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Bus Rapid Transit and Property Values in Buenos Aires: combined spatial hedonic pricing and propensity score techniques

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This study estimates the property value uplift of one of the first Bus Rapid Transit (BRT) in Buenos Aires, Argentina. Data comes from two real estate internet sites for neighborhoods surrounding the BRT. The empirical methodology is innovative since it combines traditional spatial hedonic pricing with matching and weighted regressions, using propensity score estimates. Robustness checks are based on trimmed samples. BRT has a non significant impact on property prices, which can be attributed to the fact that this BRT lies on a traditional corridor and people that come downtown for work are those that use it most.

Key words: Bus rapid transit, Buenos Aires, Argentina, property value uplift, hedonic pricing, spatial econometrics, propensity score matching, propensity score weighting, trimmed estimations

JEL codes: C21, R14, R23, R40

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1. Introduction

Bus Rapid Transit (BRT) systems began to be implemented in the 70s in Curitiba (Brasil) and are present now in 165 cities in the world.[1] Its growth has been particularly high in developing countries as China, Brazil and Indonesia, but also in cities of developed nations as Australia, Canada, the United States and several European countries. Literature reviews indicate that there are more studies on the impact of rail-based infrastructure than bus-based one (see Deng and Nelson 2011; Stokenberga 2014). This can be in part due to the extension of that latter type of transport investment, particularly in the last few years.

Part of the expansion of BRT can be attributed to its cost-effectiveness. Its deployment requires relatively low infrastructure and time costs both in absolute terms and as compared to rail systems. According to ITDP (2014), BRT´s capital costs are less than 10 per cent of the cost of metro and 30-60 per cent of the cost of light rail. BRT also passes the test of a benefit-cost evaluation. Even though buses have generally a negative reputation related to pollution and slow service, BRT has allowed changes on both grounds. Indeed, BRT´s benefits may result in positive impacts as a decrease in motorization, road safety, crime rates, travel time, greenhouse gases, and, an increase in land value. Even if, in general, investments are made without a precise understanding of their returns, there is usually a great interest to assess their economic impacts. In particular, quantifying if there is land value uplift is seen as way to encourage funding for such projects.

In Argentina, the first BRT system was implemented in Buenos Aires (capital city) by May 2011, and since then, similar ones have been introduced in different locations of the country´s capital and in several provinces (states). Despite this, there are no published studies quantifying the uplift value of transport improvements on properties in Argentina. This contrasts with available estimations for various countries, including developing cities as, for example, Bogotá in Colombia (Rodríguez and Mojica 2009, Muñoz-Raskin 2010, Perdomo, 2011) or Beijing (Zhang and Wang 2013, Ma et al 2014, Pang and Jiao 2015) and Guangzhou (Salon et al 2014) in China

This paper seeks to examine the extent to which the Metrobus 9 de Julio on the main street of the city of Buenos Aires has any impact on property values in the surrounding area.[2] Our paper contributes to the literature in two main aspects. First, we make the first quantitative estimation of BRTs´ impacts in Buenos Aires and in Argentina. Second, instead of simply estimating the value uplift with spatial hedonic pricing or matching as has been done in the related literature, we assess the impact of BRT through matched spatial hedonic pricing and

[1] See Global BRT Data: http://brtdata.org/panorama/year.

[2] In Argentina, the word "Metrobus" is used to denominate BRT. The use of other wording than BRT is usual also In Australia, where it is called "transitway" (Mulley and Tsai, 2016).

a propensity score weighted spatial hedonic estimation in order to attenuate the problems usually present in each one of the methodologies when considering them separately. We also estimate trimmed samples in order to check for the robustness of our results.

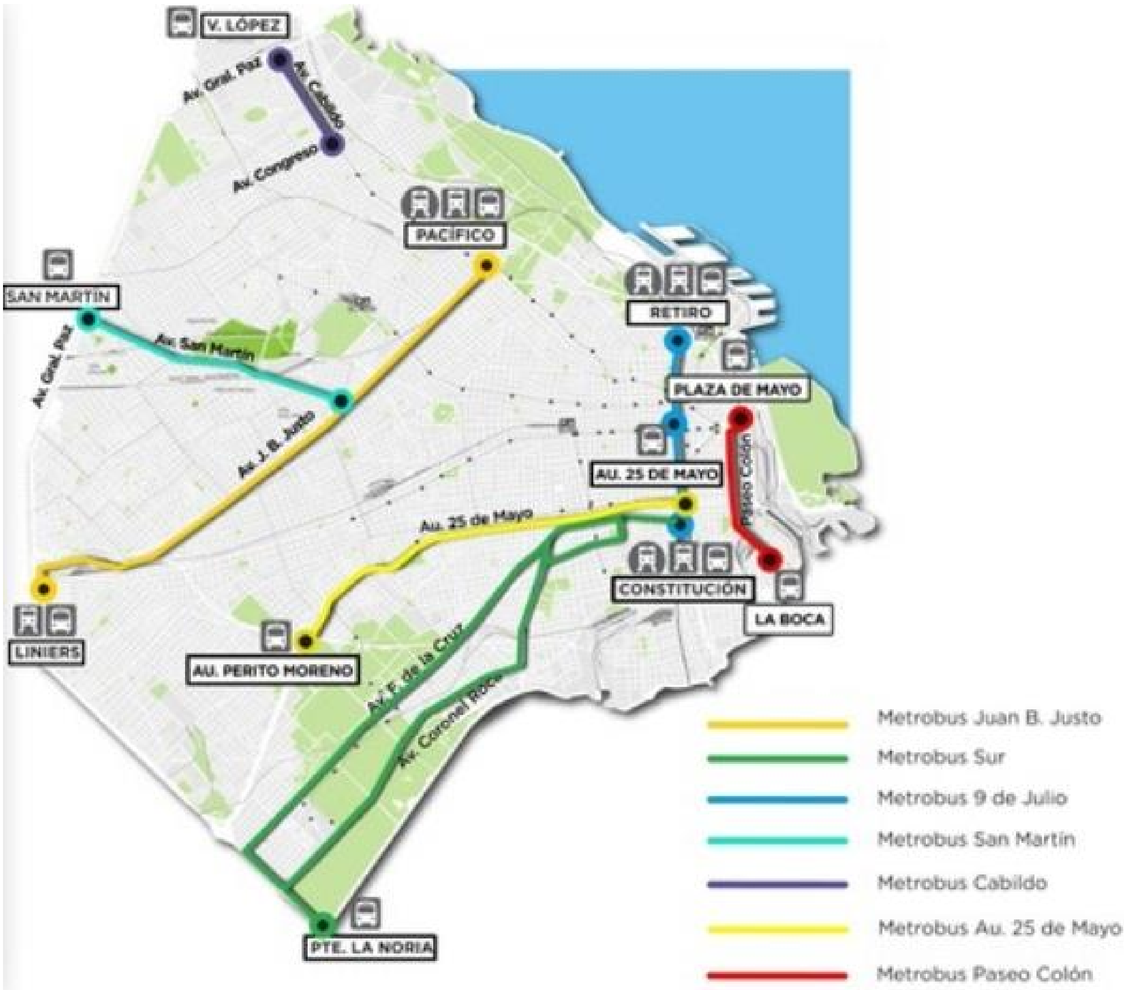
The article is structured as follows. Section II depicts the BRT network in Buenos Aires and, in particular, the Metrobus 9 de Julio. Section III provides a review of the related literature while Section IV depicts the type of data and methodology used here. Section V presents the estimation results, its robustness checks and compares them with the previous studies. Finally, Section VI concludes and discusses possible extensions of our work.

2. Bus Rapid Transit network in the city of Buenos Aires

Argentina BRTs are located in the capital city of Buenos Aires, but also in the Buenos Aires metropolitan area and some provinces in the rest of the country. There are BRTs in operation (or planned) in Vicente López, La Matanza, Morón and Tres de Febrero (districts that are adjacent to the city of Buenos Aires) and in Mar del Plata, Neuquén, Córdoba, Corrientes, Rosario, and Santa Fe (several of the largest towns in Argentina). In the particular case of the capital, there are seven BRTs that are running nowadays: Bajo; San Martín; Norte; Autopista 25 de mayo; Sur; 9 de Julio; and, Juan B. Justo (see Figure 1 for their geographic location). They cover 62.5 kms. for 91 bus lines and transport around one million people per day.[3]

[3] See http://www.buenosaires.gob.ar/movilidad/metrobus/servicios-del-metrobus.

Figure 1. BRTs in Buenos Aires city



Source: *http://www.buenosaires.gob.ar/movilidad/metrobus/servicios-del-metrobus*.

The fact that BRTs are concentrated in Buenos Aires has to do with the political will the local government had to implement this type of network, as well as the city´s particular conditions. Buenos Aires is the capital and the most populous city of the country (with approximately 3 million people residing in it). It is located on the western shore of the estuary of the Río de la Plata, on the American continent's southeast limit. The Greater Buenos Aires, that also includes several Buenos Aires Province districts, has a population of around 14 million people. It constitutes one of the most populous metropolitan areas in the Americas.

The Buenos Aires commuter network system is extensive: every day more than one million people travel to the capital. There are rail, subway and buses networks that operate the transportation system. With respect to the latter, there are over 100 city bus lines (buses are named *Colectivos*), managed by individual private companies (Muzzini et al, 2017). The colectivos´s system is very popular because it is less expensive than the underground, covers a far wider area, and has numerous stops.

