Property Value Assessment in Rio De Janeiro: The Effects of Transport Investments

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ABSTRACT

This research assesses the effects of public urban transportation investments on property prices in Rio de Janeiro, Brazil. Our hypothesis is that opening a new transportation station increases access to the city for properties in their vicinity. The closer to the station, and the more accessibility to jobs the station offers, the more likely it is expected to be valued. Our contributions for this literature are threefold: first, we assess together two types of service, Subway and BRT. Second, we test other variable that represent accessibility, as well as distance to the station. A growing number of transport agencies, particularly in North America and Europe, use similar accessibility analysis to compare the benefits of potential transportation investments and evaluate their social impacts. The third contribution is to use home-sharing data (Airbnb) as a proxy for property prices. It allows us to adopt a fixed effect control variable for houses rather than the traditional hedonic regression approach. Results corroborates literature that shows that major improvements to public transport systems result in significant changes in real-estate prices. In cities with complex geographical barriers, like Rio de Janeiro, considering distance to station rather than other measures of accessibility can underestimate the capitalization effects.

1. Introduction

The 2014 FIFA World Cup and 2016 Olympics Games held in Rio de Janeiro were accompanied by substantial public investments to improve the city's public transport network. Nevertheless, Rio’s population suffers with one of the worst congestions in Brazil. Pereira (2017) shows that, due to the concentration of transport infrastructure expansion in areas of the city that were already relatively accessible to a large part of the population, the accessibility benefits from the recent cycle of investments generally accrued to middle- and higher-income groups, reinforcing existing patterns of urban inequality.

This research broad objective is to assess the heterogenous effect of these public investments to improve the Rio de Janeiro public transport network on property prices.

If housing markets are efficient (and supply of new housing is inelastic), residential property prices will reflect all the benefits and costs to commuters that a location offers in terms of proximity to railway stations, and the level of service that the station offers (Gibbons and Machin, 2005).

A conventional approach in this field considers the Euclidian distance to the station as a proxy of accessibility gain, implicit considering that the level of service the stations offer is homogeneous. Billings (2011) also argues that estimated price gradients are insufficient to identify the impacts of rail transit. Gibbons and Machin (2005) define rail access in two ways: by distance to a station, and by the service frequency at the nearest station.

Due to transportation barriers created by the disordered urbanization or physical geography of Rio de Janeiro, it is expected to observe stations with different impact levels on the value of surrounding properties. Therefore, the distance for the station does not fully represent the potential impact for the new transportation infrastructure. We alternatively use a variable that represents how many job opportunities users could reach from their households.

In regard to the quality of service, the research assesses two types of transport infrastructures: Metro and Bus Rapid Transit (BRT). BNDES (2015) points that the cost of construction of high-capacity urban subway systems in Brazil can escalate to R$ 600 million per kilometer. In contrast, BRT lines may offer a similar capacity benefits at an 80% lower cost. Beyond the construction costs, there are some drawback that such lines would cause, as noise and pollution. Ahlfeldt et al (2019) has produced evidence on negative rail noise capitalization effects. Therefore, the potential construction cost savings must be weighed against the disamenities. So, one contribution of this research is to extend this non-trivial trade-off conducting a comparative analysis of land price capitalization effects of these two transport infrastructures.

On top of these main questions, this research contributes to the literature on transportation investments capitalization effects in developing countries, especially in Brazil. Quantitatively, the results in the literature are heterogeneous and focused in developed countries' cities. There is lack of evidences of Latin America's cities, despite the recent rise in new projects. So, this research also gains interesting insights into how the comparison of capitalization effects in developing cities and developed ones.

This work uses home-sharing data (Airbnb) as a proxy for property prices. Home sharing market has some advantages in comparison with traditional markets. The data base observes all[1] short-term rent transactions (listings) throughout time range for each property. It enables the adoption of panel model with property fixed effect in order to control for all home's characteristics, rather than standard use hedonic pricing method.

Other advantage of short-term rental market is liquidity. The general short-term rent length is a few days, while in traditional markets transactions duration takes years. It

[1] Airbnb is the main short-term rents platform in Rio de Janeiro

means that the anticipation effect, that is often identified as relevant in traditional markets, has no direct participation on short-term rents.

