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The real estate market and public transportation systems in developing countries: the case of Medellín, Colombia

Mercado imobiliário e sistemas de transporte público em países em desenvolvimento: el caso de Medellín, Colômbia

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Abstract

The objective of this study was to measure the effect of the distance between homes and the stations of the integrated public transportation system in Medellín on home prices. The hedonic models used here were calculated using ordinary least squares (OLS) and two spatial econometric models: the spatial autoregressive (SAR) model and the spatial error model (SEM). The results obtained indicate that the stations of this transportation system have an impact on home prices depending on the income level of the district where they are located. On the one hand, the price of a home in a low- or middle-income district can increase (17.1% or 15%) if it is "near" a station (1.5–2.0 km and 1.0–1.5 km, respectively), but it is not affected if the housing unit is "too close" (up to 1.0 km). On the other hand, if the housing unit is located in a high-income district, the nearer it is to a station, the lower its price (-15% between 0 and 1.0 km, and -12% between 0.5 and 1.0 km). These results are relevant for all the agents involved in real estate and public policy makers interested in executing transportation infrastructure projects in cities in developing countries.

Keywords: mass appraisal, spatial econometrics, public transportation, developing countries.

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Resumo

O objetivo deste estudo foi medir o efeito da distância entre as residências e as estações do sistema integrado de transporte público de Medellín sobre os preços das residências. Os modelos hedônicos aqui utilizados foram calculados usando mínimos quadrados ordinários (OLS) e dois modelos econométricos espaciais: o modelo espacial autorregressivo (SAR) e o modelo de erro espacial (SEM). Os resultados obtidos indicam que as estações desse sistema de transporte têm impacto nos preços das residências dependendo do nível de renda do bairro onde estão localizadas. Por um lado, o preço de uma casa em um bairro de baixa ou média renda pode aumentar (17,1% ou 15%) se estiver "perto" de uma estação (1,5–2,0 km e 1,0–1,5 km, respectivamente), mas não é afetado se a unidade habitacional estiver "muito próxima" (até 1,0 km). Por outro lado, se a unidade habitacional estiver localizada em bairro de alta renda, quanto mais próximo estiver de uma estação, menor será o seu preço (-15% entre 0 e 1,0 km e -12% entre 0,5 e 1,0 km) . Esses resultados são relevantes para todos os agentes envolvidos no setor imobiliário e formuladores de políticas públicas interessados em executar projetos de infraestrutura de transporte em cidades de países em desenvolvimento.

Palavras-chave: *avaliação em massa, econometria espacial, transporte público, países em desenvolvimento.*

Introduction

Access to public transportation is part of what is known in real estate literature as amenities. The amenities of a place can be natural (forests, lakes, rivers, etc.) or the result of transformations by public or private agents (schools, libraries, aqueduct, sewers, parks, malls, etc.). Access to public transportation is one of the most important amenities in cities because it gives citizens access to the labor market, as well as education, healthcare, and cultural opportunities, which contributes to make their life conditions more equal (Eddington, 2006). By contrast, not having access to a good transportation service limits citizen participation in society and favors spatial segregation (Thynell, 2009). Public transportation has an impact on people's level of wellbeing because it changes the environment, reduces accident rates and travel time, and increases their possibilities for leisure and participation in activities that are essential for their daily lives (Lu, et al., 2018; Schneider & Guo, T, 2013).

According to Can (1992), housing prices depend on two kinds of characteristics: non-spatial characteristics (such as plot size, construction type, and housing age) and the amenities of the location. This means that, in theory, under the assumption that home buyers are willing to pay more for proximity to amenities that improve their wellbeing (Perdomo & Arzuza, 2015), closeness to a public transportation station should positively influence housing prices. Therefore, if two homes have similar spatial and non-spatial characteristics, the one closer to a public transportation station (or in its area of influence) should fetch a higher price.

Although empirical studies in different fields have investigated the effects of public transportation stations on housing prices, they have not provided conclusive results (The World Bank, 2012). Some empirical evidence indicates that stations can increase the value of nearby properties by reducing transportation costs and travel times or encouraging commercial activity in the neighborhood (Armstrong & Rodríguez, 2006; Tulach et al., 2012). However, other evidence suggests that stations can generate externalities that negatively affect housing prices, such as damaging the neighborhood's landscape, more traffic in the surrounding area, and rising crime rates due to easier access for people who do not live in the neighborhood (Adair et al., 2000; Bowes & Ihlanfeldt, 2001; Cervero & Kang, 2011; Martínez & Viegas, 2009; Nelson, 1992).

Another problem of the existing empirical studies in this field is that they establish the relationship between transport stations and housing prices only in one area of the city (e.g., analyzing only one metro or cable car line). In addition, this relationship is usually measured using the distance between the home and the nearest metro station as an indicator or as a binary variable that indicates whether the home is inside the area of influence (buffer) of a station, ignoring or separately investigating other means of transportation in the same system (Andersson et al., 2012; Deng et al., 2012; McDonald & Osuji, 1995). Nevertheless, such measurements of influence cannot really reflect how easy it is to travel from a specific place to locations that can be reached using the entire network of a transportation system.

This aspect is particularly important in cities such as Medellín, which has an integrated public transportation system (composed of an elevated train system, streetcar, cable cars, and bus rapid transit or BRT) where users can travel from a station to any other paying only one fare. Therefore, instead of studying the effect of the nearest metro, streetcar, cable car, or BRT stations separately, the system should be considered as a whole, and the distance or area of influence of the nearest station should be used regardless of its means of transportation (He, 2020).

The objective of this study is to measure the effect of the distance between homes and stations of the integrated public transportation system in Medellín on home prices. The hypothesis here is that stations generate positive and negative effects on their surrounding areas, and the combination of both is reflected in housing prices depending on the income level of the district where homes are located. The importance of this paper lies in that it examines how the public transportation system of a city in a developing country (i.e., an externality generated by a public intervention) affects housing prices. The results of this paper are relevant for all the agents involved in real estate and public policy makers interested in executing transportation infrastructure projects in cities in developing countries.

This paper is divided into six sections, including the introduction. Section 2 presents a literature review. Section 3 defines the study area. Section 4 describes the methodology. Section 5 reports and discusses the results. Finally, Section 6 draws the conclusions.

Literature review

Most mass appraisal studies carried out in developed countries have addressed metro stations and have generally found that the latter have a significant and positive effect on housing prices. This facilitates a property tax collection system based on value capture to partially fund the construction of new metro projects or maintain existing ones. Some studies that have reported this type of results have been conducted by Grass (1992) and Damm et al. (1980) in Washington (United States), Pagliara & Papa (2011) in Naples (Italy), and McIntosh et al. (2014) in Perth (Australia). The sprawl of big cities in China has generated a particular interest in the topic, and studies such as those by Li et al. (2019) in Beijing and Yang et al. (2020) in Shenzhen also show evidence of a positive effect of access to metro stations on housing prices.

Debrezion et al. (2007) reviewed 57 studies about the impact of train stations in the United States on property value and found that, on average, hosing prices increased 2.4% for every 250 m closer to a station, while commercial property prices increased only 0.1%.

However, results can be conflicting. For instance, Nelson (1992) studied the effects of elevated heavy-rail transit stations in Atlanta (United States) on house prices with respect to neighborhood income. His results show that elevated transit stations have positive price effects on homes in lower-income neighborhoods and negative price effects on homes in higher-income areas. By contrast, Bowes and Ihlanfeldt (2001) found that proximity to stations (the same heavy-rail transit stations in Atlanta) represents an increase in house prices that is even more substantial in high-income neighborhoods.

