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# The Effect of Commuting Costs to Employment Centers on Urban Property Values: A Spatial Analysis in Bogotá, Colombia[1]

Fernando Carriazo[2], Julian Peñaranda[3].


## Abstract:

We study the effect that changes of commuting costs to intra urban employment centers may have on property prices in Bogotá, Colombia. To explore the relationship between prices and communing costs, we use a difference in difference spatial model. Parametric and non-parametric estimations suggest a negative and significant impact of commuting costs on property values for dwellings far away from employment centers. The estimated price elasticity with respect to commuting costs for housing located in distant zones, indicates that a 1% increase in fuel price, reduces property values in 1.48%. Non-parametric Geographically Weighted Regression (GWR) showed to outperform traditional Spatial Autoregressive (SAR, SEM) models.


**Keywords**: spatial econometrics, non-parametric methods, hedonic model, commuting costs

**JEL:** C14, C21, R21, R31, R32

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# El Efecto de Viajes Diarios a Centros de Empleo en el Valor de las Viviendas Urbanas: Un Análisis Espacial en Bogotá, Colombia


## Resumen:

Estudiamos el efecto que pueden tener cambios en los costos de desplazamiento del hogar al lugar de trabajo en el valor de las propiedades en Bogotá, Colombia. Para explorar la relación entre precios y costos de desplazamiento, proponemos un modelo espacial de diferencias en diferencias. Estimaciones paramétricas y no paramétricas sugieren un impacto negativo y significativo de los costos de desplazamiento en el valor de las propiedades localizadas en zonas lejanas a centros de empleo. La elasticidad precio con respecto al costo de desplazamiento para propiedades lejanas a centros de empleo, indica que un incremento de 1% en el precio de la gasolina, reduce en promedio el valor de las propiedades en un 1.48%. La regresión no paramétrica con ponderadores de localización (GWR) presentan mejor bondad de ajuste que los modelos tradicionales de rezago espacial autorregresivo (SAR y SEM).



**Palabras clave**: econometría espacial, métodos no paramétricos, modelos hedónicos, costos de desplazamiento al lugar de trabajo.

**JEL:** C14, C21, R21, R31, R32

# 1. Introduction

Commuting costs to employment centers and gasoline prices are likely to be highly correlated, mostly for private vehicle users. During 2001-2006, the city of Bogotá experienced a steadily growth of gasoline prices with average annual increases of 13% for this period. This trend in gasoline prices has raised questions on the impact of commuting costs on property values with long commuting times in this city.

Early studies have shown the influence of commuting costs on household location decisions. The standard urban economic model (Alonso, 1964; Muth, 1969) predicts that housing prices will decline with distance to the Central Business District (CBD). This finding mimics that of von Thunen's model of farmland; and like the von Thunen's result, it rests essentially on the assumption that total transport costs rise with distance to the CBD. The prevalence of multiple centers of employment within a city or region led to extend the standard urban monocentric economic model to incorporate polycentric models (Papageorgiou & Casetti, 1971; Yinger, 1992; Wheaton, 1974). However, these multi-nodal models only confirm the basic prediction of Alonso and Muth where the house price gradient is negatively related to distance from an employment node. Papageorgiou & Casetti (1971), for example, find that equilibrium residential land price is at its highest in the largest employment district, and that local maximum in land prices will occur at the local employment centers.

Molloy (2010) has argued that to reduce households' expenditures in transportation, some residents, especially car owners, are likely to change their distant household locations to places close to centers of economic activity. As a result of relocation of households, property prices at central places are expected to increase when compared to distant locations, depending on the price elasticity of housing demand. This author found that a 10 percent increase in gas prices leads to a 10 percent decrease in construction after 4 years in locations with a long average commute. If there are no significant changes in housing prices for locations far away from employment centers, thus the supply response is likely to prevent the change in housing demand from capitalizing in property values.

Considering Bogotá's commuting costs increase observed during the 2001-2006 period, driven in part by higher gasoline prices, and the likely response of the citizens' preferences for dwellings with low costs of access (Central Place Theory- Lösch (1944)), the main objective of this paper is to examine the relationship between commuting costs to employment centers and housing prices in Bogotá. We describe the housing price gradient, and estimate the statistical significance of the commuting costs for properties located nearby and far away from Central Business Districts (CBDs). These estimations are based on both a parametric model applied to cross-section data repeated on representative random samples, and a more flexible non-parametric method. We compared and evaluated the statistical robustness of parametric and non-parametric methods for an areal-spatial hedonic housing model that explores the effects of different housing characteristics, including accessibility to employment centers as the variable of interest, on property values at the Zonal Planning Unit level in Bogotá.

In the absence of repeated sales of properties, the areal feature of our data is important to disentangle the influence temporal changes of commuting costs on housing values. In our estimations we also intend to control for the presence of spatial heterogeneity or the fact that parameter estimates could vary spatially within a housing market by estimating a non-parametric approach with a Geographically Weighted Regression (GWR), thus correcting for the possible presence of bias estimators. We found that the elasticity of housing prices with respect to commuting costs for properties located in distant zones is on average -1.48% for every 1% of increase in fuel price. Goodness of fit of our estimated models suggests that Geographically Weighted Regression (GWR) outperforms traditional Spatial Autoregressive (SAR) and Spatial Error (SEM) models that control for spatial dependence but not for heterogeneity.

The rest of the article is organized as follows: the next section briefly discusses relevant literature on rental gradient and commuting costs in hedonic pricing models. Section 3 describes the study area and the database used for estimations. Section 4 explains the empirical strategy, and the last two sections present, respectively, the empirical results and a final discussion.

## 2. Rental Gradient and Commuting Costs in Hedonic Housing Models

The Hedonic Pricing Method is widely used to estimate the implicit price of non-marketable characteristics of a non-homogenous marketable good such as housing. Considering a greater variation in attributes, the implicit price of housing characteristics (i.e. number of rooms, presence of chimney and proximity to employment centers, among others) can be calculated by estimating marginal effects for every observed characteristic (Rosen, 1974, Freeman, 1974). In this framework, housing prices depend on the quantities demanded for a set of attributes for good H ($h_i$ is any quantity of H). We define $S_j$ as a vector of intrinsic characteristics (e.g., land size, area, and number of bathrooms); $N_k$ is defined as a vector of neighborhood attributes, and $Q_m$ is defined as a spatial attribute such as distance to the closest job center. Thus, $P_{hi} = P_h\,(S_{i1} \dots S_{ij}, N_{i1} \dots N_{ik}, Q_{i1} \dots Q_{im})$ is the hedonic function of implicit price for H. The derivative of this function with respect to the set Q is the marginal implicit price for those characteristics (Freeman, 1975). Similarly, $X_l$ is defined as a set of goods not associated with the real-estate market that, just like intrinsic and neighborhood characteristics, provides utility to the final consumer.