The first Metrobus is the one on the Juan B. Justo avenue and was inaugurated on May 2011, the second one was finished in July 2013 and goes along the 9 de Julio avenue. Those two BRTS are ranked by the BRT Standard, led by the Institute of Transportation and Development Policy.[4] Juan B. Justo BRT was assigned a bronze standard and 9 de Julio BRT a silver one. The rest of the metrobuses are newer and have not been evaluated under that standard. In this article, we analyze the case of Metrobus 9 de Julio, which is located along the most emblematic street of the capital. This BRT encompasses the famous *Obelisco*, a monument that is the icon of Buenos Aires, since it was erected to commemorate the fourth centenary of the first foundation of the capital city of Argentina.

According to the local transport authorities, the benefits associated to Metrobus in general are: time savings, better accessibility for less able citizens, decrease of environmental impacts (the way buses run on exclusive ways implies less air pollution), more security (less traffic accidents). The advantages cited for the Metrobus 9 de Julio in particular include also: decreases in the levels of noise (the buses run now in a larger street instead of smaller ones), improvements in waiting quality (stations include protective roofs and benches), reduction of congestion (this is attributed to the fact that buses do not run on the same ways as cars and that an improvement in buses may favor the use of public transportation instead of private cars).[5] Authorities do not mention that those gains are capitalized in land value. There are no published articles that quantify the benefits attributed to BRTs in Buenos Aires.

3. Literature review

The intuitive idea behind the link between BRT lines and residential property values is that transportation has an impact on individuals´ location choice and so, as shown in the theoretical framework developed by Alonso (1964) and Muth (1969), land value should rise as accessibility improves. Contrary to conventional buses whose routes are easy to change, BRT lines imply a more permanent infrastructure modification and that is why an impact on property values is more likely.

There is quantitative evidence on the impact of BRT systems in several cities. For example, there are recent studies for: Bogotá in Colombia (Rodriguez and Mojica 2009, or

[4] The BRT Standard evaluates corridors on the base of 30 metrics. To recognize quality, it ranks BRTs according to colors: Bronze, Silver, or Gold. The criteria have to do with six issues: basics (as if it has platforms to enter the BRT at level –i.e., without stairs-); service planning (as the exent of hours of operation); infrastructure (for example, if payments is outside of the bus); station design (to assess how confortable they are); communications and marketing (amount and clarity of information for passengers); integration; and, access (how easy it is to enter the BRT platforms). See https://www.itdp.org/library/standards-and-guides/the-bus-rapid-transit-standard/.

[5] See http://movilidad.buenosaires.gob.ar/metrobus/%C2%BFpor-que-metrobus/ for the benefits associated to Metrobus in general and http://www.buenosaires.gob.ar/movilidad/metrobus/metrobus-9-de-julio for Metrobus 9 de Julio in particular.

Muñoz-Raskin 2010); Seoul in Korea (Cervero and Kang 2011); Beijing (Zhang and Wang 2013, Ma et al 2014, Pang and Jiao 2015, Deng et al 2016) and Guangzhou (Salon et al 2014) in China; or Sydney (Mulley and Tsai, 2016) and Brisbane (Mulley et al 2016) in Australia. The regional distribution of publications seems to be related to the expansion of BRT systems in the different countries of the world.

Literature reviews indicate that value land uplift of BRT for residential as well as commercial properties exists, but varies greatly depending on the location. Several studies find significant impacts of different sizes while others do not find any impact. As illustrations of the first group, Perdomo (2011) finds that one meter further apart from the Transmilenio station in Bogotá reduces the price of housing in 0.05 per cent and Deng et al (2016) find that every 100 meters closer to the Line 1 Beijing station implies residential houses prices between 1.32 and 1.39 per cent higher. Among the second group, Zhang and Wang (2013) find for the Southern axis in Beijing that more distance from the BRT implies prices decrease but not significantly, and a similar finding holds in Ma et al (2014) for within a quarter mile distance from Beijing BRT lines.

Part of the variability in the results obtained could come from the specificity of the local conditions as dependency on private automobiles or income differences (according to Muñoz-Raskin 2010, it may happen that people have a so low income that they walk or take alternative less expensive transportation options even if BRT is available, and that may explain its low impact). Differences in estimated impacts may also derive from the data used by each of the studies as well as the empirical methodologies each of them employ.

In terms of data, most of the literature has focused on residential rather than commercial properties because, for the former, data are more available, the number of observations is larger and characteristics with which properties are described are generally more numerous (and, that allows controlling for them). A second difference in data sources is the type of residential properties that are considered. Some studies focus on previously owned properties or new ones, and on single family houses or apartments, condominiums or both. A third difference in terms of the databases is if properties considered are those for sale or for rent. Generally, in this literature, data on sales predominate because it is more likely to find accessibility effect than in rent because, in the latter, decisions are more short-term based.[6]

A fourth difference in terms of information is that there are works based on actual transaction prices versus those that rely on asking prices databases. There would be no change in the conclusions obtained from both sources if asking prices are strongly correlated with actual transaction prices. However, if it is not the case, and properties´ characteristics impacted differently on each of those types of prices, results would be biased. Almost all

[6] An often cited reference for BRT impact on property values that uses rental prices (instead of sale prices) is Rodriguez and Targa (2004).

studies in developing cities (Rodriguez and Mojica 2009, Muñoz-Raskin 2010, Zhang and Wang 2013, Ma et al 2014, among others) rely on asking prices and this is due to the fact that transaction prices are generally not accurately reported. People tend to under declare the amounts they register in paperwork in order to elude taxes, and that is possible due to fragile institutions. A fifth distinction between sources of information is that some authors choose to explain absolute prices (Rodriguez and Mojica 2009 or Mulley and Tsai 2016 and Mulley et al 2016) while others use prices per square meter (Perdomo 2011, Pang and Jiao 2015, or Deng et al 2016).

The methodology used by each of those studies is also rather diverse, even if it mainly has to do with revealed (and not stated) preference approaches (Hensher, 2010). The choice among methods is due to the fact that the former requires data on observed behavior and that type of information is generally available, while the latter needs a customized survey to derive individuals´ preferences. Traditionally, value uplifts are assessed using hedonic pricing methods (HP), which consists of regressing properties´ values on their own characteristics, those of the neighborhood and accessibility traits (Rosen, 1974). In some cases HP is estimated using simple Ordinary Least Square, while in others Weighted Least Squares is the technique chosen.

Then, with the development of spatial econometrics (Anselin, 2001), studies tend to consider spatial dependence among prices of closely located houses as well as spatial correlation in the error term of the standard hedonic pricing function. The first aspect is rationalized by the fact that there is a spillover effect of neighborhood quality that affects all houses at the same time and the second one is thought as controlling for unobservable variables that remain in the error term (those are omitted variables that are determinants of real estate prices but cannot be measured or are simply not known). Spatial hedonic pricing (SHP), which relies on maximum likelihood for its estimation, has been widely used to capture value uplift caused by an increase in transport accessibility (for example, Perdomo 2011, Zhang and Wang 2013, among others).

A more recent advance in this same line is to estimate, not a general spatial model, but a local model with a geographically weighted regression (GWR) in order to deal with regional differentiation that follows from the intrinsic uniqueness of each location. The intuition is that GWR controls for spatial heteroscedasticity of the errors (not only error autocorrelation as SHP), and allows to visualize the spatial pattern (at the local level) of the relationship between accessibility and property prices. In its estimation, observations that are close to the regression points are given higher weight than those further away. There are relatively fewer articles using GWR and this may also have to do with the fact that there are difficulties in its implementations, as are collinearity issues (Mulley et al 2016 and Olaru et al 2017 apply this technique for the BRT in Brisbane and Sydney respectively, and both refer to these problems).

A different perspective, more often taken in the statistical literature, specifies the spatial heterogeneity as a special case of random coefficient variation.[7]

On a parallel line of research, and given the difficulty in ensuring that hedonic pricing models in any of its form control for all the variables influencing the price determination process (including latent constant spatial structure), some articles began to use quasi-experimental techniques to capture BRT impacts. Two types of quasi-experimental methods have been applied to transport impacts valuation:[8] matching (MT) and difference-in difference (DID).

Matching requires calculating a "propensity score". This is the probability each house has to be influenced by accessibility based on its observed characteristics. Those estates with similar propensity score but one with and the other without treatment (influence of BRT) are matched. Then, a comparison of their average prices is taken as the impact of BRT. Matching has two main limitations. One is that the participation in a program (here, the influence of BRT or not) may be determined by unobserved variables that cannot be taken into account when calculating the propensity score used for the matching and, the other, is the difficulty encountered to find good matches (this is known as the common support requirement). There are a few estimations for BRT properties´ prices impact that use this methodology. For example, Perdomo (2011) utilize propensity score matching to assess the impact of Transmilenio on housing prices in Bogotá (Colombia).

