs best around the central values but struggles with very low or high house prices.

While the HPM semi-log outperforms the HPM linear model at the lower quantiles, the error increases significantly in the 0.75 and 0.90 quantiles, with the highest MAE values.

The double logarithmic model demonstrates the lowest overall MAEs across all quantiles, outperforming both the HPM linear and HPM semi-log models. It performs best at the median quantile with an MAE of € 101,150.7, indicating a good fit for central values. Additionally, it delivers the lowest MAEs at both the lower and upper quantiles.

All models face greater challenges at the extreme quantiles, but the HPM double-log still performs better than the other models.

In conclusion, based on the cross-validation MAE, the double logarithmic model is the most reliable for predicting house price outcomes. It achieves the lowest errors across all quantiles, indicating superior overall performance and greater stability across price ranges.

4.2.2.3. AIC and BIC Tests

The AIC and BIC methods are used to evaluate and compare statistical models, particularly when multiple models are involved, in order to identify the best fit for the data. Both methods aim to strike a balance between model fit and complexity, though they approach this slightly differently. The AIC penalises models with more parameters but is more lenient towards complex models compared to the BIC. In contrast, the BIC imposes a stronger penalty for additional parameters. Lower values of both AIC and BIC indicate a better model.

While both methods assist in balancing model fit and complexity, BIC is generally preferred when the goal is to avoid overfitting, particularly in simple models with large sample sizes. AIC, on the other hand, is more flexible in accommodating complex models (Koenker & Bassett, 1978; Koenker & Hallock, 2001; Yu & Moyeed, 2001).

Table 11 presents the application of the AIC and BIC methods for evaluating the performance of the HPM models.

Table 11

AIC & BIC Results of the Performance Models

Model	Test	
	AIC	BIC
Hedonic Price Model Linear		
0.10 quantile	135,382.6	136,697
0.25 quantile	134,579.6	135,894
0.50 quantile	134,933.3	136,247.7
0.75 quantile	136,553.9	137,868.3
0.90 quantile	138,815.1	140,129.5
Hedonic Price Model Logarithmic		
0.10 quantile	2,306.8	3,621.2
0.25 quantile	543.9	1,858.3
0.50 quantile	-51.6	1,262.8
0.75 quantile	862.2	2,176.5
0.90 quantile	2,497.6	3,812.1
Hedonic Price Model Double Logarithmic		
0.10 quantile	2,132.3	3,446.7
0.25 quantile	394.7	1,709.1
0.50 quantile	-125.6	1,188.8
0.75 quantile	799.1	2,113.4
0.90 quantile	2,344.98	3,659.4

Note. The values from the test are used for model comparison, with no specific metric associated. Lower values indicate better model performance.

The application of the AIC and BIC methods to assess the performance of the HPM models confirms that the HPM double-log yields the best results. The models were evaluated across different quantiles to determine their suitability for predicting house prices.

The HPM linear model shows stable results but consistently has higher AIC and BIC values, particularly in the higher quantiles. The model performs best in the 0.25 quantile with an AIC value of 134,579.6 and a BIC value of 135,894. However, as the quantiles increase, the AIC and BIC values rise significantly, reaching 138,815.1 (AIC) and 140,129.5 (BIC) at the 0.90 quantile. This suggests that while the HPM linear model fits lower-priced properties reasonably well, it struggles to capture the complexity of higher-priced properties.

The HPM semi-log model offers a substantial improvement in performance, particularly around the median quantile. In the 0.50 quantile, the AIC value is -51.59, and the BIC value is

1,262.831, indicating a good fit. However, like the HPM linear, the semi-log model experiences an increase in AIC and BIC values across higher quantiles, indicating that it is better suited for mid-range house prices.

The HPM double-log model performs exceptionally well across all quantiles, especially at the 0.50 quantile, where it achieves the lowest AIC value of -125.64 and a BIC value of 1,188.783, indicating an optimal balance between model fit and complexity. Even at the higher 0.90 quantile, the HPM double-log outperforms the other models with an AIC of 2,344.98 and a BIC of 3,659.41.

In conclusion, the HPM double-log offers superior performance and accuracy in predicting house price variations across different market segments.

4.2.3.4. Discussion and Conclusion of the Selection Model

After conducting a comprehensive test on the HPMs to identify the best results, this research will proceed with the HPM double-log to analyse the variation in house prices and identify the key determinants. It is important to highlight that the results were based on four measures: (1) Pseudo-r squared; (2) MAE; (3) AIC, and (4) BIC. The double-log HPM emerged as the model that provided the highest quality and performance. Moreover, the model demonstrated its flexibility and robustness across all quantiles. In contrast, the other models, according to the results, showed less favourable outcomes.

4.3. Quantile Regression Model

This section evaluates the robustness of both the QR and HPM results by testing their reliability and accuracy in handling the data. Initially, the analysis will focus on the residuals and the impact of outliers. Before delving into the study's outcomes, it is critical to assess the validity of these results.

The empirical research will be based on the HPM double-log model outlined below, as previously mentioned:

$$\log(Y_i) = \beta_0 + \beta_1 \cdot \log(SIZE_i) + \beta_2 \cdot BED_i + \beta_3 \cdot BATH_i + \beta_4 \cdot CAR_i + \beta_5 \cdot SEA_i$$
$$+\beta_6 \cdot DWTN_i + \sum_{j=1}^{7} \beta_{6+j} \cdot BER_{j,i} + \sum_{j=1}^{4} \beta_{13+j} \cdot TH_{j,i} + \sum_{j=1}^{6} \beta_{17+j} \cdot REGION_{j,i} \quad (4.1)$$
$$+\sum_{j=1}^{5} \beta_{23+j} \cdot USTAT_{j,i} + \beta_{29} \cdot GDT_i + \beta_{30} \cdot GRN_i + \varepsilon_i$$

where:

SIZE represents the area of the house; *BED* represents the number of bedrooms in the house; *BATH* represents the number of bathrooms in the house; *CAR* indicates whether the house has a garage or parking space; *SEA* indicates whether the house is near the sea or ocean; *DWTN* indicates whether the house is located in a downtown area; *BER* represents the energy efficiency rating; *TH* represents the construction type of the house; *REGION* represents the location of the house; *USTAT* represents the usage condition of the house; *GDT* indicates whether the house has a garden or terrace, and *GRN* indicates whether the house is near green spaces.