The relationship between housing prices and proximity to light rail transit (LRT) has also been studied in comparison with other transportation systems. For example, Seo et al. (2014) analyzed the relationship between housing prices and distance to highways, highway exits, light rail, and train stations in Phoenix, Arizona. Their results show that, although housing prices are not affected by distance to highways or light rail, they are positively influenced as housing units are located closer to train stations or highway exits. Nevertheless, such effect is exponentially reduced and completely disappears at 4 km in the case of train stations and at 6 km in the case of highway exits.

Hess & Almeida (2007) studied the effect of an LRT system on housing prices in Buffalo, New York, and found that a home in a 0.4-km radius around a train station commands a premium between 1300 and 1500 USD, which equals between 2% and 5% of the average housing price in that city. However, their results show that other characteristics (e.g., bathroom size, area, and location in the east or west of the city) are more important than proximity to a metro station.

Currently, the only city in Colombia that has an elevated train system is Medellín (where it is known as the Metro), and studies into the effect of its stations on housing prices are scarce. One of them was conducted by Duque et al. (2011), who applied a geographically weighted regression (GWR) model to housing prices around one of the Metro stations in Medellín located in one of the most violent and socially problematic areas in the city. Their results show that proximity to that station had a positive influence on housing prices in a 600-meter range, but a negative influence on areas that were very close to it. Agudelo et al. (2018) investigated the effect of the proximity between housing units and said station on rental prices and once again found a positive relationship.

More literature has been concerned with the effect of bus rapid transit (BRT) system stations on housing prices in cities in developing countries than in developed ones. The case is the opposite regarding metro stations.

In Colombia, much research has investigated the effect of the proximity to the stations of the BRT system in Bogotá, which is called Transmilenio. For instance, Rodríguez &Targa (2004) found that, for every 5 min of additional walking time to a BRT station, the rental price of a property decreased between 6.8 and 9.3%. Munoz-Raskin (2010) carried out an analysis classified by income level and compared the prices of housing units located less than 5 min by foot and those between 5 and 10 min. His results showed that closeness to the stations had a negative effect of 8% on the price in low-income neighborhoods, a positive effect of 3.1% and 14.9% in middle-income neighborhoods, and a negative effect of 14.9% in high-income neighborhoods. Rodríguez & Mojica (2009) researched the impact of the expansion of the service of the BRT system in Bogotá and found that properties in the area surrounding the expansion were 13% to 14% more expensive than in control areas, but there was no noticeable difference in price between properties within 500 m and those between 500 m and 1 km from the BRT.

The case of the BRT system in Medellín (called Metroplús) has also been studied adopting different approaches, with different results. For example, Gómez Hernández & Semeshenko (2018) did not find a significant effect of the proximity to the Metroplús on the rental prices of housing units and related this idea to the fact that such access had a positive but modest effect on quality of life. Echeverri Durán et al. (2019) studied the effect of the Metroplús (Line 1) on housing prices in Medellín considering the direct impact of air pollution and public transportation coverage. Their results showed that housing prices in low-income areas were positively affected, while those in middle- and high-income neighborhoods were negatively affected.

Study area and data

Study area

Medellín, the second most industrialized city in Colombia, is located 1.5 km above the sea level, in a region known as the Aburrá Valley, and its metropolitan area covers 380.64 km2. The Medellín River crosses the city from south to north, and its geological formations, topography, and hydrology determine the configuration of the natural environment of the city. In addition, numerous tributaries that flow down to said river divide the mountainsides of the valley, where its urban area continues to grow. According to the 2018 census by the Departamento Administrativo Nacional de Estadística (DANE), Medellín had an estimated population of 2.4 million inhabitants. The urban area of the city is divided into 16 districts, which can be classified as low-, middle-, and high-income (DANE, 2019).

Basic amenities in Medellín are relatively close to housing units, workplaces, and educational institutions because of the combination of land uses in its compact city model. In addition, this city model presents high density, which makes public transportation extremely efficient. Because of this, some of the most important investments in infrastructure in Medellín aim to improve the mobility of its inhabitants. The main focus of the local government's policies and plans is the Sistema Integrado de Transporte del Valle de Aburrá [Aburrá Valley Integrated Transportation System] (SITVA), whose objective is to improve public transportation, guarantee the access of all its citizens to transportation, limit the use of private transportation, improve road infrastructure, and promote less polluting means of transportation (Área Metropolitana del Valle de Aburrá, 2020). This integrated transportation system is composed of several systems, such as the Metro (an elevated train system), Metroplús (bus rapid transport), Metrocable (cable car), streetcar, and shuttle buses, whose operation is based on the use of clean energy resources such as natural gas and electricity.

Data

In this case, like in all mass appraisals of real estate, the selection of attributes depends on the available information sources. In Colombia, information on the sale prices of housing units is private due to security issues that have existed for decades in the country. As a result, few studies have explored this topic. Unfortunately, most of them have dealt with the offer prices of properties (rather than actual sale values) and some characteristics of the homes, which usually generates a bias in the estimated coefficients (Duque et al., 2011).

This study used the data of 3,597 sales of pre-owned homes that took place between May 2019 and April 2020, which were taken from the webpage of the Observatorio Inmobiliario de Medellín (OIME)1. Property taxes in Medellín are calculated based on the cadastral value of the property, which is defined by Medellín

[1] http://catastrooime.blogspot.com/

Treasurer's Office. The OIME is a completely independent organization, and their appraisals have nothing to do with the municipal taxes property owners pay. Each observation contains information about home price, area, type (apartment or house), district, geographic location, and closest distance to one of the following points of interest: public transportation system station, mall, sports center, university or school, hospital, religious center, or police station. Figure 1 presents the geographic distribution in Medellín of the homes used in this study.

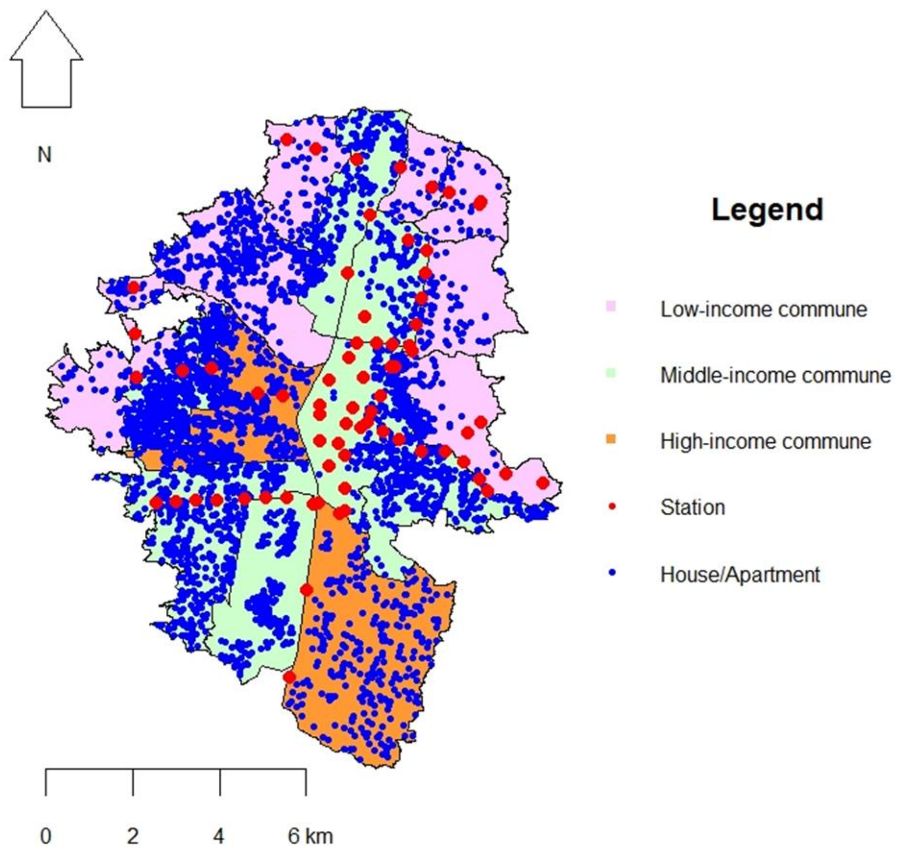

Figure 1 – Locations of sold homes and public transportation system stations in Medellín, Colombia. Source: author

Table 1 reports the descriptive statistics of the database. It shows that the sample contains similar proportions of apartments and houses (50.9% and 49.1%, respectively). In addition, most housing units are located in middle-income districts (56.3%); the rest are found in low- and high-income areas (22.2% and 21.5%, respectively). The distance to the nearest station ranges between 0.03 km and 3.29 km, with an average of 0.97 km. In the sample, 10.4% of the housing units are further than 2.0 km from the nearest station.