Many studies have empirically examined the relationship between housing prices and environmental amenities in a neighborhood. Prior literature has identified positive values for proximity to open space amenities and the natural land cover surrounding household locations (Acharya & Bennett, 2001; Cho, Poudyal, & Roberts, 2008). The most recent literature reveals that these relationships are entirely local with the presence of heterogeneity in the willingness to pay for amenities across space (Anderson & West, 2006; Chi & Marcouiller, 2011; Wu, 2012). This literature finds marginal effects that are dependent on agglomeration and local development patterns, and average estimates that substantially underestimate values. Some authors have shown that open space proximity is valued highly but decays very quickly with distance (Geoghegan et al., 1997). Previous hedonic studies have explored the relationship between accessibility to Bus Rapid Transit or employment centers and property values in Bogotá (Muñoz-Raskin, 2010; Mendieta-Perdomo, 2007; Carriazo et al, 2013). Muñoz-Raskin (2010) used a database for the period 2000-2004 and found an average annual increase per square meter of 2.2% (around North Highway) and 2.9% (close to Bus Rapid Transit (BRT) North Station) in housing units located 10 minutes by foot to the

BRT *Transmilenio* System. Mendieta-Perdomo (2007) estimated a spatial hedonic model to find average values for proximity price-elasticity of about -0.36, -0.55 and -1.13 in the first, second, and third construction phase of *Transmilenio*. Carriazo et al. (2013) used a stochastic hedonic frontier model and found that when distance to the closest employment center increases by 1%, housing prices falls by 0.07%, holding other variables constant. However, none of these studies have taken into account spatial heterogeneity in their estimates. Coulson and Engle (1987) discuss that housing prices could be negatively correlated with distance to central places. They observe that increases in fuel prices during 1974 and 1979 are associated with a price gap between central and suburban locations in a sample of six American cities.

## 3. Data

The result variable in our model comes from listing prices of 15,051 residential housing observations for the 2001-2006 period, collected by *metrocuadrado.com*, a real estate listing service site in Bogotá that includes data on structural characteristics. About 70% of total observations in the sample are concentrated in middle and upper social economic levels. 86.03% of the total housing observations have at least one garage in every property. This result corresponds to the socioeconomic level distribution of private vehicle use in the city as we can see in Table 1.

**Table 1: Distribution of Private Vehicle Property in Bogota (2005)**

| Socioeconomic Level | Percentage of Private Vehicles |
|---|---|
| 1 | 2.0 |
| 2 | 12.0 |
| 3 | 36.0 |
| 4 | 26.0 |
| 5 | 11.0 |
| **6** | **13.0** |
| **Total** | **100.0** |

Source: based on STT-DANE, Encuesta de Movilidad. Secretaría de Movilidad 2005

This database was useful to measure the relationship between commuting costs and housing prices because it contains the majority of private vehicle users. These users are likely to relocate themselves because they face a major economic cost related to the increase in gasoline prices.

To exploit time variability of housing prices, data were aggregated at the ZPU (Zonal Planning Unit) and corrected by nominal variations in prices.[4] To calculate distance-based attributes, we used digital maps of the Spatial Administrative District Unit. Access to these maps allowed us to geocode *metrocuadrado* data, to aggregate it at the ZPU level, and to calculate the distance from every polygon centroid to the closest employment center, namely the Financial Center, the Industrial Zone and Downtown. Empirical evidence suggests that employment centers are far more dispersed than previously considered. For example, Mills (1972) estimated employment gradients, and found that jobs were dispersed, contrary to a pure monocentric theory. In addition, for other cases around the world, more recent studies show that housing distribution is still dispersed and, in some cases, it clusters into sub-centers (Guiliano & Small ,1991; McMillen & Mcdonald, 2008).

The Financial Center and the Industrial Zone concentrate, respectively, 14.5% and 9% of total employment in the city. Downtown is considered the most important center of governmental jobs in Bogota, concentrating near 10.9% of total employment in the city.[5] These hubs of employment are situated in the Zonal Planning Units of *Chicó-Lago-Porciúncula* (Financial Center), *Candelaria-La Catedral* (Downtown), and *Bavaria-Lusitania* (Industrial Zone), next to *Puente Aranda* Industrial Center. (See Map 1).

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4 Nominal variables require deflation with a base year. However, this is not necessary once we have a dummy annual variable and dependent variable is used on a logarithmic basis. Using a nominal or real variables on a logarithmic function only change the intercept: none of the estimated coefficients will be altered.(Wooldridge J. Introduction to Econometrics: a modern approach) (2001, page. 412).

5 (Caracterización Económica de Bogotá y la Región V8-V11). Secretaría de Tránsito y Transporte. Alcaldía de Bogotá.

**Map 1: Urban Centers in Bogotá**

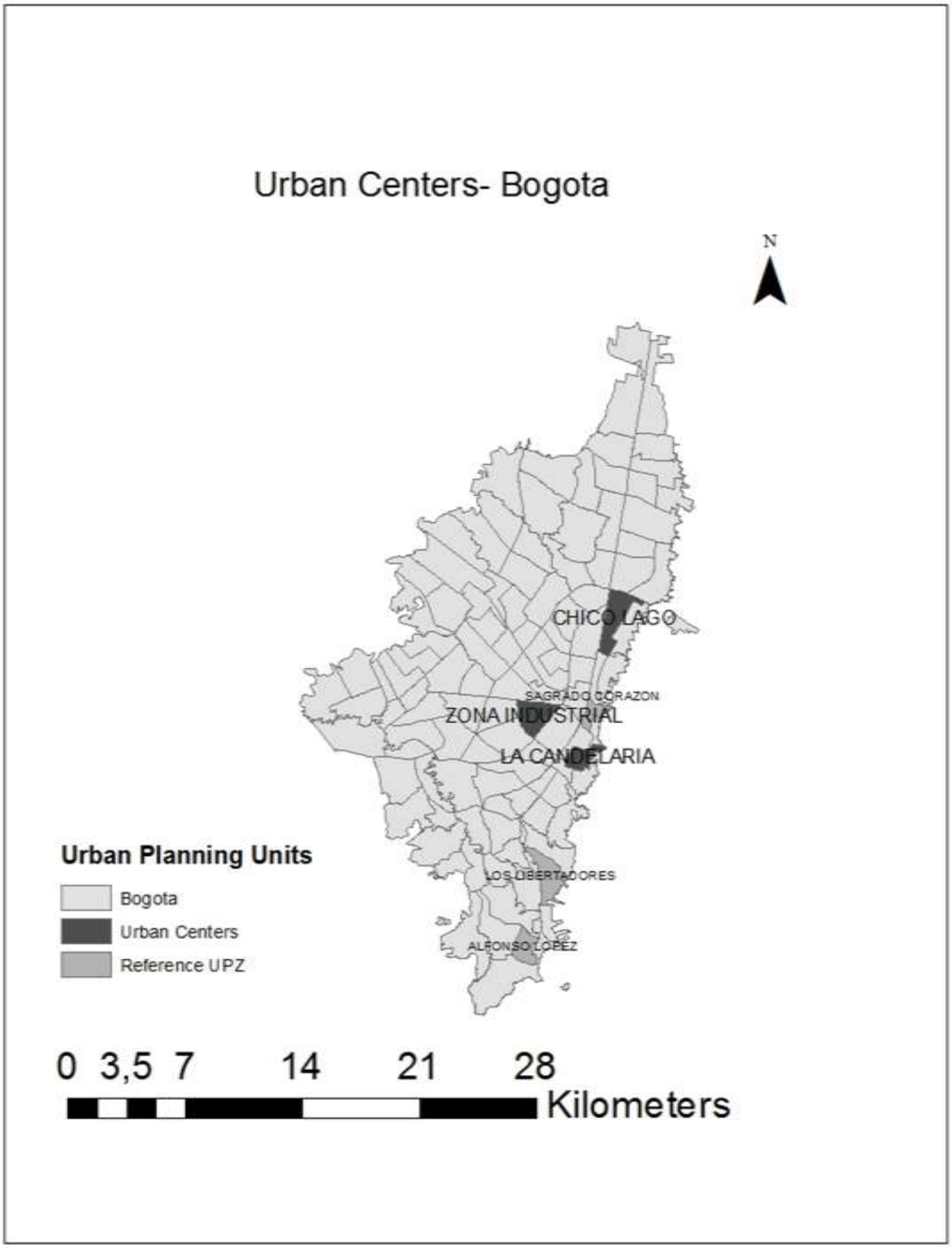


Table 2 below shows descriptive statistics for the study variables. The average distance from every polygon centroid to the closest employment center in the analyzed ZPUs is 5,242 meters. The maximum distance is 12,188 meters, corresponding to the Zonal Planning Unit (ZPU) of *Alfonso López*, and the minimum distance is 499 meters, corresponding to the ZPU of *La Candelaria*. Concerning housing price $(m^2)$, this variable has an average of US$352.68. The maximum value is US$1,457.46 in the Zonal Planning Unit (ZPU) of *Sagrado Corazón* and the minimum value is US$90.79 in the ZPU of *Los Libertadores*.