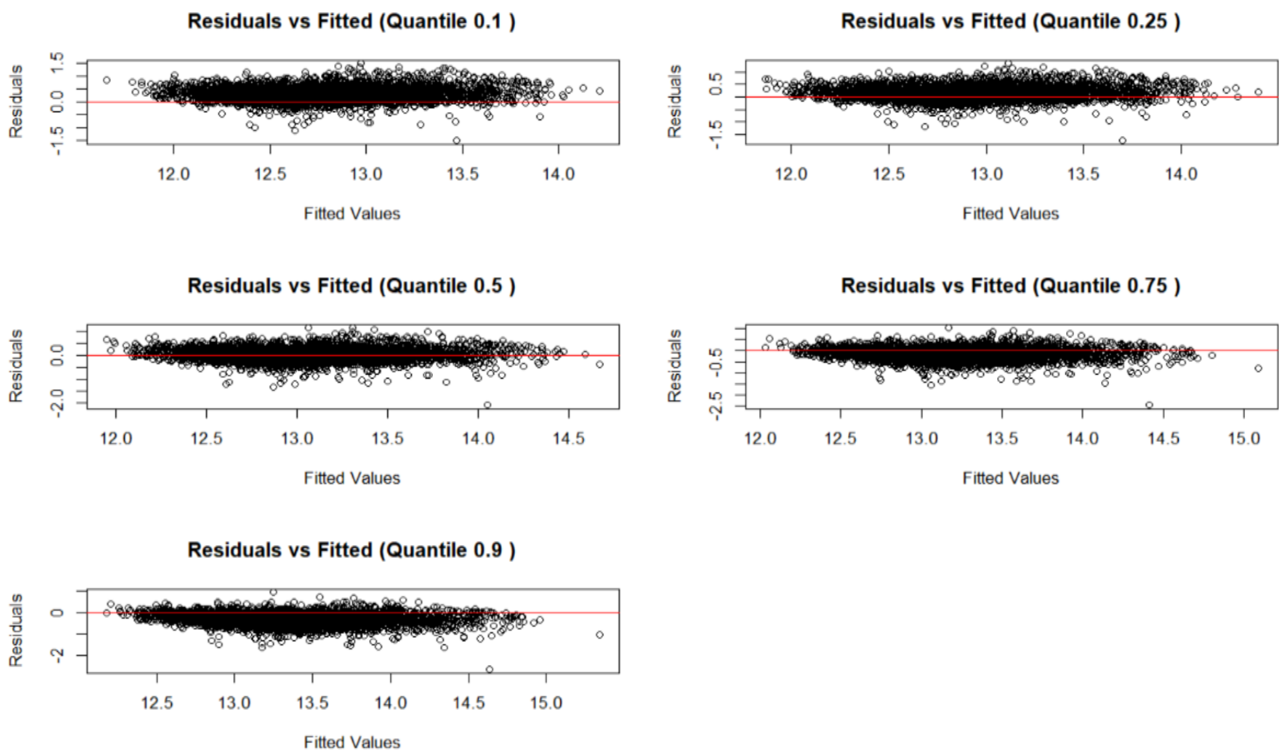
4.3.1. Residuals Valuation

Figure 5 illustrates the residuals across different quantiles. Specifically, the 0.10 and 0.25 quantiles correspond to lower-priced houses, the 0.50 quantile represents the median prices, and the 0.75 and 0.90 quantiles indicate higher-priced houses.

Across all quantiles, the residuals are mostly centered around zero, with no noticeable systematic patterns. This indicates that the model effectively captures the central tendency of the relationship between price and the independent variables.

Figure 5

*R*esidual Model Values in Each Quantile



Note. The graphs display residuals across different quantiles plotted against the fitted values, with the red line indicating the normal distribution.

Additionally, the residual graphs do not exhibit a clear upward or downward trend, suggesting that the model does not systematically bias its predictions across most quantiles. This indicates that the chosen functional form is appropriate across quantiles.

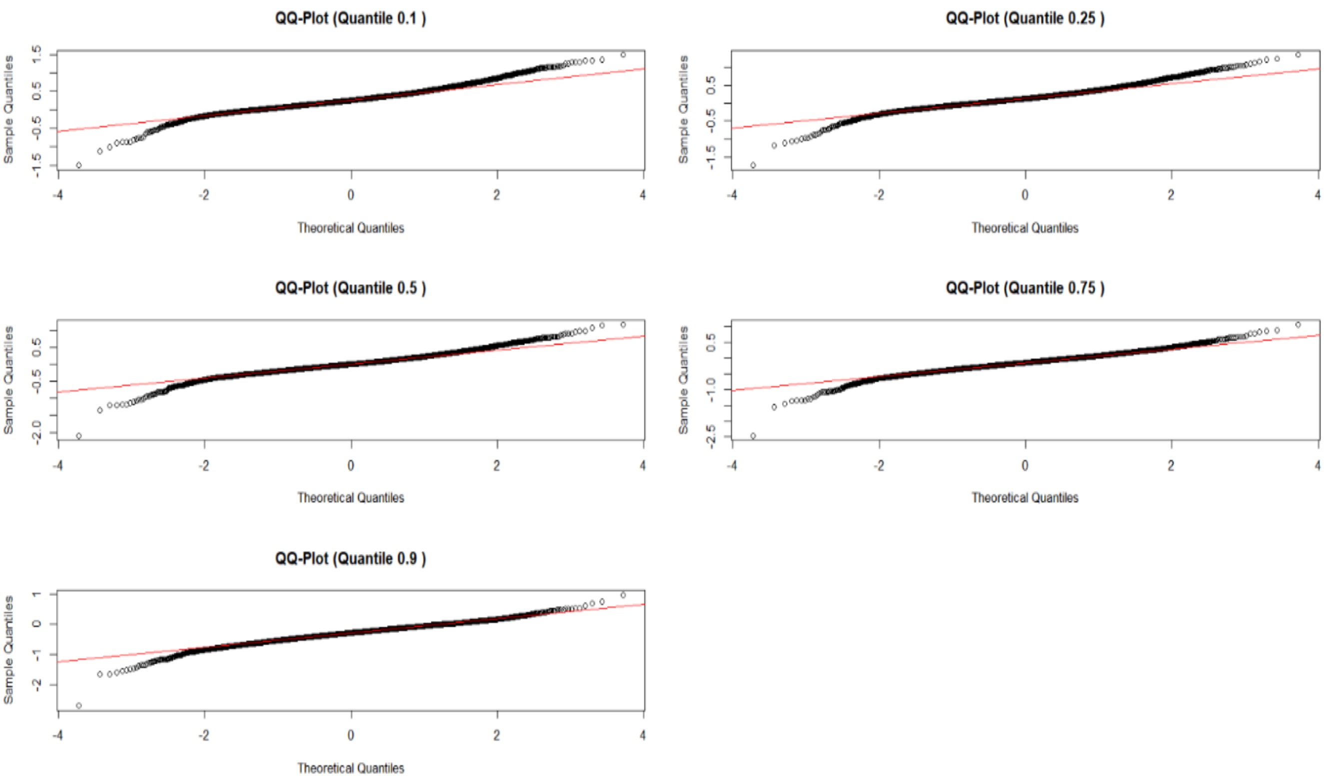
Furthermore, there is no clear evidence of heteroscedasticity, as the spread of residuals remains consistent across the range of fitted values for most quantiles. This stability in residual variation suggests that the model is well-specified and effectively captures the variability in house prices across different fitted values.

However, in the 0.75 and 0.90 quantiles, there was a slight increase in the spread of residuals, particularly for higher fitted values. This suggests some degree of heteroscedasticity or changing variability among the high-priced houses in the distribution. It is necessary to verify the number of outliers that may skew the results and adjust for potential heteroscedasticity. These outliers might represent extreme or atypical observations in the dataset, where the model may not adequately capture the unique characteristics of high-priced properties. Another possible issue is that outliers could arise from data collection or reporting errors.

Given that the residuals across most quantiles appear centred around zero and exhibit relatively homoscedastic behaviour, the model effectively captures the relationship between the dependent and independent variables. Despite the slight curvature in the lower quantiles and the presence of outliers in the higher quantiles, the model appears well-specified for the majority of the data, showing minimal signs of heteroscedasticity and no significant biases in prediction. Nonetheless, attention should be given to the minor non-linearity in the lower quantiles and the potential impact of outliers in the upper quantiles. Addressing these issues could further enhance the robustness and interpretability of the quantile regression analysis results.