Table 1 – Descriptive statistics of the database

Income level (code)	**Total**			
Continuous variables (code)	***Min***	***Mean***	***Max***	***Std. Dev***
Price [Million of Colombian pesos] (*P*)	24,35	347,89	2.801,50	291,31
Area [m^2] (*A*)	24,00	141,20	631,00	86,10
Distance to the nearest station [km] (*dstation*)	0,03	0,97	3,29	0,66
Distance to the nearest shopping center [km] (*dshop)*	0,02	0,88	4,10	0,71
Distance to the nearest sport facility [km] (*dsport)*	0,01	0,36	1,43	0,23
Distance to the nearest college/high school [km] (*dedu)*	0,00	0,23	1,00	0,16
Distance to the nearest hospital [km] (*dhosp)*	0,01	0,56	2,15	0,39
Distance to the nearest religious center [km] (*drelig)*	0,01	0,29	1,45	0,20
Distance to the nearest police station [km] (*dpoli)*	0,02	1,02	3,62	0,55
Dummy variables (code)				
# of Apartments - # of Houses (*Apartment - House*)	1,830-1,767 (50.9%-49.1%)			
# of dwellings within 0 to 0.5 km to the nearest station (*dstation1*)	957 (26.6%)			
# of dwellings within 0.5 to 1.0 km to the nearest station (*dstation2*)	1,230 (34.2%)			
# of dwellings within 1.0 to 1.5 km to the nearest station (*dstation3*)	776 (21.6%)			
# of dwellings within 1.5 to 2.0 km to the nearest station (*dstation4*)	259 (7.2%)			
# of dwellings nearest station >2 km (*Nearest station >2 km*)	375 (10.4%)			
Low-income commune (*low.inc*)	798 (22.2%)			
Middle-income district (*middle.inc*)	2,024 (56.3%)			
High-income district (*high.inc*)	775 (21.5%)			

Source: author.

Table 2 – Descriptive statistics of the database disaggregated by income level

Income level (code)	**Low-income (*low.inc*)**				**Middle-income (*middle.inc*)**				**High-income (*high.inc*)**			
Continuous variables (code)	***Min***	***Mean***	***Max***	***Std. Dev***	***Min***	***Mean***	***Max***	***Std. Dev***	***Min***	***Mean***	***Max***	***Std. Dev***
Price [Million of Colombian pesos] (*P*)	25,00	178,43	1.548,45	149,68	24,35	296,83	1.800,77	192,69	107,69	655,73	2.801,50	377,95
Area [m^2] (*A*)	24,00	109,41	569,00	72,91	27,00	136,37	631,00	79,19	33,00	186,77	627,00	96,93
Distance to the nearest station [km] (*dstation*)	0,04	1,23	2,92	0,76	0,03	0,79	2,94	0,51	0,12	1,20	3,29	0,72
Distance to the nearest shopping center [km] (*dshop*)	0,15	1,27	4,10	0,68	0,02	0,87	4,08	0,74	0,03	0,51	2,01	0,31
Distance to the nearest sport facility [km] (*dsport*)	0,02	0,27	0,93	0,16	0,01	0,36	1,30	0,23	0,03	0,46	1,43	0,23
Distance to the nearest college/high school [km] (*dedu*)	0,01	0,21	0,94	0,13	0,01	0,21	0,85	0,14	0,00	0,31	1,00	0,20
Distance to the nearest hospital [km] (*dhosp*)	0,03	0,64	2,15	0,44	0,01	0,54	1,94	0,35	0,02	0,53	2,09	0,43
Distance to the nearest religious center [km] (*drelig*)	0,01	0,27	0,77	0,16	0,01	0,25	0,89	0,15	0,03	0,41	1,45	0,27
Distance to the nearest police station [km] (*dpoli*)	0,02	0,90	2,54	0,48	0,05	0,99	2,83	0,49	0,06	1,20	3,62	0,69
Dummy variables (code)												
# of Apartments - # of Houses (*Apartment - House*)			389-409 (48.7%-51.3%)			924-1,100 (45.7%-54.3%)				517-258 (66.7%-33.3%)		
# of dwellings within 0 to 0.5 km to the nearest station (*dstation1*)			186 (23.3%)			663 (32.8%)				108 (13.9%)		
# of dwellings within 0.5 to 1.0 km to the nearest station (*dstation2*)			185 (23.2%)			786 (38.8%)				259 (33.4%)		
# of dwellings within 1.0 to 1.5 km to the nearest station (*dstation3*)			114 (14.3%)			439 (21.7%)				223 (28.8%)		
# of dwellings within 1.5 to 2.0 km to the nearest station (*dstation4*)			151 (18.9%)			58 (2.9%)				50 (6.5%)		
# of dwellings nearest station >2 km (*Nearest station >2 km*)			162 (20.3%)			741 (3.9%)				135 (17.4%)		

Source: author.

Table 2 presents the descriptive statistics of the sample disaggregated by income level. It shows that the average floor area increases along with the income level: 109.41 m2, 136.37 m2, and 186.77 m2 in low-, middle-, and high-income districts, respectively. The average property price exhibits the same behavior (although more pronounced): COP 178.4 million, COP 296.8 million, and COP 655.7 million in low-, middle-, and high-income districts, respectively. Nevertheless, the average distance to the nearest station of low-income housing units (1.23 km) is closer to that of high-income units (1.20 km) than that of their middle-income counterparts (0.79 km). This table also shows that 20.3% of the low-income housing units and 17.4% of the high-income ones are more than 2.0 km from the nearest station. In the case of middle-income properties, that percentage is only 3.9%.

Methodology

Hedonic price model

Among the mathematical models usually applied to appraise the effect of amenities on home prices, the most common is the hedonic price model, which is based on the study by Rosen (1974). In said model, all the attributes that affect the property value are analyzed together, generally through multiple linear regression, where the price is explained as a function of spatial and non-spatial attributes. The hedonic price model can be written as

$$P = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{1}$$

where P is the home price; β_0, a constant; X_i, the i-th characteristic of the home (e.g., area, type, distance to a Metro station, etc.); and ε, the error.

In order to study the relationship between access to transportation system stations and property prices, the distances between homes and stations were measured here using continuous and dummy variables. In the first case, to consider the possibility that the effect of the distance to stations on home prices has an inverted U-shape, the minimum distances of the housing units to the stations of the transportation system were squared and the sign of the coefficient is expected to be negative. Therefore, the hedonic price model (which will be called Model 1 in this paper) is written as:

$$ln\, P = \beta_0 + \alpha_1 dstation + \alpha_2 dstation^2 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon \tag{2}$$

where $ln\, P$ is the natural logarithm of the home price2; α_1 and α_2 are the coefficients of $dstation$ and $dstation^2$, respectively; and the remaining variables are defined as previously indicated. In the case of the dummy variables, the reference categories used are Apartment and Low-income for the variables Type and Income level respectively.