In addition, other independent variables were used as controls: For instance, the average distance to the closest bike path is 970.06 meters with a minimum of 13 meters in ZPU Zona Industrial and a maximum of 7,984.99 meters in ZPU *Alfonso López*. Broach et. al (2012) suggest that cyclists are sensitive to the effects of distance in their location decision and for that reason it is important to consider this characteristic of the urban space in our analysis. Housing Age was divided into various dummies where the excluded category was "Project in construction". 4.5% of housing units in the ZPUs of the sample were considered "Brand new"; 7.6% of housing units "from 0 to 5 years"; 14.6% "from 5 to 10 years"; 29.9% "from 10 to 20 years"; 2.94% was "more than 20 years old" while 13.8% belonged to the excluded category. Another group of variables to consider are implicit housing attributes. In this category we have the Housing Age and Type of vigilance dummy variables. There is also the urban density (in every ZPU) measured as the number of housing units in every hectare. There is an average of 50.8 housing units in every hectare (urban density) which implies that the analyzed sample has an average of 0.92 houses in every 182.07 sq. meters (average Housing Area in the studied sample). This indicates a precise data adjustment with respect to the universe of ZPUs in Bogotá.

**Table 2: Descriptive statistics**

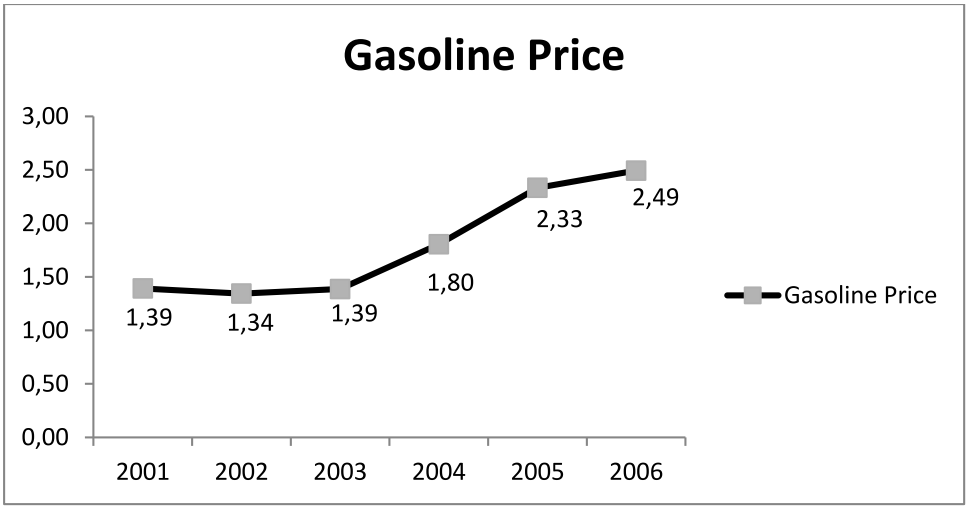
| Variable | Media | St. Desv. | Maximum | Mínimum |
|---|---|---|---|---|
| Distance to Bike Path (m) | 970.06 | 1084.76 | 7984.99 | 13.11 |
| Urban Density (#d./ha) | 50.8 | 22 | 110.3 | 0.3 |
| Brand new | 0.0451 | 0.1432 | 1 | 0 |
| Between 0 y 5 years | 0.0768 | 0.1645 | 1 | 0 |
| Between 5 y 10 years | 0.1462 | 0.2141 | 1 | 0 |
| Between 10 y 20 years | 0.2998 | 0.2894 | 1 | 0 |
| More than 20 years | 0.2947 | 0.3106 | 1 | 0 |
| Area ($m^2$) | 182.07 | 107.08 | 1057 | 32 |
| Socioeconomic level(1-6) | 3.48 | 0.9100 | 6.0 | 1 |
| 12 hours Vigilance | 0.06 | 0.1444 | 1 | 0 |
| 24 hours Vigilance | 0.36 | 0.3026 | 1 | 0 |
| 2002 | 0.1291 | 0.3357 | 1 | 0 |
| 2003 | 0.1708 | 0.3767 | 1 | 0 |
| 2004 | 0.1770 | 0.3821 | 1 | 0 |
| 2005 | 0.1750 | 0.3803 | 1 | 0 |
| 2006 | 0.1541 | 0.3614 | 1 | 0 |
| Distance to the job center (m) | 5242 | 3108 | 12188 | 499 |
| Housing Price per $m^2$ | \$352.68 | \$142.72 | \$1457.46 | \$90.79 |

Source: metrocuadrado.com, and IDECA.

Regarding gasoline prices, we used the reference price in Bogotá, mandated by the Ministry of Mines and Energy with a partially regulated margin. Figures 1 and 2 below show the historic evolution of this variable. The biggest percentage increases have occurred in 2003 and 2004 when costs rose by 18% and 19% respectively, in comparison with the previous year. In all periods we can observe increases in the fuel cost in the whole city.

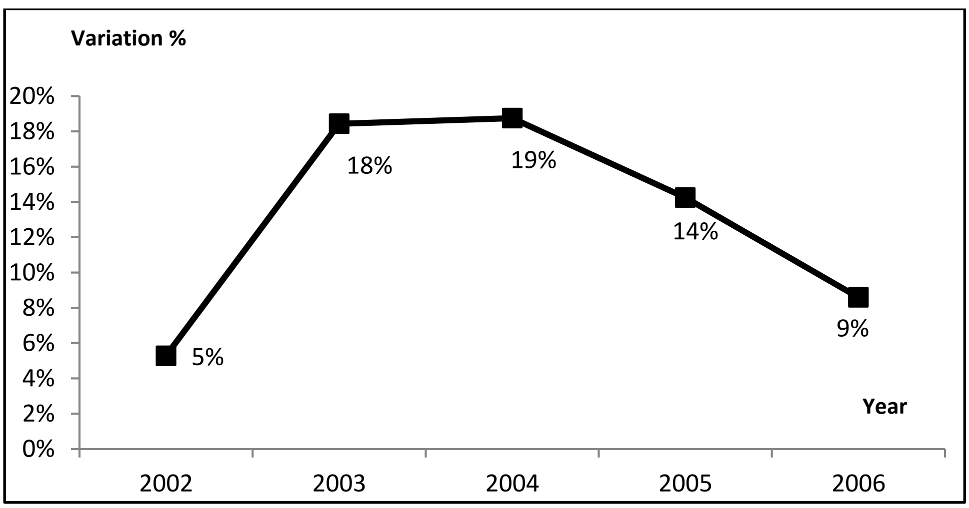
1. **Figure 1: Evolution of Gasoline Prices in Bogotá**

2.