Figure 6

Quantile-Quantile (QQ) Residuals Plots



Note. The red line indicates the normal distribution against which the residuals in each quantile are compared.

Figure 6 presents the Quantile-Quantile (QQ) plots for various quantiles (0.1, 0.25, 0.5, 0.75, 0.9). These plots compare the distribution of the residuals—the sample quantiles from the regression model—with the theoretical quantiles from a normal distribution.

The lower quantiles, represented by the 0.10 and 0.25 quantiles, deviate slightly from the assumption of normality, particularly in the extremes. The red line in the graph corresponds to the bisector of the odd quadrants (line y=x) and represents the ideal alignment between the sample quantiles of the residuals and the theoretical quantiles of a normal distribution. If the residuals are approximately normal, the points should lie close to this line. Notably, none of the quantiles follow the normal distribution in the tails; however, the lower quantiles display the most pronounced deviations, suggesting some degree of skewness. This implies that the model does not perfectly capture the distribution of the dependent variable at the extremes.

Moreover, the median quantile (0.50) and the upper quantiles (0.75 and 0.90) are closer to the red line, except at the tails where deviations similar to those in the lower quantiles are observed, although these are less critical. Therefore, the quantiles are approximately normally distributed.

In Figure 5, some outliers are identified. These deviations may stem from extreme observations where house values are either too low or too high, indicating non-normality in the data, particularly in the tails. Such deviations imply that the residuals exhibit heavier tails than a normal distribution, which could affect the model's performance in accurately predicting house prices for lower- and higher-priced properties.

4.3.2. Assessment of Outliers

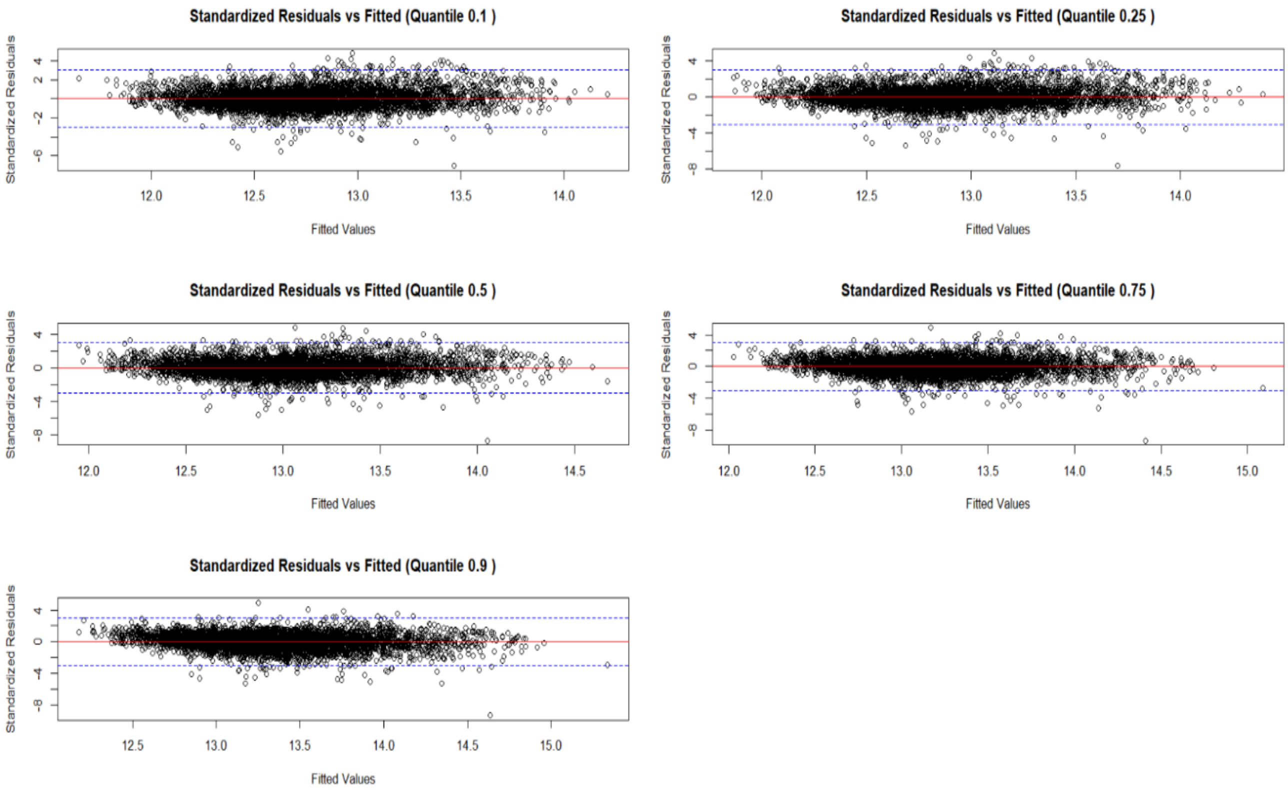
As previously mentioned, outliers may distort the accuracy of the results. This section will examine these outliers and compare the model outcomes with and without them.

4.3.2.1. Detection of Outliers

Figure 7 highlights the outliers in the residuals, with values falling outside the blue lines (i.e., house prices beyond the range defined by the blue lines) identified as outliers.

Figure 7

Detection of Outliers



Note. The blue line marks the borderline between outliers and non-outliers, with values beyond this range being classified as outliers. The red line represents the normal distribution.

Table 12 presents the total number of outliers in each quantile. In summary, the lower and median quantiles contain more outliers than the upper quantiles. Given these findings, outliers may influence the model and its outcomes. To assess their impact, the next step involves testing the model's performance with and without outliers.

Table 12

Number of Outliers

Model	Quantiles					
	.10	.25	.50	.75	.90	Total
Hedonic Price Model Double Logarithmic	65	61	61	57	50	91

Note. The figures in the table represent the number of houses with prices classified as outliers.

4.3.2.2. Pseudo-R^2

After removing the outliers, the Pseudo-R^2 values improved across all quantiles. As shown in Table 13, this measure increased by 0.02 points in each quantile, indicating enhanced accuracy in the results.

Table 13

Hedonic Price Model Double Logarithmic / Pseudo-r^2 / Outliers

Hedonic Price Model	Quantiles				
	.10	**.25**	**.50**	**.75**	**.90**
With Outliers	.2112123	.3966679	.4919252	.3764285	.04156181
Without Outliers	.2392961	.4226063	.5168771	.4018691	.07253831

As we can observe in Table 13 The Pseudo-R^2 values vary across quantiles, suggesting that the model explains house prices better at some price levels than others.

The highest explanatory power occurs around the median (0.50 quantile), where 49.19% (with outliers) and 51.69% (without outliers) of the variance in house prices is explained by the model.

The lowest explanatory power is at the 0.90 quantile, particularly with outliers (0.041), meaning that for very high-priced properties, the model struggles to explain price variation. When taking out the outliers the improvement is most noticeable in this quantile, where the Pseudo-R^2 increases from 0.041 to 0.073, indicating that removing outliers allows for a slightly better fit in higher-priced properties.

Consistent with Koenker and Hallock (2001) and Yu and Moyeed (2001), the model effectively explains low-to-middle price properties (0.50 quantile: 0.49-0.52 Pseudo-R^2) but performs less well for high-end properties (0.90 quantile: 0.04-0.07 Pseudo-R^2). Yu and Moyeed (2001) also observed that pseudo-R^2 values often decline for high-end properties, attributing this to unique factors such as luxury appeal, exclusivity, and individual negotiation power. Our findings support their argument regarding the unexplained variation in luxury property prices.