This research also has some policy implications. The results may guide decision of new investments or can be used by planners and public agencies that aim to apply Land Value Capture (LVC) schemes. Rio de Janeiro, or other cities, can deploy a LVC program that taxes a share of the property value increase from transport investments to reinvestments.

2. Related literature

The basic theory on real estate prices argue that as a location becomes more attractive, due to certain characteristics, demand increases and thus the bidding process pushes prices up. Closeness to the Center Business District (CBD) is considered as an attractive quality that increases property prices. Transport infrastructure may reduce demand frictions around CBD (Fejarang, 1994). Properties close to a transport infrastructure enjoy benefits from transportation time and cost saving to CBD. It may be expected that the price curve will have a negative slope; Negative housing price gradients indicate a positive impact of transport.

In general, the empirical studies conducted in this area, on the impact of transport investments on property values, are diverse in methodology and focus. There is no general standardized method for the calculation of changes in real estate prices. Most studies used the hedonic pricing method, but studies differed in estimation methods. Other studies reported changes in property values based on comparisons with control group areas. Overall, the literature finds heterogeneous but robust evidence that transport infrastructures increases local property values (Ingvardson and Nielsen, 2018).

Our contributions for this literature are threefold: first, this work uses home-sharing data (Airbnb) as a proxy for property prices. Kung (2016) shows that the increases to rental rates and house prices occur through two channels. In the first channel, home-sharing increases rental rates by inducing some landlords to switch from supplying the market for long-term rentals to supplying the market for short-term rentals. The increase in rental rates through this channel is then capitalized into house prices. In the second channel, home-sharing increases house prices directly by enabling homeowners to generate income from excess housing capacity. This raises the value of owning relative to renting, and therefore increases the price-to-rent ratio directly.

Methodologically, this data offers some advantages. As the average home sharing contract duration is a few days, the same property has several transactions during the sample period. It allows the repeat-sales method approach. By controlling for the effect of omitted variables that do not change over time, the repeat-sales estimates are potentially subject to less bias than standard hedonic estimates (McMillen and McDonald, 2004). In home-sharing markets, rather than in real estate markets, the reduction in bias does not comes at expense of a large decrease in sample size and possible selection bias, because almost all contracts have a few days of duration. We

improve on previous methods by using a fixed effect control variable for properties rather than the traditional hedonic regression.

Our approach is similar to Gibbons and Machin (2005). They also use a fixed effect control variable in a difference-in-difference methodology to look at before-and after outcomes of a transport infrastructure change. The main difference is that they observe repeat sales of properties in the same postcode unit, an administrative unit containing 10–15 households. This makes possible to compare the change in real estate prices in postcodes that experienced changes in rail access with the change in real estate prices in postcodes that did not in a difference-in-differences estimation. In our case, as our data set observations is on the property level, so we can control for omitted variables in the property characteristics that do not change over time.

Other advantage of this data set is that we do not expect anticipated effect on short term rents. McMillen and McDonald (2004) produced empirical results showing that the opening of the transit line had been anticipated in the housing market six years before construction was completed. They argue that housing rent does not rise before opening day, but house price does rise in anticipation of the increase in housing rent, which is caused by the improvement in accessibility. Housing rents contract that begins before but finish after the opening of the transit line may suffer anticipation effect.

The second main contribution is about the discussion of methods to account the accessibility gains and the transmission to real estate prices. A conventional approach in this field considers the Euclidian distance to the station as a proxy of accessibility gain, implicit considering that the level of service the stations offer is homogeneous. As discussed by Bowes and Ihlanfeldt (2001), a total of four factors may account for transport station on property values. One of the positive factors is the access advantage provided by rail stations. The second is the commercial services that may be attracted to neighborhoods and benefit nearby residents, regardless of whether or not they ride the transit. The other effects are negative externality effects emitted by the station, such as noise, pollution, and the unsightliness of the station, especially if it includes a parking lot. The other negative factor is that crime may be higher in station areas, because of the improved access to the neighborhood provided to outsiders.

We argue that estimate price gradients are insufficient to identify the impacts of transit investments in a context of heterogeneous neighborhoods. Billings (2011) estimates results suggest that LRT investment may be more an economic development tool for specific neighborhoods rather than a transportation amenity.