Source: UPME, Group of Hydrocarbons. Historic period 2001-2006

**Figure 2: % Variation in Gasoline Prices**




Source: UPME, Group of Hydrocarbons. Historic period 2001-2006

These fluctuations in fuel prices are useful to identify the effect of the fuel-prices variable for private vehicle users as an appropriate approximation of the cost of access in every studied Zonal Planning Unit. Although competence levels in every location of gas service stations lead to market oscillations, we consider the use of zone data analysis in fuel prices inappropriate for at least two reasons: First, the distribution margin in service stations is partially regulated. This means that prices move on a controlled margin with a reference value close to US$0.23. Price variations range within 10% from the reference price in every city, given by the Ministry of Mines and Energy.[6] Second, the variation of gasoline prices is influenced by demand in every zone. This explains why gasoline prices are endogenous to the households' location decision (Molloy, 2010).

## 4. Methods

To identify the effect of commuting costs on property values in Bogotá, we used a Difference in Difference approach. The Differences in Differences methodology assumes the existence of two housing samples, a treatment and a control group, before an exogenous shock event such as the increase in gasoline prices. This shock generates an oscillation in price average value for every zone (sample). For that reason, we find the difference in prices between two categories in the period before and after the exogenous change (Parmeter & Pope, 2002). The treatment group usually is defined as the population that receives the major impact of a shock or policy. In our case, we expect this group to receive a significant effect of the exogenous shock of higher gasoline prices only through larger commuting times (distances). As a consequence, we defined the treatment group as those property prices located in Zonal Planning Units with a centroid at a distance equal or greater than $\tau$, a threshold distance to define proximity to employment center, after 2001, the base year (in the absence of gasoline price shocks) $\tau$ was measured from the closest to the farthest ZPU in relation to the urban center and equivalent to approximately 15 minutes in commuting time. On the other hand, the control group is constituted by properties in the ZPUs that are

[6] Ministry of Mines and Energy /SICOM (Sistema de Información de Combustibles Líquidos).

located at a distance less than $\tau$ from the closest urban center with property values reported in the base year 2001.[7]

In a regression scheme, implementing an empiric version of Differences in Differences (DD) is relatively simple; the DD regression takes the following general form:

$$P_{it} = B_0 + B_1\, D_i{}^L + B_2\, D_i{}^t + B_3 D_i{}^L D_i{}^t + \epsilon_i \quad \text{for i= 1…n} \qquad (1)$$

$D_i{}^L$: Dummy variable far away from the urban center

$D_i{}^t$: Dummy variable after the shock took place.

$P_{it}$: Price of housing units expressed in nat.log.

Treatment Effect of Differences in Differences:

$[E\,(P_{it}/D_i{}^L=1;\ D_i{}^t=1) - E\,(P_{it}\,/\,D_i{}^L=1;\ D_i{}^t=0)] - [E\,(P_{it}\,/\,D_i{}^L=0;\ D_i{}^t=1) - E\,(P_{it}/D_i{}^L=0;\ D_i{}^t=0)] = B_3$

$E\,(P_{it}\,/\,D_i{}^L=1;\ D_i{}^t=1) = B_0 + B_1 + B_2 + B_3$

$E\,(P_{it}\,/\,D_i{}^L=1;\ D_i{}^t=0) = B_0 + B_1$

$E\,(P_{it}\,/\,D_i{}^L=0;\ D_i{}^t=1) = B_0 + B_2$

$E\,(P_{it}\,/\,D_i{}^L=0;\ D_i{}^t=1) = B_0$

$D_i{}^L$ is a dummy variable indicating the group for house i. The supra index L means that the shock occurred far from the job center). $D_i{}^t$ is a temporary dummy taking the value of 1 if the observation is located in the period where the change took place (after 2001). For periods before the treatment time, the dummy variable takes a value of zero and for those sold later, it takes a value of one. The parameter of interest in the regression is $\gamma_1$, the

7 We used approximately 2.5 km as a threshold distance $\tau$, corresponding to the 25th percentile of distance distribution. .

Difference in Difference estimator of the treatment. The multiplication of both dummies ($D_i{}^L D_i{}^t$) only takes the value of 1 for those housing units in the treatment group after the exogenous change occurs (Bernal, R. & Peña, X. (2011)).

The sample used in our estimations is not a data panel because the same housing units are not observed during the same periods of time. We aggregate the housing units in representative samples of Zonal Planning Units (ZPUs). Not having the same housing units in time may correct possible heterogeneity problems (Palmquist, 2005).

Given that we take 2001 as the baseline year with an intra-group differentiation, we propose the following Differences in Differences model:

$$\text{Ln (zpu price per } m^2)_{it} = \beta_o + \beta_1 \text{Far\_Urban\_Center}_i * \text{Gasoline price}_t + \beta_2 \text{T}$$

$$+ \beta_3 \text{year after}_t * \text{FUC}_i * \text{Gasoline price}_t + \beta_j \sum_{j=1}^{n} \alpha_i + \beta_k \sum_{k=1}^{n} \varphi_{it} + u_{it} \quad (2)$$

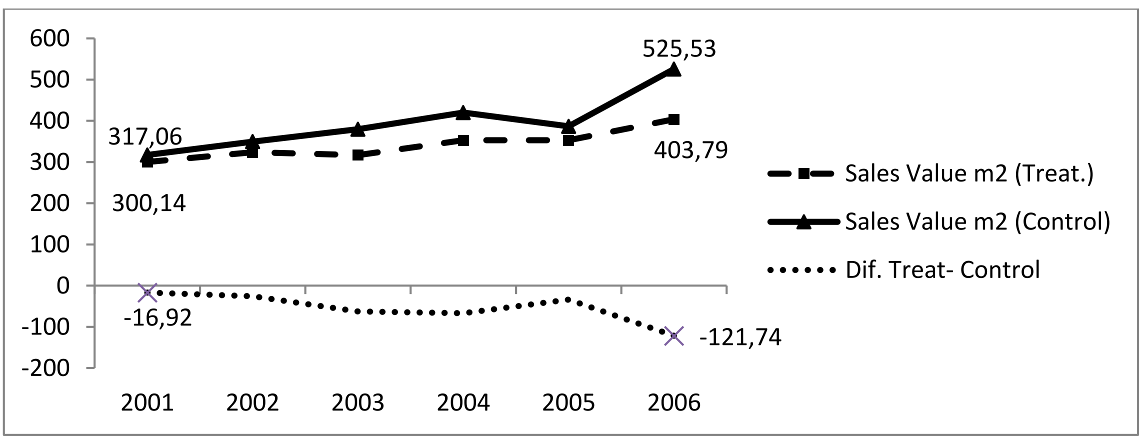
Where *i* is the indicator of every ZPU; *t* is the period of time (year); $Ln\ (ZPU\ price\ per\ \ m^2\ )_{it}$ is the average price per square meter in natural logarithm for every urban ZPU in the city. This last variable was constructed from the consolidated information of the housing units sample in the period 2001-2006. $FUC_i$ takes the value of 1 if distance to the job center is greater or equal to 2,382.9 meters, and zero otherwise. $Year\ after_t$ takes the value of 1 if the year of the observation is after 2001, and zero if the year of the observation is 2001. $Gasoline\ Price_t$ stands for the natural logarithm of gasoline price for every year between 2001 and 2006. *T* is the fixed time effect, dummy for every year except for the baseline year. $Year\ After_t * FUC_i * Gasoline\ Price_t$ is a variable of temporal and spatial interaction indicating the effect of the increase in the cost of gasoline on distant zones after 2001 when this increase took place. This variable of interest in the study measures the difference in average value per square meter between periods in the Zonal Planning Units (ZPUs) close and far from urban centers. These differences are due to increases in the commuting costs. In addition, we have other spatial and temporal effects captured by variables affecting the average housing value in every ZPU. For instance, there are some estimators associated in the following categories:

$\alpha_i$ = Effect of the distance and spatial attributes of a zone. In this category the continuous variable distance to the closest path bike comes into play.