4.3.2.3. Pinball Loss

Table 14 presents the results of the Pinball Loss (PL), the final test used to determine the best model for our predictions. The PL results for the HPM double-log model provide a quantitative assessment of its accuracy across different house price quantiles, both with and without outliers. Lower PL values indicate greater accuracy, meaning the model's predictions are closer to actual house prices in each quantile.

Table 14

Pinball Loss

Quantiles	With Outliers	Without Outliers
.10	.04057435	.03589492
.25	.07126842	.06566509
.50	.09029048	.08438613
.75	.07415533	.06928437
.95	.04143092	.03828813

Since lower-priced houses (0.10 and 0.25 quantiles) and higher-priced houses (0.75 and 0.90 quantiles) exhibit relatively moderate error levels in predicting prices—even with outliers included—the model remains reasonably accurate. However, once the outliers are removed, the Pinball Loss (PL) decreases across all quantiles, indicating that the model performs more effectively without them.

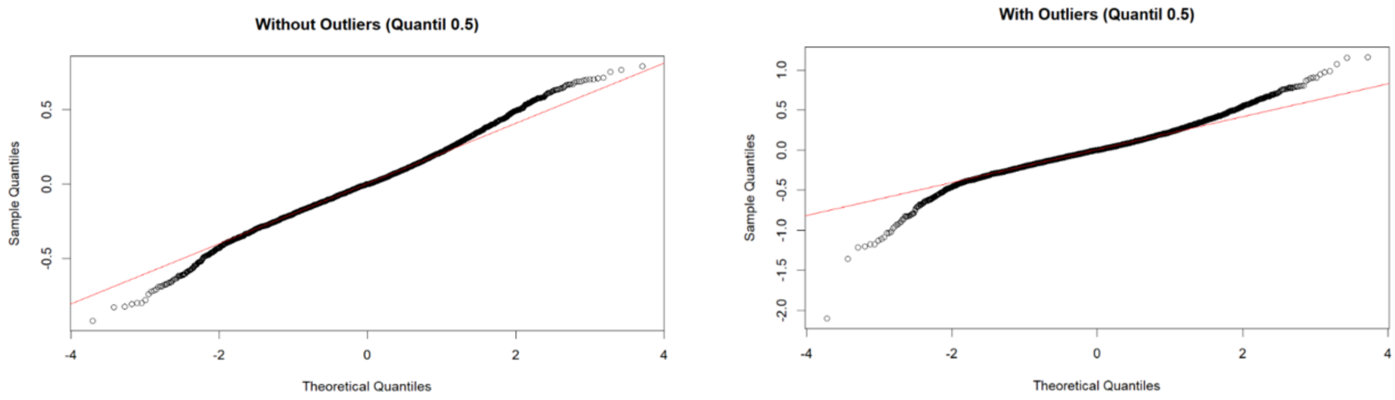
The PL values for the median quantile are the highest in both models, indicating that the model performs worst in predicting house prices in this range. This is particularly interesting, as previous tests showed that the lower and upper quantiles were of greater concern.

Overall, the PL values across the quantiles suggest that the presence of outliers significantly impacts the model's predictive accuracy, especially for lower-priced properties. Although the impact on higher-priced homes is somewhat smaller, removing outliers consistently lowers the Pinball Loss across all quantiles, underscoring the importance of addressing outliers to improve the model's performance.

4.3.3. Graphs and Outliers Conclusion

Figure 8

Residuals in the Quantile 0.50 without/with Outliers

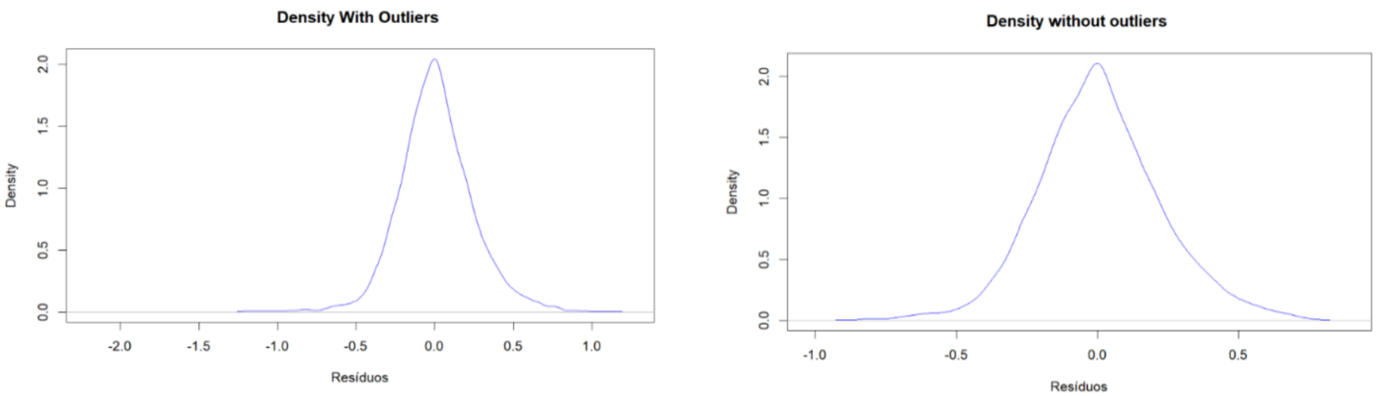


Note. The red line in the graph corresponds to the bisector of the odd quadrants (line y=x), it represents the ideal alignment between the sample quantiles of the residuals and the theoretical quantiles of a normal distribution. This graph aims to compare the residuals of the quantile regression, using the hedonic price model with/without outliers in this research, to a normal distribution.

The graphs below demonstrate the model's improvement following the removal of outliers. Figures 8 shows that the residuals more closely approximate a normal distribution, while Figure 9 indicates that, without outliers, the results display a more well-distributed density.

Figure 9

Residual Density Using the HPM Double Log with and without Outliers



Note. The graphs represent the density of the residual results and their distribution in the quantile 0.50 using a quantile regression followed by a hedonic price model of this research. The results are presented with and without outliers.

The model will be analysed without outliers. Although QR is robust against outliers, the results improve when they are removed. Since the study objectively examines the determinants of house prices, outliers may distort the findings; therefore, it is essential to ensure reliable results.

4.3.4. Variance Inflation Factor (VIF)

In relation to multicollinearity among the variables, the model was constructed without the variable *DT* (representing the districts where the houses are located) due to high levels of multicollinearity. Consequently, the variable *REGION* was created to group the various districts and enhance the model results.

Table 15 presents the VIF values for each variable. Testing the model was necessary to ensure the accuracy of the results and verify that no multicollinearity exists among the independent variables.

Table 15

VIF Values of Independent Variables

Variable	DF	GVIF	VIF
REGION	6	3.557595	1.111552
BED	1	4.332597	2.081489
SIZE	1	4.644143	2.155027
BATH	1	2.262823	1.504268
GDT	1	3.716949	1.927939
TH	4	5.819117	1.246256
USTAT	5	2.520405	1.096849
CAR	1	1.327455	1.152152
BER	7	2.955876	1.080489
SEA	1	2.229780	1.493245
DWTN	1	1.004746	1.002370
GRN	1	1.284687	1.133440

Note. The table includes the GVIF values (Generalised Variance Inflation Factor), which are adjusted based on the degrees of freedom (DF) to obtain the Variance Inflation Factor (VIF). The results are from the hedonic price model in a double-logarithmic specification. Variables are as follows: REGION represents the location of the house; BED represents the number of bedrooms in the house; SIZE represents the area of the house; BATH represents the number of bathrooms in the house; GDT indicates whether the house has a garden or terrace; TH represents the construction type of the house; USTAT represents the usage condition of the house; CAR indicates whether the house has a garage or parking space; BER represents the energy efficiency rating; SEA indicates whether the house is near the sea or ocean; DWTN indicates whether the house is located in a downtown area, and GRN indicates whether the house is near green spaces.