DID method controls for omission of variables correlated with infrastructure elements (included in the error term). It does so by comparing the difference in prices before and after the BRT, between treatment and control groups (those houses closer to BRT and those further apart). Examples of the use of this methodology exist for suburban train (not BRT) impacts: Dubé et al (2013, 2014) for Québec and Montreal in Canada. The main advantage of DID is that it takes into account the hedonic pricing limitation of omitted variables since it controls for the omissions of variables that are constant over time. However, DID weakness is related to its robustness since it attributes to the intervention (here, BRT) any differences in trends between groups that occur from the time it begins. If any other change occurs, the result ends

[7] Very few studies have been published using even an alternative technique for BRT value uplift: quantile regression (for example, Salon et al, 2014). For those studies, the impact of BRT is different for the different prices. This implies that those who buy cheaper houses could place a different value on BRT access than those who buy more expensive ones.

[8] The name "Quasi-experimental" has to do with the fact that the assignment of control to treatment groups is not build as a randomized experiment, but rather groups are chosen according to a pre intervention characteristic (Gertler et al, 2011). Note that BRT cannot be evaluated using experimental design techniques because houses along the BRT lines cannot be said to be randomly assigned treatment (having BRT) or no treatment (not having access to BRT). BRT is built at a given place following some criteria in the same way as social programs are assigned to individuals in a non random way but rather to individuals with higher needs, for example.

up being biased. Another limitation of DID is the information requirement: it needs data before and after the establishment of the BRT whose impacts has to be valued.[9]

The lack of fulfillment of hypothesis for each of the methods implies that they can be combined to overcome their limitations. For example, if a matched DID is used, DID at least controls for unobserved characteristics that are constant across time and partially solves the weakness of matching (that unobserved characteristics are not taken into account in the assignments of observations to the groups treated and untreated). In this study, we evaluate the impact of 9 de Julio Metrobus on residential property values using spatial hedonic pricing, matched spatial hedonic pricing, and propensity score weighting spatial hedonic pricing, for the full and trimmed sample. We were not able to find any published work that uses a combination of techniques to evaluate the impact of BRTs on property values.

4. Methodology and data

4.1. Spatial Hedonic Estimation

To estimate the impact of the 9 de Julio Metrobus on the value of residential properties, we begin the analysis with a traditional hedonic specification. Following Rosen (1974), when the housing market is in equilibrium, the price of a house is a function of its various attributes. Formally, **P** is a *nx1* vector of housing prices, where *n* denotes the number of observations. $\mathbf{X}_1$ is a nxk_1 matrix of k_1 physical characteristics of the properties, $\mathbf{X}_2$ is a nxk_2 matrix of k_2 neighborhood characteristics and, $\mathbf{X}_3$ is a *nx1* vector that represents the accessibility to the Metrobus. The objective is to estimate the hedonic price function (HPF):

$$\mathbf{P} = f(\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3) \tag{1}$$

As discussed in the previous section, since neighborhood properties share numerous characteristics, one possible problem that may arise in the estimation of Eq. (1) is that the estimators do not capture spatial effects. According to Anselin (2001) there are two types of spatial interactions. The first one is the *spatial dependence (or spatial autocorrelation)*, which means that prices at nearby locations may be closer in value to prices of properties farther apart. For example, let us consider a situation where a house is surrounded by others with beautifully landscaped yards. This externality that arises from neighborhood quality would

[9] There are some articles in this literature that analyze not only if there is value uplift due to BRT systems, but when it occurs. McMillen and McDonald (2004), for example, find that the market anticipated the impact on property prices in advance of implementation in the case of a BRT in the city of Chicago. But, as Mulley and Tsai (2016) acknowledge, it may happen that real estate price changes are not seen until the new transport system is in operation if governments are not fully credible.

have a positive effect on house prices, pushing up the selling price of the surrounding's houses.

The second type of spatial interaction is the *spatial heterogeneity*, which refers to structural instability either in the form of non-constant error variances in a regression model (heteroskedasticity) or in the form of variable regression coefficients (which can also be associated with heteroskedastic regression residuals). More precisely, spatial heterogeneity implies that the functional forms and the parameters are not homogeneous and vary with the location. For example, heterogeneity can be observed when houses in the north zone of the city present higher prices than similar houses in the south zone. Most of the methodological issues related to spatial heterogeneity can be tackled by means of the standard econometric tools such as random and varying coefficients models or switching regressions. A different perspective of dealing with heterogeneity includes the spatial expansion method of Casetti (1997) or the geographically weighted regression (GWR) model of Fotheringham et al. (2002).

As stated by Anselin (2001), when data come from aggregated geographical units such as census block, census tract, zip code etc., spatial heterogeneity is a relevant problem since the internal variability does not always remain constant between units, causing problems of heteroscedasticity. But, since in this paper we consider the accurate position in space of each house with the characteristics, spatial heterogeneity does not seem to be a major problem in the estimations. Besides, to deal with the omission of a latent constant spatial structure matching estimators are also included in the analysis.

If spatial dependence is expressed through a process that relates the value of the dependent variable at a given location to its value at other locations, the Ordinary Least Squares (OLS) estimates are biased and inconsistent since the price term is correlated with the errors (Anselin, 2001). Then, the price term must be treated as an endogenous variable. In addition, if the disturbances exhibit spatial autocorrelation, the OLS estimates are not efficient.

Ord (1975), Anselin (2001) and LeSage and Pace (2009) develop a wide range of econometric methods that deal with these issues. One of such methods is the specification of a spatial autoregressive process represented by a *spatial lag model* (SAR) as follows:

$$\mathbf{P} = \rho\mathbf{WP} + \mathbf{X}_1 \quad {}_1 + \mathbf{X}_2 \quad {}_2 + \mathbf{X}_3 \quad {}_3 + \qquad (2)$$

where ρ is the spatial autoregressive coefficient, **W** is a *nxn* spatial weights matrix which captures the definition of "neighborhood" chosen, and   is a *nx1* vector of independent and identically distributed (iid) error terms. **W** contains the spatial relations among observations and controls for the impact of any house price on neighboring houses prices across space.

Moreover, when the autocorrelation occurs because some causal factors that are omitted in the hedonic price function exhibit spatial autocorrelation in the disturbance term , the data generation process can be represented by the *spatial error model* (SEM), which accounts for the fact that housing price at any location may also be explained by the omitted variables at neighboring housing observations:

$$\mathbf{P} = \mathbf{X}_1 \ {}_1 + \mathbf{X}_2 \ {}_2 + \mathbf{X}_3 \ {}_3 + \qquad \text{with} \quad = \lambda.\mathbf{W}. \ + \mathbf{u} \tag{3}$$

where λ is the coefficient on the spatially correlated error structure and $\mathbf{u}$ is a *nx1* vector of iid errors uncorrelated with the observed explanatory variables.

It is also possible that both kinds of spatial dependence are simultaneously present across a sample. In this case, the *generalized spatial model* (SAC), which is combination of the SAR and SEM models above, controls for both issues:

$$\mathbf{P} = \rho\mathbf{W}\mathbf{P} + \mathbf{X}_1 \ {}_1 + \mathbf{X}_2 \ {}_2 + \mathbf{X}_3 \ {}_3 + \ , \quad \text{with} \quad = \lambda.\mathbf{W}. \ + \mathbf{u} \tag{4}$$

We can easily obtain the reduced form of equation (4) as:

$$\mathbf{P} = (\mathbf{I} - \rho\mathbf{W})^{-1}.[\mathbf{X}_1 \ {}_1 + \mathbf{X}_2 \ {}_2 + \mathbf{X}_3 \ {}_3 + (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{u}] \tag{5}$$

with **I** as the identity matrix.

Maximum-likelihood is used to estimate SAC, or alternatively SAR or SEM, which are special cases of SAC when λ =0 and ρ =0 respectively. [10]

With the SAR, SEM and SAC specifications, the marginal effect summarizes the impact of a change in an independent variable on the dependent variable, as well as the feedback loops depicting the effect of a change in a given dependent variable on the neighboring dependent variable and so on (LeSage and Pace, 2009). In our case, with a log-lin specification of the HPF, [11] the matrix of partial derivatives of the dependent variable with respect to the r^{th} explanatory variable (where *r* is the total number of independent variables: *k1+k2+k3*) is given by:

$$\frac{\partial \mathbf{P}_i}{\partial \mathbf{X}_{ri}} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{I}\hat{\beta}_r\mathbf{P} \tag{6}$$

[10] In addition, the Spatial Durbin Model was developed as an extension of the SAR. This specification includes a spatial lag of the dependent variable, as well as the explanatory variables. This model was not considered in this work because of the potential problems of multicollinearity and the loss of grades of freedom (Soundararajan, 2013).

[11] Mention to the choice of a specific functional form is usual in the literature of hedonic pricing in general, and that also holds for BRT impacts. The form adopted for the hedonic function varies from simple linear (Muñoz-Raskin, 2010), to log-log (Salon et al 2014), log-lin (Ma et al 2014, Deng et al 2016, Mulley et al 2016) or even the use of a linear Box-Cox specification (Perdomo 2011 and Pang and Jiao 2015). For our study, we opted for one of the most usual functional forms: log-lin.

4.1.1. Spatial Weights matrices

As it was stated above, employing SAR, SEM or SAC models requires the use of a spatial weight matrix **W** to assign nearby houses a higher weight than those that are further away.