$\varphi_{it}$ = Effects of spatial and temporal attributes of the characteristics in every ZPU, taken from the information of urban properties. For example, we have the following numeric variables: *Housing Prices*, *Housing Area* (logarithm), *Socioeconomic Level* and *Type of Vigilance*.

The Differences in Differences Model assumes that external effects have the same impact on treated and non-treated ZPUs. For that reason, omitted variable endogeneity is eliminated once controlling for spatial and temporal effects of zone and geographic units.[8] Additionally, similarities between treatment and control groups do not need to be proven because there is only one baseline period by definition. The Differences in Differences Model is a way to control for possible differences between groups before program implementation.[9] Property values for treatment and control groups are shown in Figure 3 below.

**Figure 3: Evolution of property values for Treatment and Control Groups**




8 Introduction to econometrics: A modern approach. J. Wooldridge (2001).
9 Guía Práctica para Evaluación de Impacto. Bernal & Peña (2010).

Once we formalized and specified the empirical model, we carried out a test of difference of averages to guarantee that the included variables are relevant in the model and to avoid a possible loss of efficiency and non-significance in the estimators.[10] Next, we used spatial parametric and non-parametric regressions to control for spatial dependence and spatial heterogeneity:

Urban housing prices are geographically distributed at the Zonal Planning Unit (ZPU) level in a representative spatial aggregation of housing units. The price of housing observed in a location *i* may be influenced by the price observed in a contiguous location *j*. This phenomenon is called spatial dependence (Anselin, 1988), and it is not usually taken into account in standard econometric procedures such as OLS estimations on cross-sectional data, violating the postulation of independence in the sample observations with self-correlated residuals. Even if estimators are still unbiased, there is a problem of heterogeneity with inefficient estimators and a misspecified variance-covariance matrix that may lead to type I or II errors when formulating hypothesis tests on standard OLS coefficients (LeSage, 1999).

To give a solution to this problem and considering the process of interaction and multidirectional dependence[11] in spatial data, we added a contiguity spatial matrix, taking into account the concept of proximity between spatial units. This matrix is defined as follows:

$$W = \begin{bmatrix} 0 & W_{12} & W_{1n} \\ W_{21} & 0 & W_{2n} \\ W_{n1} & W_{n2} & 0 \end{bmatrix}$$

We have a square non-stochastic matrix, where elements $W_{ij}$ capture the interdependence between ZPUs located at contigous geographic zones (spatial correlation). We have a decreasing grade of spatial dependence between points in space as distance between polygons increases. This contiguity matrix is defined for N-ZPUs with symmetry in dimensions (NxN), presence of zeros in the diagonal, indicating the standard convention

[10] Results from these tests are available from the authors upon request.

[11] It means all ZPUs can be related between them. For that reason it is not possible to implement the lag operator of time series. Instead, it appears the concept of contiguity matrix The Theory and Practice of Spatial Econometrics. James P. LeSage (1999).

where a ZPU is not neighbor of itself, and the rest of elements indicating neighborhood criteria or proximity (lineal distance). $W_{ij}$ takes the value of 1 if distance between $N_i$ and $N_j$ is less than a parameter μ which guarantees that all observations count at least with a neighbor, thus avoiding islands, and are defined with the economic criteria of proximity in the study[12]. The contiguity matrix was transformed through the row-standardization method (LeSage, 1998). We estimated two spatial parametric models; a spatial lag or autoregresive model (SAR), introducing the spatial effect as a lag of the dependent variable, and a spatial error model (SEM), which assumes that the source of the spatial dependence is captured by the unobserved error term which we assume is spatially correlated. The reduced form of the SAR model takes the form $y = \rho W y + X\beta + \varepsilon$ where $\varepsilon \sim N(0,\sigma^2 I_n)$, $y$ is the vector Nx1 of the dependent variable (property values per square meter), ρ is the parameter of the spatial lag of the dependent variable, X is a NxK vector of explanatory variables as it was previously defined in equation(2) and $W$ is the NxN spatial weights matrix. The reduced form of the SEM model is given by $y = X\beta + u$, where $u = \lambda W u + \varepsilon$ where $\varepsilon \sim N(0,\sigma^2 I_n)$ and λ is the parameter of the lagged error $Wu$.

Besides the spatial dependence problem of geographic order, corrected by using the spatial error (SEM) and the spatial lag (SAR) models mentioned before, there is an additional problem of spatial heterogeneity or spatial parameter variation due to the lack of spatial stability in the relationship between the dependent variable and one or more explanatory variables. The heterogeneity problem means that the estimators may vary depending on the geographic location. It is quite common that geographic units present complex interactions in terms of structure, leading to the existence of spatial dependence as well as spatial heterogeneity, two problems difficult to distinguish in statistical analysis. McMillen (2008) proves that a parametric approach of neighboring effects used to control for spatial variation in housing prices leaving fixed the proximity to Central Business District (CBD) is not always correct, given the variation in the effect of proximity across the city. For that reason, he suggests to use the parametric approach only as a reference method to capture housing prices patterns. McMillen (2010) shows that a non-parametric estimation is plausible for various datasets applying less degrees of freedom compared to fixed effects regression. These results

12 Through Geoda program the optimal parameter was 3022 meters.

warn about the wrong specification of traditional econometric methods with spatial autocorrelation problems. The fixed effects approach is useful when spatial effects are constant in well-defined zones. Considering variation in spatial effects, inefficient estimators are generated in the calculations (McMillen, 2008).

Geographically Weighted Regression (GWR[13]) is the most common non-parametric technique in spatial analysis literature to account for spatial heterogeneity. In this article we introduce and discuss the version developed by McMillen (1996) and Brunsdon, Fotheringham and Charlton (1996). The main contribution of GWR method is the use of sub-samples with distance weighing to calculate parameters in every point in space.

The spatial weights for every observation i take the form of a vector $\mathrm{W_i}$ , using the distance $\mathrm{d_i}$ between the observation i and the rest of the samples. Additionally, this vector includes a concept of spatial decay to give a major weight to nearby observations in the data sample. In this study we make use of the gaussian decay function, based on Anselin (1988) & LeSage (1999):

$$W_i = \varphi\,(d_i/\sigma\,\Theta) \quad (3)$$

Where φ is the normal standard density and σ represents the standard deviation of the distance vector $d_i$. The parameter $\Theta$ is the bandwidth or decay parameter. This value is applied uniformly for all observations in the sample and is determined through a process of minimization of a score function taking the following form:

$$\sum_{i=1}^{n}[y_i - \widehat{y_{\neq\iota}}(\Theta)]^2 \quad (4)$$

$\widehat{y_{\neq\iota}}(\Theta)$ is the adjusted value of $y_i$ ,omitting observation i in the estimation for a determined point.

In short, the non-parametric method GWR carries out local regression calculations to produce estimators in every point of space using sub-samples in neighboring points. $y$ is a

13 GWR (Generally Weighted Regression) as a special case of Locally Weighted Regression developed by Cleveland y Devlin (1988).

vector of Nx1 observations of the dependent variable collected on N points in space. X is a matrix of NxK observations of explanatory variables. Y and X are as defined in Equation (2) while ε is a vector of Nx1 disturbances normally distributed with constant variance. $W_i$ is a diagonal matrix of NxN spatial weights, based on distance calculations with the gaussian function, which reflects the distance between observation i and the rest of data. The estimated regression takes the following form:

$$W_i^{1/2}\, y = W_i^{1/2} \mathrm{X} \beta_i + W_i^{1/2}\, \varepsilon_i \quad (5)$$

The index i on $\beta_i$ indicates that vector Kx1 of parameter estimates is associated with observation i. In other words, the Generalized Weighted Regression (GWR) estimation produce N estimated parameters, one for every present observation. It is also important to see that $\beta_i$ estimation is conditioned on the bandwidth Θ, coming from the optimization procedure previously described. It means that any change in this vector will modify the regression results. This is different to the selection of the spatial decay function that has no significant interference on the estimated results (McMillen, 2008). GWR model was estimated using the proposed routine by LeSage (1999).