In the second case, the hedonic price model (which will be called Model 2 in this paper) is written as:

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[2] The logarithmic transformation of prices is very common in this kind of studies because this variable is highly skewed.

$$ln\,P = \beta_0 + \gamma_1 dstation1 \; + \gamma_2 dstation2 + \gamma_3 dstation3 + \gamma_4 dstation4 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon \tag{3}$$

where $dstation1$, $dstation2$, $dstation3$, and $dstation4$ are dummy variables that take a value of 1 if the distance to the closest station is 0–0.5 km, 0.5–1.0 km, 1.0–1.5 km, or 1.5–2.0 km, respectively, or 0 otherwise[3]. The reference category corresponds to the case in which the closest station to the dwelling is located further than 2.0 km.

Spatial econometric models

Applying the traditional econometric methodology to spatial data is problematic due to the spatial correlation that occurs when there are levels of spatial dependency between variables. This is particularly valid in the real estate market, where cheap and expensive homes tend to be concentrated in specific areas (Anselin, 1988b; Basu & Thibodeau, 1998). Among the models that consider the geographic location of the observations, the most commonly used are the spatial autoregressive (SAR) model and the spatial error model (SEM) (Arbia, 2014). Both of them include a W matrix (nxn) of spatial weights, where each of its inputs w_{ij} reflects the spatial structure between observations i and j. The W matrix inputs are generally 1 and 0 (or reverse distance) depending on if a vicinity criterion is met or not, which can be defined based on a distance range or a given number of k-nearest neighbors (Arbia, 2014). This study uses a matrix with reverse distances of k-nearest neighbors in a distance range that guarantees at least one neighbor for each case under study.

A testing procedure for the hypothesis of no spatial correlation among the OLS regression residuals is done based on Moran's I statistics (Moran, 1950). However, this test statistic does not consider explicitly an alternative hypothesis to contrast the null of uncorrelation. Figure 2 shows a model selection process using Lagrange Multiplier (LM) test and Robust LM test to test for lag and error spatial dependence (Anselin, 1988a; Anselin et al., 1996). After applying the ordinary least squares (OLS) regression model, the LM-Error and LM-Lag tests are conducted. If the results of none of these tests were significant, it is assumed that the residuals of the model do not present spatial correlation. If any of them is significant, the respective model is run. If the results of both tests are significant, the robust versions of the LM test are conducted to explore the possibility of discarding one of the models.

[3] The 500-meter distance is used in this type of studies as a reference point of the distance someone is willing to walk to a destination or to take public transportation (Echeverri Durán et al., 2019).

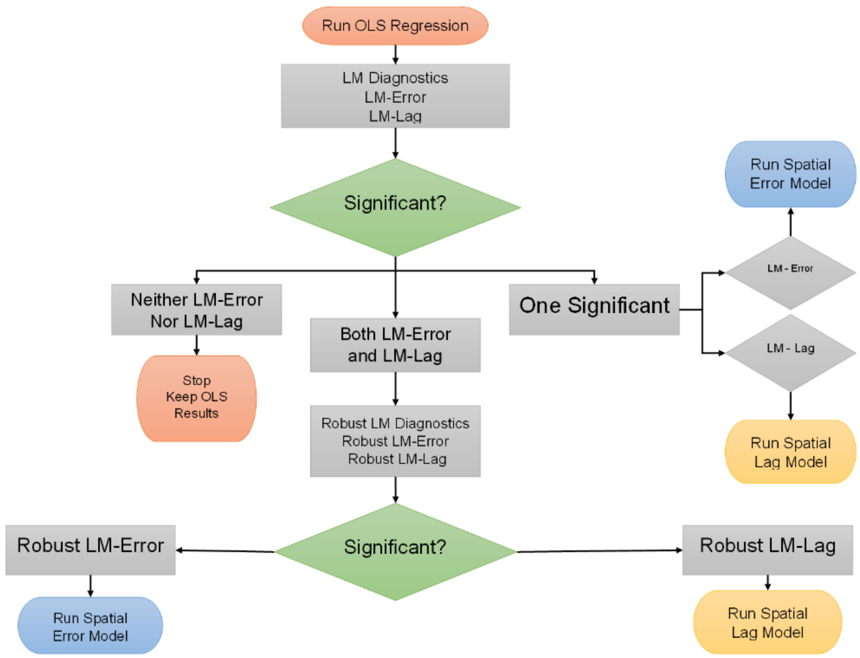

Figure 2 – Model selection process using Lagrange Multiplier (LM) test and Robust LM (Anselin, 1988a; Anselin et al., 1996).

Models 1 and 2 adapted to the SAR model are expressed as:

$$ln\,P = \rho W\,ln\,P + \beta_0 + \alpha_1 dstation + \alpha_2 dstation^2 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon \tag{4}$$

$$ln\,P = \rho\,W ln\,P + \beta_0 + \gamma_1 dstation1 + \gamma_2 dstation2 + \gamma_3 dstation3 + \gamma_4 dstation4 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{5}$$

where $W\,ln\,P$ is a vector that represents the spatial lag of the natural logarithm of the home prices, and ρ is the coefficient of said vector.

Models 1 and 2 adapted to the SEM model are expressed as:

$$ln\,P = \beta_0 + \alpha_1 dstation + \alpha_2 dstation^2 + \sum_{i=1}^{n} \beta_i X_i + u \tag{6}$$

$$u = \lambda W u + \varepsilon$$

$$ln\, P = \beta_0 + \gamma_1 dstation1\ + \gamma_2 dstation2 + \gamma_3 dstation3 + \gamma_4 dstation4 + \sum_{i=1}^{n} \beta_i X_i + u \qquad (7)$$

$$u = \lambda W u + \varepsilon$$

where Wu is a vector that represents the spatial lag of the errors, and λ is the coefficient of said vector.

Spatial models are estimated by Maximum Likelihood (ML) and all the calculations were performed using the spdep library of R software.

Results and discussion

Table 3 presents the results obtained with Models 1 and 2, which were estimated using ordinary least squares (OLS) and the SAR and SEM specifications for all the homes in the sample. In the three cases of Model 1 (i.e., Mod1-OLS, Mod1-SAR, and Mod1-SEM), all the coefficients of the variables dstation and dstation2 are significant in addition to positive and negative, respectively. According to Moran's test, Lagrange Multiplier (LM) tests and their robust versions, Mod1-OLS and Mod2-OLS present spatial correlation. This use of spatial econometric models is valid given that, in Mod1-SAR and Mod2-SAR, the ρ coefficient is positive and significant; and, in Mod1-SAR and Mod2-SAR, the λ coefficient is positive and significant as well.

This finding is important because it indicates that the effect of the distance to stations on home prices is not linear; instead, it presents an inverted U-shape. In other words, the price of a home increases as it is further from a station up to an optimal distance; after that, the effect of the distance is the opposite, and it causes the home price to decrease. These results are in agreement with those obtained in the three cases of Model 2 (i.e., Mod2-OLS, Mod2-SAR, and Mod2-SEM), where the dummy, dstation1, and dstation2 coefficients are significant with a negative sign; those of dstation1 are higher (in absolute value); dstation3 coefficients are positive but not significant; and dstation4 coefficients are positive and significant (at least at 10%). This means that the price of a home decreases if it is located in a 0.5-km radius around a station, and it is also reduced (to a lesser degree) if it is located between 0.5 and 1.0 km from a station. Likewise, if a home is located between 1.0 and 1.5 km from a station, there is no effect on its price; however, the latter increases if the property is located between 1.5 and 2.0 km from a station.