To build **W**, we first calculate the distance between houses *i* and *j* of the sample following the Great Circle Distance (d) specification in Jeanty (2010):

$$d_{ij} = a\cos^{-1}[\cos\delta_i \cos\delta_j \cos(\vartheta_i - \vartheta_j) + \sin\delta_i \sin\delta_j] \tag{7}$$

where δ and ϑ represent latitude and longitude coordinates and a is the Earth radius. Then, a distance $\bar{d}$ delimits if houses *i* and *j* are neighbors of one another or not. With this information, the following spatial weights matrix is built:

$$\mathbf{W} = \begin{pmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & 0 \end{pmatrix} \tag{8}$$

with:

$$w_{ij} = \begin{cases} 1 \ \text{if}\, d_{ij} \le \bar{d} \quad \forall i,j = 1,\ldots,n; i \ne j \\ 0 \ \text{otherwise} \end{cases} \tag{9}$$

As usual, the final step of the construction of the spatial weight matrix consists of a row-standardization of (8). Each element in a row is divided by the sum of the elements in that row so that all rows sum to one. Hence, the elements of the standardized spatial weights matrix (denoted as $\mathbf{W}^{\mathbf{S}}$) are defined as:

$$w_{ij}^{S} = w_{ij} \cdot \frac{1}{\sum_{j=1}^{n} w_{ij}} \tag{10}$$

4.1.2. Testing the need for Spatial Modeling

The most commonly used tests for the existence of spatial autocorrelation effects are due to Patrick Moran (Moran, 1948) and Roy C. Geary (Geary, 1954). The first statistic, usually referred to as Moran's I, is defined as:

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}.(p_i - \bar{p}).(p_j - \bar{p})}{\sum_{i=1}^{n}(p_i - \bar{p})^2} \tag{11}$$

where $\bar{p}$ is the mean of housing prices and w_{ij} are the elements of the spatial matrix.

In the absence of spatial autocorrelation and regardless of the specified weight matrix, this statistic has expectation $-\left(\frac{1}{n-1}\right)$ which tends to zero as the sample size increases. The associated null hypothesis is no global spatial autocorrelation. A Moran's I coefficient larger than the expected value indicates positive spatial autocorrelation (that is, similar prices occur near one another), and a Moran's I less than the expected value indicates negative spatial autocorrelation (that is, dissimilar prices occur near one another).

By calling **P*** the vector of the demeaning variable p_i of dimension *nx1* (that is, $p_i^* = p_i - \bar{p}$), it is possible to rewrite Moran's I statistics in matrix notation as follows:

$$Moran's\ I = \frac{n}{S_0} \frac{\mathbf{P}^{*\prime}\mathbf{W}\mathbf{P}^{*}}{\mathbf{P}^{*\prime}\mathbf{P}^{*}} \tag{12}$$

where $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$.

Similarly, but to test against spatial error autocorrelation, Moran's I statistics is:

$$Moran's\ I = \frac{n}{S_0} \frac{\mathbf{e}'\mathbf{W}\mathbf{e}}{\mathbf{e}'\mathbf{e}} \tag{13}$$

where $\mathbf{e}$ is a vector of OLS residuals. When **W** is the row-standardized spatial matrix, (for example, $\mathbf{W^S}$), n=S_0.

Finally, the Geary's C statistic is defined as:

$$Geary's\ \mathrm{C} = \frac{n-1}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}.(p_i - p_j)^2}{\sum_{i=1}^{n}(p_i - \bar{p})^2} \tag{14}$$

Or, in matrix notation (see Lee, 2004):

$$Geary's\,C: \frac{n-1}{n}\frac{(\mathbf{z}_p)'(\quad -\mathbf{W})\mathbf{z}_p}{\mathbf{1'W1}} \tag{15}$$

where $\mathbf{z}_p$ is a transformed vector of P (an element of $\mathbf{z}_p$ is given by $(p_i-\overline{p})\left[\sum_i (p_i-\overline{p})^2/n\right]^{-1/2} = (p_i-\overline{p})/\sigma_P$); **W** is the spatial weights matrix; Ω is a diagonal matrix with each element given by $\frac{1}{2}\sum_j (w_{ij}+w_{ji})$ and 1 is a vector of ones.

Geary's C ranges from 0 (maximal positive autocorrelation) to 2 (maximal negative autocorrelation). Its expectation is 1 in the absence of autocorrelation, regardless of the specified weight matrix (Sokal and Oden, 1978). If the value of Geary's C is less than 1, it indicates positive global spatial autocorrelation. If the value is higher than 1, it denotes negative global spatial autocorrelation.

In line with the empirical literature, we also perform a Lagrange Multiplier (LM) diagnostic for inference on the spatial autoregressive coefficients. One advantage of this test is that it only requires the estimation of the model under the null (that is, OLS model). Following Anselin (2001), the one-directional LM test for spatial lag dependence takes the form:

$$LM_{Lag} = \left[\mathbf{e'WP}/\sigma^2\right]^2 / \left[(\mathbf{WXb})'\mathbf{MWXb}/\sigma^2 + tr(\mathbf{W'W}+\mathbf{W}^2)\right] \tag{16}$$

while the LM test for spatial error dependence takes the form:

$$LM_{Err} = \left[\mathbf{e'We}/\sigma^2\right]^2 / tr(\mathbf{W'W}+\mathbf{W}^2) \tag{17}$$

where $\mathbf{e}$ are the OLS residuals, **P** is the vector of houses prices, **X** is the vector of independent variables, $\mathbf{M=I-X(X'X)^{-1}X'}$ (with I as the identity matrix), **b** is the OLS estimate of β, *tr* is the matrix trace operator, **W** is the spatial weights matrix for the spatially lagged dependent variable, and σ^2 is the variance of the errors. Both statistics have an asymptotic χ^2 (1) distribution with a null hypothesis that the OLS specification is the correct one.

We also perform log-likelihood ratio tests based on the log-likelihood estimates for the unrestricted (spatial) versus the restricted (ordinary least squares) models. A high calculated χ^2 statistics $(-2\cdot(\ln\mathfrak{L}^* - \ln\mathfrak{L})\sim\chi^2_J$, where $\ln\mathfrak{L}^*$ is the log likelihood evaluated at the restricted (OLS) estimates, $\ln\mathfrak{L}$ is the log-likelihood evaluated at the unrestricted spatial hedonic estimates, and J are the number of restricted parameters) implies rejection of the null hypothesis that the restrictions to the model are correct (Greene, 2012). Finally, within the set of candidate spatial models, we consider that the best model is the one with the minimum

Akaike Information Criteria (AIC) value. AIC rewards goodness of fit (as assessed by the likelihood function) and penalizes the number of estimated parameters.

In the models described above, it is assumed that being inside or outside the Metrobus area of influence is random. However, it is reasonable to think that there are initial conditions (such us existing infrastructure) which are likely to determine the Metrobus placement, as well as to influence the housing price levels. In this context, a bias can be expected when assessing the public mass transit system impacts on houses price, given that the measured values of those homes will partly reflect those pre-existing differences. Then, as stated above, to isolate the impact of the Metrobus on the price determination process, the spatial hedonic models are combined with two commonly used propensity score methods to control for the possible selection bias based on observed characteristics: matching and weighted regression.

4.2. Propensity score matching and weighted regression

One quantity of interest to measure the effect of the Metrobus on housing prices is the difference between the potential prices of the houses inside and outside its area of influence:

$$D = E(P_1) - E(P_0) \tag{18}$$

where $E(P_1)$ is the mean of the prices if all the houses are in near the Metrobus and $E(P_0)$ refers to the mean of the potential prices if all the houses are outside the Metrobus area. This parameter (*D*) is known as Average Treatment Effect (ATE). The potential outcomes P_0 and P_1 are never both observed for any house at the same time thus, whether estimation of D is possible relies on whether $E(P_0)$ and $E(P_1)$ may be identified from the observed data.

In the hedonic regressions, the effect of the Metrobus is estimated considering the houses outside the area of influence of that bus rapid transit system as the comparison group of the houses near the Metrobus. Formally, the difference calculated is:

$$\Delta = E(P_1 \mid T = 1) - E(P_0 \mid T = 0) \tag{19}$$

where $E(P_1 \mid T = 1)$ is the mean of the observed prices of the houses near the Metrobus, while $E(P_0 \mid T = 0)$ refers to the mean of the observed prices of the houses located far away from the Metrobus. The problem of this calculation arises when treatment (*T*) is not assigned randomly among properties and "treated" and "untreated" observations differ before treatment. Indeed, the same characteristics that lead an observation to be exposed to treatment (that is, being inside or outside the Metrobus area of influence) may also be associated (or confounded) with its potential response (properties' prices). If this is the case, the expected difference between those groups of houses may not be due entirely to the rapid transit system.

Since the potential outcomes are not statistically independent of the treatment status, $E(P \mid T=1) = E(P_1 \mid T=1) \neq E(P_1)$ and $E(P \mid T=0) = E(P_0 \mid T=0) \neq E(P_0)$. Then, the average difference of Eq. (19) is a biased estimator of D. However, if it is possible to identify observed characteristics related to both the treatment status and the potential outcome (confounders) and collect them in a vector **Z**, then for houses sharing a particular value of **Z** there would be no association between treatment and outcome, that is, $(P_0, P_1) \perp T \mid \mathbf{Z}$. In this sense, Rosenbaum and Rubin (1983) (hereafter RR) introduced the assumption of strong ignorable treatment assignment and showed that $E\{E(P \mid T=1,\mathbf{Z})\} = E\{E(P_1 \mid T=1,\mathbf{Z})\} = E\{E(P_1 \mid \mathbf{Z})\} = E(P_1)$ and $E\{E(P \mid T=0,\mathbf{Z})\} = E\{E(P_0 \mid T=0,\mathbf{Z})\} = E\{E(P_0 \mid \mathbf{Z})\} = E(P_0)$. Thus, it should be possible to make inferences on *D* if the ignorability of treatment assumption (also known as the conditional independence assumption) holds. Methods using the propensity score (as propensity score matching and weighted regression) are one way to make unbiased inference on D.