In addition to distance to the closest station, we test the effect of an alternative accessibility measures on real estate prices, in terms of how many job opportunities people could reach from their households via public transport and walking under 60 minutes (Pereira et al, 2017). A growing number of transport agencies particularly in North America and Europe use similar accessibility analysis to compare the benefits of potential transportation investments and evaluate their social impacts. Billings (2011) uses distance to the Downtown (Distance to CBD) as proxy to accessibility to the city.

The third main contribution is to assess two types of service, Metro and BRT, which allows us to take account on the difference of quality that each type provide, on the perspective of property prices. It is possible because both types of service were open almost at the same time. Gibbons and Machin (2005) have similar approach, considering differences between Metro style London Underground/Docklands Light Railway services and the scheduled, limited stop services provided on the main-line Network Rail system.

Also, to our knowledge, ours is the first ex-post effects evaluation of transport improvements in a Brazilian city. There is lack of such empirical literature in development countries. Rio de Janeiro, in particular, is one of the largest and richest cities in the global south, with the most expensive property prices in Brazil. In addition, the city's transportation investment was part of the preparation to host 2016 Olympic Summer Games. So, this research is also related to the literature that assess the legacy of sports mega events.

3. Background

In preparation for the mega sport events, Rio de Janeiro invested more than 4.5 billion dollars in its public transport network. Some of the most significant investments included the extension of a Metro line, the construction of a light-rail system and two BRT corridors that together stretch approximately 108 kilometers across the city. One of the key motivations of public authorities was to use those mega-events to leverage urban development and improve the city's transport conditions.

In regard to mobility conditions, Cariocas (who lives in the city of Rio) are, in general, public transit heavy users. Public transit ridership represents about 50% of commute trips in Rio de Janeiro metro area. It is almost the same share of New York, who has the higher share of public transit in US. Despite it, most of the population of Rio also faces extremely poor transport conditions. The city's public transport system stands out as one of the most expensive in the world (UN HABITAT, 2013) and is coupled with a rapid motorization trend, giving Rio one of the highest average commute times among global cities (Pereira and Schwanen, 2013). Average one-way commute time reached 49.6 minutes in 2014, when the new stations were open. This is the worst commuting time in Brazil. So, it is likely that new stations that offers commute time savings will succeed in attracting new users.

Rio de Janeiro is one of the largest and richest urban areas in the Global South, with over 12 million inhabitants. It is also among the most unequal cities in the world in terms of income distribution (UN-HABITAT, 2010), having experienced increasing income inequality in recent decades (Ipea, 2016) and historical spatial segregation (Ribeiro et al., 2010). Most of the population of Rio also faces extremely poor transport conditions. The high income inequality is usually related to spatial inequality, and, consequently, heterogeneous effects on property prices.

In regard to physical geography, Rio de Janeiro has its geography marked by the presence of three mountainous structures the shapes the city's areas. Although this feature offers city dwellers lush natural beauties, on the other hand it poses challenges

to the transportation infrastructure and hampers travel in the urban space. The east side of the city, where the Center and the South Zone are located, is squeezed between the sea and the mountains of the Tijuca mountain structure. This region is home to 58% of jobs in only 8% of the territory. Displacements from the outside to the inside of the eastern part of the city usually suffer with long congestion.

3.1 Rio's Transportation Infrastructure

Between 2010 and 2016 Rio mobilized an investment of approximately U$5.7 billion in the public transport system. It includes the construction of a light-rail system in the city center, three new BRT corridors and the expansion of a subway line that, combined, form a high-capacity transport ring connecting several neighborhoods across the city, two airports and the Olympic sports venues.

Subway Line 4 allows the connection between Line 1 and Line 2 and the BRT system through 16 km of extension and 5 stations: Jardim Oceânico, São Conrado, Antero de Quental, Jardim de Alah and Nossa Senhora da Paz. Jardim Oceânico station connects Barra da Tijuca neighborhood (West Zone) to the Ipanema neighborhood, where the subway system was already in operation. West zone has 41% of city's population.

The BRT was implemented from June 6, 2012 through Aug 1, 2016 in the city of Rio and currently at a cost of R$ 4.7 billion and has 3 bus corridors: TransOeste, TransCarioca and TransOlímpica. There is also an expansion of the BRT Transoeste, called Lote Zero, that connects Alvorada Terminal with Jardim Oceânico Subway Station.