Analysing Table 15, it is evident that the VIF values for BED and SIZE are the highest. Nonetheless, these values remain within a reasonable range; had they exceeded 5, it would have raised concerns about multicollinearity. Therefore, there are no significant multicollinearity issues in this model.

4.4. Results and Discussion

This study aims to find the determinants of house prices in Dublin and the prime factors that influence the variation of house prices. For that, it is necessary to comprehensively understand the factors influencing house prices across different market segments. The variation of coefficients across quantiles, provides valuable information on the heterogeneity of the housing market, particularly as different segments of the market, lower-priced to higher-priced houses, respond differently to the same characteristics. Moreover, using the OLS and the QR allows us to empirically explore how the impact of critical determinants changes not only on average but also across different quantiles, reflecting the varying behaviour of the housing market from lower to higher-priced homes. However, the OLS was used to compare the results and have another perception of how valuable the QR method is, demonstrating the limitations of the OLS.

The following analysis presents the results of each attribute's impact on price variation, based on the HPM double-log model using the QR method.

Table 16 provides the elasticities of each variable in house prices. According to those values, it was calculated based on the average of each quantile, the monetary impact the attribute has on the property value; thus, Table 16 provides each monetary value variation over the different house price levels.

Table 16

HPM Double Logarithmic Coefficients by Quantile Regression

	OLS	**0,1**	**0,25**	**0,5**	**0,75**	**0,9**
Constant	9.474466***	9.647***	9.69022***	9.68522***	9.37449***	9.36323***
REGION_East	.406128***	.45073***	.42946***	.4081***	.40741***	.33333***
REGION_North	.189019***	.19493***	.19512***	.19778***	.20327***	.14835***
REGION_North_Cent	.308232***	.33215***	.33342***	.32927***	.32821***	.26594***
REGION_South	.229169***	.17205***	.16543***	.20807***	.31615***	.34729***
REGION_South_Cent	.494436***	.48392***	.49599***	.5037***	.50788***	.43399***
REGION_West	.041347	.06148**	.03262	.01852	.06012*	.02869
BED	.010664	.02361*	.02635**	.03127***	.00256	-.01551
Log (SIZE)	.737409***	.6285***	.64824***	.67791***	.78074***	.83913***
BATH	-.00894	-.00736	-.00612	-.00896	-.01688*	-.01072
GDT	.026548**	.05475***	.06198***	.02442**	-.00391	.0244
Detached house	.24812***	.22259***	.23649***	.26601***	.28446***	.26104***
End-of-terrace house	.088684***	.07963*	.05254*	.09479**	.13223***	.08671***
Semi-detached house	.114529***	.11834***	.12085***	.13244***	.13265***	.10263***
Terrace house	.068954***	.03352	.04954**	.07736***	.1064***	.07576***
Old	-.07749**	-.05424	-.05895	-.0712**	-.06865	-.07329
Renovated	.033131	.1004***	.04876*	.02343	.02344	-.01677
Semi-new	.044658	.10435***	.06992***	.03587	.0322	-.01958
To recover	-.17925***	-.11233	-.18192***	-.16008***	-.17671***	-.23113*
Used	-.05071*	.00963	-.02009	-.05146*	-.05933	-.08581
CAR	-.01098	.01555	.00638	-.01763	-.00531	-.0224
BER_B	-.077***	-.1231***	-.08964***	-.06022***	-.06868*	-.07272*
BER_C	-.07792***	-.12292***	-.07603***	-.05075***	-.07666**	-.13878***
BER_D	-.05144**	-.10716***	-.05517***	-.02952*	-.06177*	-.10642**
BER_E	-.05063**	-.11784***	-.05358**	-.0275	-.05464*	-.08614*
BER_Exempt	.165722***	.03556	.09956	.19412***	.20452***	.09427
BER_F	-.02837	-.06978**	-.04605*	-.01923	-.04399	-.09212*
BER_G	-.05628*	-.09675*	-.06704**	-.06207*	-.07266	-.07246*
SEA	.050151***	.03574*	.02375*	.04018***	.06286***	.07333***
DWTN	.007161	-.02409	-.03264	.02657	.00769	-.00122
GRN	-.05982***	-.08795***	-.10899***	-.08205***	.00979	.07098***

Note. The numbers in the table represent the results of the quantile regression model using the double logarithmic hedonic price model. These values correspond to the coefficients of the model and indicates the relationship between price and them individually, as well as the significance of each variable. t-values of the regressions coefficients (note reported here) are computed using robust standard errors. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Variables are as follows: REGION represents the location of the house; BED represents the number of bedrooms in the house; SIZE represents the area of the house; BATH represents the number of bathrooms in the house; GDT indicates whether the house has a garden or terrace; TH represents the construction type of the house, which is here represented by: detached house, end-of-terrace house, semi-detached house and terrace house; USTAT represents the usage condition of the house, which is here represented by: old, renovated, semi-new, to-recover and used; CAR indicates whether the house has a garage or parking space; BER represents the energy efficiency rating; SEA indicates whether the house is near the sea or ocean; DWTN indicates whether the house is located in a downtown area, and GRN indicates whether the house is near green spaces.

Analysing the location attributes, the variable *REGION* plays a crucial role in determining house prices, as evidenced by the statistically significant coefficients across all regions. The south-central region is the most expensive, consistently commanding the highest premium across all quantiles. This appears to reflect the prestige of areas such as Portobello, Ranelagh, Rathmines, and Dublin 8, which are highly desirable due to their blend of historic charm, trendy culture, and convenience. Additionally, the south-central region benefits from its proximity to the city centre, an abundance of amenities and lifestyle options, and its historical and architectural appeal.

As presented in Table 16, properties in the south-central region experience a substantial increase in value, with the average price rising from € 224,667 at the 0.10 quantile to € 377,470 at the 0.90 quantile. Similarly, the east and north-central regions also contribute to higher property prices, although to a lesser extent than the south-central zones. The price increases are not strictly progressive and vary depending on individual property values. However, in the south region, high-priced properties have appreciated by € 288,434, indicating a more significant value increase compared to the east and north-central zones.

Although all variables significantly influence house prices, the West region has the lowest impact. Based on the p-values, this region only significantly affects two price ranges. Analysing the results, while the West region may attract buyers seeking lower-priced properties, areas such as South-Central and East Dublin are preferred by wealthier buyers. Therefore, the location of a property is a key determinant of its value.

Although North and South Central are among the most expensive regions, properties in the downtown area do not significantly affect house prices. An analysis of Tables 15 and 16 indicates that, particularly in the lower-priced quantiles and at the 0.90 quantile, houses located downtown tend to have a negative impact on price. Statistically, the variable DWTN is not significant based on the p-values. These results are somewhat unexpected, potentially due to the relatively small number of downtown houses in the sample compared to the overall dataset. Moreover, it is anticipated that downtown areas, which are likely to be more congested and polluted, might be less attractive to wealthier buyers who may prefer locations further from the city centre. Consequently, the location in the downtown area does not appear to be a key determinant of house values.

