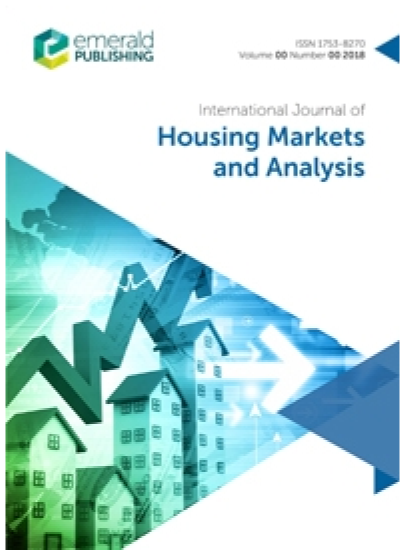

Housing Price Determinants in Ecuador: A Spatial Hedonic Analysis

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Abstract: It is crucial to understand the spatial effects of relevant factors on housing price variations, especially under the context of market imperfections. However, few studies have applied methods such as the hedonic price model in developing countries. This study compares both non-spatial and spatial regression models to examine the factors associated with housing prices based on the municipal housing appraisal and real estate datasets for the city of Quito, Ecuador. A set of 17 variables including structural, neighborhood and location characteristics are investigated using a traditional linear regression model and a Geographically Weighted Regression (GWR) model. The results suggest that compared to the traditional regression model, the GWR model is more effective at capturing housing market variations on a fine scale. Moreover, it reveals interesting findings on the spatial varying, sometimes opposite effects of some housing attributes on housing prices in different areas of the city, suggesting the potential impact from segregation.

Keywords: spatial effects, housing prices, hedonic price model, spatial dependence, spatial heterogeneity, Geographically Weighted Regression, housing submarkets, Latin America

1 Introduction

Housing price is a primary constraint in household residential decisions, thus making it one of the most important determinants of residential choices. Property value has been a major focus in housing studies in the past five decades (Malpezzi, 2008; Sirmans et al., 2006; Zietz et al., 2008). It is well understood that the determinants of housing prices, especially in urban environments, are quite complex. Early studies have suggested that property prices are determined mainly by their physical characteristics (e.g., size, use, services), locations, and other external factors related to the non-tangible values of the properties (Sirmans et al., 2006).

Since its introduction by Rosen (1974), the Hedonic Price Model (HPM) has been the most applied method for both estimating housing prices and identifying the contribution of the elements related to housing prices. It is one of the earliest applications of multivariate statistical techniques to housing price evaluation (Xiao, 2017). Within the HPM, a house is composed of various attributes including structural characteristics and the surrounding spatial conditions. The hedonic price model allows to account for both a heterogeneous housing stock and the different ways consumers value these characteristics (Malpezzi, 2008; Sirmans et al., 2005). Since its early applications, the empirical results of the HPM suggested the existence of housing submarkets based on the heterogeneity of the stock and preferences as well as the uniqueness of housing location itself (Schnare & Struyk, 1976). However, most studies on housing prices are based on data from cities in the developed countries (Abidoye & Chan, 2017; Chin & Chau, 2003). Given the cultural, social, economic, and morphological differences between cities in developed and developing countries (Griffin & Ford, 1980), it is necessary to examine what variables are influential in housing prices and how they affect housing prices in developing countries.

Under this context, this study employs both non-spatial and spatial regression models to examine the factors associated with housing prices for the city of Quito, Ecuador. This study expects to contribute to a better understanding of the housing price determinants from both non-spatial and spatial perspectives. Additionally, this paper fills a gap in the literature on the study of housing prices from a spatial perspective in Latin American cities. The purpose of this article, therefore, is threefold. First, we employ a traditional Hedonic Price Model – Ordinary Least Squares model (OLS) to identify which factors influence housing prices in Quito on a global scale. Secondly, we compare the results of the model based on two different datasets: the municipal housing appraisal dataset and a real estate dataset. Lastly, we consider the impact of locations and examine the spatial varying effects of those determinants on housing prices from a spatial perspective using Geographical Weighted Regression (GWR). We compare the results of two traditional Hedonic Price Models with the GWR model. We explore the existence of housing submarkets, where the coefficients of the factors differ, within the city. Findings from our study provide insights to the effectiveness of applying those models to cities similar to Quito.

This paper is structured as follows. First, we provide a literature review of common findings on housing price determinants using hedonic price models, including their spatial variations and case studies. Next, we employ OLS and GWR models to analyze the determinants and their spatial effects on housing prices in Quito. Then we compare the results from those models and discuss their relative effectiveness in capturing the characteristics of the housing price and housing market in Quito. In the conclusion, we discuss the issues related to housing price modelling and the applicability of these models in Latin American cities.

2 Literature Review

2.1 Hedonic Price Models (HPM models)

According to Rosen (1974), the value of a product is equal to the value assigned to each of its attributes based on the utility perceived by consumers, which he calls implicit prices. The model assumes a differentiated product market in which an equilibrium is reached when consumers are willing to pay the implicit prices of the attributes offered by producers. In that respect, the model allows the study of consumer preferences based on the implicit, or hedonic, prices of each of the product attributes. It is then understood that market prices reflect these preferences. Prices are modeled from a vector of the prices of each of the product characteristics, in a linear regression. Thus, the price of a house is determined by its structural characteristics (size, bathrooms, materials) and by its location (specially accessibility to the Central Business District as suggested in the Alonso-Muth-Mills model)(Malpezzi, 2008). Housing markets are considered an extreme example of product differentiation since each home is unique, not so much for its structural characteristics but for its location.

The form in which location can be considered as a characteristic determining housing prices traces back to theoretical foundations such as the Alonso-Muth-Mills model that considers proximity to the central business district and its associated cost of travel as a major factor affecting prices (Wheaton, 1982). This model assumes income and preferences as constant for all individuals, which is not even close to reality. Tiebout (1956), for example, shows how based on individual preferences and a differentiated spatial distribution of public goods, people sort in the city landscape forming clusters of population with similar characteristics. What remains clear from these approaches is that housing prices are highly dependent not only on the structural characteristics of the units but mostly on the location of it in relation with other goods and from the consumer perspective.

Many researchers recognized the HPM as one of the best methods to estimate the effects of non-observable values such as environmental factors, accessibility, or neighborhood characteristics on housing prices (Janssen et al., 2001; Pagourtzi et al., 2003). Despite the critiques for its assumption of a perfectly competitive market, that is, the price of each individual attribute is determined upon people's willingness to pay for it, this model has proven to be a powerful tool in predicting housing prices and the effects of various factors.

The hedonic price model has been widely used in housing markets, especially in cities in developed countries. A study by Malpezzi's (2008) outlines various ways in which the HPM has been commonly utilized in several studies. These include enhancing housing price indices, evaluating urban models, creating environmental quality measures, investigating socio-economic disparities in housing prices, determining subsidy programs, appraising individual properties, and examining the impact of amenities on property values. While the findings tend to be specific for each place, studies have suggested some general patterns emphasizing the importance of location, property features, and environmental factors. Proximity to amenities, property size, condition, and aesthetic appeal positively impacts housing prices. Desirable neighborhoods, attractive views, and green spaces contribute to higher values, while economic conditions, transportation access, and school quality are pivotal factors. The interplay of these elements, combined with market dynamics, underscores the multidimensional nature of housing valuation in diverse regions.

Despite the wide range of variables and model specifications utilized in HPM studies, some authors suggest a certain degree of comparability. Sirmans et al. (2006) conducted an analysis of 82 studies in the United States and discovered that the coefficients exhibit less fluctuation based on location and time than expected. Usman, Lizam, and Burhan (2020) propose that the divergent effects of these factors could be attributed to variations in the specific location under study and local consumer preferences.

In general, structural characteristics exert a greater impact on housing prices compared to neighborhood and location characteristics. However, there is greater divergence in the effects of structural and locational attributes on prices than with neighborhood attributes (Usman et al., 2020). In their review, Chin, and Chau (2003) present a list of 22 commonly used independent variables in hedonic price models and their effects on housing prices. They identified certain consistencies in the impact of structural characteristics, such as area, number of bedrooms, or age. However, the influence of neighborhood characteristics varied depending on the study's location. For instance, the proximity to hospitals, shopping centers, and forests were location-specific due to certain cultural aspects. This shows the importance of investigating the effects of these variables in different regions and at different scales, as we intend to do in this study. Herath and Maier (2010) revealed that empirical studies focus on neighborhood characteristics, with a notable emphasis on environmental factors, particularly air pollution. Infrastructure, especially public goods, also receives considerable attention. In contrast, social factors such as racial segregation and crimes receive less attention in these studies. We tried to include variables that are related to social factors, although considering the limited availability of these in the study area. Several authors (A. C. Goodman & Thibodeau, 1998, 2003; J. L. Goodman, 1976) point out that using averages of census variables allows an approximation to the neighborhood effects on housing prices in an HPM. Malpezzi (2008) suggests using these in a granular unit (block in this case) to maximize the variation of these factors.

2.2 Spatial models, spatial heterogeneity, and market segmentation

Although the advantages of the HPM are recognized widely, some studies pointed out that the global approach of this model is incapable of capturing spatial effects on housing prices (Anselin, 1998; Cabral & Crespo, 2011; Crespo & Grêt-Regamey, 2013). Therefore, some studies have recognized the importance of calibrating the HPM to capture both the housing price dynamics and the contextual urban space (de Araujo & Cheng, 2017; Orford, 2000; Tse, 2002). Can (1990a, 1992a) has highlighted location as one of the most important determinants of housings prices that have not been well captured by the traditional hedonic price models. One of the strategies to control spatial heterogeneity in hedonic price models has been the segmentation of the datasets into submarkets. However, this approach has limitations due to its arbitrary definition of neighborhood boundaries or segments. Even though some authors have found that the difference in the results between a segmented model and a global one is insignificant (Schnare & Struyk, 1976), the uniqueness and dynamism of housing markets may determine the significant formation of housing submarkets in certain areas rather than others (Orford, 2017). Recent studies applying the HPM to housing prices conclude on the importance to consider spatial effects to improve model predictions and conclusions (Basu & Thibodeau, 1998; Bera et al., 2018; Cajias & Ertl, 2018; Can, 1992b; Helbich et al., 2014; Huang et al., 2010; Osland, 2010; Sheppard, 1999).

According to Anselin (1995), spatial models explicitly account for two major spatial effects in housing prices that were typically ignored in global models: spatial dependency and spatial heterogeneity. As many studies suggest (Taylor, 2008), the price of a housing unit is not determined exclusively by the structural and locational characteristics, the prices of the neighboring units also affect its value. This spatial effect, known as spatial dependence, has been considered in models that modify the traditional HPM. Among these models, the Spatial Lag and Spatial Error regression models introduced more than three decades ago have been applied in multiple cases. Some of them report that neighboring unit price can affect up to 25% on a house price (Can, 1990b, 1992b). The work of Koschinsky et al. (2012) is one of the studies that compare the performance of non-spatial and spatial regression models when considering the spatial structure. They found that testing for spatial structure in datasets is crucial due to potential substantial differences in estimation results. Incorporating spatial fixed effects in OLS models is not an effective alternative to spatial methods in accounting for spatial structure. This highlights the need to correct for spatial effects when present in hedonic models.

Along with the effect of the prices of neighboring houses, other elements near a house may influence its value as well. Although the effect of amenities and disamenities[1] nearby is well captured by the original HPM global coefficients, there might be some cases where the same effect on price varies depending on the location. For instance, proximity to public transportation may be valued positively in a high-density college student neighborhood while it may be avoided by a young couple with children looking for a suburban housing unit. This effect, spatial heterogeneity, has been captured by models that include a spatial weight matrix and report local coefficients, such as Geographical Weighted Regression – GWR proposed by Brunsdon, Fotherigham et al. (1996).

As Fotheringham and Crespo (2015) suggest, few studies on housing prices focused on spatial dependency and spatial heterogeneity. Can (1992c) showed the importance of incorporating neighborhood effects within the HPM specifications in segmented markets as neighborhood differentials may cause a different attribute price depending on the location. This reflects a differentiated structure of demand and supply in a city that can be understood by the study of different subsets of housing (Knox & Pinch, 2010). Goodman and Thibodeau (2003) opened an extensive debate on housing market segmentation because of a disequilibrium between housing demand and supply. Since the house location in a city is an inseparable attribute of a housing unit, it is responsible in part for this inelasticity as there could only be one house in a certain location (Orford, 2000). Consequently, housing markets are constituted by submarkets

[1] Amenities such as parks, public services, and goods or disamenities such as a garbage deposit, night clubs, etc.

defined by structural and locational characteristics (Adair et al., 1996). From a geographical perspective, a submarket refers to a group of residences that closely resemble each other and can serve as viable alternatives within the group, yet they are not as suitable substitutes for residences in different submarkets (Islam & Asami, 2009).

Finally, Goodman and Thibodeau (A. C. Goodman & Thibodeau, 1998, 2003) found that hedonic coefficients for neighborhood characteristics varied across space and concluded that metropolitan markets were segmented based on geography. We aim to explore the use of GWR, a local regression on the HPM as ways to unveil these submarkets in Latin America (Crespo & Grêt-Regamey, 2013).

2.3 Studies in developing countries.

Although housing prices have been studied extensively in developed countries, only a few have focused on developing countries, e.g., Abidoye and Chan (2017, 2018) in Nigeria, Selim (2009) and Hülagü (2016) in Turkey, Roy (2020) in India, Aliyev et al. (2019) in Azerbaijan, Zakaria (2021) in Morocco, in Africa and Asia. In Latin America studies have examined housing prices for cities in Chile (Banco Central de Chile, 2011; Figueroa & Lever, 1992; Iturra & Paredes, 2014; Vergara-Perucich, 2021), Venezuela (Contreras et al., 2014), Peru (Quispe, 2012), Mexico (Lara Pulido et al., 2017; Moreno & Alvarado, 2011), and Colombia (Cabrera-Rodriguez et al., 2019; Castaño et al., 2013; Duque et al., 2011; Morales & Arias, 2005; Perdomo Calvo, 2017). Most of these studies focus on the effect of a single variable such as proximity to public transport (Perdomo Calvo, 2017) or risk of invasion or expropriation (Contreras et al., 2014). Others, e.g., Banco Central de Chile (2011), focus on the effect of macroeconomic variables in the price change in time, as well as identifying the effect of financialization in the prize variation (Vergara-Perucich, 2021) (Vergara-Perucich 2021). Finally, while Figueroa & Lever (1992), Quispe (2012), Lara-Pulido (2017), and Moreno & Alvarado (2011) analyzed the price determinants in a comprehensive way, they did not consider spatial configurations of their regression models.