RR define the propensity score as the probability of treatment given the covariates **Z**: $P(\mathbf{Z}) = \Pr(T=1 \mid \mathbf{Z})$, with $0 < P(\mathbf{Z}) < 1$. These authors showed that under the ignorability of treatment assumption, potential outcomes are also independent of participation T given the propensity score (that is, $(P_0, P_1) \perp T \mid P(\mathbf{Z})$), and so observations from either treatment group with the same propensity score are balanced in that the distribution of **Z** is the same regardless the treatment status.

In practice, the propensity score is unlikely to be known, so it is estimated using a probit function:

$$P(\mathbf{Z}) \equiv P(T=1 \mid \mathbf{Z}) = \int_{-\infty}^{\mathbf{Z}} \frac{1}{\sqrt{2\pi}} \cdot e^{\frac{s^2}{2}} \, ds \tag{21}$$

where **Z** is a matrix of explanatory variables, **β** is a vector of coefficients and s is the standardized normal variable.

To assess the selection bias, we re-estimate the spatial hedonic models constructing a statistical comparison group. We first estimate a propensity score for each observation of the full sample of houses using (Eq. (21)) and then we match the properties on that score using the nearest-neighbor matching technique.[12] Finally, we estimate the spatial hedonic models only with the observations in the matched sample.[13]

As discussed above, matching only addresses selection bias based on observable characteristics. Hence, matched hedonic pricing do not solve the bias that arises if houses are closer to BRT due to unobserved characteristics. Another issue in spatial hedonic matching is that it implies the use of less data (due to the need of a common support).

Then, we performed an alternative use of propensity score suggested in the literature (see Hirano, Imbens and Ridder, 2003) which consists in weighting the observations in terms of the propensity score (and indirectly also in terms of the covariates) to create balance between treated and control units in the weighted sample and not lose any observation. Hirano et al. (2003) derive an unbiased and consistent weighting estimator for estimating both the Average Treatment Effect (ATE) on the entire population and the Average Treatment Effect on the Treated population (ATT).[14] Heckman et al. (1997) note that ATE could not be especially relevant for policy purposes since it averages units who would never be eligible for treatment. So, we performed the following weighting estimator of ATT:

$$A\hat{T}T = \left(N^{-1} \sum_{i=1}^{N} T_i \right)^{-1} \left\{ N^{-1} \sum_{i=1}^{N} \frac{\left[T_1 - \hat{P}(\mathbf{Z}_i) \right] P_i}{\left[1 - \hat{P}(\mathbf{Z}_i) \right]} \right\} \tag{22}$$

Eq. (22) shows that the control units are weighted by the estimated propensity score divided by one minus the estimated propensity score. Although these authors show that weighting the controls this way yields an efficient estimator, some problems could appear in practice. For example, the value of the inverse of the propensity score may be extremely high for observations that have a very low probability of being treated and that affects the results.

Hence, we also apply the method proposed by Crump et al. (2006) for estimating ATT for the cases there are differences in low and high values of propensity scores among treated and untreated groups. Hence, we limit comparisons to a trimmed sub-sample with sufficient

[12] The nearest-neighbor matching is the most frequently used matching technique: each treatment unit is matched to the *n* comparison unit with the closest propensity score. In this study, we match one untreated house with each treated one.

[13] Additional to the conditional independence assumption, the propensity score matching technique requires that for each possible value of the vector of covariates **Z**, there must be a positive probability of finding both a treated and an untreated unit to ensure that each treat observation can be matched with an untreated one (common support condition).

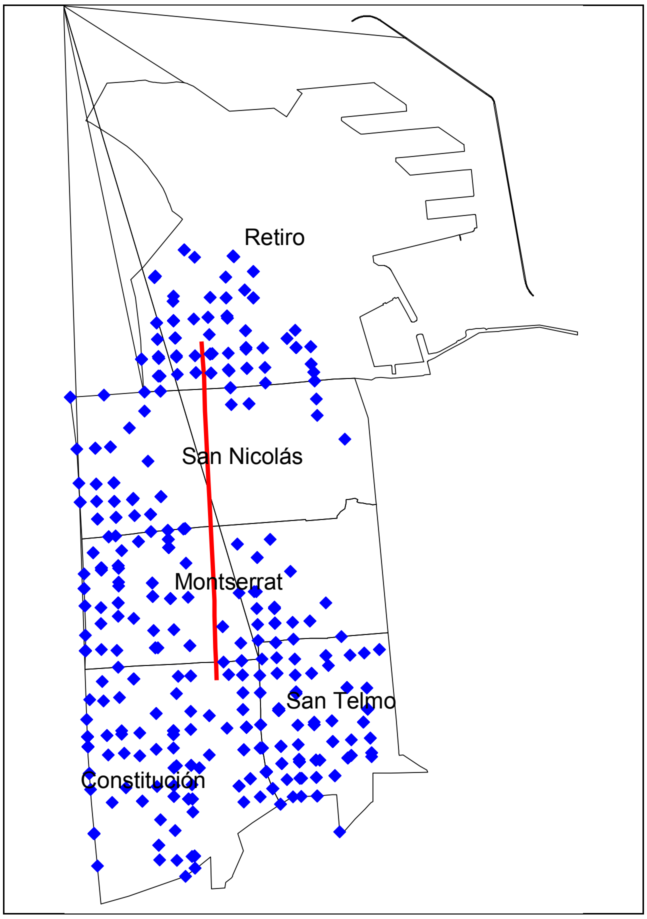
[14] Where ATE is defined as: $ATE = E(P_1 \mid \mathbf{Z}) - E(P_0 \mid \mathbf{Z}) = E(P_1 \mid \mathbf{Z}, T=1) - E(P_0 \mid \mathbf{Z}, T=0)$ under the ignorability of treatment assumption, and ATT is defined as: $ATT = E(P_1 \mid \mathbf{Z}, T=1) - E(P_0 \mid \mathbf{Z}, T=1) = E(P_1 \mid \mathbf{Z}, T=1) - E(P_0 \mid \mathbf{Z}, T=0)$ under the ignorability of treatment assumption.

overlap in propensity scores (that is,, this ensures that regressions are estimated with a sample including only covariates cells with at least a few treated and control observations). For our “trimmed sample” we choose an interval (0.1, 0.9) which are the efficiency bounds recommended by Crump et al (2006).

4.3. Data

The database was built based on two real state internet sites: *Buscainmueble.com* and *Argenprop.com*. It contains new and previously-owned apartments for sale in the City of Buenos Aires in August 2014, one year after the inauguration of Metrobus 9 de Julio. We restrict our sample to residential properties in neighborhoods surrounding the BRT path: Retiro, San Nicolás, Constitución, Monserrat, and San Telmo. Figure 2 shows the spatial distribution of observations around the Metrobus way. Note that each dot represents the several houses around each street junction and not each house in particular.

Figure 2. Metrobus 9 de Julio’s Route Line and spatial distribution of observations



Source: Own elaboration with sample data and information from Buenos Aires Data (GCBA).

Both internet sites report several characteristics for each of the properties they advertise. We select those we consider more relevant for our analysis: the sale price, converted to US dollars (*Price*); the whole area of the property, in square meters (Area); the number of rooms (*Rooms*); the number of bathrooms (*Bathrooms*); the age of the property, with 0 for new ones (*Age*), if it has or not a garage (*Garage*); if the apartment is located in the front of the apartment building (those are usually considered having a better view) or in the back (*Front*); if it is an apartment that belongs to a small condomimum (*Ph*, for the Spanish *propiedad horizontal*); and if it has a swimming pool or not (*Pool*).

We complement each property´s own traits with characteristics related to the neighborhood where they are located. In particular, we control for: being on an avenue instead of a small street (*Avenue*); the actual neighborhood; the distance from the closest subway station (*SubwayD*), park (*ParkD*); and school (*SchoolD*). For the latter group of variables, when we build dichotomous variables, they take the value of 1 within a distance of 200 meters. For accessibility, we build a bus rapid transit station dummy (*BRTD*) that takes the value of 1 if the apartment is within 400 meters of the closest station. We use a different benchmark for the BRT variable because, as shown in Figure A.1 of Annex A, the 9 de Julio is a wide street and so closest houses are farther from the stations than what is usual for other streets. The descriptive statistics for our 672 observations are shown in Table 1 (Table A.1 in Annex A reports units and data sources for each variable). As it is clear from Table 1, the downtown area that Metrobus 9 de Julio crosses is relatively traditional (on average, apartments on the market are 38 years old), there are no large houses (apartments on sale are on average 68 square meters, with between 2 and 3 rooms).