Table 17

The Price Effect of Each Characteristic in the House Prices in Using OLS and QR

Independent Variables	OLS	Quantiles				
		0.10	0.25	0.50	0.75	0.90
Price Mean	**518,925(1)**	**360,955.5(2)**	**420,107.5(2)**	**499,320.8(2)**	**592,608.6(2)**	**694,641.2(3)**
REGION_East	259,979***	205,549***	225,357***	251,636***	298,035***	274,805***
REGION_North	107,970***	77,687***	90,515***	109,199***	133,576***	111,086***
REGION_North_Cent	187,341***	142,203***	166,251***	194,712***	230,217***	211,627***
REGION_South	133,651***	67,765***	75,577***	115,493***	220,353***	288,434***
REGION_South_Cent	331,891***	224,667***	269,761***	326,972***	392,167***	377,470***
REGION_West	21,906	22,888**	13,930	9,334	36,720*	20,218
BED(4)	5,563	8,624**	11,217**	15,860***	1,519	-10,691
SIZE(5)	3,841***	2,276***	2,732***	484,220***	4,645***	5,853***
BATH(4)	-4,620	-2,647	-2,563	-4,454	-9,919*	-7,407
GDT(3)	13,961**	20,313***	26,862***	12,344**	-2,313	17,158
Detached house(3)	146,136***	89,989***	112,083***	152,167***	194,994***	207,197***
End-of-terrace house(3)	48,123***	29,918*	22,663*	49,646**	83,778***	62,921***
Semi-detached house(3)	62,969***	45,346***	53,965***	70,709***	84,062***	75,078***
Terrace house(3)	37,044***	12,304	21,336**	40,161***	66,530***	54,671***
Old(3)	-38,693**	-19,057	-24,050	-34,316**	-39,318	-49,089
Renovated(3)	17,480	38,122***	20,992*	11,837	14,055	-11,552
Semi-new(3)	23,699	39,701***	30,425***	18,236	19,393	-13,469
To recover(3)	-85,157***	-38,352	-69,877***	-73,862***	-95,989***	-143,349*
Used(3)	-25,658*	3,493	-8,356	-25,045*	-34,137	-57,121
CAR(3)	-5,669	5,657	2,689	-8,726	-3,138	-15,387
BER_B(3)	-38,458***	-41,808***	-36,020***	-29,182***	-39,334*	-48,721*

Note: (Continues)

Table 17: (Continued)

BER_C(3)	-38,901***	-41,750***	-30,757***	-24,708***	-43,732**	-90,012***
BER_D(3)	-26,017**	-36,680***	-22,550***	-14,525*	-35,498*	-70,126**
BER_E(3)	-25,617**	-40,124***	-21,917**	-13,544	-31,511*	-57,332*
BER_Exempt(3)	93,534***	13,067	43,979	106,975***	134,484***	68,670
BER_F(3)	-14,514	-24,329**	-18,907*	-9,510	-25,504	-61,131*
BER_G(3)	-28,398*	-33,286*	-27,241**	-30,051*	-41,532	-48,553*
SEA(3)	26,688***	13,134*	10,097*	20,471***	38447***	52,852***
DWTN(3)	3,729	-8,592	-13,491	13,445	4,575	-847
GRN(3)	-30,131***	-30,390***	-43,381***	-39,334***	5,830***	51,098***

Note. The table presents values in Euros (€), illustrating the change in price associated with a variation in each independent variable under the double-logarithmic hedonic price model using Quantile Regression. *t*-values of the regression's coefficients (note reported here) are computed using robust standard errors. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Variables are as follows: *REGION* represents the location of the house; *BED* represents the number of bedrooms in the house; *SIZE* represents the area of the house; *BATH* represents the number of bathrooms in the house; *GDT* indicates whether the house has a garden or terrace; *TH* represents the construction type of the house, which is here represented by: detached house, end-of-terrace house, semi-detached house and terrace house; *USTAT* represents the usage condition of the house, which is here represented by: old, renovated, semi-new, to-recover and used; *CAR* indicates whether the house has a garage or parking space; *BER* represents the energy efficiency rating; *SEA* indicates whether the house is near the sea or ocean; *DWTN* indicates whether the house is located in a downtown area, and *GRN* indicates whether the house is near green spaces. In the table we have three types of independent variables: dummies variables (*REGION, GDT, TH, USTAT, CAR, BER, SEA, DWTN* and *GRN*), one continuous variable that is used in a logarithmic form (*SIZE*), and two discrete quantitative variables (*BED* and *BATH*).

(1) When OLS method is applied, the mean house prices of all distribution is used as the reference value for all calculations and is calculated without outliers. (2) When QR method is applied, it is calculated the mean price value by each quantile without outliers. (3) In this regression model, where the dependent variable is the log of price and several independent variables are dummies, each dummy's coefficient represents the change in the log of price relative to the base group. To convert this coefficient into a percentage change in price and subsequently into the absolute price change, we apply the following formula:

$$\Delta Y = Y \times \left(e^{\beta} - 1\right)$$

where ΔY is the change in price, Y is the mean price value and β is the coefficient for each dummy.

(4) In this regression model, where the dependent variable is the log of price and the independent variable is not logged (in this case, discrete quantitative variables), the coefficient represents the semi-elasticity. This means that a one-unit increase in the independent variable is associated with a change in the log of price. To convert this into a percentage change and subsequently into the absolute price change, we apply the following formula:

$$\Delta Y = Y \times \left(e^{\beta} - 1\right)$$

where ΔY is the change in price, Y is the mean price value and β is the coefficient for each dummy.

(5) For the variable SIZE, the coefficient reported in Table 15 represents the elasticity of price with respect to size. In other words, for a 1% increase in size, the price is expected to increase by approximately β%. The change in price is calculated using the following formula:

$$\Delta Y = Y \times \left(e^{\beta \times \Delta \log(SIZE)} - 1\right)$$

where ΔY is the change in price, Y is the mean price value, β is the coefficient for *SIZE*, and $\Delta\log$ (*SIZE*) denotes the percentage change in size.

Structural characteristics - the physical features of a house - are crucial in determining its value. Looking at the results for the variable *SIZE*, there is a statistically significant positive relationship between *SIZE* and house prices across all quantiles: as property values increase, so do prices within each quantile. For example, for high-priced houses in the 0.90 quantile, a 1% increase in size is associated with a price increase of around € 5,853. This suggests that larger properties are strongly associated with higher valued houses and are favoured by wealthier buyers, reflecting a clear preference for larger living spaces in the high-end market. Similarly, at the lower end (the bottom 10%), a 1% increase in size results in an average price increase of € 2,276. Overall, the size of a property is a key determinant of its price.

Focusing on the number of bathrooms (*BATH*), the results are unexpected. Rather than having the anticipated positive effect on house prices, the variable exhibits an opposite impact. However, the overall statistical evidence is insufficient to confirm a significant effect on price variation, with a statistically significant negative impact observed only at the 0.75 quantile.

Regarding the number of bedrooms (*BED*), there is a significant positive impact on lower and mid-priced houses. For instance, in the 0.10 and 0.50 quantiles, an additional bedroom increases the price by € 8,624 and € 15,860, respectively. However, contrary to expectations, at the 0.90 quantile, the effect reverses, leading to a price reduction of € 10,691. This suggests that additional bedrooms do not necessarily add value to higher-priced properties. Moreover, the results indicate insufficient statistical evidence to confirm a significant impact of the number of bedrooms on price variation in high-priced houses.