Table 3 – Results of Models 1 and 2 estimated using OLS and the SAR and SEM specifications applied to homes located in all districts

	Mod1-OLS			**Mod1-SAR**			**Mod1-SEM**			**Mod2-OLS**			**Mod2-SAR**			**Mod2-SEM**		
	Coeffic.	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*	
Constant	14,3351	0,0000	***	14,3017	0,0000	***	14,3713	0,000	***	14,5292	0,0000	***	14,4538	0,0000	***	14,5563	0,0000	***
Distance to stations																		
dstation	0,2100	0,0000	***	0,1644	0,0000	***	0,1943	0,000	***	—			—			—		
dstation²	-0,0503	0,0000	***	-0,0380	0,0007	***	-0,0451	0,000	***	—			—			—		
dstation1	—			—			—			-0,1075	0,0000	***	-0,0811	0,0009	***	-0,1048	0,0000	***
dstation2	—			—			—			-0,0886	0,0002	***	-0,0713	0,0022	**	-0,0879	0,0003	***
dstation3	—			—			—			0,0172	0,4773		0,0105	0,6583		0,0099	0,6887	
dstation4	—			—			—			0,0583	0,0380	*	0,0768	0,0054	**	0,0539	0,0569	.
Nearest station >2 km		—		—			—			REF			REF			REF		
Structural variables																		
logarea	0,9634	0,0000	***	0,9584	0,0000	***	0,9557	0,000	***	0,9606	0,0000	***	0,9554	0,0000	***	0,9532	0,0000	***
Apartment	REF			REF			REF			REF			REF			REF		
House	0,1861	0,0000	***	0,1916	0,0000	***	0,1818	0,000	***	0,1829	0,0000	***	0,1884	0,0000	***	0,1787	0,0000	***
Locational variables																		
dshop	-0,1751	0,0000	***	-0,1618	0,0000	***	-0,1749	0,000	***	-0,1736	0,0000	***	0,1603	0,0000	***	0,1733	0,0000	***
dsport	0,1226	0,0000	***	0,1423	0,0000	***	0,1272	0,000	***	0,1133	0,0001	***	0,1330	0,0000	***	0,1185	0,0000	***
dedu	0,1707	0,0001	***	0,1775	0,0000	***	0,1656	0,000	***	0,1859	0,0000	***	0,1869	0,0000	***	0,1787	0,0001	***
dhosp	-0,0856	0,0000	***	-0,0809	0,0000	***	-0,0820	0,000	***	-0,0820	0,0000	***	-0,0773	0,0000	***	0,0832	0,0000	***
drelig	0,2044	0,0000	***	0,2205	0,0000	***	0,2077	0,000	***	0,2006	0,0000	***	0,2177	0,0000	***	0,2059	0,0000	***
dpoli	-0,0385	0,0035	**	-0,0267	0,0399	*	-0,0361	0,007	**	0,0377	0,0039	**	-0,0253	0,0484	*	-0,0349	0,0086	**
Wy (ρ)	—			0,0009	0,0000	***	—			—			0,0009	0,0000	***	—		
Wu (λ)	—			—			0,0181	0,000	***	—			—			0,0181	0,000	***
Income variables																		
low.inc	REF			REF			REF			REF			REF			REF		
middle.inc	0,2901	0,0000	***	0,269291	0,0000	***	0,2884	0,000	***	0,2929	0,0000	***	0,2753	0,0000	***	0,2911	0,0000	***
high.inc	0,6264	0,0000	***	0,616252	0,0000	***	0,6331	0,000	***	0,6358	0,0000	***	0,6294	0,0000	***	0,6426	0,0000	***
Spatial dependence																		
Moran's I	0,3669	0,0000	***	—			—			0,3557	0,0000	***	—			—		
LM-Error	5868,2	0,0000	***	—			—			5927,8	0,0000	***	—			—		
LM-Lag	1615,9	0,0000	***	—			—			1624,1	0,0000	***	—			—		
Robust LM-Error	4780,8	0,0000	***	—			—			4828,1	0,0000	***	—			—		
Robust LM-Lag	528,4	0,0000	***	—			—			524,5	0,0000	***	—			—		
Fit model																		
R2	0,8095			0,8157			0,8165			0,8101			0,8164			0,8169		
N	3597			3597			3597			3597			3597			3597		
AIC	2427,8250			2311,2380			2307,1350			2421,7530			2302,6440			2303,9000		

Source: author.

In all the cases of Models 1 and 2, the coefficients of all the remaining independent variables are significant and keep the same sign. Clearly, the variable logarea is by far the most important to determine home prices because its coefficients are considerably higher than those of other variables. Also, the coefficients of the variable House show that houses are more expensive than apartments. The negative sign of the variables dshop, dhosp, and dpoli indicates that shopping centers, hospitals, and police stations are considered positive amenities, and their proximity increases housing prices. The opposite happens with the variables dsport, dedu, and drelig, whose positive sign indicates that proximity to sport centers, educational institutions, and religious centers reduces housing prices. Finally, the values of the variables middle.inc and high.inc show that housing is more expensive in high-income districts than in low- or middle-income ones.

Tables 4 and 5 present the results of Models 1 and 2 that were applied to housing units located in low- and middle-income districts, respectively. The results in both tables are similar to those obtained with all the aggregate homes. According to Moran's test, Lagrange Multiplier (LM) tests and their robust versions, Mod1-OLS and Mod2-OLS present spatial correlation in low- and high-income districts. Using spatial econometric models in this case is valid because, in Mod1-SAR and Mod2-SAR, the ρ coefficient is positive and significant; and, in Mod1-SAR and Mod2-SAR, the λ coefficient is positive and significant as well. In the three cases of Model 1 (i.e., Mod1-OLS, Mod1-SAR, and Mod1-SEM), both tables show that all the coefficients of the variables dstation and dstation2 are significant as well as positive and negative, respectively. This indicates that the effect of distance to stations on home prices presents an inverted U-shape in low- and middle-income districts.

Table 4 – Results of Models 1 and 2 estimated using OLS and the SAR and SEM specifications applied to homes located in low-income districts