Transoeste was the first express corridor in operation with its first phase inaugurated in 2012 with 52 km, connecting the Alvorada Terminal in Barra da Tijuca, Santa Cruz and Campo Grande. The reduction of travel time was almost 50% and is integrated with other modes and corridors expressed.

The TransCarioca connect the Alvorada Terminal in Barra da Tijuca to Tom Jobim International Airport and has 39 km. The implementation reduced travel time by 60% and carried up to 500,000 passengers per day.

The TransOlímpica has an extension of 26 km and its capacity is estimated at 400 thousand passengers per day.

4. Methodology

Our hypothesis is that opening a new transportation station increases access to the city for properties in their vicinity, and that impacts the local housing market dynamics. The closer to the station, and the more access the station offers, the more likely it is to be valued.

We adopt a difference-in-differences methodology with a continuous treatment variable. It means that the intensity of the treatment varies with the distance from

property to the new station. We compare property prices before (untreated) and after (treated) the Subway Line 4 (treatment) at august 2016. As the Line 4 connected BRT lines to Subway, BRT is also considered as suffering the treatment.

We drop from the sample the Olympic games month, august 2016 because during this period the demand was extraordinarily high. So, we chose to have only two months after the treatment. We think it is enough because we have a good sample in these two months and the more time we include in our sample after the treatment, the more the station vicinity may be affected by other factors, such as the commercial services that emerges.

4.1 Standard hedonic regression

We follow two approaches. The starting point is the standard hedonic regression with observed home characteristics. Then, we run regressions with property and time fixed effects. The property fixed effects are used to control the effect of changes in observed and non-observed product quality.

We estimate the effects on property prices (with data at the home level) through the following equation. Let Y_{isct} be the property price of property *i* and closest transport station *s* in Neighborhood *c* in year-month *t*, and let $Dist_{isct}$ be Euclidean distance between the property and the closest urban transportation station. We assume the following causal relationship between Y_{isct} and $Dist_{isct}$ before and after the new station, controlled by the dummy *Dtreat*, that is equal 1 during the months after treatment:

$$ln(Y_{ist}) = \alpha + \beta_1 ln(Dist_{ist}) + \beta_2 ln(Dist_{ist}) * Dtreat + X_{it}\gamma + Z_{ct} + T_s\theta + W_t\tau + \varepsilon_{isct} \quad (1)$$

X_{isct} is a vector of observed home characteristics, Z_{ct}, is a vector of neighborhood public transportation accessibility, T_s is a vector of observed transport station characteristics and W_t is fixed effects for month-year.

4.2 Fixed effect panel model

In the fixed effect panel model, we deploy a fixed effect panel model, controlling for home characteristics and time:

$$ln(Y_{isct}) = \beta_1 ln(Dist_{isct}) * Dtreat + \alpha_i + W_t\tau + \varepsilon_{isct} \quad (2)$$

Doing so, we remove the effect of the time-invariant home and neighborhood characteristics, in order to assess the net effect of the predictors (type of service, distance and accessibility) on the outcome variable (price).

Each property is linked to it closest station, considering station impacts up to a maximum distance of 2.5 kilometers. We consider a distance cap of 0.5 km for the continuous treatment variable. It means that beyond this distance the treatment remains fixed in 0.5. In other words, we assume that there are no capitalization losses (or gain) beyond this distance. It is important to highlight that in general the walking distance in comparison to Euclidean distance is 1.6, that is, 0.5 km in Euclidean

distance represent 0.8 km in walking distance. It is also important to notice that Rio's warm and humid weather, mainly during the summer, may impact the willingness to walk to the station.

5. Data

The study uses micro-level data for an entire city of Rio de Janeiro, rather than designated sample areas. For home characteristics, we use property's quantitative information available. For vector of observed transport station characteristics, we use the station's accessibility data. For transport infrastructure database, we have information about all the BRT and Subway stations, including the latitude – longitude and the opening date. In regard to accessibility data, it is used Pereira et al (2017), which consider geolocated timetables of Rio's public transport organized in GTFS format combined with fine-grained sociodemographic data from the population census and geolocated data on jobs.