Table 1. Descriptive statistics (n = 672)

Variables	Mean	Standard Deviation	Minimum	Maximum
Price	144,334	135,972	40,500	1,000,000
Area	68.13	50.56	14	372
Rooms	2.49	1.28	1	8
Bathrooms	1.26	0.59	1	5
Age	37.72	28.30	0	100
Garage	0.06	0.24	0	1
Front	0.56	0.50	0	1
Ph	0.05	0.23	0	1
Pool	0.09	0.28	0	1
Avenue	0.29	0.46	0	1
Retiro	0.19	0.40	0	1

San Nicolás	0.10	0.30	0	1
Constitución	0.27	0.44	0	1
Montserrat	0.18	0.38	0	1
San Telmo	0.26	0.44	0	1
SubwayD	0.19	0.40	0	1
ParkD	0.25	0.43	0	1
SchoolD	0.83	0.38	0	1
BRTD	0.31	0.46	0	1

Source: Own elaboration.

5. Empirical results

5.1. Effect of proximity to BRT on residential property value: hedonic models

As described in the previous section, we run Moran and Geary´s tests to assess if there is spatial dependence and spatial error autocorrelation. As shown in Table 2, we find that there is evidence of positive spatial autocorrelation among housing prices along the whole sample according to both spatial statistics.

Table 2. Global Spatial autocorrelation tests on prices

Indicator	Calculated Value	Expected Value	Standar Deviation	z statistic
W Matrix				
I de Moran	0.241 ***	-0,001	0,007	35.672
C de Geary	0.461 ***	1,000	0.105	-5.151
Standarized W Matrix				
I de Moran	0.414 ***	-0.001	0.009	45.296
C de Geary	0.559 ***	1.000	0.023	-18,994

Source: Own elaboration.
*Note: Two tail tests. ***, **, and * indicate 1%, 5% and 10% significance respectively.*

To confirm the need of a spatial specification of the hedonic model, we run the Lagrange Multiplier Test (for spatial lag and error dependence models vs. OLS) and the Moran's I Test for spatial error autocorrelation vs. OLS. Results indicate that the different spatial hedonic models are always preferred to OLS (see Table 3).

Table 3. Models contrasts specifications

	Model with dummies
	Statistics
Spatial lag dependence	
Lagrange Multiplier	48,695***
Spatial error dependence	
Moran's I	7.980***
Lagrange Multiplier	33.308 ***

Source: Own elaboration.
*Note: Two tail tests. ***, **, and * indicate 1%, 5% and 10% significance respectively.*

Given the evidence that spatial modeling is desirable, we evaluate simple and spatial hedonic pricing regressions (spatial lag model SAR, spatial error model SEM and the combination of both -SAC-) using a semi-log specification. As shown in Table 4, for the spatial lag model the ρ coefficient is significant, which reflects the average influence of one price observation to its nearby values. Similarly, a significant λ for the SEM models indicates that there is error spatial correlation. All LR tests confirm that there are spatial issues to take into account and so there are gains in considering them. According to AIC, the model to select among spatial ones is SAR.

As can be seen in Table 4, the BRT accessibility effect on residential prices is no significant independently of the model used (OLS versus SAR, SEM and SAC). The results can be considered reasonable for the rest of the variables: those houses that have larger areas, more rooms, garages, a pool and are located on the front of the building, close to an avenue or a park, are valued more while age and less advantages neighborhoods (all except Retiro) have a negative effect on prices.

Table 4. Results for Hedonic pricing models

Variables	**Models**			
	OLS	SAR	SEM	SAC
Area	0.0079***	0.0074***	0.0076***	0.0074***
	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Rooms	0.1139***	0.1149***	0.1127***	0.1147***
	(0.0181)	(0.0123)	(0.0122)	(0.0122)
Bathrooms	-0.0623**	-0.0634***	-0.0615***	-0.0628***
	(0.0295)	(0.0199)	(0.0197)	(0.0198)
Age	-0.0013***	-0.0012***	-0.0010**	-0.0011***

	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Garage	0.1477***	0.1455***	0.1384***	0.1442***
	(0.0443)	(0.0396)	(0.0395)	(0.0395)
Front	0.0887***	0.0969***	0.0930***	0.0961***
	(0.0184)	(0.0180)	(0.0180)	(0.0180)
Ph	-0.0650	-0.0544	-0.0679*	-0.0561
	(0.0419)	(0.0392)	(0.0389)	(0.0392)
Pool	0.1264***	0.1266***	0.1242***	0.1272***
	(0.0342)	(0.0327)	(0.0312)	(0.0324)
Avenue	0.0482**	0.0343*	0.0424**	0.0351*
	(0.0194)	(0.0196)	(0.0196)	(0.0196)
Retiro	0.2639***	0.1157***	0.2672***	0.1239***
	(0.0344)	(0.0381)	(0.0568)	(0.0429)
San Nicolás	-0.0690**	-0.0603*	-0.0032	-0.0580
	(0.0301)	(0.0325)	(0.0575)	(0.0356)
Constitución	-0.2016***	-0.1486***	-0.1477***	-0.1489***
	(0.0267)	(0.0281)	(0.0383)	(0.0298)
Montserrat	-0.1121***	-0.0789***	-0.0516	-0.0772**
	(0.0265)	(0.0279)	(0.0503)	(0.0306)
SubwayD	0.0066	-0.0068	-0.0093	-0.0076
	(0.0270)	(0.0251)	(0.0266)	(0.0255)
ParkD	0.0400*	0.0521**	0.0563**	0.0536**
	(0.0228)	(0.0213)	(0.0246)	(0.0220)
SchoolD	0.0351	0.0114	0.0019	0.0078
	(0.0257)	(0.0234)	(0.0269)	(0.0244)
BRTD	-0.0041	0.0193	0.0249	0.0218
	(0.0223)	(0.0209)	(0.0265)	(0.0222)
Constant	10.8550***	7.6759***	10.8607***	7.8775***
	(0.0498)	(0.4937)	(0.0500)	(0.5834)
Rho (ρ)		0.2776***		0.2600***
		(0.0430)		(0.0508)
Lambda (λ)			0.6102***	0.1305
			(0.1002)	(0.1538)
Observations	672	672	672	672
R-squared	0.8690			
LR Test: Model vs. OLS		41.7287***	37.0948***	39.9131***
AIC		0.0497	0.0534	0.0498

Source: Own elaboration.
*Note: We report here coefficient and not marginal effects. Standard errors are in parenthesis. ***, **, and * indicate 1%, 5% and 10% significance respectively.*

5.2. Effect of proximity to BRT on residential property value: matched and propensity score weighted hedonic models

For the matching and weighting, we calculate propensity scores using a Probit for the probability of being up to 400 meters from the BRT with Avenue, neighborhood dummies, and localization dummies. The results of such models are presented in Table B.1 of Appendix B. Figure B.1 in the same appendix shows that the prices of apartments within Metrobus access have common support with those that are further away. In addition, Table B.2 reports that there are no significant differences between descriptive statistics of the treated and non treated group of houses.

Based on propensity scores, we estimate simple and spatial hedonic pricing models for those observations that could be matched (569 over 672). We also run our models for a trimmed sample (that is,, when we reduce the lower and upper tail of the estimated propensity scores and, as a result, we are left with 490 observations). The results are reported in Table 5 and show that the accessibility to Metrobus is again no significant in any of the cases and that SAR is again the preferred model.[15] The estimated coefficients for the rest of the variables only change slightly for some of them (this is the case, for PH and Avenue).

Then, Table 6 reports the results when, alternatively, we estimate the hedonic models using the propensity score to construct a weight for the full sample (n = 672). The best model is again SAR, which indicates that prices spatial dependence modeling is important. BRT impact on prices is again not significant. The effects of the other determinants remain, except for a few ones (this is the case of housings´ age and proximity to schools). Table 6 also shows that some of the models yield a negative significant coefficient for Metrobus. However, those models perform worse than SAR. Trimming the estimations does not change the sign and significance in any case (see last four columns in Tables 5 and 6) for the preferred model (SAR). Then, the no significance of BRT is robust to different models.

6. Summary and Conclusions

Bus Rapid Transit systems are expanding to several cities in the world. Part of that expansion is attributed to the cost-effectiveness of that type of transportation. There are several studies that assess the economic impacts of BRTs, and this is specially the case for land value uplift. There is quantitative evidence on the impact of BRTs on property values in several developing countries. This is particularly the case for Bogotá (Colombia), Seoul (Korea), Beijing and Guangzhou (China), Sydney and Brisbane (Australia), for example. The literature indicates

[15] Note that even if the effect is not significant, when we combine the estimated coefficients of BRT with average prices, the effect in prices is around $AR 2000, approximately 1.5% of property values.

that there are value land uplifts, but there are different in terms of size and significance. That difference may be attributed to specific local conditions as well as to data and methodological issues. With respect to the former, the impact may depend on: accessibility factors as urban crosswalks and sidewalks design (Estupinan and Rodriguez, 2008) and amenities provided (Salon et al, 2014); socio-demographic characteristics of transit users (Ma et al 2014), the distance to city center (Ma et al, 2014), consolidated tastes toward automobiles (Muñoz-Raskin, 2010), etc. In terms of the former, methods that predominate in the field are: spatial hedonic pricing (Zhang and Wang, among others) and quasi-experimental methods as propensity score matching (Perdomo 2011) and difference-in-difference (Mulley et al 2016 and Olaru et al 2017, for example).