Some studies involved traditional hedonic price models as well as spatial regressions. For example, Cabrera-Rodriguez et al. (2019), Morales & Arias (2005) and, Duque et al. (2011) attempted to generate a complete price index and to estimate the effect of housing quality in the city of Bogota considering the location of the properties and found that a spatial error model outperformed the OLS model. Iturra & Paredes (2014) conducted a similar study focusing on the whole country of Chile. In Ecuador, the application of hedonic price models is more recent in literature and has been applied to study the housing prices in the cities of Guayaquil (Zambrano-Monserrate et al., 2021, 2022; Zambrano-Monserrate & Ruano, 2019), Machala (Zambrano-Monserrate, 2016; Zambrano-Monserrate & Ruano, 2021), and Quito (Borja-Urbano et al., 2021; Cornejo-Vasconez et al., 2022; Vallejo Albuja et al., 2015). The studies by Zambrano & Ruano (2019, 2021) and Zambrano et al. (2021, 2022) focus on the effect of environment (e.g., noise, proximity to estuaries, and urban green spaces on housing rental prices. Their studies indicate a significative spatial heterogeneity for some of the rental price determinants, suggesting the existence of housing submarkets. The study of Borja-Urbano et al. (2021), on the other hand, focused on analyzing the effects of air pollution as well as structural and neighborhood characteristics on housing prices in the city of Quito. However, they did not include social or economic variables, nor did they consider spatial models. A similar study by Cornejo-Vásconez et al. (2022) also analyzed the effect of pollution on housing prices in two zones, the historical city center, and a wealthy neighborhood in the modern business district. They found out that a decrease in the level of pollutants results in an increase in property prices. The work of Vallejo-

Albuja et al. (2015), on the other hand, attempts to identify the effect of a single park on the price of the housing properties and found the distance to the park was insignificant.

None of the studies in the city of Quito is comprehensive in the number of variables considered. Also, none of them include spatial specifications of the regressions as we do in this research. Our study provides a more comprehensive analysis of the effects of all variables in housing prices, exploring which are more important and how model calibrations improve the results. We also evaluate the spatial forms of regressions to understand spatial dependence and spatial heterogeneity. Additionally, our study compares the results between two different dataset sources, which helps improve the variable selection results and facilitate further comparations. One of the main reasons that there are limited studies on housing prices in developing countries is the lack of detailed and consistent data. Existing studies had to rely on different datasets to meet research needs, which resulted in limitations. Nevertheless, studies on Latin America highlighted fundamental differences in housing markets compared to those in developed countries. Despite differences in public policies and regulations, certain general conditions can explain these disparities. For example, the rapid urbanization rates in developing countries lead to a less flexible housing market. Additionally, higher numbers of young people compared to developed countries, combined with an unequal distribution of urban infrastructure, land market accessibility, housing informality and a longtime spatial segregation can affect market segmentation (Blanco et al., 2016; Fay, 2005; Gilbert, 1992, 1999, 2017; McTarnaghan et al., 2004; Rojas, 2015; Rojas & Medellin, 1995; Ward, 1993).

This study delves deeper into understanding the determinants of housing prices for cities in the developing world. It also contributes to the discussion on the importance of space in the use of hedonic prices to model these housing markets and to theorize their particularities.

3 Methodology

3.1 Study Area and Data

Quito, capital of Ecuador, is in the northern highlands of Ecuador with a population of nearly 3 million. It experienced significant population growth since the 1960s, owing to the economic inputs from oil exports. This economic growth triggered the inflow of population from rural areas and smaller cities to Quito and the expansion of its boundaries towards the suburbs in the east. As a result of this rapid expansion, the city structure evolved from a concentric form established during the colonial period, to a longitudinal multi nuclei during most of the twentieth century and to a metropolitan multicenter at the beginning of the twenty-first century (Carrión & Erazo Espinosa, 2012). The rapid and fragmented process of expansion, coupled with an urban policy that favored spatial segregation, has resulted in a segmented housing market. This segmentation can be identified and illustrated through the models employed in this study.

3.2 Data

The data for this study comes from three main sources. The socio-economic variables at the city block level were obtained from the 2010 Ecuadorian National Census[2]. The housing prices and structural attributes were obtained from the 2015 municipal property cadaster as well as a real estate data portal called Properati[3]. The base unit of analysis is the points that represent the

[2] As of the date of publication of this article, the 2020 census data at the block level have not been published by the official institution, mainly due to the postponement of it until 2022 because of the pandemic.

[3] Properati has data for more than 1.7 million properties located in Argentina, Colombia, Ecuador, Peru and Uruguay. The company has a data division that presents periodical reports on real estate markets, open data and other geo-visualization tools. Source: www.properati.com

location of the housing units included in the sample of each of the data sources.

For each housing unit in the datasets, the corresponding socioeconomic variables from the 2010 census block they are located at were assigned using the spatial join tool in QGIS software. Five demographic variables were selected for this study: population of ethnic minorities, number of people with private health insurance, population that speaks an indigenous language, foreign born population and people who used internet in the last six months, all these measured as the percentage in the corresponding census block. Additionally, five variables that capture information at the housing unit level were also included: the proportion of housing units with more than two bedrooms, the proportion of housing units with the roof in good condition, the ratio of apartments over houses, the ratio of rented over owned housing units and the proportion of housing units with internet access. Finally, the Euclidean distances to the CBD (Alonso, 1960; Kain & Quigley, 1970), nearest school (Agarwal et al., 2016; Downes & Zabel, 2002), nearest park (C. Wu et al., 2017), nearest health service (hospitals, clinics, and urgent care facilities) and the nearest public transport (Perdomo Calvo, 2017; Zhang & Jiao, 2019) were calculated. Table 1 shows a detailed description for each variable.

Table 1. Variable description.

Dimension	*Variable*		*Description*
	HP	Housing Price	The price of a housing unit in US dollars, as listed in the city's cadaster or real estate portal. In the models, this variable is presented in its log form according to the recommendations of previous research.
Structural characteristics	AR	Housing area	The total built surface area of the dwelling in square meters. This is one of the variables that most significantly influences the price due to the requirement for a greater volume of materials and resources for its construction, as well as higher specifications for usage.
	BR	Number of bedrooms	The number of bedrooms within the residential unit. This information is exclusively available within the Properati dataset.
	TR	Number of bathrooms	The number of bathrooms within the residential unit. This information is exclusively available within the Properati dataset.
Neighborhood characteristics	RC	Proportion of houses with roof in good condition	In the Ecuadorian census, residential roofing conditions are assessed with three levels: good, fair, and poor. This variable is calculated by dividing the number of units with a good roof by the total number of units in that block.
	IA	Percentage of houses with internet access	Derived from the number of dwellings with internet access divided by the total number of dwellings in the block. These variable captures household income, with higher-income neighborhoods expected to have a greater proportion of houses with internet access.
	PHI	Percentage of population with private health insurance	Census variable capturing the number of individuals with access to private health insurance. It serves as a proxy for income level due to the high costs associated with these insurances in the country.

	INT	Percentage of population that used internet in the last six months	Unlike the variable measuring households with internet access (IA), this one is computed based on individuals who used the internet in the months preceding the census. It's noteworthy that this figure may differ from household access values since other locations like schools, libraries, etc., provide access to this service.
	ET	Proportion of ethnic minorities	This question in the Ecuadorian census pertains to individuals' self-identification based on their culture and customs. Options include mestizo, white, Afro-Ecuadorian, black, montubio, indigenous, and mulatto. The latter five were considered ethnic minorities in this study.
	IND	Proportion of individuals that speak indigenous language	This variable specifically refers to individuals who speak an indigenous language. Like the ethnic minority variable, it constitutes an important aspect to consider given the historical process of ethnic segregation (Capello, 2011; Guevara-Rosero & Bonilla-Bolaños, 2021)).
	FOR	Percentage of foreign-born individuals	The census question used to calculate this variable considers individuals born in another country who reside in Ecuador on the day of the census. The distribution of foreigners has been explored in terms of residential satisfaction(Carrión, 2005; Martí-Costa et al., 2016; Urdaneta & Burke, 2020). It is important to mention that different nationalities have different effects and distributions. For example, Colombians have a uniform distribution, while Americans are mostly concentrated in suburbs and the financial center.
	TY	Proportion of apartments over houses	Captures urban and architectural characteristics, particularly distinguishing areas dominated by apartments in the central city from suburbs with houses. Derived by dividing the number of apartments by the total number of houses in the block.
	HT	Proportion of owners over renters	Reflects the distribution of owners and tenants and its implications for housing submarkets and policy considerations, given the importance of rental housing as a potential solution to housing challenges in Latin America (Blanco et al., 2014).
Locational characteristics	DC	Distance to the Central Business District CBD	Euclidean distance measured from the location of the dwelling to the nearest point of the polygon defining the CBD, in meters. The relationship between land values and distance to the Central Business District (CBD) follows common urban theories, where residential land farther from the CBD tends to be cheaper, allowing for larger properties (Richards, 2011). However, in some European and Latin American, expensive residential properties can be found near or within the CBD, alongside lower-income settlements in the suburbs.
	DS	Distance to the closest school	Euclidean distance in meters measured from the dwelling's location to the nearest school. Studies have found that quality influences prices more than proximity (Kane et al., 2003). However, due to the lack of standardized quality indicators in Quito, we used the distance as a proxy.
	DH	Distance to the closest health service	Euclidean distance in meters measured from the dwelling's location to the nearest healthcare service.
	DK	Distance to the closest park	Euclidean distance in meters measured from the dwelling's location to the nearest park. While an influence of this factor on prices has been identified, specific mechanisms are still under study(Chen & Jim, 2010).
	DT	Distance to public transport	Euclidean distance in meters from the dwelling's location to public transportation. In Quito, more than 60% of the population uses public transportation(D.M.Q, 2014).

Table 2 shows the descriptive statistics for the variables, revealing a slight variation in average prices across datasets. The 6% difference between the average sale price in the 2019 Properati dataset and the 2015 cadaster dataset aligns with national price inflation between 2016 and 2018, supporting a viable comparison despite the difference in the timeframe.

Table 2. Variables descriptive statistics.

	Cadaster 2015					Properati 2019				
Number of properties	6000					11446				
Variable	Average	Median	Min	Max	Std Dev	Average	Median	Min	Max	Std Dev
House Price (PR)	118932	86953	3855	1830828	121343	132842	120000	2001	390000	88056
House Area (AR)	279.48	222.21	20.0	3910.90	247.93	227.62	133.00	30.00	4127.00	265.37
Number of bedrooms (BR)	-	-	-	-	-	4.01	3.00	1.00	26.00	3.69
Houses with more than 3 bedrooms (BR)	0.40	0.37	0.00	1.00	0.19	0.47	0.47	0.00	1.00	0.22
Houses with roof in good condition (RC)	0.69	0.71	0.00	1.00	0.18	0.76	0.82	0.00	1.00	0.23
Houses with Internet access (IA)	0.27	0.21	0.00	1.00	0.22	0.47	0.49	0.00	1.00	0.27
People with private health insurance (PHI)	0.19	0.15	0.00	1.00	0.15	0.35	0.34	0.00	1.00	0.22
People who used internet (INT)	0.46	0.45	0.00	1.00	0.19	0.61	0.67	0.00	1.00	0.23
Ethnic minorities (ET)	0.10	0.08	0.00	1.00	0.11	0.07	0.04	0.00	1.00	0.11
People who speak indigenous language (IND)	0.02	0.00	0.00	0.80	0.05	0.01	0.00	0.00	0.50	0.03
Foreign-born population (FOR)	0.03	0.01	0.00	0.72	0.04	0.07	0.04	0.00	1.00	0.08
Ratio apartments/houses (TY)	1.03	0.43	0.00	129.00	3.21	4.24	0.64	0.00	301.00	17.58
Ratio owners/renters (HT)	0.97	0.75	0.00	24.00	1.03	0.82	0.57	0.00	12.50	0.96
Distance to CBD (DC)	8222.92	8240.19	0.00	25539.89	4435.58	5023.12	4298.19	0.00	22774.11	4630.97
Distance to schools (DS)	170.86	121.56	0.00	1480.90	175.17	118.90	73.90	0.00	1191.07	139.79
Distance to parks (DK)	297.80	236.98	0.00	4654.14	276.56	240.72	189.44	0.00	1951.28	219.19
Distance to health services (DH)	651.75	516.39	0.00	6515.26	563.88	816.87	755.05	0.00	5529.98	529.17
Distance to public transport (DT)	350.33	18.34	0.00	11332.20	1088.43	292.88	4.53	0.00	15046.40	1056.80

3.3 Data sampling and handling

Both datasets resulting from the process previously described were cleaned or sampled. From the 411,220 data points in the cadaster dataset, we selected only residential properties. For those property types that have multiple housing units (horizontal property in the local law), we calculated the average price and area. The housing prices in the property cadaster are not based on actual market prices but city property valuations[4] instead which tend to present a bias towards a higher asking price (Kolbe, Schulz et al. 2021). To make the dataset more manageable, we extracted a random sample of 6000 points using the "random extract" tool in QGIS software[5].

On the other hand, the Properati dataset captures actual market prices, thus it can be more informative and provides a complimentary insight into housing values from another market perspective. The Properati dataset also contains more information on the structural characteristics including the number of bedrooms and bathrooms, as well as other amenities in a housing unit and a building.

Of the 33,736 residential units in the Properati dataset, only 23,315 were complete cases including price and area in their attributes. Among these, only 15,151 were published for sale while the remaining 8,164 were published for rent. From the properties for sale, we removed those with inconsistent prices and areas. For instance, any property with a smaller area than the minimum habitable area established by local regulations was removed. Also, based on the prices in the national policy for public housing, units with prices below $2,000 were eliminated. The final Properati dataset includes 11,446 housing units for sale, which represent 33% of the total records for the city of Quito.

[4] The Local Government uses a tool to retrieve land and property taxes which is based on an extrapolation model of market prices. This tool called AIVAS, areas of valuation intervention. It synthesizes the land and property values based on real market prices extrapolated to the whole city.