## 5. Results

The estimation results of the Difference in Difference estimations from model in equation (2) and its spatial versions are shown in Table 5. The first three columns report the OLS specification and the remaining the spatial models (SAR, SEM and GWR). The goodness of fit, measured by the adjusted- $R^2$ , improves as we move from the OLS model to the Spatial regressions; the values of the adjusted $R^2$ for the OLS, SEM, SAR and GWR models are 0.4973, 0.5092,0.5228, 0.7034 respectively. The coefficients *rho* and lambda that indicate the presence of spatial dependence for the SAR and SEM models are significant at all conventional values. A significant value of *rho* means that the value per square meter of properties in a Zonal Planning Unit is likely to be influenced by neighboring values. Also, the significant value of *lambda* suggests that non-observed contiguous variables affect property values, thus generating a spillover effect in housing prices.

In order to identify the most likely type of spatial correlation for the data generating process, we analyze the Lagrange Multiplier statistic in the LM-Lag and LM-error versions. These tests shed light on model selection between the Spatial Lag (SAR) and Spatial Error models (SEM). The null hypothesis implies a better adjustment in the OLS model with no lag while the alternative hypothesis implies the presence of a lag in the dependent variable or in the error term. We thus compare the rejection probability of the null hypothesis in the LM-Lag with the rejection probability in the LM-error model. Results from these tests are summarized in Table 3. Accordingly, we choose the model that rejects the null hypothesis with the major level of probability and precision. Lagrange Multiplier tests conclude in favor of the Spatial Error Model compared with the Spatial Lag Model. In other words, the spatial dependence is most likely driven by omitted variables that are spatially correlated and captured in the error term of the regression model.

**Table 3: Lagrange Multiplier Test**

| **Test value** | **LM-SAR** | **LM-ERROR** |
|---|---|---|
| LM value | 3.6289 | 6.6237 |
| p-value | 0.05678 | 0.0100 |

The parameter for *Housing Age* suggests that price for properties "More than 20 years" old is about 10.6% lower than properties in construction (the omitted category). The effect of distance to bike paths is ambiguous. The parameter estimate for this variable is positive for the SEM model and negative for the GWR model but not significant for the OLS or SAR parametric models. Properties with 24 hours Vigilance have a higher price than properties without vigilance. Results from the GWR suggest that properties with 24 hours vigilance had a premium of 13.7% in price per square meter. Having 12 hours partial vigilance is not significant for price determination.

The spatio-temporal parameter ($\beta_3$) for the cost of access variable, the variable of interest in this study, is significant at all conventional levels for all four estimated models. In the OLS model, this parameter takes the value of -0.0139 and it is significant at 10% ; in the spatial parametric SAR model, this value is -0.0140 and also significant at the 10%, in the spatial parametric SEM model it takes a similar value of -0.0140 and finally in the GWR estimation, the value is -0.0172 and the significance level improves to 5%.

As it was previously mentioned, the SEM model better captures the nature of the spatial dependence. The parameter $\beta_3$ in the SEM model indicates that an increase of 1% in the cost of fuel implies a decrease in the housing price per square meter of 1.40% in zones far from the urban centers. Further, the parameter Lambda is positive and significant, indicating spatial spillover effects of property values.

The last two columns of Table 4 report the results of the Geographically Weighted Regression for the Zonal Planning Unit (ZPU) Muzu in the Puente Aranda Locality[14]. An increase of 1% in the cost of fuel brings as a result a decrease in the housing price per square meter of 1.72% in ZPU Muzu between 2001 and periods afterwards. Such a decrease is estimated in relation to the Puente Aranda Industrial Zone, the closest employment center to the estimated point. This result suggests that an increase in the housing price gap between ZPUs near and far from the urban centers has a correct statistic validation of heterogeneous spatial effects. An increase in the commuting cost measured through gasoline prices has a significant influence on urban housing prices in Bogota during period 2001-2006.

[14] However it is important to remind this is not the only estimated point in space.There is a regression per ZPU (geographic location)

**Table 4. Difference in Difference Estimations.**

| | OLS | | SAR | | SEM | | GWR | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **coef.** | **p-val** | **coef.** | **p-val** | **coef.** | **p-val** | **coef.** | **p-val** |
| Intercept | **12.616*** ** | 0.00 | **8.007*** ** | 0.00 | **12.729*** ** | 0.00 | **12.702*** ** | 0.00 |
| | (-0.16) | | (0.98) | | (0.16) | | (0.16) | |
| Dist. Bike Path | **-0.000018** | 0.11 | **-0.000011** | 0.34 | **-0.000031** ** | 0.04 | **-0.000023* ** | 0.08 |
| | (0.000011) | | (0.000011) | | (0.000015) | | (0.000013) | |
| Urban Density | **-19.060*** ** | 0.00 | **-16.607*** ** | 0.00 | **-16.292*** ** | 0.00 | **-23.706*** ** | 0.00 |
| | (5.53) | | (5.28) | | (5.32) | | (5.64) | |
| Brand new | **-0.095** | 0.29 | **-0.082** | 0.33 | **-0.072** | 0.40 | **-0.033** | 0.67 |
| | -0,09 | | -0,08 | | -0,09 | | -0,08 | |
| 0 and 5 years | **0.232*** ** | 0.00 | **0.231*** ** | 0.00 | **0.249*** ** | 0.00 | **0.326*** ** | 0.00 |
| | -0,08 | | -0,08 | | -0,08 | | -0,08 | |
| 5 and 10 years | **0.034** | 0.58 | **0.029** | 0.63 | **0.014** | 0.82 | **0.032** | 0.60 |
| | -0,06 | | -0,06 | | -0,06 | | -0,06 | |
| 10 and 20 years | **0.019** | 0.70 | **0.015** | 0.75 | **0.016** | 0.74 | **0.004** | 0.94 |
| | -0,05 | | -0,05 | | -0,05 | | -0,05 | |
| More than 20 y. | **-0.118** ** | 0.04 | **-0.116** ** | 0.03 | **-0.131** ** | 0.02 | **-0.106** ** | 0.05 |
| | -0,06 | | -0,05 | | -0,05 | | -0,05 | |
| Area | **0.161*** ** | 0.00 | **0.127*** ** | 0.00 | **0.150*** ** | 0.00 | **0.152*** ** | 0.00 |
| | -0,03 | | -0,03 | | -0,03 | | -0,03 | |
| Medium | **0.094*** ** | 0.00 | **0.062** ** | 0.04 | **0.051* ** | 0.09 | **0.072*** ** | 0.01 |
| | (0.03) | | (0.03) | | (0.03) | | (0.03) | |
| High | **0.433*** ** | 0.00 | **0.343*** ** | 0.00 | **0.342*** ** | 0.00 | **0.367*** ** | 0.00 |
| | (0.05) | | (0.05) | | (0.06) | | (0.09) | |