	Mod1-OLS		Mod1-SAR		Mod1-SEM		Mod2-OLS		Mod2-SAR		Mod2-SEM	
	Coeffic.	*p-value*	*Coeffic.*	*p-value*	*Coeffic.*	*p-value*	*Coeffic.*	*p-value*	*Coeffic.*	*p-value*	*Coeffic.*	*p-value*
Constant	14,3713	0,0000 ***	14,3099	0,0000 ***	14,4060	0,0000 ***	14,6104	0,0000 ***	14,5303	0,0000 ***	14,6277	0,0000 ***
Distance to stations												
dstation	0,2928	0,0006 ***	0,2747	0,0010 **	0,2709	0,0015 **	—		—		—	
dstation²	-0,0936	0,0020 **	-0,0891	0,0027 **	-0,0862	0,0046 **	—		—		—	
dstation1	—		—		—		-0,0018	0,9693	0,0120	0,7991	-0,0049	0,9186
dstation2	—		—		—		-0,0629	0,1614	-0,0551	0,2105	-0,0632	0,1623
dstation3	—		—		—		0,0894	0,0726 .	0,0930	0,0567 .	0,0787	0,1183
dstation4	—		—		—		0,1717	0,0005 ***	0,1753	0,0003 ***	0,1576	0,0015 **
Nearest station >2 km	—		—		—		REF		REF		REF	
Structural variables												
logarea	0,9759	0,0000 ***	0,9781	0,0000 ***	0,9687	0,0000 ***	0,9609	0,0000 ***	0,9628	0,0000 ***	0,9554	0,0000 ***
Apartment	REF		REF		REF		REF		REF		REF	
House	0,1632	0,0000 ***	0,1770	0,0000 ***	0,1629	0,0000 ***	0,1475	0,0000 ***	0,1613	0,0000 ***	0,1486	0,0000 ***
Locational variables												
dshop	-0,2389	0,0000 ***	-0,2311	0,0000 ***	-0,2363	0,0000 ***	-0,2445	0,0000 ***	-0,2366	0,0000 ***	-0,2420	0,0000 ***
dsport	-0,0224	0,8193	-0,0041	0,9661	-0,0227	0,8171	-0,0967	0,3310	-0,0785	0,4214	-0,0897	0,3670
dedu	0,3859	0,0021 **	0,3734	0,0024 **	0,3873	0,0019 **	0,3136	0,0134 *	0,2978	0,0165 *	0,3178	0,0118 *
dhosp	-0,2434	0,0000 ***	-0,2414	0,0000 ***	-0,2405	0,0000 ***	-0,2362	0,0000 ***	-0,2343	0,0000 ***	-0,2339	0,0000 ***
drelig	0,0836	0,4247	0,0930	0,3661	0,0795	0,4484	0,0719	0,4885	0,0798	0,4327	0,0702	0,4991
dpoli	0,0906	0,0200 *	0,0980	0,0104 *	0,0893	0,0216 *	0,1026	0,0080 **	0,1111	0,0034 **	0,1013	0,0087 **
Wy (ρ)	—		0,0011	0,0000 ***	—		—		0,0011	0,0000 ***	—	
Wu (λ)	—		—		0,0222	0,0000 ***	—		—		0,022032	0,0000 ***
Spatial dependence												
Moran's I	0,5157	0,0000 ***	—		—		0,4713	0,0000 ***	—		—	
LM-Error	568,2	0,0000 ***	—		—		560,6	0,0000 ***	—		—	
LM-Lag	486,3	0,0000 ***	—		—		455,7	0,0000 ***	—		—	
Robust LM-Error	196,6	0,0000 ***	—		—		207,3	0,0000 ***	—		—	
Robust LM-Lag	114,7	0,0000 ***	—		—		102,3	0,0000 ***	—		—	
Fit model												
R2	0,6557		0,6628		0,6680		0,6623		0,6697		0,6733	
N	798		798		798		798		798		798	
AIC	806,5790		792,1170		785,2900		795,2222		779,4629		776,0800	

Source: author.

Table 5 – Results of Models 1 and 2 estimated using OLS and the SAR and SEM specifications applied to homes located in middle-income districts

	Mod1-OLS			**Mod1-SAR**			**Mod1-SEM**			**Mod2-OLS**			**Mod2-SAR**			**Mod2-SEM**		
	Coeffic.	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*	
Constant	14,6382	0,0000	***	14,6058	0,0000	***	14,6561	0,0000	***	14,7736	0,0000	***	14,6801	0,0000	***	14,7602	0,0000	***
Distance to stations																		
dstation	0,3118	0,0000	***	0,2850	0,0000	***	0,3040	0,0000	***	—			—			—		
dstation²	-0,1008	0,0000	***	-0,0972	0,0000	***	-0,1012	0,0000	***	—			—			—		
dstation1	—			—			—			-0,0465	0,3416		0,0059	0,9038		-0,0183	0,7192	
dstation2	—			—			—			0,0111	0,8163		0,0559	0,2361		0,0362	0,4648	
dstation3	—			—			—			0,1215	0,0108	*	0,1516	0,0013	**	0,1397	0,0048	**
dstation4	—			—			—			0,0202	0,7290		0,0680	0,2392		0,0479	0,4212	
Nearest station >2 km	—			—			—			REF			REF			REF		
Structural variables																		
logarea	0,9541	0,0000	***	0,9526	0,0000	***	0,9499	0,0000	***	0,9527	0,0000	***	0,9511	0,0000	***	0,9487	0,0000	***
Apartment	REF			REF			REF			REF			REF			REF		
House	0,1984	0,0000	***	0,2029	0,0000	***	0,1965	0,0000	***	0,1975	0,0000	***	0,2020	0,0000	***	0,1955	0,0000	***
Locational variables																		
dshop	-0,1674	0,0000	***	-0,1603	0,0000	***	-0,1675	0,0000	***	-0,1666	0,0000	***	-0,1605	0,0000	***	-0,1671	0,0000	***
dsport	0,2551	0,0000	***	0,2682	0,0000	***	0,2591	0,0000	***	0,2417	0,0000	***	0,2562	0,0000	***	0,2459	0,0000	***
dedu	0,1097	0,0611	.	0,1167	0,0430	*	0,1136	0,0532	.	0,1308	0,0270	*	0,1361	0,0192	*	0,1323	0,0257	*
dhosp	-0,1110	0,0000	***	-0,1101	0,0000	***	-0,1122	0,0000	***	-0,1105	0,0000	***	-0,1076	0,0000	***	-0,1097	0,0000	***
drelig	0,3051	0,0000	***	0,3121	0,0000	***	0,3024	0,0000	***	0,3228	0,0000	***	0,3266	0,0000	***	0,3174	0,0000	***
dpoli	-0,1019	0,0000	***	-0,0923	0,0000	***	-0,0988	0,0000	***	-0,0947	0,0000	***	-0,0838	0,0000	***	-0,0911	0,0000	***
Wy (ρ)	—			0,0005	0,0000	***	—			—			0,0005	0,0000	***	—		
Wu (λ)	—			—			0,0124	0,0000	***	—			—			0,0124	0,000	***
Spatial dependence																		
Moran's I	0,4466	0,0000	***	—			—			0,4300	0,0000	***	—			—		
LM-Error	3793,3	0,0000	***	—			—			3816,1	0,0000	***	—			—		
LM-Lag	1528,9	0,0000	***	—			—			1526,5	0,0000	***	—			—		
Robust LM-Error	2565,4	0,0000	***	—			—			2588,8	0,0000	***	—			—		
Robust LM-Lag	301,0	0,0000	***	—			—			299,2	0,0000	***	—			—		
Fit model																		
R2	0,7374			0,7443			0,7456			0,7379			0,7448			0,7459		
N	2024			2024			2024			2024			2024			2024		
AIC	1195,7520			1144,1590			1140,5000			1196,2740			1144,2000			1142,5720		

Source: author.

However, the results of Model 2 in Tables 4 and 5 exhibit an important difference regarding the analysis of aggregate data. The coefficients of the variables dstation and dstation2 are not significant in any case. In Table 4, dstation3 coefficients are positive in the three cases, but significant only at 10% in Mod2-OLS and Mod2-SAR; and they are not significant in Mod2-SEM. The coefficients of the variable dstation4 are positive, significant, and higher than those of dstation3 in all cases. Additionally, in Table 5, Model 2 shows that dstation3 coefficients are positive and significant in all cases, while dstation1, dstation2, and dstation4 coefficients are not significant in any case.

This indicates that the proximity of homes to stations up to 1.0 km has no effect on housing prices in low- and middle-income districts. Nevertheless, in low-income districts, home prices increase when housing units are located between 1.0 and 1.5 km from a station, and said increase is even higher if the distance to a station is between 1.5 and 2.0 km. In the case of middle-income districts, home prices only increase if housing units are located between 1.5 and 2.0 km from a station.