Table 5. Results Hedonic price models with matching

	Matched simple				**Matched trimmed sample**			
	OLS	SAR	SEM	SAC	OLS	SAR	SEM	SAC
Area	0.0075***	0.0069***	0.0071***	0.0070***	0.0073***	0.0068***	0.0069***	0.0068***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Rooms	0.1305***	0.1326***	0.1278***	0.1318***	0.1435***	0.1431***	0.1407***	0.1428***
	(0.0178)	(0.0132)	(0.0130)	(0.0132)	(0.0194)	(0.0146)	(0.0144)	(0.0146)
Bathrooms	-0.0537	-0.0558**	-0.0505**	-0.0540**	-0.0415	-0.0473*	-0.0420*	-0.0453*
	(0.0330)	(0.0226)	(0.0223)	(0.0226)	(0.0371)	(0.0254)	(0.0249)	(0.0253)
Age	-0.0011**	-0.0009**	-0.0007	-0.0008*	-0.0014**	-0.0011**	-0.0009*	-0.0010**
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Garage	0.1279***	0.1261***	0.1101**	0.1226***	0.1077*	0.1153**	0.0960*	0.1092**
	(0.0491)	(0.0456)	(0.0449)	(0.0456)	(0.0579)	(0.0532)	(0.0523)	(0.0532)
Front	0.0862***	0.0933***	0.0959***	0.0939***	0.0897***	0.0967***	0.0978***	0.0967***
	(0.0199)	(0.0195)	(0.0194)	(0.0195)	(0.0218)	(0.0216)	(0.0213)	(0.0215)
Ph	-0.0952**	-0.0842**	-0.0919**	-0.0853**	-0.1252**	-0.1107**	-0.1267***	-0.1153**
	(0.0436)	(0.0426)	(0.0422)	(0.0426)	(0.0503)	(0.0478)	(0.0473)	(0.0478)
Pool	0.1702***	0.1742***	0.1824***	0.1786***	0.1485***	0.1453***	0.1529***	0.1505***
	(0.0425)	(0.0396)	(0.0377)	(0.0396)	(0.0469)	(0.0453)	(0.0428)	(0.0449)
Avenue	0.0293	0.0225	0.0274	0.0219	0.0293	0.0216	0.0266	0.0211
	(0.0218)	(0.0217)	(0.0208)	(0.0215)	(0.0250)	(0.0245)	(0.0233)	(0.0241)
Retiro	0.3090***	0.1705***	0.2627***	0.1759***	0.3610***	0.2076***	0.2872***	0.2183***
	(0.0376)	(0.0428)	(0.0676)	(0.0474)	(0.0395)	(0.0470)	(0.0599)	(0.0519)
San Nicolás	-0.0611*	-0.0407	-0.0285	-0.0431				
	(0.0329)	(0.0372)	(0.0636)	(0.0408)				
Constitución	-0.1983***	-0.1380***	-0.2068***	-0.1475***	-0.1460***	-0.1024***	-0.2011***	-0.1142***
	(0.0298)	(0.0348)	(0.0524)	(0.0401)	(0.0320)	(0.0347)	(0.0624)	(0.0423)
Montserrat	-0.1073***	-0.0622*	-0.0929*	-0.0681*	-0.0487	-0.0197	-0.0604	-0.0242
	(0.0316)	(0.0344)	(0.0562)	(0.0385)	(0.0327)	(0.0351)	(0.0521)	(0.0396)
SubwayD	0.0387	0.0186	0.0086	0.0162	0.0405	0.0224	0.0157	0.0193
	(0.0256)	(0.0266)	(0.0282)	(0.0272)	(0.0260)	(0.0276)	(0.0292)	(0.0283)
ParkD	0.0493*	0.0466*	0.0863***	0.0534*	0.0503*	0.0507*	0.0901***	0.0604**
	(0.0291)	(0.0268)	(0.0303)	(0.0291)	(0.0298)	(0.0278)	(0.0321)	(0.0306)
SchoolD	0.0711**	0.0405	0.0346	0.0381	0.0633**	0.0367	0.0264	0.0325

	(0.0287)	(0.0274)	(0.0318)	(0.0285)	(0.0296)	(0.0287)	(0.0332)	(0.0302)
BRTD	-0.0030	0.0198	0.0399	0.0242	0.0010	0.0267	0.0478	0.0333
	(0.0218)	(0.0213)	(0.0276)	(0.0232)	(0.0234)	(0.0230)	(0.0306)	(0.0258)
Constant	10.7836***	7.7579***	10.8155***	8.0431***	10.7117***	7.7766***	10.7785***	8.1730***
	(0.0532)	(0.5055)	(0.0623)	(0.6821)	(0.0566)	(0.5436)	(0.0689)	(0.7423)
Rho		0.2634***		0.2387***		0.2575***		0.2230***
		(0.0438)		(0.0590)		(0.0475)		(0.0644)
Lambda			0.6063***	0.1323			0.5998***	0,1818
			(0.0984)	(0.1787)			(0.1063)	(0.1807)
Observations	569	569	569	569	490	490	490	490
R-squared	0.8769				0.8796			
LR Test:								
Model vs.								
OLS		36.1670***	37.9688***	33.7239***		29.4387***	31.8227***	27.5292***
AIC		0.0505	0.0543	0.0506		0.0539	0.0579	0.0625

Source: Own elaboration.
Note: We report here coefficient and not marginal effects. Standard errors are in parenthesis.
****, **, and * indicate 1%, 5% and 10% significance respectively.*

Table 6. Results for weighted hedonic pricing models

	Weighted full sample				Weighted trimmed sample			
	OLS	SAR	SEM	SAC	OLS	SAR	SEM	SAC
Area	0.0056***	0.0050***	0.0051***	0.0049***	0.0056***	0.0049***	0.0050***	0.0049***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Rooms	0.1761***	0.1633***	0.1688***	0.1557***	0.1774***	0.1642***	0.1695***	0.1645***
	(0.0129)	(0.0118)	(0.0117)	(0.0120)	(0.0150)	(0.0138)	(0.0135)	(0.0142)
Bathrooms	-0.0367**	-0.0409**	-0.0357**	-0.0474***	-0.0383*	-0.0424**	-0.0354*	-0.0421**
	(0.0183)	(0.0167)	(0.0162)	(0.0169)	(0.0213)	(0.0194)	(0.0188)	(0.0197)
Age	0.0005	0.0006	0.0007*	0.0005	0.0005	0.0006	0.0008*	0.0006
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Garage	0.1352***	0.1452***	0.1391***	0.1437***	0.1473***	0.1600***	0.1481***	0.1598***
	(0.0381)	(0.0348)	(0.0342)	(0.0351)	(0.0456)	(0.0416)	(0.0407)	(0.0417)
Front	0.1433***	0.1555***	0.1450***	0.1632***	0.1441***	0.1567***	0.1473***	0.1565***
	(0.0212)	(0.0194)	(0.0190)	(0.0196)	(0.0250)	(0.0228)	(0.0222)	(0.0229)
Ph	-0.2058***	-0.1437***	-0.1648***	-0.1368**	-0.2081***	-0.1421**	-0.1610***	-0.1425**
	(0.0578)	(0.0531)	(0.0527)	(0.0531)	(0.0674)	(0.0618)	(0.0605)	(0.0620)
Pool	0.2739***	0.2438***	0.2452***	0.2447***	0.2747***	0.2422***	0.2537***	0.2430***
	(0.0479)	(0.0439)	(0.0396)	(0.0454)	(0.0561)	(0.0512)	(0.0456)	(0.0519)
Avenue	0.0437*	0.0228	0.0379*	0.0170	0.0454	0.0209	0.0365	0.0211
	(0.0248)	(0.0228)	(0.0219)	(0.0233)	(0.0292)	(0.0268)	(0.0252)	(0.0268)
Retiro	0.3340***	0.1717**	0.4554***	0.1255***	0.4075***	0.1909***	0.2211***	0.1915***
	(0.0721)	(0.0678)	(0.1251)	(0.0485)	(0.0543)	(0.0548)	(0.0794)	(0.0557)
San Nicolás	-0.0734	-0.0299	0.2244*	-0.0619				
	(0.0818)	(0.0748)	(0.1214)	(0.0548)				
Constitución	-0.2067***	-0.1053	-0.0906	-0.1205**	-0.1335**	-0.0696	-0.3641***	-0.0710
	(0.0735)	(0.0678)	(0.0640)	(0.0513)	(0.0538)	(0.0495)	(0.1294)	(0.0527)
Montserrat	-0.0613	-0.0084	0.1365	-0.0351	0.0131	0.0317	-0.0757	0.0312
	(0.0765)	(0.0700)	(0.0959)	(0.0513)	(0.0606)	(0.0553)	(0.1054)	(0.0562)
SubwayD	-0.0498*	-0.0367	-0.0232	-0.0470*	-0.0499	-0.0376	-0.0286	-0.0374