## Table 4. Difference in Difference Estimations (continues)

| | OLS | | SAR | | SEM | | GWR | |
|---|---|---|---|---|---|---|---|---|
| Variable | coef. | p-val | coef. | p-val | coef. | p-val | coef. | p-val |
| 12 hours Vig. | -0.101 | 0.23 | -0.113 | 0.16 | -0.131 | 0.11 | -0.093 | 0.26 |
| | (0.08) | | (0.08) | | (0.08) | | (0.08) | |
| 24 hours Vig. | 0.216*** | 0.00 | 0.162*** | 0.00 | 0.187*** | 0.00 | 0.137*** | 0.00 |
| | (0.05) | | (0.05) | | (0.05) | | (0.05) | |
| 2002 | 0.124* | 0.07 | 0.116* | 0.07 | 0.122* | 0.06 | 0.123* | 0.06 |
| | (0.07) | | (0.06) | | (0.07) | | (0.06) | |
| 2003 | 0.137** | 0.04 | 0.139** | 0.03 | 0.140** | 0.03 | 0.114** | 0.06 |
| | (0.07) | | (0.06) | | (0.,06) | | (0.06) | |
| 2004 | 0.251*** | 0.00 | 0.253*** | 0.00 | 0.249*** | 0.00 | 0.243*** | 0.00 |
| | (0.07) | | (0.06) | | (0.06) | | (0.06) | |
| 2005 | 0.243*** | 0.00 | 0.241*** | 0.00 | 0.240*** | 0.00 | 0.201*** | 0.00 |
| | (0.07) | | (0.06) | | (0.06) | | (0.06) | |
| 2006 | 0.353*** | 0.00 | 0.352*** | 0.00 | 0.352*** | 0.00 | 0.320*** | 0.00 |
| | (0.07) | | (0.06) | | (0.06) | | (0.06) | |
| FUC | 0.00575 | 0.46 | 0.00618 | 0.40 | 0.00499 | 0.53 | 0.00870 | 0.25 |
| | (0.01) | | (0.01) | | (0.01) | | (0.01) | |
| year af*FUC*gas | -0.01396* | 0.10 | -0.01407* | 0.08 | -0.01406* | 0.09 | -0.01721** | 0.03 |
| | (0.01) | | (0.01) | | (0.01) | | (0.01) | |
| rho | | | 0.35*** | 0.00 | | | | |
| | | | (0.07) | | | | | |
| lamda | | | | | 0.44*** | 0.00 | | |
| | | | | | (0.12) | | | |
| $R^2$ | 0.5173 | | 0.5417 | | 0.5287 | | 0.7112 | |
| Adj.$R^2$ | 0.4973 | | 0.5228 | | 0.5092 | | 0.7034 | |
| # Obs. | 480 | | 480 | | 480 | | 480 | |

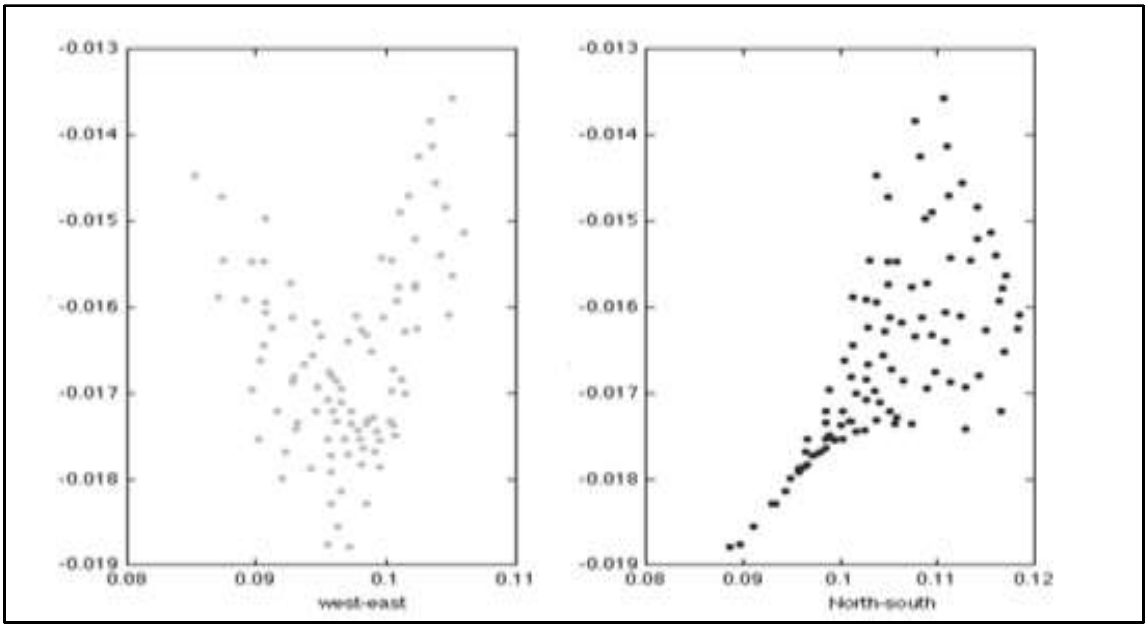
How can we interpret the previous results in the context of Bogota´s housing market? The commuting cost-housing price elasticity for properties located in distant zones, for all 4 estimated models, is on average -1.48% for every 1% of increase in fuel price. This elasticity could be interpreted as follows: for a distant household with an average price per square meter (2001-2006) of US $352.68, an average housing area of 182.07 m2 and a housing value[15] of $64,213, this elasticity implies an average decrease of $950.35 in the real-estate household wealth for a five year time horizon. The previous amount is equivalent to a $15.83monthly households´ loss of property value, representing near 11.44% of the average minimum monthly wage.

For those individuals who usually commute by private vehicles and locate in distant zones from the urban centers, there is double cost of being located far away: first, they face a higher commuting cost but this cost at the same time de-capitalizes property values. Overall, these results agree with the Central Place Theory in which property values decrease as houses are located far away from the employment centers.

In Figure 4 we observe the variation of parameters for the commuting cost variable across space in the West-East and South-North directions. The coefficients vary between -0.013 and -0.019 in the South-North direction of the city with a major impact in the North Zone. This variation indicates an important influence of spatial heterogeneity in the commuting cost variable measured through structural changes of parameters in space.

[15] Value is defined in terms of supply in a market defined by demanders and suppliers (metrocuadrado.com).

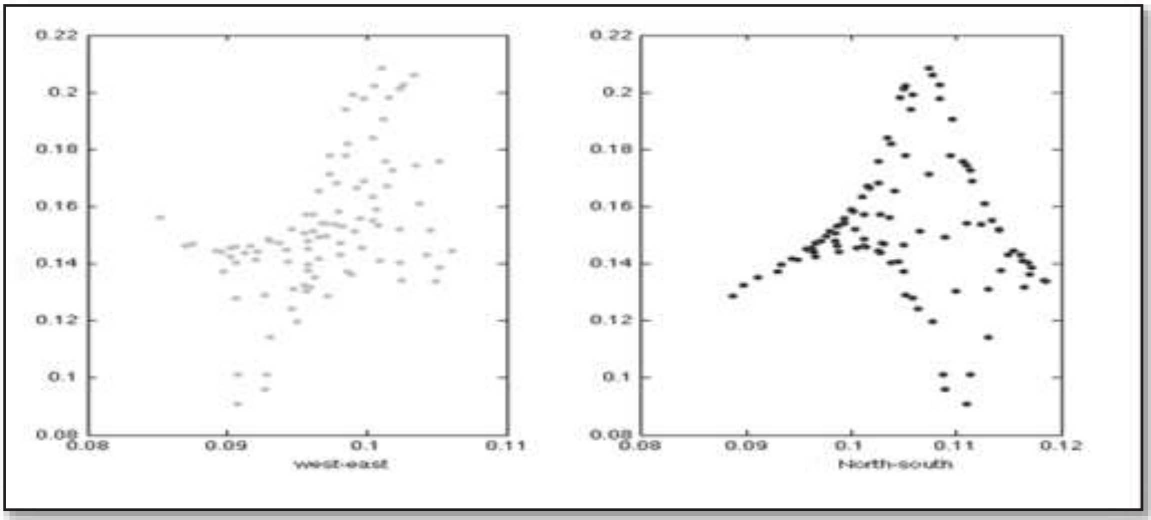
**Figure 4: Coefficient ($\text{year after}_t * \text{FUC}_i * \text{gasoline price}_t$) : GWR**