Table 6 presents the results of Models 1 and 2 that were applied to homes located in high-income districts only. According to Moran's test, Lagrange Multiplier (LM) tests and the robust version of the LM Error test, Mod1-OLS and Mod2-OLS present spatial correlation. The ρ coefficient is not significant in Mod1-SAR or Mod2-SAR, while the λ coefficient is positive and significant in Mod1-SEM and Mod2-SEM. This time, the results of Model 1 differ considerably from those obtained in all previous cases. The coefficients of dstation are positive and significant, while those of dstation2 are negative but not significant. Additionally, Model 2 shows that dstation1 and dstation2 coefficients are negative and significant (those of dstation1 being higher in absolute value), while dstation3 and dstation4 coefficients are not significant.

This indicates that, unlike in previous cases, the effect of the distance from homes to stations in high-income districts does not exhibit an inverted U-shape; instead, it is linear with a positive slope, as shown by Model 1. Therefore, proximity to stations in these districts reduces home prices. This is in agreement with the results of the three cases of Model 2, which show that the prices of homes decrease if the latter are located between 0 and 0.5 km from a station, and they also decrease (to a lesser degree) in a distance between 0.5 and 1.0 km. In turn, a distance beyond 1.0 km does not have any effect on home prices in high-income areas.

Table 6 – Results of Models 1 and 2 estimated using OLS and the SAR and SEM specifications applied to homes located in high-income districts

	Mod1-OLS			**Mod1-SAR**			**Mod1-SEM**			**Mod2-OLS**			**Mod2-SAR**			**Mod2-SEM**		
	Coeffic.	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*		*Coeffic.*	*p-value*	
Constant	15,5292	0,0000	***	15,5293	0,0000	***	15,5407	0,0000	***	15,7495	0,0000	***	15,7451	0,0000	***	15,75558	0,0000	***
Distance to stations																		
dstation	0,1574	0,0039	**	0,1574	0,0038	**	0,1542	0,0055	**	—			—			—		
dstation^2	-0,0175	0,3511		-0,0175	0,3482		-0,0167	0,3796		—			—			—		
dstation1	—			—			—			-0,1660	0,0018	**	-0,1645	0,0019	**	-0,16203	0,0026	**
dstation2	—			—			—			-0,1307	0,0101	*	-0,1292	0,0108	*	-0,12750	0,0130	*
dstation3	—			—			—			-0,0746	0,1346		-0,0741	0,1339		-0,07450	0,1390	
dstation4	—			—			—			0,0405	0,3926		0,0415	0,3779		0,04176	0,3807	
Nearest station >2 km	—			—			—			REF			REF			REF		
Structural variables																		
logarea	0,8530	0,0000	***	0,8530	0,0000	***	0,8511	0,0000	***	0,8512	0,0000	***	0,8513	0,0000	***	0,84929	0,0000	***
Apartment	REF			REF			REF			REF			REF			REF		
House	0,0795	0,0016	**	0,0795	0,0015	**	0,0762	0,0023	**	0,0788	0,0019	**	0,0795	0,0017	**	0,07557	0,0027	**
Locational variables																		
dshop	0,0310	0,4200		0,0310	0,4165		0,0246	0,5274		0,0475	0,2237		0,0474	0,2205		0,04174	0,2912	
dsport	0,0393	0,3849		0,0393	0,3813		0,0417	0,3646		0,0302	0,5169		0,0302	0,5137		0,03297	0,4853	
dedu	0,1079	0,0937	.	0,1079	0,0911	.	0,1006	0,1235		0,1293	0,0531	.	0,1285	0,0524	.	0,12125	0,0730	.
dhosp	0,0260	0,4142		0,0260	0,4111		0,0371	0,2529		0,0163	0,6411		0,0167	0,6315		0,02737	0,4416	
drelig	0,1073	0,0328	*	0,1073	0,0312	*	0,1160	0,0234	*	0,1387	0,0042	**	0,1388	0,0038	**	0,14850	0,0025	**
dpoli	-0,0401	0,0966	.	-0,0401	0,0979	.	-0,0422	0,0872	.	-0,0304	0,2264		-0,0295	0,2415		-0,03218	0,2099	
Wy (ρ)	—			0,0000	0,9966		—			—			0,0000	0,8090		—		
Wu (λ)	—			—			0,0267	0,0171	*	—			—			0,0269	0,016	*
Spatial dependence																		
Moran's I	0,1259	0,0049	**	—			—			0,1258	0,0045	**	—			—		
LM-Error	73,0	0,0000	***	—			—			74,9	0,0000	***	—			—		
LM-Lag	27,8	0,0000	***	—			—			33,2	0,0000	***	—			—		
Robust LM-Error	45,7	0,0000	***	—			—			42,9	0,0000	***	—			—		
Robust LM-Lag	0,4	0,5417		—			—			1,2	0,2689		—			—		
Fit model																		
R2	0,7359			0,7359			0,7388			0,7343			0,7344			0,7373		
N	775			775			775			775			775			775		
AIC	138,6322			140,6300			134,9428			147,3177			149,2593			143,5309		

Source: author.

In Tables 4, 5, and 6, the models with SEM specifications (i.e., Mod1-SEM and Mod2-SEM) always exhibit the highest R2 coefficient and the lowest AIC coefficient. Additionally, none of the models calculated using OLS presents multicollinearity issues because the variance inflation factor is lower than 10 in all the cases. Figure 3 shows the predicted vs. observed values of Models 1 and 2 with SEM specifications at the three income levels. The predictive capability of both models is almost the same at different income levels; however, it is better for high- and middle-income areas than for their low-income counterparts.