Surprisingly, the presence of a garage or parking space does not have a statistically significant impact on house prices.

The property's *BER* has a significantly negative effect on house prices, aligning with our expectations, but only for low *BER* rating levels, for properties exempt from *BER* certification in the 0.50 and 0.75 price quantiles. *BER exempt* properties are often historical buildings, which have a strong and positive price impact in the mid-to-upper quantiles, with price increases reaching up to €106,975 relative to the mean price of the quantile. This suggests that, despite being exempt from energy rating requirements, these properties are highly valued for their uniqueness and cultural significance, outweighing concerns about energy efficiency.

All other *BER* rating results contrast with our expectations. For instance, both *BER B* and *BER C* exhibit statistically significant negative coefficients across quantiles, indicating that higher-rated properties tend to have lower prices. This effect is more pronounced in the higher quantiles. As shown in Table 17, the price impact for *BER B* ranges from -€ 41,808 at the 0.1 quantile to -€ 48,721 at the 0.9 quantile, while *BER C* follows a similar trend, with price effects ranging from -€ 90,012 to -€ 24,708. Although *BER* ratings play a significant role in property valuation, their influence does not align with expectations.

Furthermore, the condition of a house plays a crucial role in property valuation (*USTAT*). The results align with expectations: *older* homes consistently show a negative coefficient across all quantiles, as do properties in need of renovation. The impact of both factors becomes more pronounced for higher-priced houses. In particular, the price effect for homes requiring repairs becomes increasingly negative, reaching -€ 143,349 in the 0.90 quantile. This suggests that buyers of more expensive properties are especially reluctant to invest in homes that require extensive repairs, making older houses generally less desirable, particularly in the high-priced market.

However, *Renovated* and *Semi-new* houses have the opposite effect of *Old* and *To-recover* properties, exerting a significant positive influence on house prices. However, their impact on higher-priced houses is less pronounced, suggesting that renovations and newer conditions are not the most critical determinants of value in the high-end market. These factors play a more significant role in lower- and mid-priced homes, whereas buyers of high-priced properties tend to prioritise other attributes. Therefore, while the condition of a property is a key determinant of its value, it is less crucial for high-priced properties. Additionally, it is important to note that the dummy variable *Used* does not have a significant impact on price, possibly because the majority of houses in the study sample fall under this category.

The location of properties (*REGION*) and the type of house (*TH*) are the most critical attributes in the property valuation. In Table 16 and Table 17, the results of the variable type of house (*TH*), show that the construction type significantly influences the value. *Detached houses* are the most valued, and the results exhibit a statistically positive effect across all quantiles, with the impact increasing as house prices rise. In Table 17, we observe that being a *detached house* increases property values by € 89,989 at the 0.1 quantile and up to € 207,197 at the 0.9 quantile, highlighting that *detached house* are particularly prized, especially in the higher price range. Additionally, *semi-detached houses* show a similar effect on the price, with positive coefficients across quantiles. The impact on the prices starts at € 45,346 and rises to € 75,078, which indicates their consistent value across price ranges. Another type is the *terrace houses*, which have a weaker, but still positive effect, with lower prices than *detached* and *semi-detached houses*. The price effect is lower but significantly positive. In conclusion, house type is an essential determinant of property price valuation.

An important amenity is a garden or terrace, which is generally associated with higher house values. The results provide strong statistical evidence that low- and middle-priced houses benefit from having a garden. However, for high-priced houses, the evidence is not statistically significant. Specifically, for the 0.10, 0.25, and 0.50 house price quantiles, having a garden increases property values by € 20,313, € 26,862, and € 12,394, respectively - amounts that are particularly impactful for low-priced houses. This underscores the value of outdoor space for buyers in these segments.

The effect of proximity to green spaces on house prices reveals a complex picture when analysing the results for the variable GRN in Tables 16 and 17:
(1) The OLS result shows a statistically significant negative effect of -€ 30,131, suggesting that, on average, properties with this green space attribute are priced lower than those without it. However, this single estimate masks the heterogeneity of the effect across the distribution of house prices.
(2) The coefficients are negative (-€ 30,390 at the 0.10, -€ 43,381 at the 0.25, and -€ 39,334 at the 0.50 quantiles). This indicates that in the lower- to middle-priced houses, the presence of green spaces is associated with a reduction in house prices. This could be due to several factors such as green spaces being more prevalent in older or less developed neighbourhoods where other amenities may be lacking.
(3) At the upper priced segment of the market, the effect reverses significantly. The coefficient becomes positive, as expected: € 5,830 at the 0.75 quantile and € 51,098 at the 0.90 quantile. This suggests that for high-end properties, green spaces add substantial value.

Summing up, the results have strong statistical evidence that the variable has significance on the house prices. Only higher quantiles affect the price positively, contrary to the low and mid quantiles. This indicates that proximity to green spaces is less valued in lower-priced homes, where practical considerations such as house size and location may take precedence. However, for wealthier buyers, green spaces become a more desirable feature, likely due to their association with luxury, tranquillity, and lifestyle quality.

As expected, houses near the sea consistently command higher prices, as evidenced by the increasing coefficients across all quantiles. Coastal access or sea views is a highly desirable amenity, particularly for high-end buyers who are willing to pay a premium. At the 0.90 quantile, high-priced houses appreciate by an average of € 52,852.

Compared to the HPM model's average effects, quantile regression provides a more nuanced view of how determinants vary across different points in the house price distribution. While OLS offers an overall picture, it fails to capture the heterogeneous effects revealed by quantile regression. For instance, Table 17 shows that OLS estimates a price variation of € 259,979 for the east region, but this average mask stronger effects at lower quantiles and weaker effects at higher quantiles. Similarly, OLS estimates a € 3,841 price variation for the *SIZE* variable, yet QR indicates that its impact grows significantly for higher-priced properties, reaching an average variation of € 5,853 at the 0.9 quantile. This comparison underscores OLS's limitations in capturing distributional effects, whereas quantile regression offers a more detailed and accurate understanding of how different factors influence house prices across market segments. Moreover, the QR analysis reveals that several variables, statistically insignificant in OLS, become significant in specific market segments, with their effects varying by quantile.

In Table 18, we present a summary of the empirical results, while Table 18 provides a final summary of the conclusions regarding the predicted hypotheses.