5.1 Airbnb

The world's biggest online marketplace and hospitality service for people to lease or rent short-term lodging. Our data source is AirDNA analytics, that is based on Airbnb data gathered from information publicly available on the Airbnb website. According to Barron et al. (2017), these approaches rely on Airbnb advertised listings rather than booked listings, which means they are not capable of determining whether an advertised listing was booked or not and are likely to overestimate bookings. Second, and related, they fail to collect accurate occupancy rates. Third, these sources collect Airbnb asking prices rather than transaction prices. Some asking prices are far above the market price, resulting in no booking activity, and in other cases guests receive lower rates via negotiations with the host or longer-term stay (e.g. 7+ days) discounts. Using asking prices overestimates Airbnb prices and profitability, and consequently, measures of short-term rental rates.

Our sample is composed for Rio de Janeiro city data, from October 2014 to October, 2016. The data is composed by two databases. The first is property data, containing location information (Neighborhood and lat-long), quantitative information (# bedrooms; # bathrooms; # Max guests), qualitative information (Overall rating; # of reviews), business conditions (Cancellation policy; Minimum Stay; Extra People Fee; Security Deposit). The sample is composed by 65650 homes.

The second database is the advertised listings. It is aggregated monthly and daily. We use the monthly data, that contains 705709 information, each one represents a month report for property. The data also brings other information, as Occupancy Rate; Revenue; ADR (average daily rate); Number of Reservations; Reservation Days; Available Days; Blocked Days.

5.2 Transport infrastructure database

We have information about all the BRT and Subway stations, including the latitude – longitude and the opening date.

5.3 Accessibility

Rio de Janeiro's accessibility database from Pereira et al (2018), which consider geolocated timetables of Rio's public transport organized in GTFS format combined with fine-grained sociodemographic data from the population census and geolocated data on jobs. The paper conducts a before-and-after comparison of Rio's transport system to estimate the change in accessibility that resulted from recent policies implemented in Rio between 2014 and 2017.

They estimate accessibility in terms of how many job opportunities people could reach from their households via public transport and walking under 60. A growing number of transport agencies particularly in North America and Europe use similar accessibility analysis to compare the benefits of potential transportation investments and evaluate their social impacts.

Figure 1. Histogram of job accessibility for the entire sample (1 = 100% of jobs reached within 60 minutes)

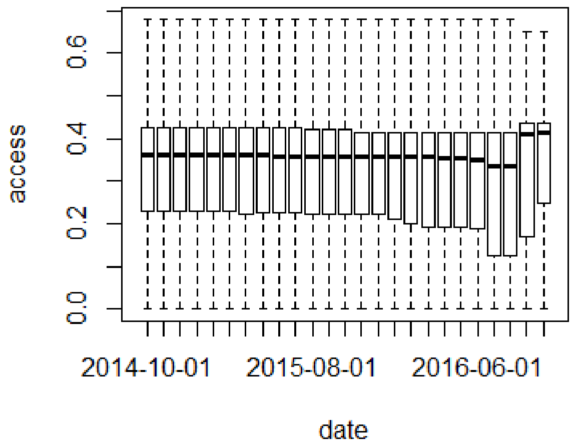

Figure 1 shows the increase in job accessibility caused by the new transport infrastructure.

6. Regression estimates

Initial results provide estimates for the hedonic price estimator. We begin by estimating the more aggregated impact on Subway Line 4 and BRT to show the results without considering regional heterogeneity.

We deploy the same approach to fixed effect panel model. In additional, we try other variables as measure of accessibility, rather than distance to station. Then, we run the Subway Line 4 regression splitting the sample in stations in order to highlight the differences in the results due to heterogeneity in neighborhoods.

We run log-log regression in order to interpret the coefficients as elasticity.

6.1 Hedonic Regression

Figure 2 shows regression estimates of the model in equation (1) using the data described in the previous section. After controlling for observed house and neighborhood characteristics[2], and allowing time fixed effects, we estimate the effects of station accessibility and distance on average daily rate (ADR).