The year indicators in the GWR regression are specified as controls and are intended to capture variation in macroeconomic variables such as inflation or interest rate variations that may influence property values. Each year indicator is statistically significant to explain the variation in urban housing prices per square meter in Bogota; the same result was observed in all parametric models. The effect through the years is useful to control for variation in macroeconomic variables. Between 2001 and 2002 there is a difference of 12.30% in housing value per square meter. Between 2001 and 2003 this difference falls to 11.4%, in 2004 the difference climbs to 24.30% while in 2005 it ends up in 20.1%. Finally, the difference between 2001 and 2006 is 32.30%.

Regarding the *Area* attribute, parameter estimates for this variable were significant and similar in magnitude in both parametric and non-parametric models. This is a proof of a robust statistic relation in a key attribute to explain the hedonic pricing function (Freeman, 1974). Houses situated to the east of the city show a major effect of Area on prices (See Figure 5). Similarly, dispersion in estimated parameters in the southern area (with a range from 0.08 to 0.22) can be explained by a major variation of intrinsic attributes in housing units. In Bogota, it is not rare to observe a spatial mix in socioeconomic levels, reflected on a great extent by heterogeneity in the estimators.

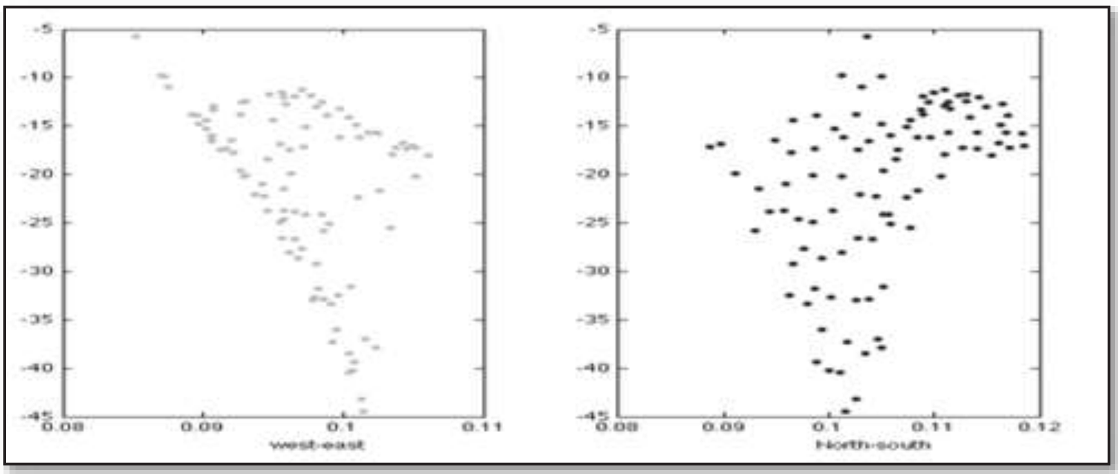
**Figure 5: Area Coefficient: GWR**




Regarding the *socioeconomic level* variables at the signaled point, the non-parametric model estimates suggest a statistically significant difference of about 7.2% in property values per square meter between low and medium socioeconomic levels. Similarly, the price difference between low socio economic and high socio economic levels increases to 36.7%.

The coefficient for *urban density* variable in the non-parametric case, suggests that an increase of 100 dwellings per hectare generates a decrease in the average price of housing per square meter of 23.71%. For all parametric estimations, the sign and level of significance are similar to the non-parametric case. The biggest effect is observed in Muzu´s Zonal Planning Unit explained in part by a prevalence of overcrowding. Some have argued that higher densities could be accompanied some unwanted social contacts, deficiencies in the access to certain urban facilities with a hyper-densified use and the arising of incompatible uses (Pun, 199, 54-55). Figure 6 shows the spatial heterogeneity for density where the effect for this parameter grows in magnitude through the West-East direction, suggesting that higher densities may be perceived as a negative amenity in the east zone, an area of middle-high socioeconomic status dwellings. Further research would be needed to establish if congestion for the same facilities and closeness among residents may cause social discomfort (Pun, 1994).

**Figure 6: Urban Density Coefficient: GWR**




Overall, we observe robust results for the parametric and non-parametric spatial models´ estimations. Spatial models improve overall goodness of fit compared to the Ordinary Least Squares specification. The spatial models specifications corroborate the presence of spatial dependence and spatial heterogeneity in the data generating process. The parameter estimates for the variables "$\text{year after}_t * FUC * \text{gasoline price}_t$", that measures the impact of commuting costs to urban employment centers, "area" and "urban density" shows a heterogeneous spatial structure for the housing market in Bogotá.

## 6. Discussion

We analyzed spatio-temporal effects of the relationship between cost of access to employment centers and housing prices in Bogota, Colombia. This study intends to innovate upon traditional applications of hedonic models by combining impact evaluation tools and spatial methods (parametric and non-parametric) to account for spatial dependence and heterogeneity problems common in geographic data, exploiting spatio-temporal features of data when data panels are not available. Using the concept of spatial weights matrix (parametric) and the function of spatial decay (non-parametric) it is relatively easy to consider the process of interaction between agents in space and spatial differentiation of property values in an urban context.

The econometric results show a negative relationship between proximity to central places and property values. These results corroborate the multi-nodal version of the Central Place Theory in which property values decrease as houses are located far away from employment centers. Housing price elasticity conditioned to being far away to employment centers suggests a significant impact on property values that may translate on household monthly wealth losses close to 11.44% of the average minimum monthly wage.

Spatial models´ results suggest significant spatial dependence in prices between geographic units. When comparing between SAR and SEM models, Lagrange Multiplier tests conclude in favor of the Spatial Error Model (SEM). This test suggests that omitted variables captured in the error term of the regression may drive the spatial dependence of property values. This dependence could be explained by spillover effects of housing attributes, the proximity to employment centers and higher price externalities from neighboring Zonal Planning Units.

More flexible estimations of parameters allowed in the Geographically Weighted Regression (GWR) made it possible to measure heterogeneous effects of commuting costs on property values; GWR estimations suggest variation of parameters for the commuting cost variable across space in the West-East and South-North direction. In addition, when comparing all 4 methods of estimation, GWR showed to outperform traditional spatial autoregressive (SAR) and spatial error (SEM) models.

Our results are suggestive but not conclusive; differences in prices and the spatial dependence of them can be related to increases in gasoline prices. Higher gasoline prices that face property owners located far away from employment centers increase commuting costs and may affect location decisions for residents who try to lower the monetary costs of commuting. Further location models need to be implemented to explore the channels through which commuting costs ultimately affects housing demand and property values. Without data restrictions, future research could include estimations with a panel database to guarantee continuity in time without randomizing independent cross-section observations. It is also important to consider a longer period of time to capture variations in prices and to take into account household decisions in the long run.

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