Table 18

Summary of the Empirical Results

Variable	Independent Variable	Expected sign	HPM	Low-Priced Houses	Mid-Priced Houses	High-Priced Houses
Structural Characteristics						
SIZE	Size	Positive (+)	Positive (+)	Positive (+)	Positive (+)	Positive (+)
BED	Number of bedrooms	Positive (+)	No evidence	Positive (+)	Positive (+)	No evidence
BATH	Number of bathrooms	Positive (+)	No evidence	No evidence	No evidence	Negative (-)
USTAT	Usage status	Positive (+) / Negative (-)	Positive (+) / Negative (-)	No evidence/ Negative (-)	No evidence/ Negative (-)	No evidence/ Negative (-)
BER	BER code	Positive (+) / Negative (-)	No evidence/ Negative (-)	No evidence/ Negative (-)	Positive (+) / Negative (-)	Positive (+) / Negative (-)
TH	Type of house	Positive (+) / Negative (-)	Positive (+)	Positive (+)	Positive (+)	Positive (+)
GDT	Garden or terrace	Positive (+)	Positive (+)	Positive (+)	Positive (+)	No evidence
CAR	Parking or Garage	Positive (+)	No evidence	No evidence	No evidence	No evidence
Locational Characteristics						
DWTN	Districts in downtown	Positive (+)	No evidence	No evidence	No evidence	No evidence
REGION	Region	Positive (+) / Negative (-)	Positive (+)	Positive (+)	Positive (+)	Positive (+)

Note: (Continues)

Table 18: (Continued)

Neighbourhood Characteristics						
GRN	Green Spaces	Positive (+)	Negative (-)	Negative (-)	Negative (-)	Positive (+)
SEA	Near Sea	Positive (+)	Positive (+)	Positive (+)	Positive (+)	Positive (+)

Note. This table summarizes both the expected and empirical results, highlighting how house prices vary. The third column presents the expected outcomes, which are compared to the overall empirical findings of the hedonic price model shown in the fourth column. Additionally, the final three columns group the quantile results by price levels: the lower-priced segment (0.1 and 0.25 quantiles) reflects the impact on more affordable houses, the mid-priced segment (0.5 quantile) represents properties in the middle of the price distribution, and the upper-priced segment (0.75 and 0.90 quantiles) illustrates the impact on high-priced houses.

Table 19

Summary of the conclusions about the predicted hypotheses

Hypothesis	**Statement**	**Empirical Result**
Hypothesis 1	An increase in property size leads to a positive variation in price.	Yes
Hypothesis 2	An increase in the number of bedrooms leads to a positive variation in price.	Mix results
Hypothesis 3	An increase in the number of bathrooms leads to a positive variation in price.	No evidence
Hypothesis 4	The price of a property varies positively or negatively depending on its usage status.	Mix results
Hypothesis 5	The price of a property varies positively or negatively depending on its type.	Yes
Hypothesis 6	Properties with a car park or garage experience a positive variation in price.	No evidence
Hypothesis 7	Properties with a garden or terrace experience a positive variation in price.	Yes
Hypothesis 8	The price of a property varies positively or negatively depending on its BER (Building Energy Rating) code.	Mixed results
Hypothesis 9	Properties located in Dublin city centre experience a positive variation in price.	No evidence
Hypothesis 10	The price of a property varies positively or negatively depending on its location.	Yes

Note. Continues

Table 19 (Continued)

Hypothesis 11	Properties near green spaces experience a positive variation in price.	Mix results
Hypothesis 12	Properties near the sea and beach experience a positive variation in price.	Yes

Note. The table lists the theoretical predictions and the corresponding empirical evidence. Those empirical results whose findings provide significant evidence for the theoretical prediction appear after the word "Yes"; those whose findings provide significant evidence but are contrary to the theoretical prediction appear after the word "No"; those studies that do not support the theoretical prediction appear after the words "No evidence"; those studies that whose findings provide significant evidence for the theoretical prediction + provide significant evidence but are contrary to the theoretical prediction or do not support the theoretical prediction appear after the word "Mix results";.

The results of the HPM and quantile QR highlight the heterogeneity of the housing market in Dublin, where the effects of various property characteristics vary significantly across different price segments. Key findings indicate that location, house size, and property type are consistently important determinants of house prices, as Mathur (2020), Zakaria and Fatine (2021), and McCord et al. (2020) conclude in their studies. However, the impact of factors such as proximity to green spaces, number of bedrooms, and energy efficiency is more nuanced and varies depending on the market segment. Higher-end buyers prioritise space, proximity to the sea, and prestigious locations, whereas lower-priced homes are more influenced by practical amenities such as additional bedrooms and access to gardens. In the contrary of the study of Evangelista et al. (2022), the number of bedrooms is a crucial characteristic in the variation of house prices and the study of McMillern (2008) number of bathrooms. These insights can help policymakers, real estate developers, and professionals tailor their strategies to different market segments, recognising the buyers' varying preferences across the price spectrum. The use of quantile regression in this analysis provides a more gradual understanding of how house price determinants operate across different market levels, offering a more detailed picture than OLS alone. This approach is beneficial to understand the behaviour of house prices in a heterogeneous and dynamic market such as Dublin. The analysis of Dublin house prices through both OLS and QR models highlights the complex and heterogeneous nature of the housing market. Variables such as house size, location, and housing type have strong, positive, and significant effects across the market, with these effects magnifying in the upper quantiles. On the other hand, characteristics such as energy efficiency, green spaces, and the number of bedrooms have different impacts across price distributions.

5. CONCLUSION

The study seeks to identify the key determinants of house prices in Dublin, with the central question being: "What are the most significant factors influencing house prices in Ireland's capital?" By utilizing the Hedonic Price Model (HPM) and Quantile Regression (QR) to examine price patterns across the distribution, the analysis emphasizes the importance of location, neighbourhood, and structural factors.

The study explored various methodologies used to assess property values, highlighting their differences, applications in the property market, and limitations. A thorough review of previous research was essential to understand these methods' shortcomings and develop a structured approach for this study.

The research began by collecting housing market data, followed by data cleaning to identify and address errors. Multiple tests were conducted to assess data quality, and various models were tested to determine the most effective approach for this analysis. Ultimately, the double logarithmic HPM model was found to be the most efficient, yielding accurate results for further investigation of house price determinants in Dublin.

The findings demonstrate the complexity and heterogeneity of the Dublin housing market. By employing both HPM and QR methods, this study illustrates how different characteristics affect house prices across various market segments. The QR method provided a more granular understanding of how characteristics influence prices at different price levels.

Key findings include that location is one of the most significant determinants of house prices. Properties in the south-central region of Dublin consistently experience the highest price appreciation, while areas like the West region have a lower impact on prices, especially for lower-priced homes. Property size is also a crucial factor, with larger houses being more highly valued, particularly by wealthier buyers. A 1% increase in size can lead to considerable price increases in higher-priced houses.

Structural features, such as the number of bedrooms and bathrooms, show mixed results. Additional bedrooms increase the value of lower and mid-priced houses. The number of bathrooms, however, does not show statistically significant impact on price.

The presence of gardens or terraces had varying effects. These features are valued in lower and mid-priced houses but show inconsistent and non-statistically significant results for higher-priced properties. Also, proximity to green spaces holds significant value for wealthier buyers as predicted. Access to coastal areas consistently adds value, particularly in the higher-priced market segments. The Building Energy Rating (BER) of a property also strongly influences prices, with lower ratings leading to price reductions, especially in the lower-priced segments where energy costs are more impactful.

Other important determinants include the type of dwelling and the state of use. Detached and semi-detached houses command higher prices, especially in the upper market segments. Usage status plays an important role: older or "fixer-upper" houses tend to lower prices, while renovated or semi-new houses have a positive impact on values, especially in the lower and mid-market segments.

Despite the valuable insights, there are several limitations to this study. The most significant challenge was the collection of data, as there was limited information available on houses in Dublin. The sample size varied across different areas of the city, with some areas having much less available data. Additionally, some relevant variables, such as distance from the city centre, were omitted due to programming errors. The hand-built dataset also faced limitations in terms of available attributes, as not all house features were listed. Furthermore, the relatively small sample size compared to larger studies resulted in less robust statistical analysis.

In conclusion, this research provides useful insights for policymakers, developers, and real estate professionals by identifying the key determinants of house prices and how these factors vary across different segments of the Dublin housing market. The study underscores the importance of tailoring strategies to specific market segments, recognizing that buyer preferences shift depending on the property price range.

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