[5] https://docs.qgis.org/3.28/en/docs/user_manual/processing_algs/qgis/vectorselection.html#random-extract

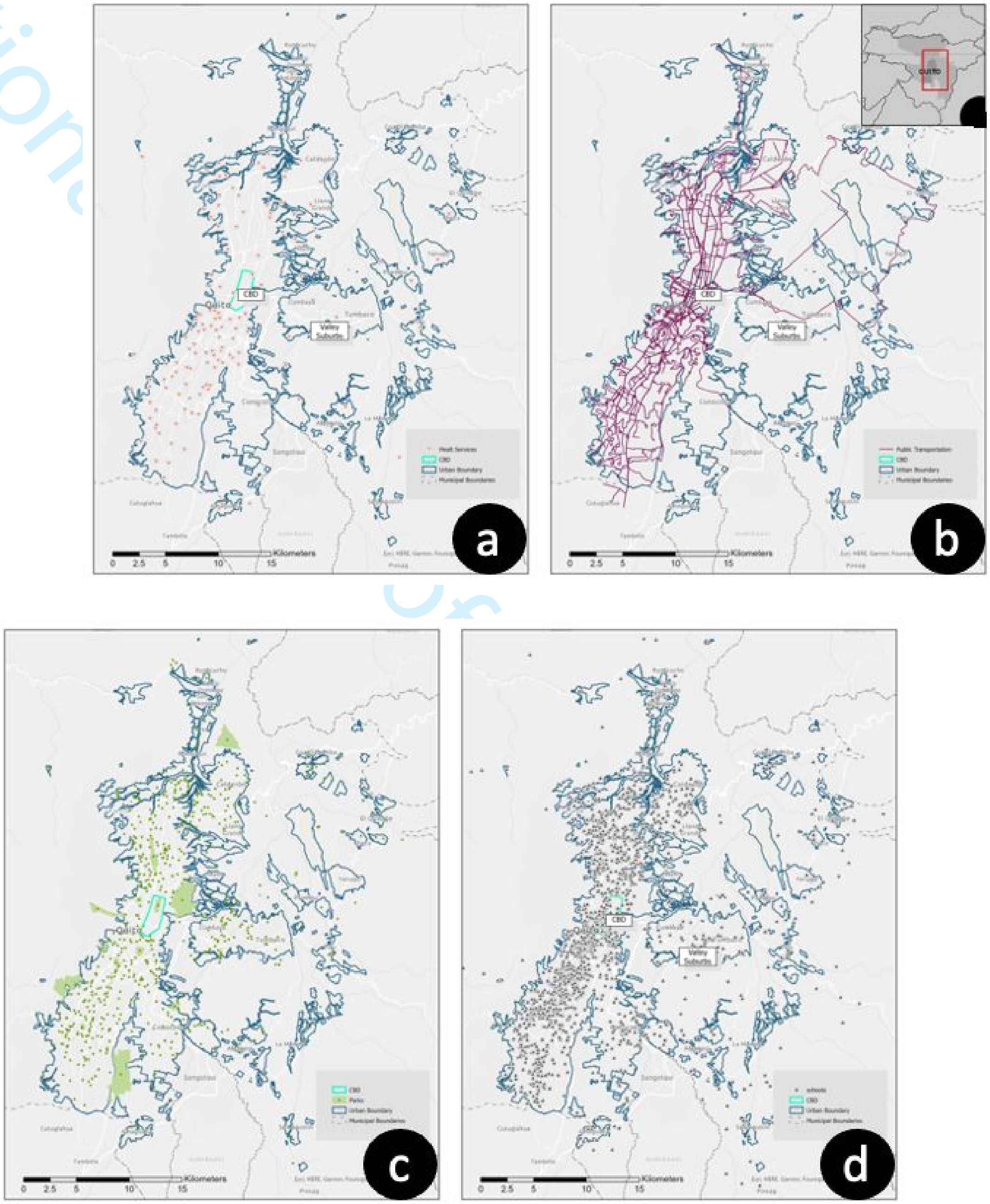

Figure 1. Locational characteristics variables: a) health services, b) public transport routes, c) parks and d) schools in the city.

3.4 Model Specifications

With the variables described previously, the HPM is defined as follows:

$$(1)\quad HP(\log) = \beta_0 + \beta_1\mathrm{AR} + \beta_2\mathrm{BR} + \beta_3\mathrm{RC} + \beta_4\mathrm{IA} + \beta_5\mathrm{PHI} + \beta_6\mathrm{INT} + \beta_7\mathrm{ET} + \beta_8\mathrm{IND} + \beta_9\mathrm{FOR} + \beta_{10}\mathrm{TY} + \beta_{11}\mathrm{HT} + \beta_{12}\mathrm{DC} + \beta_{13}\mathrm{DS} + \beta_{14}\mathrm{DK} + \beta_{15}\mathrm{DH} + \beta_{16}\mathrm{DT} + \varepsilon$$

Where HP is the dependent variable housing price in the log form, β_0 is the coefficient of the intercept term, $\beta_1 \ldots \beta_n$ are the coefficients for the independent variables and, ε represents the error term. In all the models we used the log form of the price (dependent variable) as its distribution presents a slight skewness towards lower values. As a result, we employ a semi-log linear regression suggested by the literature (Basu & Thibodeau, 1998; A. C. Goodman & Thibodeau, 2003). Non-significant variables were eliminated in the stepwise regression. It is worth to note that we also attempted to examine the spatial structure of housing prices on a global scale with a spatial lag model and a spatial error model. However, given that the improvements in model fit were negligible, we decide to focus our discussion on a local spatial regression model, the Geographic Weighted Regression model.

OLS models, spatial lag and spatial error models capture the impacts of housing price determinants from a global scale, even when spatial effects are accommodated in the spatial versions. Geographic Weighted Regression, however, can reveal the spatial heterogeneity of those determinants across the study area. Different from those global models in which a single common coefficient of each determinant applies to the entire study area, the GWR calculates a coefficient for each variable at each location in the regression respectively. Thus, the values of the coefficients for an explanatory variable vary across space, in other words, the spatial varying effects of the explanatory variables can be measured and visualized on a map. The GWR is defined as:

$$(2)\quad HP_i = \sum_{j=1}^{p} x_{ij}\beta_{ij} + \varepsilon_i$$

Where HP_i denotes the value of the housing price in the log form at location i, $x_{ij}$is the value of the jth independent variable at location i, β_{ij} denotes the location specific coefficient of x_{ij}, and ε_i is the error at location i.

All significant independent variables derived from the OLS models are included in the GWR model. The GWR model is capable of accommodating both spatial homogeneity (similarities) and spatial heterogeneity (also known as spatial non-stationarity). Spatial heterogeneity occurs when a variable's effect on the dependent variable varies depending on the observed point's location. Factors such as proximity to transportation can have different effects on housing prices in different areas, depending on residents' preferences and market conditions. As Goodman and Thibodeau (2003) suggest, market inelasticity caused by a disequilibrium in supply and demand is another source of spatial heterogeneity.

As aforementioned, the difference between an OLS model and a GWR model lies in whether the entire dataset is used in the calibration of the model, or the calculations of the coefficients. A GWR model only considers the neighbors of a property when generating the coefficients for the independent variables. Thus, it is critical to determine the neighbors of properties. In GWR, a distance band is typically used to identify neighboring properties for a property. Within such a distance band, factors affecting housing prices are more spatially homogeneous whereas outside the distance band, they are more spatially heterogenous. This approach allows for the identification of areas within the city where certain variables better explain price variations. In this study, we used the GWR tool in MGWR software application (Oshan et al., 2019) to implement the analysis. All factors were considered local in the GWR since the objective of this research was to explore spatial variations compared to the OLS results. All factors were considered local in the GWR since the objective of this research was to explore spatial variations compared to the OLS results, To calculate the spatial weights matrix, an Adaptative Kernel function was employed in the GWR. The function uses different distance bands across the study area to ensure: 1) a sufficient number of properties are included for generating the local coefficients; 2) the adaptive distances in the final model generate the lowest Akaike Information Criterion (AIC) score. The AIC scores are usually used to compare regression model performance. The smaller the AIC score, the better fit a model (Oshan et al., 2019).

4 Results

4.1 OLS Model

We conducted OLS models, based on equation (1), for the cadaster dataset (Model 1) and the Properati dataset (Model 2). The results are shown in Table 3. Considering the collinearity between some variables, we used Variable Inflation Factor (VIF) values to identify and discard those variables with the highest correlation values. Variables of internet access and internet usage were removed from the model due to collinearity. All remaining variables have VIF values lower than 3, which is acceptable considering the effect of spatial dependence in collinearity. Most variables are common across the two datasets, except for the number of bedrooms (BR) in the Properati dataset.

Table 3. Results for Model 1 and Model 2

		Model 1		*Model 2*	
		Coeff.		Coeff.	
	Intercept (House Price log)	6.67320	***	11.50405	***
AR	Housing area	0.81111	***	0.18279	***
BR	Number of bedrooms	-	-	-0.26559	***
BRn	Proportion of housing units with more than 2 bedrooms	0.13357	***	0.05416	

RC	Proportion of housing units with roof in good condition	0.00872		-0.22809	***
PHI	Population with private health insurance	0.59689	***	0.44753	***
ET	Ethnic minorities	0.20313	***	-0.21009	.
IND	People that speak indigenous languages	0.08998		0.51182	
FOR	Proportion of foreign born	1.21522	***	0.21033	
TY	Proportion of apartments	-0.00140		-0.00147	*
HT	Proportion of rented housing units	-0.02861	***	-0.01778	
DC	Distance to CBD	0.00002	***	-0.00001	**
DS	Distance to schools	0.00003		0.00022	**
DK	Distance to parks	-0.00009	***	-0.00029	***
DH	Distance to health services	0.00007	***	0.00005	*
DT	Distance to public transportation	0.00001	*	0.00003	**
	R2	0.78260		0.49199	
	Adj. R2	0.78200		0.49102	
	AIC	4694.55		26495.1	
	Moran's I of residuals	0.1721***		0.0871***	

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Both models are proved statistically significant. In terms of the goodness-of-fit, Model 1(based on 2015 cadaster dataset) explains 78% of the variation of housing prices while Model 2 (based on the Properati dataset) explains slightly over 49% of the variation on prices.

In Model 1, the variables with the strongest positive influence on price are the proportion of foreign-born residents in the neighborhood (FOR), the housing unit area (AR), and the proportion of people with private health insurance (PHI). The effect of housing unit area on price aligns with previous studies (Kwong Wing, 2003; Xiao, 2017). The proportion of foreign-born individuals captures a socioeconomic aspect of the city as specific neighborhoods attract people with similar characteristics. Conversely, a higher number of apartments and rented units in a city block leads to lower housing prices. Notably, the proportion of rented housing units has the most negative impact. Among the distance-based variables, only proximity to parks has a positive effect, while greater distance from these elements results in lower prices.

Similar significant coefficients are found in Model 2. Positive effects on price are observed for housing area (AR), proportion of people with private health insurance (PHI), and proportion of foreign-born residents (FOR). The variable representing the proportion of people speaking indigenous languages (IND) is particularly interesting as it has a greater impact on price than the structural characteristics of the house. On the other hand, the number of bedrooms (BR), proportion of housing units with a good roof condition (RC), and proportion of ethnic minorities (ET) have strong negative effects on price. The negative impact of ethnic minorities may be linked to spatial segregation. Distance-based variables have lower impacts, with proximity to parks and the central business district (CBD) positively influencing price.

Comparing the coefficients of the two models, we observe expected similarities, highlighting the influence of structural and socioeconomic factors over distance-based variables. However, differences in certain variables, such as the proportion of houses with a good roof condition, proportion of ethnic minorities, and distance to the CBD, indicate the need of a local approach in the analysis.

4.2 GWR

To examine the presence of spatial effects, we analyzed the regression residuals of the two OLS models. We calculated the global Moran's I index as well as the robust Lagrange Multiplier (LM) test for the residuals of models 1 and 2 (Anselin et al., 1996). The results suggest significant positive spatial autocorrelations in the residuals (Table 2). Thus, it warranties the use of the GWR model to capture the spatial structure. Two GWR models based on equation (2) are presented here, Model 3 using the cadaster dataset and Model 4 using the Properati dataset.

Table 4 compares the model performance of the OLS and GWR models. The Moran's I of the residuals was reduced to 0.097 in Model 3 and 0.036 in Model 4. Therefore, it suggests that the GWR models helped reduce the spatial dependency.

Table 4. Model Comparison

Dataset	*Model*	*AIC*	*R2*	*Moran's I*
CAD6000	OLS (Model 1)	4694.55	0.7826	0.1721***
	GWR (Model 3)	3222.31	0.832	0.0974***
PROPSALE	OLS (Model 2)	26495.1	0.4919	0.0871***
	GWR (Model 4)	19282.5	0.559	0.0364***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

When comparing the R^2 values with those obtained from previous spatial regressions, GWR outperforms the other models in both datasets, with an increase of at least 4% in explained variation. The smaller AIC scores of the GWR models also suggest that they explained the relationship between the housing prices and the determinants better in both datasets.

The spatial distribution of local R^2 values in Model 3 and Model 4 reveals interesting patterns (figure 2). The overall R^2 for Model 3 dataset is higher and evenly distributed, whereas the local R^2 for the Model 4 dataset is lower and displays a distinct distribution. Lower R^2 values are concentrated in the central north area of the city, while higher values are observed in the northern and southern borders, as well as a suburb in the southeast area. The range of local R^2 values for this dataset is significant, falling below 30% in the central area and exceeding 90% in the far north and south limits.

The uneven spatial distribution of local R^2 values can be explained by two factors. Firstly, the higher concentration of observation points in the central area leads to lower local R^2 values due to increased variability. Secondly, the presence of submarkets in these areas could contribute to the lower local R^2 values, as omitted variables may explain price variations better than the selected variables significant in other areas. However, it is worth noting that certain variables still demonstrate significant relevance in the areas with lower local R^2 values, suggesting that omitted variables are not the sole reason for these results.

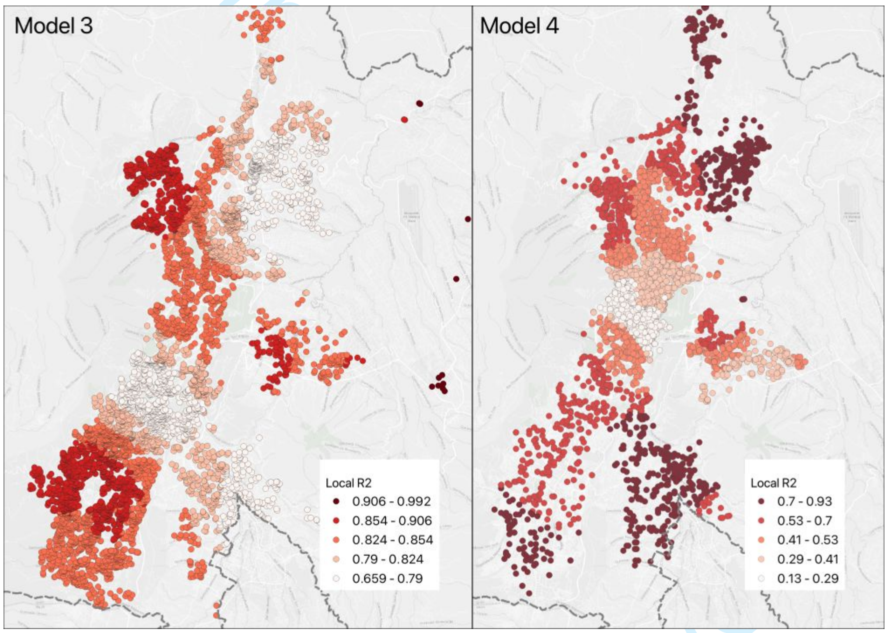

Figure 2. Local R2 distribution

Table 4 displays the variation of the coefficient values based on the distance bandwidths that yielded the lowest AIC value in Model 3 and Model 4. As shown in Table 5, in both models, the coefficients for the distance-based variables have a lower effect on housing prices than in the OLS models. Notably, some coefficients present a high internal variation, measured by the standard deviation and the difference between the maximum and the minimum values. The variables BR, ET and PHI reveal this contrasting pattern, indicating the effect of the variable is not only heterogenous but even polarized in space.