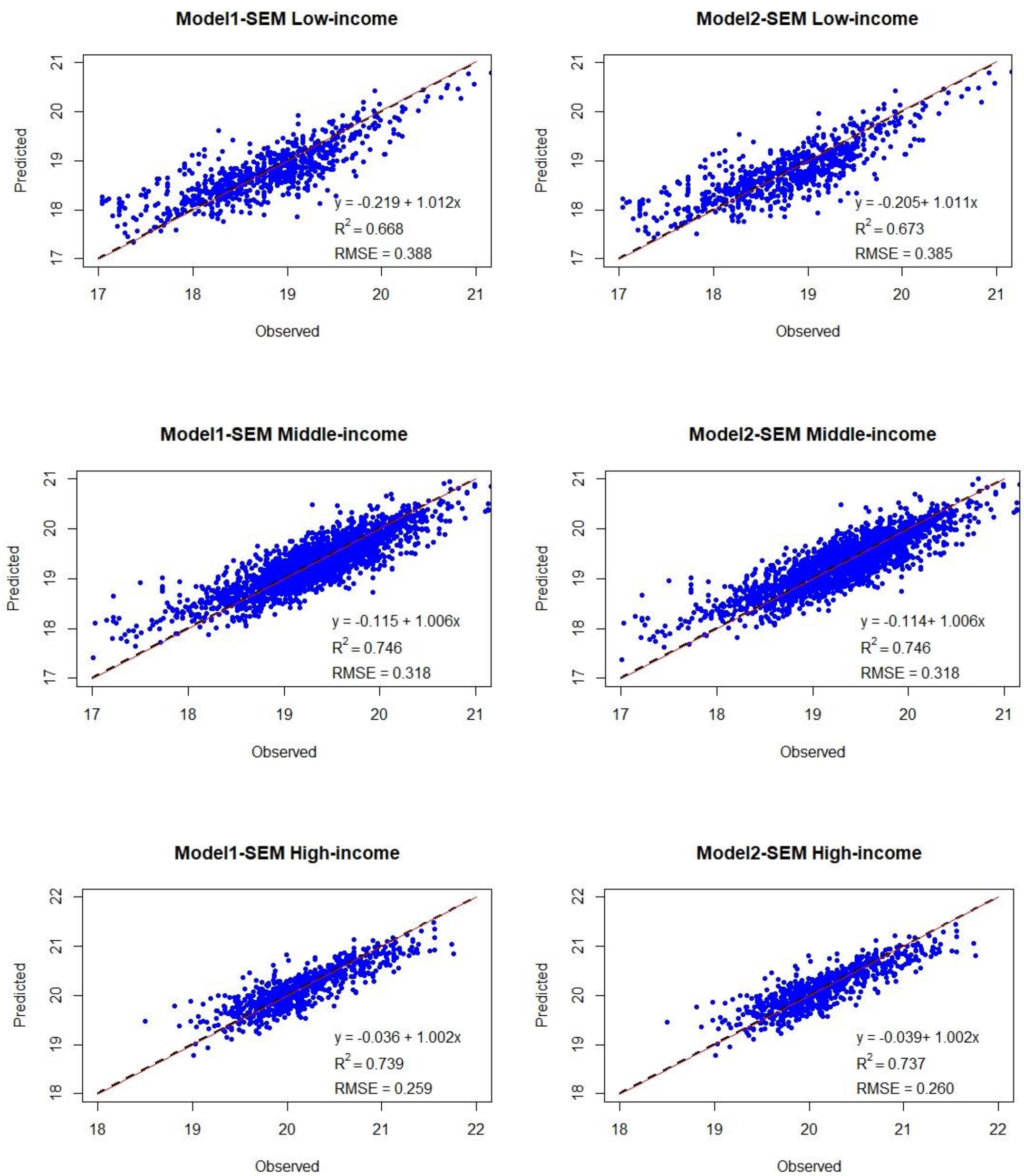

Figure 3 – Predicted vs. observed values of Models 1 and 2 with SEM specifications at three income levels. The dashed line represents the y = x equation, and the solid red line represents the equation of the adjusted line. Source: author

Since the dummy variables of Model 2 cannot be interpreted directly because the independent variable is in a logarithmic form, it is necessary to use the following expression:

$$Percentual\ change\ =\ (e^{\gamma} - 1) * 100 \tag{8}$$

Table 7 presents the percentual effect of the distance to the nearest station and the income level of the district on home prices based on the results of Model 2 with SEM specifications. These results show that the average home price is COP 348,000,000. Such price increases to COP 407,000,000 if the home is located between 1.5 and 2.0 km from a station in a low-income district, it rises to COP 400,000,000 if it is located between 1.0 and 1.5 km from a station in a middle-income district, and it decreases to COP 296,000,000 if it is located between 0 and 0.5 km from a station in a high-income district.

Table 7 – Percentual effect of the distance to the nearest station and the income level of the district on home prices based on the results of Model 2 with SEM specifications

bajo	medio	alto	Income level	Distance to the nearest station [km]							
0,0%	0,0%	-15,0%		0-0.5	0.5-1.0	1.0-1.5	1.5-2.0				
0,0%	0,0%	-12,0%	Low	0,0%	0,0%	0,0%	17,1%	348	348	348	407
0,0%	15,0%	0,0%	Middle	0,0%	0,0%	15,0%	0,0%	348	348	400	348
17,1%	0,0%	0,0%	High	-15,0%	-12,0%	0,0%	0,0%	296	306	348	348

Source: author.

Conclusions and recommendations

The objective of this paper was to measure the effect of the distance between homes and stations of the integrated public transportation system in Medellín (composed of an elevated train system, streetcar, cable cars, and BRT) on home prices. We used data of 3,597 home sales and applied hedonic models calculated by OLS and by SAR and SEM spatial econometric models in an aggregate and disaggregate manner classified by income level. Distance to stations was considered a constant variable in some models and a dummy variable in others. The aggregate results show that the effect of the distance on home prices exhibits inverted U-shape; thus, said prices decrease if the housing units are located less than 1.0 km from a station, but they increase if the units are located between 1.0 and 2.0 km from one.

The results obtained with the disaggregated sample indicate that the effect of the distance to stations on home prices presents an inverted U-shape in low- and middle-income districts, but there is no evidence that indicates that the prices of these homes decrease because of their proximity to a station. In low-income districts, the price of homes increases (17.1%) if they are located between 1.5 and 2.0 km from a station; and, in middle-income districts, their price rises (15%) if they are located between 1.0 and 1.5 km from a station. Homes in high-income districts constitute a different case because the effect of the distance to a station does not exhibit an inverted U-shape; instead, such effect is negative on the price of homes located up to 1.0 km from a station (i.e., -15% between 0 and 0.5 km, and -12% between 0.5 and 1.0 km).

This effect of distance to a station on home prices in low- and middle-income districts can be derived, as claimed by Bowes and Ihlanfeldt (2001) and Nelson (1992), from the perception that the disadvantages of proximity to stations (noise, vibrations, insecurity, etc.) equal the benefits (time and money saving, increased commercial activity in the area, etc.) in a 1.0-km radius around stations. Thus, at these income levels, a distance of up to 1.0 km to stations has no effect on home prices. However, the perception that the benefits outweigh the disadvantages between 1.0 and 2.0 km around stations raises home prices in said districts. This effect on the price of housing in low-income and middle-income districts may also occur due to the lack of competition that the public transport system has there compared to the competition that it may have in more developed areas of the city (Mulley et al., 2016).

The case of homes in high-income districts is special because social inequality is one of the main characteristics of cities in developing countries such as Medellín. This is reflected in the way that the high-income population get around the city, since they prefer private vehicles over public transportation systems, as mentioned by Thynell (2009). As a consequence, inhabitants of higher-income districts may only perceive the disadvantages of the proximity to stations and ignore its benefits, which may be the reason why the results show that proximity to stations only reduces home prices in these districts.

The fact that some public transportation solutions had no or counterintuitive relationships with house prices but, above all, that these results exhibited spatial variations throughout the study area is no exclusive of cities in developing countries given that these results have also been observed in some cities of developed (Bulteau et al., 2018; Q. Li et al., 2021; Weinberger, 2001).

The results obtained in this study are useful for the participants of the real estate market to make investment and home appraisal decisions and especially for makers of public policies oriented to improving mobility and the environment in cities in developing countries. This is due to three reasons. First, the results show that the implementation of a tax collection system based on value capture would present difficulties because said tax would have to be paid by low- and middle-income district homeowners instead of their high-income counterparts. This is not viable because it would increase social inequality even more in these cities. Second, the fact that stations have no effect (in low- and middle-income districts) or a negative effect (in high-income districts) on the prices of homes that are "very close" to them indicates that the construction of public transportation systems must be accompanied by suitable land use planning that adequately integrates stations into their environment in order to minimize negative factors. Third, improving the mobility and pollution levels in cities in developing countries is not only a matter of investing in infrastructure. It is necessary to offer a high-quality transportation service and study the possibility of creating mechanisms (such as urban road tolls in strategic areas of the city) that encourage the high-income population to use public transportation instead of private vehicles. This would be reflected in a home price increase near stations, instead of the decrease that high-income districts showed here.

Finally, future research into this topic should use techniques such as kriging or geographically weighted regression (GWR), where the effect of the distance to stations on home prices can be distributed in a way that is not necessarily concentric but irregular or even discontinuous in space.

Declaración de disponibilidad de datos

El conjunto de datos que respalda los resultados de este artículo está disponible en SciELO DATA y se puede acceder a él enhttps://doi.org/10.48331/scielodata.4JOCZG

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