	(0.0290)	(0.0265)	(0.0285)	(0.0245)	(0.0338)	(0.0308)	(0.0323)	(0.0310)
ParkD	0.1570***	0.1339***	0.1577***	0.1234***	0.1563***	0.1343***	0.1825***	0.1347***
	(0.0418)	(0.0382)	(0.0355)	(0.0347)	(0.0487)	(0.0444)	(0.0422)	(0.0447)
SchoolD	0.1216***	0.0692***	0.0710**	0.0656***	0.1226***	0.0672**	0.0719*	0.0673**
	(0.0289)	(0.0269)	(0.0330)	(0.0232)	(0.0336)	(0.0312)	(0.0383)	(0.0314)
BRTD	-0.1028***	-0.0302	-0.0190	-0.0427**	-0.1042***	-0.0247	-0.0066	-0.0241
	(0.0218)	(0.0212)	(0.0262)	(0.0182)	(0.0255)	(0.0248)	(0.0307)	(0.0258)
Constant	10.7095***	6.7660***	10.7309***	6.1846***	10.6331***	6.5393***	11.0425***	6.5707***
	(0.0812)	(0.3918)	(0.1374)	(0.3693)	(0.0747)	(0.4527)	(0.1751)	(0.5817)
Rho		0.3432***		0.3984***		0.3602***		0.3575***
		(0.0335)		(0.0323)		(0.0394)		(0.0509)
Lambda			0.8227***	-0.5425***			0.8795***	0.0196
			(0.0621)	(0.1737)			(0.0569)	(0.2218)
Observations	672	672	672	672	497	497	497	497
R-squared	0.9195				0.9191			
LR Test: Model vs.								
OLS		105.0819***	175.6095***	157.5672***		83.6863***	239.1986***	82.4879***
AIC		0.0600	0.0943	0.0613		0.0642	0.1506	0.0643

Source: Own elaboration.
*Note: We report here coefficient and not marginal effects. Standard errors are in parenthesis. ***, **, and * indicate 1%, 5% and 10% significance respectively.*

This paper gathers residential properties´ data around Avenue 9 de Julio Metrobus (the local word for BRT), which is on one of the main streets of Buenos Aires (Argentina´s capital). This is one of the innovations since there is no study for the impact on property values of any of Argentina´s BRTs. A second novelty of this article is that it combines different methodologies in order to compensate for their limitations. Spatial hedonic pricing (SHP) controls for spatial dependence (the fact that prices of surrounding properties are related) and spatial error autocorrelation (to take into account that there are unobservable variables that determine neighborhood real estate prices). However, when considering a BRT variable as a determinant of house prices, the assumption behind the SHP estimation is that being outside or inside the BRT influence is random. That may not be the case. In fact, the location of BRT may depend on pre-existing infrastructure conditions. Not considering them may bias the estimation of the impact of BRT on real estate prices. Hence, we combine the SHP regressions using matching and weighted regressions using propensity score estimates. In addition, we take into account that those score may be based on few observations when they take very low and high values. Hence, we run robustness checks using a trimmed sample for all our estimations.

The database is built with data from two real estate internet sites for five neighborhoods surrounding the 9 de Julio Metrobus extension. It contains several characteristics for each residential property (area, age of construction, if it has a garage or a pool, etc.). In addition to if it is or not in the area of influence of BRT (calculated as within 400 m. of the station), the empirical strategy adds other determinants of apartment prices as if it is located close to a subway station, a park, etc. The number of observations is around 600, varying with the regressions types.

The findings show that BRT has no significant impact on property prices for Metrobus 9 de Julio. This lack of significance is similar to results on Zhang and Wang (2013) and Ma et al (2014) for Beijing (China). The lack of a significant impact may be due to local conditions. In particular, the Avenue 9 de Julio is a traditional corridor and people living there are not the only ones that use the services of the BRT. People that come to downtown only for work (and often from outside of the city limits) are those that use most that transportation mode.[16]

This study can be considered an important step to knowledge of BRT impact in Latin American cities. Limitations of the study remain. One is sample size. A larger sample size could provide more robust results. However, that limitation goes beyond our control since it results from the real estate market movement. Another drawback is related to working with asking and not real prices. Again, this is unavoidable since, being Argentina a developing country, relatively few transactions are based on banking loans. Hence, people tend to under declare the value of the transaction when buying a house, and so there is no easy way to construct a database with actual prices.

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[16] The lack of significance could also be due to the fact that the BRT dummy variable may capture two effects at the same time. A positive one (related to accessibility) and a negative one (linked to nuisance effects associated to the proximity of a BRT station as air pollution, vibrations, visual impacts or noise). One effect can predominate over the other or they can cancel each other. However, the fact that the Metrobus 9 de Julio is located in the middle of a broad street reduces the nuisance effect. Hence, that explanation is less likely for this particular case.

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Annex A. Database for Metrobus 9 de Julio

Figura A.1. Picture of Metrobus 9 de Julio

Source: http://www.telam.com.ar/notas/201706/191028-el-metrobus-9-de-julio-distinguido-como-el-mejor-logro-de-transporte-mundial.html

Table A.1. Variables names, units and sources

	Detail	Source
Apartment´characteristics		
Price	in US dollars	Argenprop y Buscainmueble
Area	in m^2	Argenprop y Buscainmueble
Rooms	Number of rooms	Argenprop y Buscainmueble
Bathrooms	Number of bathrooms	Argenprop y Buscainmueble
Age	in years	Argenprop y Buscainmueble
Garage	=1 if it has a garaje	Argenprop y Buscainmueble
Front	=1 if it is located in the front of the building	Argenprop y Buscainmueble
Ph	=1 if it is a condominium	Argenprop y Buscainmueble
Pool	=1 if it has a pool	Argenprop y Buscainmueble
Localization		
Avenue	=1 if it is on an avenue	Mapa Interactivo GCBA
Retiro	=1 if it is in Retiro	Mapa Interactivo GCBA
San Nicolás	=1 if it is in San Nicolás	Mapa Interactivo GCBA
Constitución	=1 if it is in Constitución	Mapa Interactivo GCBA
Monserrat	=1 if it is in Monserrat	Mapa Interactivo GCBA
San Telmo	=1 if it is in San Telmo	Mapa Interactivo GCBA

SubwayD	=1 if within 200 meters of subway station	Buenos Aires Data, GCBA
ParkD	=1 if within 200 meters of a park	Buenos Aires Data, GCBA
SchoolD	=1 if within 200 meters of a school	Buenos Aires Data, GCBA
BRTD	=1 if within 400 meters from a BRT station	Buenos Aires Data, GCBA

Source: Own elaboration.

Appendix B.

Table B.1. Probit models to calculate propensity scores

	Modelos Probit
	Dependent variable: BRTD
Avenue	0.0210
	(0.1312)
Retiro	1.9265***
	(0.2078)
San Nicolás	0.8689***
	(0.2428)
Constitución	1.3568***
	(0.2075)
Montserrat	0.9934***
	(0.2172)
SubwayD	0.1236
	(0.1526)
ParkD	-0.6009***
	(0.1557)
SchoolD	0.2965**
	(0.1488)
Constant	-1.7854***
	(0.2205)
Observations	672

Source: Own elaboration.
Note: We report here coefficient. Standard errors are in parenthesis.
****, **, and * indicate 1%, 5% and 10% significance respectively.*

Figure B.1. Common support among properties close and far (400 m.) from BRT

Before **After**

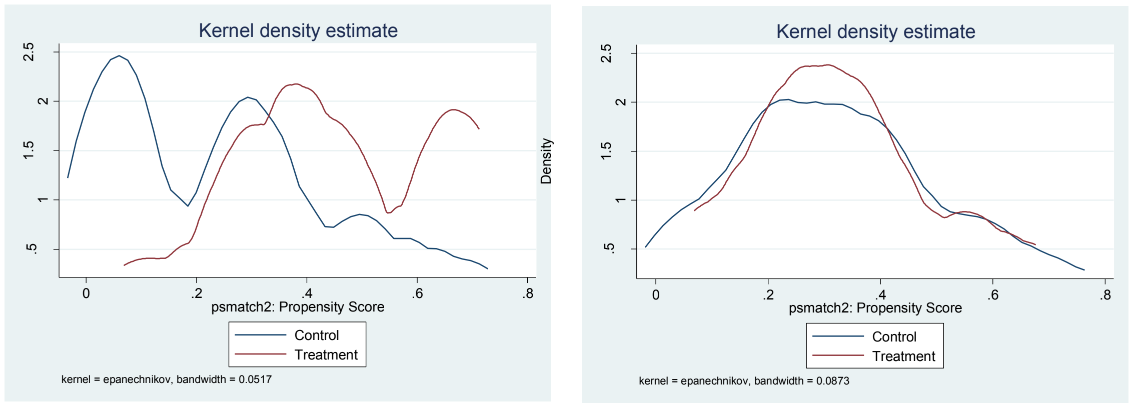

Table B.2. Comparison descriptive statistics for treated and untreated

Variables for matching	**With matching**		
	Mean		t-test
	Treated	*Control*	*Difference in Means*
Avenue	0.29	0.27	0.44***
Retiro	0.37	0.36	0.21***
San Nicolás	0.08	0.12	-1.15***
Constitución	0.35	0.29	1.28***
Monserrat	0.16	0.19	-0.91***
SubwayD	0.20	0.16	0.9***
ParkD	0.11	0.09	0.65***
SchoolD	0.84	0.92	-2.61**
n	203	366	569

Source: Own elaboration.
Notes: Treated/untreated means within/ouside 400 m. from nearest BRT station.
****, **, and * indicate 1%, 5% and 10% significance respectively.*