Table 5. GWR coefficient summary

		Model 3				*Model 4*			
		Mean	*Min*	*Max*	*S.D*	*Mean*	*Min*	*Max*	*S.D*
	Intercept (House Price log)	6.6071	5.8328	13.7144	0.5418	11.9753	-16.0284	15.4092	1.6417
AR	Housing area	0.8449	0.2911	0.9411	0.0527	0.0680	-0.6784	0.9793	0.3523
BR	Housing units w/ 2+ bedrooms	0.1077	-3.4895	0.8753	0.2119	-0.2327	-0.3781	-0.0450	0.0726
RC	Housing units w/ roof in good condition	-	-	-	-	-0.4015	-2.0899	3.2217	0.4085
PHI	Population w/ private insurance	0.2560	-10.9855	2.2176	0.3434	0.5181	-1.1755	5.8066	0.5960
ET	Ethnic minorities	0.2686	-0.6538	7.3957	0.3573	0.3053	-2.3839	19.5581	0.7906
FOR	Foreign-born population	0.2319	-6.9231	3.8068	0.6813	-	-	-	-
TY	Ratio apartments/houses	-	-	-	-	-0.0016	-0.1824	3.0204	0.0584
HT	Ratio rented/owned	-0.0203	-0.3092	0.2958	0.0331	-	-	-	-
DC	Distance to CBD	0.0000	-0.0003	0.0001	0.0000	0.0002	-0.0003	0.0027	0.0004
DS	Distance to Schools	0.0000	-0.0017	0.0032	0.0002	0.0003	-0.0048	0.0019	0.0006
DK	Distance to Parks	0.0000	-0.0027	0.0011	0.0001	-0.0002	-0.0014	0.0020	0.0003
DH	Distance to Health Services	0.0000	-0.0039	0.0003	0.0002	0.0001	-0.0009	0.0026	0.0002
DT	Distance to Public Transport	-0.0001	-0.0008	0.0090	0.0003	0.0002	-0.0034	0.0032	0.0010

Furthermore, the coefficient analysis of the two datasets reveals more differences than similarities. In Model 3, house area emerges as the most influential variable on price, consistent with previous models. However, in Model 4, the proportion of people with private health insurance (PHI) is more important. In addition, some coefficients exhibit opposing influences across the study area, such as the number of bedrooms and distance to parks. The variation in coefficient values, standard deviation, and significance levels indicates spatial heterogeneity.

Housing area stands out in terms of spatial heterogeneity. While it is expected to positively impact prices, Model 4 displays negative coefficients in the central-north area, signifying a significant negative influence. This raises questions about the diverse types and sizes of properties in this region, necessitating further investigation.

The number of bedrooms also produces unexpected results in Model 4, with all local coefficients negatively impacting prices. Conversely, Model 3 presents both positive and negative coefficients, primarily concentrated in rural areas and a limited northwest region. However, most negative coefficients lack statistical significance.

The proportion of ethnic minorities exhibits an interesting spatial pattern exhibit in Figure 2. Positive coefficients cluster in affluent central-north and suburban areas, while negative coefficients concentrate in the northwestern and southern limits. This suggests a preference for ethnic diversity in wealthier areas, necessitating a detailed analysis of various minority groups' distribution and their impact on spatial heterogeneity.

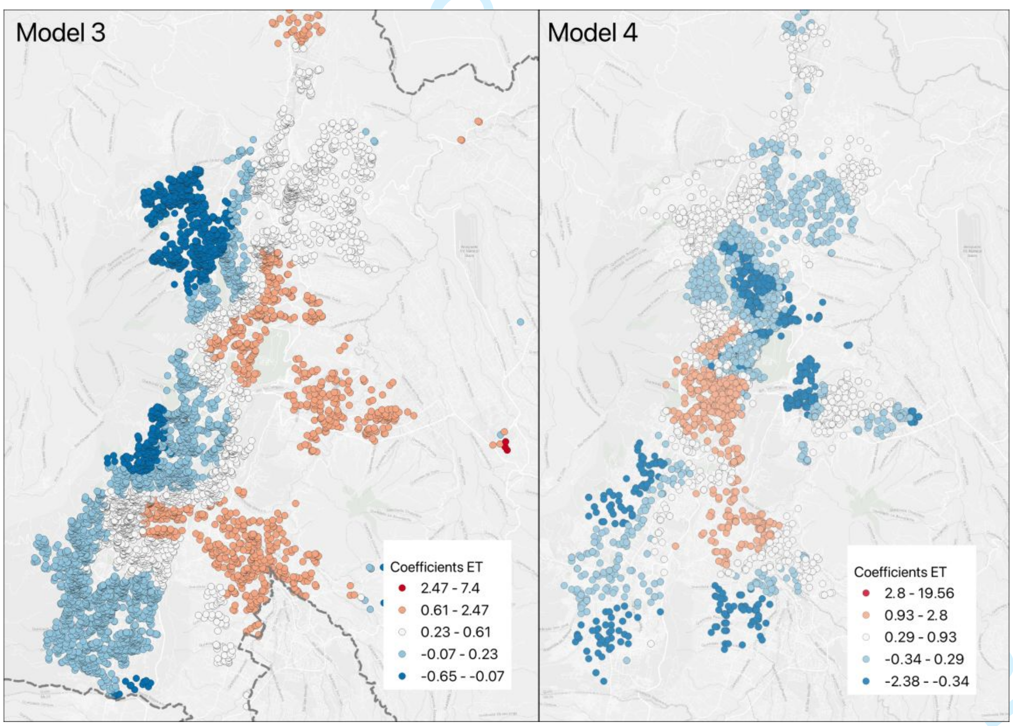

Figure 3. Local coefficients for Ethnic Minorities

Despite the unexpected negative effect of the percentage of people with private insurance on prices, the coefficients lack statistical significance in the Model 4. Conversely, Model 3 indicates a positive and more pronounced impact in the north and suburbs, reflecting a spatial association with income distribution.

Distance-based variables also contribute to understanding spatial heterogeneity. For example, Model 3 demonstrates that distance to the central business district (CBD) positively affects prices in suburbs and nearby areas, while negative coefficients appear in the western side. This corresponds to low-income working-class areas and suggests a preference for proximity to the CBD. However, Model 4 presents a different pattern, with only the central-north affluent neighborhoods showing a positive impact. Negative coefficients are observed in the north, south, and suburbs, indicating a complex relationship between distance to the CBD and prices.

Similar contrasts are found in the variable of distance to schools. Model 3 shows a positive impact in the central area and south but negative impacts in the north and south extremes, aligning with the higher concentration of schools in the center, due to a lower density, access to schools in the northern and southern areas has a higher value for these households. In contrast, Model 4 primarily exhibits positive coefficients, with only those in the north statistically significant.

Distance to parks also presents different effects. Model 3 demonstrates a positive impact in central, center-north, and far south areas, but negative impact in the center-south and far north. Notably, statistically significant positive coefficients in the north suggest a relative disregard for park proximity. The areas with a negative impact of distance to parks located in the center/south and far north is both significant and suggest a desire to be closer to this infrastructure. Model 4 has fewer significant coefficients, primarily in the central area and northern suburbs, suggesting a preference for proximity to parks. In this case too, a deeper analysis of the reasons explaining this preference may help explain the difference. The distribution of parks infrastructure, the characteristics of these parks as well as other phenomena associated with them, e.g. the impact on the perceived safety, can shed light on the mechanism behind the difference (Byrne & Wolch, 2009; Moran et al., 2020).

Spatial patterns of coefficients for distance to health services vary as well. In Model 3, positive impacts are observed in the central and north areas, while negative impacts occur in the southern limit and rural remote areas. Model 4 presents more detailed patterns, with positive coefficients in smaller central and center-north areas and negative coefficients in the center-south, far north, and eastern suburbs. These differences may be related to the distribution and access to health infrastructure. It also suggests that in much of the city people tend to avoid being close to a health service as the distance has a positive impact on housing prices. The most notable difference between the two maps is on the northern area where the effect on price is contrary in the two datasets. This area is characterized by a recent important process of densification that resulted in a low coverage of certain services. This can suggest that the spatial pattern resulting for Model 4 is more coherent.

Distance to public transportation shows varying effects as well. Negative impacts on housing prices are seen in the south and north on Model 3, but exclusively in the northwest on Model 4. Positive impacts are observed in the center and south on Model 4 and center-south on Model 3. The significance of locations also differs. Model 4 suggests higher demand for proximity to public transportation in the northwest and avoidance near the CBD, while Model 3 aligns more with expectations based on income and location. Contrary to expectations based on literature, the coefficients for distance to transportation do not align with the anticipated spatial pattern. However, significant findings in Model 4 suggest a higher demand for proximity to public transportation in the northwest and avoidance in the central areas near the CBD. Additionally, Model 3 shows negative impacts in the south and far north, along with positive impacts in the southern suburbs, which align more closely with expectations.

The two additional variables in Model 3, proportion of renters over owners and proportion of foreign-born residents, show no spatial heterogeneity. However, they indicate lower effects in areas with more renters and higher effects in areas with a greater proportion of foreign-born residents.

Overall, these findings highlight the spatial heterogeneity in coefficient values and their impacts on housing prices between the two datasets. The contrast and some unexpected variations of the coefficients call for a more in-depth analysis of various factors, such as property types, minority groups, distribution of infrastructure, and socioeconomic dynamics, to better understand the underlying patterns of spatial heterogeneity.

5 Summary and Discussion

The HPM has proven to be an effective approach to understanding the effect of different attributes in housing prices in the literature (Rosen, 1974). Most of the variables used in this study were selected based on the recommendations of the literature. Although many of these studies were conducted in regions different from Latin America, the performance of the models applied in this study suggest a validity of these variables for the selected case.

The results demonstrate the spatial effects of various price determinants, highlighting a distinct urban structure marked by spatial inequity. This structure underscores enduring inequalities in the housing market over time. Notably, the OLS model partially illustrates this, revealing the influence of sociodemographic factors on price, such as the percentage of individuals with private health insurance and foreign-born residents. These factors exhibit equal or greater influence than structural housing variables. GWR further emphasizes their significance in price determination, exposing spatial inequities. For instance, the proportion of ethnic minorities notably impacts prices, exhibiting substantial spatial variation. While seemingly paradoxical, areas with lower ethnic minority proportions, like suburban locales, witness a positive impact on price. Conversely, peripheral areas experience a negative impact on price due to concentrated minority populations, reflecting historical segregation effects.

Variables measuring distances to amenities also display spatial variability, albeit with less influence on prices. However, their spatial distribution mirrors sociodemographic patterns. This intertwined relationship underscores the impact of sociodemographic factors and service distribution on housing prices. It's crucial to note that distance variable coefficients do not merely reflect preferences; rather, they signify historical residential segregation and amenity distribution. Understanding this requires interpreting them alongside sociodemographic variables to decode longstanding spatial structures.

Each Latin American census defines categories like ethnicity uniquely, necessitating careful selection of sociodemographic variables to unveil housing market spatial structures. Granular demographic data, as utilized in this study, proves vital in unraveling complex spatial associations. Future research should delve into the implications of sociodemographic variables on housing price spatial structures and their ties to historical segregation processes. Given varying segregation patterns across Latin American cities, a one-size-fits-all variable approach may not suffice. Similar considerations apply to variables like the proportion of foreign-born individuals, whose settlement patterns differ based on historical social formations in each locale.

It is important to mention that, despite having been able to build complementary models that explain the variability of housing prices in the city based on official and commercial data sources, the availability and update of data with sufficient detail on housing prices and their characteristics continue to be a limitation for studying this phenomenon in the region. In this case, while the cadaster is a more comprehensive data source as it includes all existing properties, it does not measure the actual sale price in the market. Therefore, this price does not represent the valuation that people make at the time of the study. Also, at least in the case of Quito, it does not include variables such as year of construction, number of bedrooms, etc.

On the other hand, the real estate data source has a lower spatial representativeness, as it only covers units in the market with a greater representation of the most dynamic and desirable areas. However, it better represents the market price, although with a bias towards higher prices in real sales. Furthermore, it provides more details about the characteristics of the housing unit, especially amenities. Perhaps the most interesting aspect of analyzing this type of data source is the information on rental prices, which are not available in the cadaster, and its update speed, which allows measuring rapid changes in the market.

One of the study's main objectives was to compare the results of standard and spatial calibrations of the Hedonic Price Model to study housing prices. The GWR models resulted in a higher explanation of the variation of housing prices overall along with a decrease in spatial autocorrelation of the model residuals. These results reinforce the argument that spatial effects determine housing prices. In all the models and for all the datasets used in this study, the GWR models showed an improvement not only in the goodness-of-fit of the model but also on the significance of the coefficients. Being said so, although spatial models perform better than non-spatial models, the decision on which model to use should rely on a good diagnosis as it depends on the dataset used.

Our analyses also suggest that both spatial dependence and spatial heterogeneity are important in housing prices. The GWR models were able to capture both spatial homogeneity and spatial heterogeneity. In this case study, spatial heterogeneity was of special interest to better understand the effect of urban spatial structure in the housing markets. The variables that capture this effect the most are those associated with the distance to the city services, infrastructures, and amenities. These variables reflect not only a difference but a divergence in the way the proximity to these features is valued by households in certain areas of the city.

Regardless of some differences and contradictions between the two datasets, the resulting coefficients in general show a disruption on the value system amid the wealthy areas (center-north and suburban valleys) and the rest of the city (far north and south, and rural areas), suggesting the existence of housing submarkets. These submarkets, however, are by no means to be considered static in time. In some cases, as in the health services and the schools, this pattern is modified by the distribution of the infrastructure. In other cases, as public transportation, this pattern is also affected by the population's use of the infrastructure. Despite the low values of the coefficients for these variables, these are not negligible on housing prices.

The GWR revealed spatial patterns at a finer scale that are not well captured when using discrete zones of the city as variables within a spatial regression model. This is of particular interest for fast changing urban structures like the Latin American cities. In this case study the most interesting finding related to spatial heterogeneity was the opposing and contrasting effect of certain variables depending on the location. The GWR is relevant to unveil other patterns such as spatial residential segregation and inequality as suggested by Wu (2002) and others.

All these results suggest the existence of housing submarkets that are significant in the city. As these housing submarkets are dynamic in both space and time, the application of the GWR considering time changes would be valuable. For that, more frequent update of the data is needed. The implementation of a housing survey with a stratified spatial sample is highly suggested for this end.

Finally, further research needs to be done at the individual level to better understand the underlying process of valuing a house for different socio-demographic groups and in different areas of the city.

6 Conclusions

In this study, we conducted a comparative analysis between OLS models and GWR models. We intended to provide some insights on the application of those models to analyze housing markets in developing countries.

The variables influencing housing prices in our analysis are like those tested in other regions, enabling a certain level of comparability despite variations in housing price recording methodologies. However, we emphasize the importance of standardizing housing price recording instruments within our study region to enhance the generalizability of findings.

Furthermore, we have assessed the performance of two distinct data sources: the city's cadastral records and a real estate sales and rental web portal. Each source presented advantages and limitations for our analysis. While the cadastral records provide a more comprehensive representation of the housing stock, thereby better capturing the variability of housing prices, the real estate portal data offer valuable insights into rental prices and more detailed information on structural characteristics. Nonetheless, it is crucial to acknowledge the inherent bias towards inflated prices within the real estate portal data.

Consistent with existing literature, our findings underscore the significant role of variables related to housing structure and functionality in explaining price variations. However, we also highlight the relevance of spatial dependence, which manifests as the influence of neighboring property prices. Moreover, variables concerning neighborhood composition and housing locations (proximity to services) contribute valuable insights to the analysis of price determinants. Notably, certain variables exhibit intriguing spatial heterogeneity, a phenomenon effectively identified through the application of Geographically Weighted Regression.

Our research sheds light on the identification of housing submarkets, particularly in cases where a single variable yield contrasting effects across different areas within the city. It is worth noting that the exploration of housing submarkets in Latin American cities remains limited in the existing literature. Thus, our findings contribute to filling this research gap and emphasize the significance of combining diverse and complementary data sources while considering spatial effects in future studies.

Overall, this study enriches the limited body of literature on spatial hedonic price models of housing in Latin American cities. By employing rigorous analytical techniques and providing empirical evidence, our research advances the understanding of housing price determinants and the implications of spatial dynamics in the context of Latin America.

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Housing Price Determinants in Ecuador: A Spatial Hedonic Analysis

Abstract: It is crucial to understand the spatial effects of relevant factors on housing price variations, especially under the context of market imperfections. However, few studies have applied methods such as the hedonic price model in developing countries. This study compares both non-spatial and spatial regression models to examine the factors associated with housing prices based on the municipal housing appraisal and real estate datasets for the city of Quito, Ecuador. A set of 17 variables including structural, neighborhood and location characteristics are investigated using a traditional linear regression model and a Geographically Weighted Regression (GWR) model. The results suggest that compared to the traditional regression model, the GWR model is more effective at capturing housing market variations on a fine scale. Moreover, it reveals interesting findings on the spatial varying, sometimes opposite effects of some housing attributes on housing prices in different areas of the city, suggesting the potential impact from segregation.

Keywords: spatial effects, housing prices, hedonic price model, spatial dependence, spatial heterogeneity, Geographically Weighted Regression, housing submarkets, Latin America

1 Introduction

Housing price is a primary constraint in household residential decisions, thus making it one of the most important determinants of residential choices. Property value has been a major focus in housing studies in the past five decades (Malpezzi, 2008; Sirmans et al., 2006; Zietz et al., 2008). It is well understood that the determinants of housing prices, especially in urban environments, are quite complex. Early studies have suggested that property prices are determined mainly by their physical characteristics (e.g., size, use, services), locations, and other external factors related to the non-tangible values of the properties (Sirmans et al., 2006).

Since its introduction by Rosen (1974), the Hedonic Price Model (HPM) has been the most applied method for both estimating housing prices and identifying the contribution of the elements related to housing prices. It is one of the earliest applications of multivariate statistical techniques to housing price evaluation (Xiao, 2017). Within the HPM, a house is composed of various attributes including structural characteristics and the surrounding spatial conditions. The hedonic price model allows to account for both a heterogeneous housing stock and the different ways consumers value these characteristics (Malpezzi, 2008; Sirmans et al., 2005). Since its early applications, the empirical results of the HPM suggested the existence of housing submarkets based on the heterogeneity of the stock and preferences as well as the uniqueness of housing location itself (Schnare & Struyk, 1976). However, most studies on housing prices are based on data from cities in the developed countries (Abidoye & Chan, 2017; Chin & Chau, 2003). Given the cultural, social, economic, and morphological differences between cities in developed and developing countries (Griffin & Ford, 1980), it is necessary to examine what variables are influential in housing prices and how they affect housing prices in developing countries.

Under this context, this study employs both non-spatial and spatial regression models to examine the factors associated with housing prices for the city of Quito, Ecuador. This study expects to contribute to a better understanding of the housing price determinants from both non-spatial and spatial perspectives. Additionally, this paper fills a gap in the literature on the study of housing prices from a spatial perspective in Latin American cities. The purpose of this article, therefore, is threefold. First, we employ a traditional Hedonic Price Model – Ordinary Least Squares model (OLS) to identify which factors influence housing prices in Quito on a global scale. Secondly, we compare the results of the model based on two different datasets: the municipal housing appraisal dataset and a real estate dataset. Lastly, we consider the impact of locations and examine the spatial varying effects of those determinants on housing prices from a spatial perspective using Geographical Weighted Regression (GWR). We compare the results of two traditional Hedonic Price Models with the GWR model. We explore the existence of housing submarkets, where the coefficients of the factors differ, within the city. Findings from our study provide insights to the effectiveness of applying those models to cities similar to Quito.

This paper is structured as follows. First, we provide a literature review of common findings on housing price determinants using hedonic price models, including their spatial variations and case studies. Next, we employ OLS and GWR models to analyze the determinants and their spatial effects on housing prices in Quito. Then we compare the results from those models and discuss their relative effectiveness in capturing the characteristics of the housing price and housing market in Quito. In the conclusion, we discuss the issues related to housing price modelling and the applicability of these models in Latin American cities.

2 Literature Review

2.1 Hedonic Price Models (HPM models)

According to Rosen (1974), the value of a product is equal to the value assigned to each of its attributes based on the utility perceived by consumers, which he calls implicit prices. The model assumes a differentiated product market in which an equilibrium is reached when consumers are willing to pay the implicit prices of the attributes offered by producers. In that respect, the model allows the study of consumer preferences based on the implicit, or hedonic, prices of each of the product attributes. It is then understood that market prices reflect these preferences. Prices are modeled from a vector of the prices of each of the product characteristics, in a linear regression. Thus, the price of a house is determined by its structural characteristics (size, bathrooms, materials) and by its location (specially accessibility to the Central Business District as suggested in the Alonso-Muth-Mills model)(Malpezzi, 2008). Housing markets are considered an extreme example of product differentiation since each home is unique, not so much for its structural characteristics but for its location.

The form in which location can be considered as a characteristic determining housing prices traces back to theoretical foundations such as the Alonso-Muth-Mills model that considers proximity to the central business district and its associated cost of travel as a major factor affecting prices (Wheaton, 1982). This model assumes income and preferences as constant for all individuals, which is not even close to reality. Tiebout (1956), for example, shows how based on individual preferences and a differentiated spatial distribution of public goods, people sort in the city landscape forming clusters of population with similar characteristics. What remains clear from these approaches is that housing prices are highly dependent not only on the structural characteristics of the units but mostly on the location of it in relation with other goods and from the consumer perspective.

Many researchers recognized the HPM as one of the best methods to estimate the effects of non-observable values such as environmental factors, accessibility, or neighborhood characteristics on housing prices (Janssen et al., 2001; Pagourtzi et al., 2003). Despite the critiques for its assumption of a perfectly competitive market, that is, the price of each individual attribute is determined upon people’s willingness to pay for it, this model has proven to be a powerful tool in predicting housing prices and the effects of various factors.

The hedonic price model has been widely used in housing markets, especially in cities in developed countries. A study by Malpezzi's (2008) outlines various ways in which the HPM has been commonly utilized in several studies. These include enhancing housing price indices, evaluating urban models, creating environmental quality measures, investigating socio-economic disparities in housing prices, determining subsidy programs, appraising individual properties, and examining the impact of amenities on property values. While the findings tend to be specific for each place, studies have suggested some general patterns emphasizing the importance of location, property features, and environmental factors. Proximity to amenities, property size, condition, and aesthetic appeal positively impacts housing prices. Desirable neighborhoods, attractive views, and green spaces contribute to higher values, while economic conditions, transportation access, and school quality are pivotal factors. The interplay of these elements, combined with market dynamics, underscores the multidimensional nature of housing valuation in diverse regions.

Despite the wide range of variables and model specifications utilized in HPM studies, some authors suggest a certain degree of comparability. Sirmans et al. (2006) conducted an analysis of 82 studies in the United States and discovered that the coefficients exhibit less fluctuation based on location and time than expected. Usman, Lizam, and Burhan (2020) propose that the divergent effects of these factors could be attributed to variations in the specific location under study and local consumer preferences.

In general, structural characteristics exert a greater impact on housing prices compared to neighborhood and location characteristics. However, there is greater divergence in the effects of structural and locational attributes on prices than with neighborhood attributes (Usman et al., 2020). In their review, Chin, and Chau (2003) present a list of 22 commonly used independent variables in hedonic price models and their effects on housing prices. They identified certain consistencies in the impact of structural characteristics, such as area, number of bedrooms, or age. However, the influence of neighborhood characteristics varied depending on the study's location. For instance, the proximity to hospitals, shopping centers, and forests were location-specific due to certain cultural aspects. This shows the importance of investigating the effects of these variables in different regions and at different scales, as we intend to do in this study. Herath and Maier (2010) revealed that empirical studies focus on neighborhood characteristics, with a notable emphasis on environmental factors, particularly air pollution. Infrastructure, especially public goods, also receives considerable attention. In contrast, social factors such as racial segregation and crimes receive less attention in these studies. We tried to include variables that are related to social factors, although considering the limited availability of these in the study area. Several authors (A. C. Goodman & Thibodeau, 1998, 2003; J. L. Goodman, 1976) point out that using averages of census variables allows an approximation to the neighborhood effects on housing prices in an HPM. Malpezzi (2008) suggests using these in a granular unit (block in this case) to maximize the variation of these factors.

2.2 Spatial models, spatial heterogeneity, and market segmentation

Although the advantages of the HPM are recognized widely, some studies pointed out that the global approach of this model is incapable of capturing spatial effects on housing prices (Anselin, 1998; Cabral & Crespo, 2011; Crespo & Grêt-Regamey, 2013). Therefore, some studies have recognized the importance of calibrating the HPM to capture both the housing price dynamics and the contextual urban space (de Araujo & Cheng, 2017; Orford, 2000; Tse, 2002). Can (1990a, 1992a) has highlighted location as one of the most important determinants of housings prices that have not been well captured by the traditional hedonic price models. One of the strategies to control spatial heterogeneity in hedonic price models has been the segmentation of the datasets into submarkets. However, this approach has limitations due to its arbitrary definition of neighborhood boundaries or segments. Even though some authors have found that the difference in the results between a segmented model and a global one is insignificant (Schnare & Struyk, 1976), the uniqueness and dynamism of housing markets may determine the significant formation of housing submarkets in certain areas rather than others (Orford, 2017). Recent studies applying the HPM to housing prices conclude on the importance to consider spatial effects to improve model predictions and conclusions (Basu & Thibodeau, 1998; Bera et al., 2018; Cajias & Ertl, 2018; Can, 1992b; Helbich et al., 2014; Huang et al., 2010; Osland, 2010; Sheppard, 1999).

According to Anselin (1995), spatial models explicitly account for two major spatial effects in housing prices that were typically ignored in global models: spatial dependency and spatial heterogeneity. As many studies suggest (Taylor, 2008), the price of a housing unit is not determined exclusively by the structural and locational characteristics, the prices of the neighboring units also affect its value. This spatial effect, known as spatial dependence, has been considered in models that modify the traditional HPM. Among these models, the Spatial Lag and Spatial Error regression models introduced more than three decades ago have been applied in multiple cases. Some of them report that neighboring unit price can affect up to 25% on a house price (Can, 1990b, 1992b). The work of Koschinsky et al. (2012) is one of the studies that compare the performance of non-spatial and spatial regression models when considering the spatial structure. They found that testing for spatial structure in datasets is crucial due to potential substantial differences in estimation results. Incorporating spatial fixed effects in OLS models is not an effective alternative to spatial methods in accounting for spatial structure. This highlights the need to correct for spatial effects when present in hedonic models.

Along with the effect of the prices of neighboring houses, other elements near a house may influence its value as well. Although the effect of amenities and disamenities[1] nearby is well captured by the original HPM global coefficients, there might be some cases where the same effect on price varies depending on the location. For instance, proximity to public transportation may be valued positively in a high-density college student neighborhood while it may be avoided by a young couple with children looking for a suburban housing unit. This effect, spatial heterogeneity, has been captured by models that include a spatial weight matrix and report local coefficients, such as Geographical Weighted Regression – GWR proposed by Brunsdon, Fotherigham et al. (1996).

As Fotheringham and Crespo (2015) suggest, few studies on housing prices focused on spatial dependency and spatial heterogeneity. Can (1992c) showed the importance of incorporating neighborhood effects within the HPM specifications in segmented markets as neighborhood differentials may cause a different attribute price depending on the location. This reflects a differentiated structure of demand and supply in a city that can be understood by the study of different subsets of housing (Knox & Pinch, 2010). Goodman and Thibodeau (2003) opened an extensive debate on housing market segmentation because of a disequilibrium between housing demand and supply. Since the house location in a city is an inseparable attribute of a housing unit, it is responsible in part for this inelasticity as there could only be one house in a certain location (Orford, 2000). Consequently, housing markets are constituted by submarkets

[1] Amenities such as parks, public services, and goods or disamenities such as a garbage deposit, night clubs, etc.

defined by structural and locational characteristics (Adair et al., 1996). From a geographical perspective, a submarket refers to a group of residences that closely resemble each other and can serve as viable alternatives within the group, yet they are not as suitable substitutes for residences in different submarkets (Islam & Asami, 2009).

Finally, Goodman and Thibodeau (A. C. Goodman & Thibodeau, 1998, 2003) found that hedonic coefficients for neighborhood characteristics varied across space and concluded that metropolitan markets were segmented based on geography. We aim to explore the use of GWR, a local regression on the HPM as ways to unveil these submarkets in Latin America (Crespo & Grêt-Regamey, 2013).

2.3 Studies in developing countries.

Although housing prices have been studied extensively in developed countries, only a few have focused on developing countries, e.g., Abidoye and Chan (2017, 2018) in Nigeria, Selim (2009) and Hülagü (2016) in Turkey, Roy (2020) in India, Aliyev et al. (2019) in Azerbaijan, Zakaria (2021) in Morocco, in Africa and Asia. In Latin America studies have examined housing prices for cities in Chile (Banco Central de Chile, 2011; Figueroa & Lever, 1992; Iturra & Paredes, 2014; Vergara-Perucich, 2021), Venezuela (Contreras et al., 2014), Peru (Quispe, 2012), Mexico (Lara Pulido et al., 2017; Moreno & Alvarado, 2011), and Colombia (Cabrera-Rodriguez et al., 2019; Castaño et al., 2013; Duque et al., 2011; Morales & Arias, 2005; Perdomo Calvo, 2017). Most of these studies focus on the effect of a single variable such as proximity to public transport (Perdomo Calvo, 2017) or risk of invasion or expropriation (Contreras et al., 2014). Others, e.g., Banco Central de Chile (2011), focus on the effect of macroeconomic variables in the price change in time, as well as identifying the effect of financialization in the prize variation (Vergara-Perucich, 2021) (Vergara-Perucich 2021). Finally, while Figueroa & Lever (1992), Quispe (2012), Lara-Pulido (2017), and Moreno & Alvarado (2011) analyzed the price determinants in a comprehensive way, they did not consider spatial configurations of their regression models.

Some studies involved traditional hedonic price models as well as spatial regressions. For example, Cabrera-Rodriguez et al. (2019), Morales & Arias (2005) and, Duque et al. (2011) attempted to generate a complete price index and to estimate the effect of housing quality in the city of Bogota considering the location of the properties and found that a spatial error model outperformed the OLS model. Iturra & Paredes (2014) conducted a similar study focusing on the whole country of Chile. In Ecuador, the application of hedonic price models is more recent in literature and has been applied to study the housing prices in the cities of Guayaquil (Zambrano-Monserrate et al., 2021, 2022; Zambrano-Monserrate & Ruano, 2019), Machala (Zambrano-Monserrate, 2016; Zambrano-Monserrate & Ruano, 2021), and Quito (Borja-Urbano et al., 2021; Cornejo-Vasconez et al., 2022; Vallejo Albuja et al., 2015). The studies by Zambrano & Ruano (2019, 2021) and Zambrano et al. (2021, 2022) focus on the effect of environment (e.g., noise, proximity to estuaries, and urban green spaces on housing rental prices. Their studies indicate a significative spatial heterogeneity for some of the rental price determinants, suggesting the existence of housing submarkets. The study of Borja-Urbano et al. (2021), on the other hand, focused on analyzing the effects of air pollution as well as structural and neighborhood characteristics on housing prices in the city of Quito. However, they did not include social or economic variables, nor did they consider spatial models. A similar study by Cornejo-Vásconez et al. (2022) also analyzed the effect of pollution on housing prices in two zones, the historical city center, and a wealthy neighborhood in the modern business district. They found out that a decrease in the level of pollutants results in an increase in property prices. The work of Vallejo-

Albuja et al. (2015), on the other hand, attempts to identify the effect of a single park on the price of the housing properties and found the distance to the park was insignificant.

None of the studies in the city of Quito is comprehensive in the number of variables considered. Also, none of them include spatial specifications of the regressions as we do in this research. Our study provides a more comprehensive analysis of the effects of all variables in housing prices, exploring which are more important and how model calibrations improve the results. We also evaluate the spatial forms of regressions to understand spatial dependence and spatial heterogeneity. Additionally, our study compares the results between two different dataset sources, which helps improve the variable selection results and facilitate further comparations. One of the main reasons that there are limited studies on housing prices in developing countries is the lack of detailed and consistent data. Existing studies had to rely on different datasets to meet research needs, which resulted in limitations. Nevertheless, studies on Latin America highlighted fundamental differences in housing markets compared to those in developed countries. Despite differences in public policies and regulations, certain general conditions can explain these disparities. For example, the rapid urbanization rates in developing countries lead to a less flexible housing market. Additionally, higher numbers of young people compared to developed countries, combined with an unequal distribution of urban infrastructure, land market accessibility, housing informality and a longtime spatial segregation can affect market segmentation (Blanco et al., 2016; Fay, 2005; Gilbert, 1992, 1999, 2017; McTarnaghan et al., 2004; Rojas, 2015; Rojas & Medellin, 1995; Ward, 1993).

This study delves deeper into understanding the determinants of housing prices for cities in the developing world. It also contributes to the discussion on the importance of space in the use of hedonic prices to model these housing markets and to theorize their particularities.

3 Methodology

3.1 Study Area and Data

Quito, capital of Ecuador, is in the northern highlands of Ecuador with a population of nearly 3 million. It experienced significant population growth since the 1960s, owing to the economic inputs from oil exports. This economic growth triggered the inflow of population from rural areas and smaller cities to Quito and the expansion of its boundaries towards the suburbs in the east. As a result of this rapid expansion, the city structure evolved from a concentric form established during the colonial period, to a longitudinal multi nuclei during most of the twentieth century and to a metropolitan multicenter at the beginning of the twenty-first century (Carrión & Erazo Espinosa, 2012). The rapid and fragmented process of expansion, coupled with an urban policy that favored spatial segregation, has resulted in a segmented housing market. This segmentation can be identified and illustrated through the models employed in this study.

3.2 Data

The data for this study comes from three main sources. The socio-economic variables at the city block level were obtained from the 2010 Ecuadorian National Census[2]. The housing prices and structural attributes were obtained from the 2015 municipal property cadaster as well as a real estate data portal called Properati[3]. The base unit of analysis is the points that represent the

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[2] As of the date of publication of this article, the 2020 census data at the block level have not been published by the official institution, mainly due to the postponement of it until 2022 because of the pandemic.

[3] Properati has data for more than 1.7 million properties located in Argentina, Colombia, Ecuador, Peru and Uruguay. The company has a data division that presents periodical reports on real estate markets, open data and other geo-visualization tools. Source: www.properati.com

location of the housing units included in the sample of each of the data sources.

For each housing unit in the datasets, the corresponding socioeconomic variables from the 2010 census block they are located at were assigned using the spatial join tool in QGIS software. Five demographic variables were selected for this study: population of ethnic minorities, number of people with private health insurance, population that speaks an indigenous language, foreign born population and people who used internet in the last six months, all these measured as the percentage in the corresponding census block. Additionally, five variables that capture information at the housing unit level were also included: the proportion of housing units with more than two bedrooms, the proportion of housing units with the roof in good condition, the ratio of apartments over houses, the ratio of rented over owned housing units and the proportion of housing units with internet access. Finally, the Euclidean distances to the CBD (Alonso, 1960; Kain & Quigley, 1970), nearest school (Agarwal et al., 2016; Downes & Zabel, 2002), nearest park (C. Wu et al., 2017), nearest health service (hospitals, clinics, and urgent care facilities) and the nearest public transport (Perdomo Calvo, 2017; Zhang & Jiao, 2019) were calculated. Table 1 shows a detailed description for each variable.

Table 1. Variable description.

Dimension	*Variable*		*Description*
	HP	Housing Price	The price of a housing unit in US dollars, as listed in the city's cadaster or real estate portal. In the models, this variable is presented in its log form according to the recommendations of previous research.
Structural characteristics	AR	Housing area	The total built surface area of the dwelling in square meters. This is one of the variables that most significantly influences the price due to the requirement for a greater volume of materials and resources for its construction, as well as higher specifications for usage.
	BR	Number of bedrooms	The number of bedrooms within the residential unit. This information is exclusively available within the Properati dataset.
	TR	Number of bathrooms	The number of bathrooms within the residential unit. This information is exclusively available within the Properati dataset.
Neighborhood characteristics	RC	Proportion of houses with roof in good condition	In the Ecuadorian census, residential roofing conditions are assessed with three levels: good, fair, and poor. This variable is calculated by dividing the number of units with a good roof by the total number of units in that block.
	IA	Percentage of houses with internet access	Derived from the number of dwellings with internet access divided by the total number of dwellings in the block. These variable captures household income, with higher-income neighborhoods expected to have a greater proportion of houses with internet access.
	PHI	Percentage of population with private health insurance	Census variable capturing the number of individuals with access to private health insurance. It serves as a proxy for income level due to the high costs associated with these insurances in the country.

	INT	Percentage of population that used internet in the last six months	Unlike the variable measuring households with internet access (IA), this one is computed based on individuals who used the internet in the months preceding the census. It's noteworthy that this figure may differ from household access values since other locations like schools, libraries, etc., provide access to this service.
	ET	Proportion of ethnic minorities	This question in the Ecuadorian census pertains to individuals' self-identification based on their culture and customs. Options include mestizo, white, Afro-Ecuadorian, black, montubio, indigenous, and mulatto. The latter five were considered ethnic minorities in this study.
	IND	Proportion of individuals that speak indigenous language	This variable specifically refers to individuals who speak an indigenous language. Like the ethnic minority variable, it constitutes an important aspect to consider given the historical process of ethnic segregation (Capello, 2011; Guevara-Rosero & Bonilla-Bolaños, 2021)).
	FOR	Percentage of foreign-born individuals	The census question used to calculate this variable considers individuals born in another country who reside in Ecuador on the day of the census. The distribution of foreigners has been explored in terms of residential satisfaction(Carrión, 2005; Martí-Costa et al., 2016; Urdaneta & Burke, 2020). It is important to mention that different nationalities have different effects and distributions. For example, Colombians have a uniform distribution, while Americans are mostly concentrated in suburbs and the financial center.
	TY	Proportion of apartments over houses	Captures urban and architectural characteristics, particularly distinguishing areas dominated by apartments in the central city from suburbs with houses. Derived by dividing the number of apartments by the total number of houses in the block.
	HT	Proportion of owners over renters	Reflects the distribution of owners and tenants and its implications for housing submarkets and policy considerations, given the importance of rental housing as a potential solution to housing challenges in Latin America (Blanco et al., 2014).
Locational characteristics	DC	Distance to the Central Business District CBD	Euclidean distance measured from the location of the dwelling to the nearest point of the polygon defining the CBD, in meters. The relationship between land values and distance to the Central Business District (CBD) follows common urban theories, where residential land farther from the CBD tends to be cheaper, allowing for larger properties (Richards, 2011). However, in some European and Latin American, expensive residential properties can be found near or within the CBD, alongside lower-income settlements in the suburbs.
	DS	Distance to the closest school	Euclidean distance in meters measured from the dwelling's location to the nearest school. Studies have found that quality influences prices more than proximity (Kane et al., 2003). However, due to the lack of standardized quality indicators in Quito, we used the distance as a proxy.
	DH	Distance to the closest health service	Euclidean distance in meters measured from the dwelling's location to the nearest healthcare service.
	DK	Distance to the closest park	Euclidean distance in meters measured from the dwelling's location to the nearest park. While an influence of this factor on prices has been identified, specific mechanisms are still under study(Chen & Jim, 2010).
	DT	Distance to public transport	Euclidean distance in meters from the dwelling's location to public transportation. In Quito, more than 60% of the population uses public transportation(D.M.Q, 2014).

Table 2 shows the descriptive statistics for the variables, revealing a slight variation in average prices across datasets. The 6% difference between the average sale price in the 2019 Properati dataset and the 2015 cadaster dataset aligns with national price inflation between 2016 and 2018, supporting a viable comparison despite the difference in the timeframe.

Table 2. Variables descriptive statistics.

	Cadaster 2015					Properati 2019				
Number of properties	6000					11446				
Variable	Average	Median	Min	Max	Std Dev	Average	Median	Min	Max	Std Dev
House Price (PR)	118932	86953	3855	1830828	121343	132842	120000	2001	390000	88056
House Area (AR)	279.48	222.21	20.0	3910.90	247.93	227.62	133.00	30.00	4127.00	265.37
Number of bedrooms (BR)	-	-	-	-	-	4.01	3.00	1.00	26.00	3.69
Houses with more than 3 bedrooms (BR)	0.40	0.37	0.00	1.00	0.19	0.47	0.47	0.00	1.00	0.22
Houses with roof in good condition (RC)	0.69	0.71	0.00	1.00	0.18	0.76	0.82	0.00	1.00	0.23
Houses with Internet access (IA)	0.27	0.21	0.00	1.00	0.22	0.47	0.49	0.00	1.00	0.27
People with private health insurance (PHI)	0.19	0.15	0.00	1.00	0.15	0.35	0.34	0.00	1.00	0.22
People who used internet (INT)	0.46	0.45	0.00	1.00	0.19	0.61	0.67	0.00	1.00	0.23
Ethnic minorities (ET)	0.10	0.08	0.00	1.00	0.11	0.07	0.04	0.00	1.00	0.11
People who speak indigenous language (IND)	0.02	0.00	0.00	0.80	0.05	0.01	0.00	0.00	0.50	0.03
Foreign-born population (FOR)	0.03	0.01	0.00	0.72	0.04	0.07	0.04	0.00	1.00	0.08
Ratio apartments/houses (TY)	1.03	0.43	0.00	129.00	3.21	4.24	0.64	0.00	301.00	17.58
Ratio owners/renters (HT)	0.97	0.75	0.00	24.00	1.03	0.82	0.57	0.00	12.50	0.96
Distance to CBD (DC)	8222.92	8240.19	0.00	25539.89	4435.58	5023.12	4298.19	0.00	22774.11	4630.97
Distance to schools (DS)	170.86	121.56	0.00	1480.90	175.17	118.90	73.90	0.00	1191.07	139.79
Distance to parks (DK)	297.80	236.98	0.00	4654.14	276.56	240.72	189.44	0.00	1951.28	219.19
Distance to health services (DH)	651.75	516.39	0.00	6515.26	563.88	816.87	755.05	0.00	5529.98	529.17
Distance to public transport (DT)	350.33	18.34	0.00	11332.20	1088.43	292.88	4.53	0.00	15046.40	1056.80

3.3 Data sampling and handling

Both datasets resulting from the process previously described were cleaned or sampled. From the 411,220 data points in the cadaster dataset, we selected only residential properties. For those property types that have multiple housing units (horizontal property in the local law), we calculated the average price and area. The housing prices in the property cadaster are not based on actual market prices but city property valuations[4] instead which tend to present a bias towards a higher asking price (Kolbe, Schulz et al. 2021). To make the dataset more manageable, we extracted a random sample of 6000 points using the "random extract" tool in QGIS software[5].

On the other hand, the Properati dataset captures actual market prices, thus it can be more informative and provides a complimentary insight into housing values from another market perspective. The Properati dataset also contains more information on the structural characteristics including the number of bedrooms and bathrooms, as well as other amenities in a housing unit and a building.

Of the 33,736 residential units in the Properati dataset, only 23,315 were complete cases including price and area in their attributes. Among these, only 15,151 were published for sale while the remaining 8,164 were published for rent. From the properties for sale, we removed those with inconsistent prices and areas. For instance, any property with a smaller area than the minimum habitable area established by local regulations was removed. Also, based on the prices in the national policy for public housing, units with prices below $2,000 were eliminated. The final Properati dataset includes 11,446 housing units for sale, which represent 33% of the total records for the city of Quito.

[4] The Local Government uses a tool to retrieve land and property taxes which is based on an extrapolation model of market prices. This tool called AIVAS, areas of valuation intervention. It synthesizes the land and property values based on real market prices extrapolated to the whole city.

[5] https://docs.qgis.org/3.28/en/docs/user_manual/processing_algs/qgis/vectorselection.html#random-extract

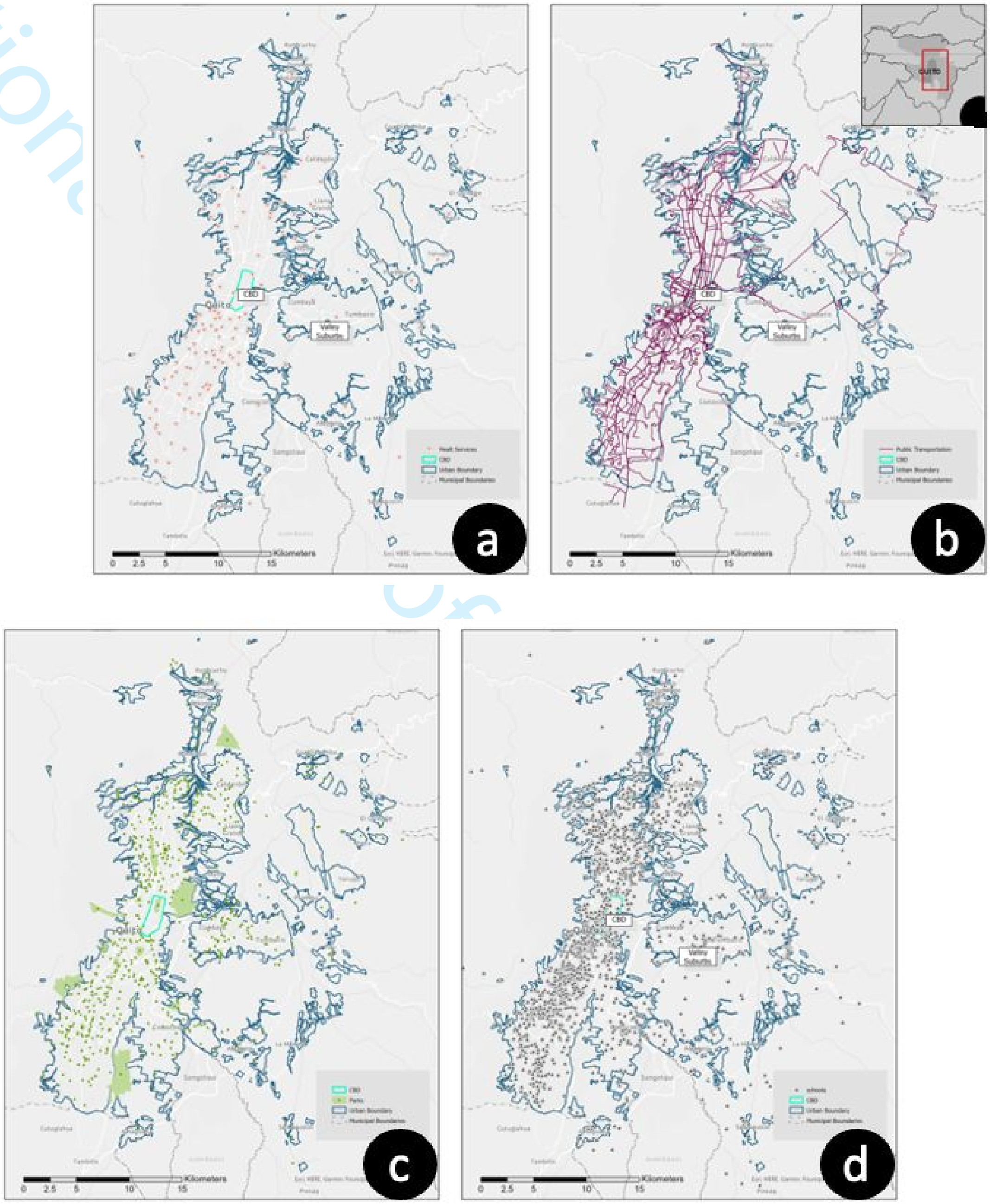

Figure 1. Locational characteristics variables: a) health services, b) public transport routes, c) parks and d) schools in the city.

3.4 Model Specifications

With the variables described previously, the HPM is defined as follows:

$$(1)\quad HP(\log) = \beta_0 + \beta_1\text{AR} + \beta_2\text{BR} + \beta_3\text{RC} + \beta_4\text{IA} + \beta_5\text{PHI} + \beta_6\text{INT} + \beta_7\text{ET} + \beta_8\text{IND} + \beta_9\text{FOR} + \beta_{10}\text{TY} + \beta_{11}\text{HT} + \beta_{12}\text{DC} + \beta_{13}\text{DS} + \beta_{14}\text{DK} + \beta_{15}\text{DH} + \beta_{16}\text{DT} + \varepsilon$$

Where HP is the dependent variable housing price in the log form, β_0 is the coefficient of the intercept term, $\beta_1 \ldots \beta_n$ are the coefficients for the independent variables and, ε represents the error term. In all the models we used the log form of the price (dependent variable) as its distribution presents a slight skewness towards lower values. As a result, we employ a semi-log linear regression suggested by the literature (Basu & Thibodeau, 1998; A. C. Goodman & Thibodeau, 2003). Non-significant variables were eliminated in the stepwise regression. It is worth to note that we also attempted to examine the spatial structure of housing prices on a global scale with a spatial lag model and a spatial error model. However, given that the improvements in model fit were negligible, we decide to focus our discussion on a local spatial regression model, the Geographic Weighted Regression model.

OLS models, spatial lag and spatial error models capture the impacts of housing price determinants from a global scale, even when spatial effects are accommodated in the spatial versions. Geographic Weighted Regression, however, can reveal the spatial heterogeneity of those determinants across the study area. Different from those global models in which a single common coefficient of each determinant applies to the entire study area, the GWR calculates a coefficient for each variable at each location in the regression respectively. Thus, the values of the coefficients for an explanatory variable vary across space, in other words, the spatial varying effects of the explanatory variables can be measured and visualized on a map. The GWR is defined as:

$$(2)\quad HP_i = \sum_{j=1}^{p} x_{ij}\beta_{ij} + \varepsilon_i$$

Where HP_i denotes the value of the housing price in the log form at location i, $x_{ij}$is the value of the jth independent variable at location i, β_{ij} denotes the location specific coefficient of x_{ij}, and ε_i is the error at location i.

All significant independent variables derived from the OLS models are included in the GWR model. The GWR model is capable of accommodating both spatial homogeneity (similarities) and spatial heterogeneity (also known as spatial non-stationarity). Spatial heterogeneity occurs when a variable's effect on the dependent variable varies depending on the observed point's location. Factors such as proximity to transportation can have different effects on housing prices in different areas, depending on residents' preferences and market conditions. As Goodman and Thibodeau (2003) suggest, market inelasticity caused by a disequilibrium in supply and demand is another source of spatial heterogeneity.

As aforementioned, the difference between an OLS model and a GWR model lies in whether the entire dataset is used in the calibration of the model, or the calculations of the coefficients. A GWR model only considers the neighbors of a property when generating the coefficients for the independent variables. Thus, it is critical to determine the neighbors of properties. In GWR, a distance band is typically used to identify neighboring properties for a property. Within such a distance band, factors affecting housing prices are more spatially homogeneous whereas outside the distance band, they are more spatially heterogenous. This approach allows for the identification of areas within the city where certain variables better explain price variations. In this study, we used the GWR tool in MGWR software application (Oshan et al., 2019) to implement the analysis. All factors were considered local in the GWR since the objective of this research was to explore spatial variations compared to the OLS results. All factors were considered local in the GWR since the objective of this research was to explore spatial variations compared to the OLS results, To calculate the spatial weights matrix, an Adaptative Kernel function was employed in the GWR. The function uses different distance bands across the study area to ensure: 1) a sufficient number of properties are included for generating the local coefficients; 2) the adaptive distances in the final model generate the lowest Akaike Information Criterion (AIC) score. The AIC scores are usually used to compare regression model performance. The smaller the AIC score, the better fit a model (Oshan et al., 2019).

4 Results

4.1 OLS Model

We conducted OLS models, based on equation (1), for the cadaster dataset (Model 1) and the Properati dataset (Model 2). The results are shown in Table 3. Considering the collinearity between some variables, we used Variable Inflation Factor (VIF) values to identify and discard those variables with the highest correlation values. Variables of internet access and internet usage were removed from the model due to collinearity. All remaining variables have VIF values lower than 3, which is acceptable considering the effect of spatial dependence in collinearity. Most variables are common across the two datasets, except for the number of bedrooms (BR) in the Properati dataset.

Table 3. Results for Model 1 and Model 2

		Model 1		*Model 2*	
		Coeff.		Coeff.	
	Intercept (House Price log)	6.67320	***	11.50405	***
AR	Housing area	0.81111	***	0.18279	***
BR	Number of bedrooms	-	-	-0.26559	***
BR n	Proportion of housing units with more than 2 bedrooms	0.13357	***	0.05416	

RC	Proportion of housing units with roof in good condition	0.00872		-0.22809	***
PHI	Population with private health insurance	0.59689	***	0.44753	***
ET	Ethnic minorities	0.20313	***	-0.21009	.
IND	People that speak indigenous languages	0.08998		0.51182	
FOR	Proportion of foreign born	1.21522	***	0.21033	
TY	Proportion of apartments	-0.00140		-0.00147	*
HT	Proportion of rented housing units	-0.02861	***	-0.01778	
DC	Distance to CBD	0.00002	***	-0.00001	**
DS	Distance to schools	0.00003		0.00022	**
DK	Distance to parks	-0.00009	***	-0.00029	***
DH	Distance to health services	0.00007	***	0.00005	*
DT	Distance to public transportation	0.00001	*	0.00003	**
	R2	0.78260		0.49199	
	Adj. R2	0.78200		0.49102	
	AIC	4694.55		26495.1	
	Moran's I of residuals	0.1721***		0.0871***	

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Both models are proved statistically significant. In terms of the goodness-of-fit, Model 1(based on 2015 cadaster dataset) explains 78% of the variation of housing prices while Model 2 (based on the Properati dataset) explains slightly over 49% of the variation on prices.

In Model 1, the variables with the strongest positive influence on price are the proportion of foreign-born residents in the neighborhood (FOR), the housing unit area (AR), and the proportion of people with private health insurance (PHI). The effect of housing unit area on price aligns with previous studies (Kwong Wing, 2003; Xiao, 2017). The proportion of foreign-born individuals captures a socioeconomic aspect of the city as specific neighborhoods attract people with similar characteristics. Conversely, a higher number of apartments and rented units in a city block leads to lower housing prices. Notably, the proportion of rented housing units has the most negative impact. Among the distance-based variables, only proximity to parks has a positive effect, while greater distance from these elements results in lower prices.

Similar significant coefficients are found in Model 2. Positive effects on price are observed for housing area (AR), proportion of people with private health insurance (PHI), and proportion of foreign-born residents (FOR). The variable representing the proportion of people speaking indigenous languages (IND) is particularly interesting as it has a greater impact on price than the structural characteristics of the house. On the other hand, the number of bedrooms (BR), proportion of housing units with a good roof condition (RC), and proportion of ethnic minorities (ET) have strong negative effects on price. The negative impact of ethnic minorities may be linked to spatial segregation. Distance-based variables have lower impacts, with proximity to parks and the central business district (CBD) positively influencing price.

Comparing the coefficients of the two models, we observe expected similarities, highlighting the influence of structural and socioeconomic factors over distance-based variables. However, differences in certain variables, such as the proportion of houses with a good roof condition, proportion of ethnic minorities, and distance to the CBD, indicate the need of a local approach in the analysis.

4.2 GWR

To examine the presence of spatial effects, we analyzed the regression residuals of the two OLS models. We calculated the global Moran's I index as well as the robust Lagrange Multiplier (LM) test for the residuals of models 1 and 2 (Anselin et al., 1996). The results suggest significant positive spatial autocorrelations in the residuals (Table 2). Thus, it warranties the use of the GWR model to capture the spatial structure. Two GWR models based on equation (2) are presented here, Model 3 using the cadaster dataset and Model 4 using the Properati dataset.

Table 4 compares the model performance of the OLS and GWR models. The Moran's I of the residuals was reduced to 0.097 in Model 3 and 0.036 in Model 4. Therefore, it suggests that the GWR models helped reduce the spatial dependency.

Table 4. Model Comparison

Dataset	*Model*	*AIC*	*R2*	*Moran's I*
CAD6000	OLS (Model 1)	4694.55	0.7826	0.1721***
	GWR (Model 3)	3222.31	0.832	0.0974***
PROPSALE	OLS (Model 2)	26495.1	0.4919	0.0871***
	GWR (Model 4)	19282.5	0.559	0.0364***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

When comparing the R^2 values with those obtained from previous spatial regressions, GWR outperforms the other models in both datasets, with an increase of at least 4% in explained variation. The smaller AIC scores of the GWR models also suggest that they explained the relationship between the housing prices and the determinants better in both datasets.

The spatial distribution of local R^2 values in Model 3 and Model 4 reveals interesting patterns (figure 2). The overall R^2 for Model 3 dataset is higher and evenly distributed, whereas the local R^2 for the Model 4 dataset is lower and displays a distinct distribution. Lower R^2 values are concentrated in the central north area of the city, while higher values are observed in the northern and southern borders, as well as a suburb in the southeast area. The range of local R^2 values for this dataset is significant, falling below 30% in the central area and exceeding 90% in the far north and south limits.

The uneven spatial distribution of local R^2 values can be explained by two factors. Firstly, the higher concentration of observation points in the central area leads to lower local R^2 values due to increased variability. Secondly, the presence of submarkets in these areas could contribute to the lower local R^2 values, as omitted variables may explain price variations better than the selected variables significant in other areas. However, it is worth noting that certain variables still demonstrate significant relevance in the areas with lower local R^2 values, suggesting that omitted variables are not the sole reason for these results.

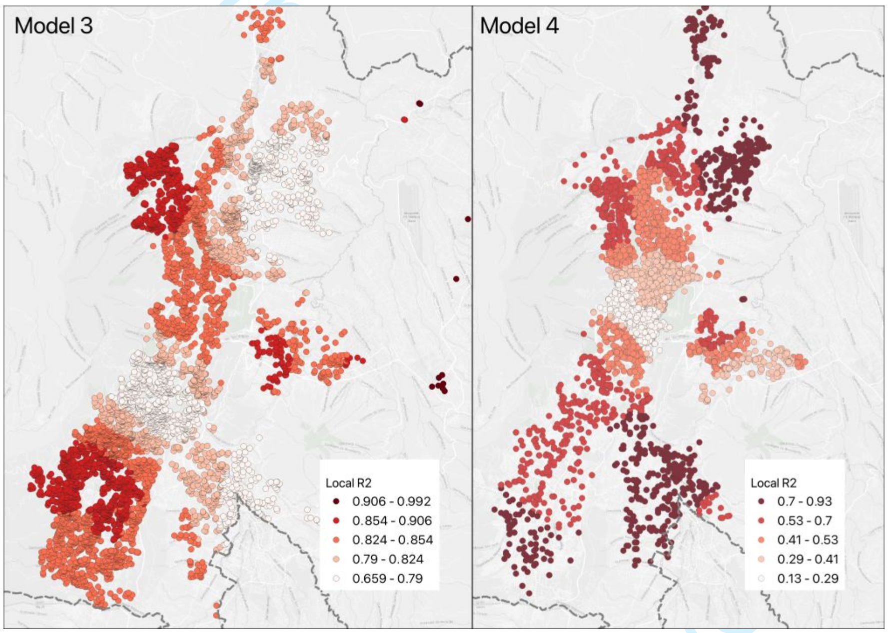

Figure 2. Local R2 distribution

Table 4 displays the variation of the coefficient values based on the distance bandwidths that yielded the lowest AIC value in Model 3 and Model 4. As shown in Table 5, in both models, the coefficients for the distance-based variables have a lower effect on housing prices than in the OLS models. Notably, some coefficients present a high internal variation, measured by the standard deviation and the difference between the maximum and the minimum values. The variables BR, ET and PHI reveal this contrasting pattern, indicating the effect of the variable is not only heterogenous but even polarized in space.

Table 5. GWR coefficient summary

		Model 3				*Model 4*			
		Mean	*Min*	*Max*	*S.D*	*Mean*	*Min*	*Max*	*S.D*
	Intercept (House Price log)	6.6071	5.8328	13.7144	0.5418	11.9753	-16.0284	15.4092	1.6417
AR	Housing area	0.8449	0.2911	0.9411	0.0527	0.0680	-0.6784	0.9793	0.3523
BR	Housing units w/ 2+ bedrooms	0.1077	-3.4895	0.8753	0.2119	-0.2327	-0.3781	-0.0450	0.0726
RC	Housing units w/ roof in good condition	-	-	-	-	-0.4015	-2.0899	3.2217	0.4085
PHI	Population w/ private insurance	0.2560	-10.9855	2.2176	0.3434	0.5181	-1.1755	5.8066	0.5960
ET	Ethnic minorities	0.2686	-0.6538	7.3957	0.3573	0.3053	-2.3839	19.5581	0.7906
FOR	Foreign-born population	0.2319	-6.9231	3.8068	0.6813	-	-	-	-
TY	Ratio apartments/houses	-	-	-	-	-0.0016	-0.1824	3.0204	0.0584
HT	Ratio rented/owned	-0.0203	-0.3092	0.2958	0.0331	-	-	-	-
DC	Distance to CBD	0.0000	-0.0003	0.0001	0.0000	0.0002	-0.0003	0.0027	0.0004
DS	Distance to Schools	0.0000	-0.0017	0.0032	0.0002	0.0003	-0.0048	0.0019	0.0006
DK	Distance to Parks	0.0000	-0.0027	0.0011	0.0001	-0.0002	-0.0014	0.0020	0.0003
DH	Distance to Health Services	0.0000	-0.0039	0.0003	0.0002	0.0001	-0.0009	0.0026	0.0002
DT	Distance to Public Transport	-0.0001	-0.0008	0.0090	0.0003	0.0002	-0.0034	0.0032	0.0010

Furthermore, the coefficient analysis of the two datasets reveals more differences than similarities. In Model 3, house area emerges as the most influential variable on price, consistent with previous models. However, in Model 4, the proportion of people with private health insurance (PHI) is more important. In addition, some coefficients exhibit opposing influences across the study area, such as the number of bedrooms and distance to parks. The variation in coefficient values, standard deviation, and significance levels indicates spatial heterogeneity.

Housing area stands out in terms of spatial heterogeneity. While it is expected to positively impact prices, Model 4 displays negative coefficients in the central-north area, signifying a significant negative influence. This raises questions about the diverse types and sizes of properties in this region, necessitating further investigation.

The number of bedrooms also produces unexpected results in Model 4, with all local coefficients negatively impacting prices. Conversely, Model 3 presents both positive and negative coefficients, primarily concentrated in rural areas and a limited northwest region. However, most negative coefficients lack statistical significance.

The proportion of ethnic minorities exhibits an interesting spatial pattern exhibit in Figure 2. Positive coefficients cluster in affluent central-north and suburban areas, while negative coefficients concentrate in the northwestern and southern limits. This suggests a preference for ethnic diversity in wealthier areas, necessitating a detailed analysis of various minority groups' distribution and their impact on spatial heterogeneity.

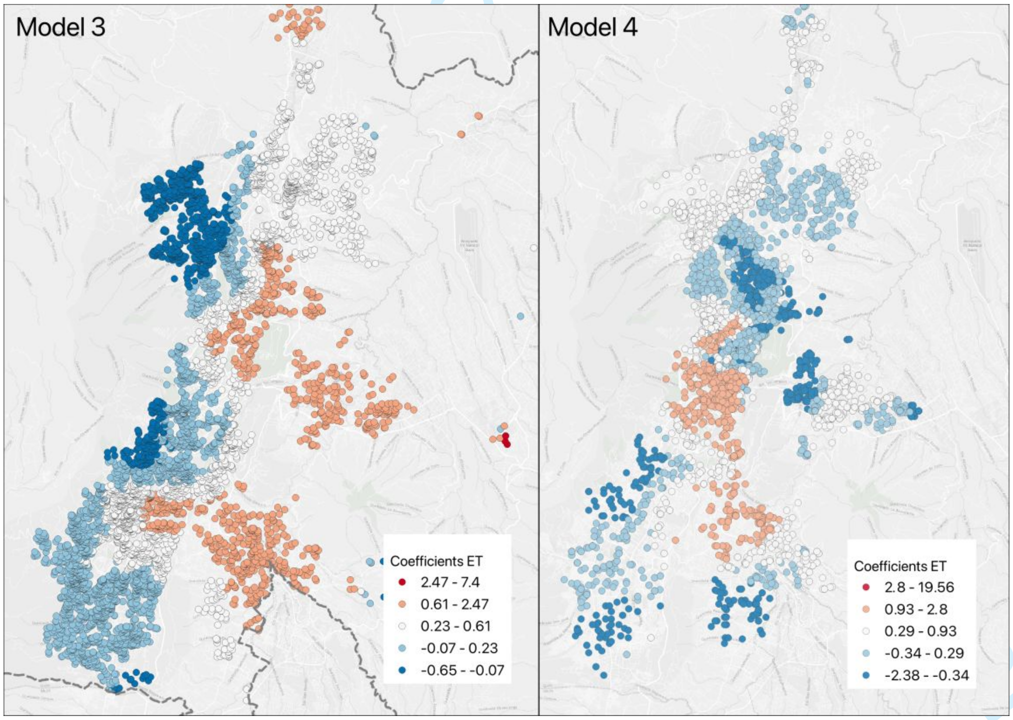

Figure 3. Local coefficients for Ethnic Minorities

Despite the unexpected negative effect of the percentage of people with private insurance on prices, the coefficients lack statistical significance in the Model 4. Conversely, Model 3 indicates a positive and more pronounced impact in the north and suburbs, reflecting a spatial association with income distribution.

Distance-based variables also contribute to understanding spatial heterogeneity. For example, Model 3 demonstrates that distance to the central business district (CBD) positively affects prices in suburbs and nearby areas, while negative coefficients appear in the western side. This corresponds to low-income working-class areas and suggests a preference for proximity to the CBD. However, Model 4 presents a different pattern, with only the central-north affluent neighborhoods showing a positive impact. Negative coefficients are observed in the north, south, and suburbs, indicating a complex relationship between distance to the CBD and prices.

Similar contrasts are found in the variable of distance to schools. Model 3 shows a positive impact in the central area and south but negative impacts in the north and south extremes, aligning with the higher concentration of schools in the center, due to a lower density, access to schools in the northern and southern areas has a higher value for these households. In contrast, Model 4 primarily exhibits positive coefficients, with only those in the north statistically significant.

Distance to parks also presents different effects. Model 3 demonstrates a positive impact in central, center-north, and far south areas, but negative impact in the center-south and far north. Notably, statistically significant positive coefficients in the north suggest a relative disregard for park proximity. The areas with a negative impact of distance to parks located in the center/south and far north is both significant and suggest a desire to be closer to this infrastructure. Model 4 has fewer significant coefficients, primarily in the central area and northern suburbs, suggesting a preference for proximity to parks. In this case too, a deeper analysis of the reasons explaining this preference may help explain the difference. The distribution of parks infrastructure, the characteristics of these parks as well as other phenomena associated with them, e.g. the impact on the perceived safety, can shed light on the mechanism behind the difference (Byrne & Wolch, 2009; Moran et al., 2020).

Spatial patterns of coefficients for distance to health services vary as well. In Model 3, positive impacts are observed in the central and north areas, while negative impacts occur in the southern limit and rural remote areas. Model 4 presents more detailed patterns, with positive coefficients in smaller central and center-north areas and negative coefficients in the center-south, far north, and eastern suburbs. These differences may be related to the distribution and access to health infrastructure. It also suggests that in much of the city people tend to avoid being close to a health service as the distance has a positive impact on housing prices. The most notable difference between the two maps is on the northern area where the effect on price is contrary in the two datasets. This area is characterized by a recent important process of densification that resulted in a low coverage of certain services. This can suggest that the spatial pattern resulting for Model 4 is more coherent.

Distance to public transportation shows varying effects as well. Negative impacts on housing prices are seen in the south and north on Model 3, but exclusively in the northwest on Model 4. Positive impacts are observed in the center and south on Model 4 and center-south on Model 3. The significance of locations also differs. Model 4 suggests higher demand for proximity to public transportation in the northwest and avoidance near the CBD, while Model 3 aligns more with expectations based on income and location. Contrary to expectations based on literature, the coefficients for distance to transportation do not align with the anticipated spatial pattern. However, significant findings in Model 4 suggest a higher demand for proximity to public transportation in the northwest and avoidance in the central areas near the CBD. Additionally, Model 3 shows negative impacts in the south and far north, along with positive impacts in the southern suburbs, which align more closely with expectations.

The two additional variables in Model 3, proportion of renters over owners and proportion of foreign-born residents, show no spatial heterogeneity. However, they indicate lower effects in areas with more renters and higher effects in areas with a greater proportion of foreign-born residents.

Overall, these findings highlight the spatial heterogeneity in coefficient values and their impacts on housing prices between the two datasets. The contrast and some unexpected variations of the coefficients call for a more in-depth analysis of various factors, such as property types, minority groups, distribution of infrastructure, and socioeconomic dynamics, to better understand the underlying patterns of spatial heterogeneity.

5 Summary and Discussion

The HPM has proven to be an effective approach to understanding the effect of different attributes in housing prices in the literature (Rosen, 1974). Most of the variables used in this study were selected based on the recommendations of the literature. Although many of these studies were conducted in regions different from Latin America, the performance of the models applied in this study suggest a validity of these variables for the selected case.

The results demonstrate the spatial effects of various price determinants, highlighting a distinct urban structure marked by spatial inequity. This structure underscores enduring inequalities in the housing market over time. Notably, the OLS model partially illustrates this, revealing the influence of sociodemographic factors on price, such as the percentage of individuals with private health insurance and foreign-born residents. These factors exhibit equal or greater influence than structural housing variables. GWR further emphasizes their significance in price determination, exposing spatial inequities. For instance, the proportion of ethnic minorities notably impacts prices, exhibiting substantial spatial variation. While seemingly paradoxical, areas with lower ethnic minority proportions, like suburban locales, witness a positive impact on price. Conversely, peripheral areas experience a negative impact on price due to concentrated minority populations, reflecting historical segregation effects.

Variables measuring distances to amenities also display spatial variability, albeit with less influence on prices. However, their spatial distribution mirrors sociodemographic patterns. This intertwined relationship underscores the impact of sociodemographic factors and service distribution on housing prices. It's crucial to note that distance variable coefficients do not merely reflect preferences; rather, they signify historical residential segregation and amenity distribution. Understanding this requires interpreting them alongside sociodemographic variables to decode longstanding spatial structures.

Each Latin American census defines categories like ethnicity uniquely, necessitating careful selection of sociodemographic variables to unveil housing market spatial structures. Granular demographic data, as utilized in this study, proves vital in unraveling complex spatial associations. Future research should delve into the implications of sociodemographic variables on housing price spatial structures and their ties to historical segregation processes. Given varying segregation patterns across Latin American cities, a one-size-fits-all variable approach may not suffice. Similar considerations apply to variables like the proportion of foreign-born individuals, whose settlement patterns differ based on historical social formations in each locale.

It is important to mention that, despite having been able to build complementary models that explain the variability of housing prices in the city based on official and commercial data sources, the availability and update of data with sufficient detail on housing prices and their characteristics continue to be a limitation for studying this phenomenon in the region. In this case, while the cadaster is a more comprehensive data source as it includes all existing properties, it does not measure the actual sale price in the market. Therefore, this price does not represent the valuation that people make at the time of the study. Also, at least in the case of Quito, it does not include variables such as year of construction, number of bedrooms, etc.

On the other hand, the real estate data source has a lower spatial representativeness, as it only covers units in the market with a greater representation of the most dynamic and desirable areas. However, it better represents the market price, although with a bias towards higher prices in real sales. Furthermore, it provides more details about the characteristics of the housing unit, especially amenities. Perhaps the most interesting aspect of analyzing this type of data source is the information on rental prices, which are not available in the cadaster, and its update speed, which allows measuring rapid changes in the market.

One of the study's main objectives was to compare the results of standard and spatial calibrations of the Hedonic Price Model to study housing prices. The GWR models resulted in a higher explanation of the variation of housing prices overall along with a decrease in spatial autocorrelation of the model residuals. These results reinforce the argument that spatial effects determine housing prices. In all the models and for all the datasets used in this study, the GWR models showed an improvement not only in the goodness-of-fit of the model but also on the significance of the coefficients. Being said so, although spatial models perform better than non-spatial models, the decision on which model to use should rely on a good diagnosis as it depends on the dataset used.

Our analyses also suggest that both spatial dependence and spatial heterogeneity are important in housing prices. The GWR models were able to capture both spatial homogeneity and spatial heterogeneity. In this case study, spatial heterogeneity was of special interest to better understand the effect of urban spatial structure in the housing markets. The variables that capture this effect the most are those associated with the distance to the city services, infrastructures, and amenities. These variables reflect not only a difference but a divergence in the way the proximity to these features is valued by households in certain areas of the city.

Regardless of some differences and contradictions between the two datasets, the resulting coefficients in general show a disruption on the value system amid the wealthy areas (center-north and suburban valleys) and the rest of the city (far north and south, and rural areas), suggesting the existence of housing submarkets. These submarkets, however, are by no means to be considered static in time. In some cases, as in the health services and the schools, this pattern is modified by the distribution of the infrastructure. In other cases, as public transportation, this pattern is also affected by the population's use of the infrastructure. Despite the low values of the coefficients for these variables, these are not negligible on housing prices.

The GWR revealed spatial patterns at a finer scale that are not well captured when using discrete zones of the city as variables within a spatial regression model. This is of particular interest for fast changing urban structures like the Latin American cities. In this case study the most interesting finding related to spatial heterogeneity was the opposing and contrasting effect of certain variables depending on the location. The GWR is relevant to unveil other patterns such as spatial residential segregation and inequality as suggested by Wu (2002) and others.

All these results suggest the existence of housing submarkets that are significant in the city. As these housing submarkets are dynamic in both space and time, the application of the GWR considering time changes would be valuable. For that, more frequent update of the data is needed. The implementation of a housing survey with a stratified spatial sample is highly suggested for this end.

Finally, further research needs to be done at the individual level to better understand the underlying process of valuing a house for different socio-demographic groups and in different areas of the city.

6 Conclusions

In this study, we conducted a comparative analysis between OLS models and GWR models. We intended to provide some insights on the application of those models to analyze housing markets in developing countries.

The variables influencing housing prices in our analysis are like those tested in other regions, enabling a certain level of comparability despite variations in housing price recording methodologies. However, we emphasize the importance of standardizing housing price recording instruments within our study region to enhance the generalizability of findings.

Furthermore, we have assessed the performance of two distinct data sources: the city's cadastral records and a real estate sales and rental web portal. Each source presented advantages and limitations for our analysis. While the cadastral records provide a more comprehensive representation of the housing stock, thereby better capturing the variability of housing prices, the real estate portal data offer valuable insights into rental prices and more detailed information on structural characteristics. Nonetheless, it is crucial to acknowledge the inherent bias towards inflated prices within the real estate portal data.

Consistent with existing literature, our findings underscore the significant role of variables related to housing structure and functionality in explaining price variations. However, we also highlight the relevance of spatial dependence, which manifests as the influence of neighboring property prices. Moreover, variables concerning neighborhood composition and housing locations (proximity to services) contribute valuable insights to the analysis of price determinants. Notably, certain variables exhibit intriguing spatial heterogeneity, a phenomenon effectively identified through the application of Geographically Weighted Regression.

Our research sheds light on the identification of housing submarkets, particularly in cases where a single variable yield contrasting effects across different areas within the city. It is worth noting that the exploration of housing submarkets in Latin American cities remains limited in the existing literature. Thus, our findings contribute to filling this research gap and emphasize the significance of combining diverse and complementary data sources while considering spatial effects in future studies.

Overall, this study enriches the limited body of literature on spatial hedonic price models of housing in Latin American cities. By employing rigorous analytical techniques and providing empirical evidence, our research advances the understanding of housing price determinants and the implications of spatial dynamics in the context of Latin America.

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