Figure 2. Hedonic regression

	Dependent variable: log(ADR)					
	Line 4	BRT	Line 4	BRT	Line 4	BRT
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)	-0.031***	0.032*	-0.028***	0.024	-0.030***	0.050***
	(0.009)	(0.017)	(0.008)	(0.016)	(0.009)	(0.018)
log(Distance)*dtreat	0.028	-0.136***			0.021	-0.111***
	(0.025)	(0.034)			(0.025)	(0.034)
log(jobs)			-0.040**	0.115***	-0.038*	0.110***
			(0.020)	(0.018)	(0.020)	(0.019)
Housing and Neighborhood characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Property fixed effects	No	No	No	No	No	No
Observations	17,341	9,592	17,334	9,365	17,334	9,365
R2	0.552	0.464	0.552	0.469	0.552	0.469
Adjusted R2	0.551	0.460	0.551	0.465	0.551	0.466
Note:				*p<0.1; **p<0.05; ***p<0.01		

Columns (1), (3) and (5) use as sample all properties that the closest transportation station is in Metro Line 4. Columns (2), (4) and (6) are the same for BRT. We use as accessibility measure in columns (1) and (2) distance to closest station; in columns (3) and (4) job opportunities; in columns (5) and (6) we combine both measures together.

The first line shows that, during pre-treatment period, the closer properties are to the at Line 4 station localization, higher the ADR. It means that even before the treatment, properties closer to stations had higher prices. The opposite happens in BRT, that is, before the treatment, properties closer to stations had lower prices.

In post-treatment period, we see a negative housing price gradient to BRT line (negative housing price gradients indicate a positive impact of opened transit) in both columns (2) and (6). Distance post-treatment showed no capitalizations effect. In regard to accessibility to jobs, the estimation presents the opposite effects in Line 4

[2] We use data available at Airdna database: number of beds, maximum number of guests, listing type (entire home/apt, private room and shared room), Property type (apartment, house, loft, etc.), neighborhood and station.

and BRT. The first showed unexpected negative effect and the second a positive effect. In all cases the effect are statically significant.

6.2 Panel regressions

Erro! Fonte de referência não encontrada.e 3 shows regression estimates of the model in equation (2) using the data described in the previous section. After allowing time and property fixed effects, we estimate the effects of station accessibility and distance on average daily rate (ADR). We performed the same samples as described in Figure 1.

Figure 3. Aggregated Panel Regression

	Dependent variable:					
	log(ADR)					
	Line 4	BRT	Line 4	BRT	Line 4	BRT
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)*dtreat	0.014	-0.043*			0.001	-0.049**
	(0.014)	(0.025)			(0.015)	(0.025)
log(jobs)			-0.062**	-0.050	-0.061**	-0.068
			(0.027)	(0.063)	(0.030)	(0.063)
Housing and Neighborhood characteristics	No	No	No	No	No	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Property fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,056	9,465	18,049	9,246	18,049	9,246
R2	0.00001	0.001	0.00003	0.0003	0.00004	0.001
Adjusted R2	-0.318	-0.782	-0.317	-0.784	-0.317	-0.783
Note:				*p<0.1; **p<0.05; ***p<0.01		

In this regression all variables that were constant before and after treatment are captured by the property fixed effect. For this reason, just accessibility would cause changes in property price. Figure 2 shows that distance to station remain effective in explaining price for BRT, even with less significance. In regard to Line 4, neither accessibility variable could explain.

Figure 4. Line 4 Panel Regression

	Dependent variable:					
	log(ADR)					
	JdOceanico	Ipanema/Leblon	JdOceanico	Ipanema/Leblon	JdOceanico	Ipanema/Leblon
	(1)	(2)	(3)	(4)	(5)	(6)
log(Distance)*dtreat	-0.171*	0.019			-0.087	0.003
	(0.100)	(0.014)			(0.115)	(0.016)
log(jobs)			0.193**	-0.084***	0.155	-0.082***
			(0.088)	(0.028)	(0.101)	(0.031)

Observations	1,469	16,587	1,462	16,587	1,462	16,587
R2	0.003	0.0001	0.010	0.0005	0.010	0.0005
Adjusted R2	-0.606	-0.305	-0.592	-0.305	-0.593	-0.305
Note:						*p<0.1; **p<0.05; ***p<0.01

In Figure 3, we desegregate Line 4 sample in stations. Columns (1), (3) and (5) use as sample the properties that have as closest station Jardim Oceanico Station. Columns (2), (4) and (6) uses the remining Line 4 properties.

These regressions disclose the different patterns in Line 4. Jardim Oceanico Stations real estate prices are (weakly) related to distance and significantly related to the increase in accessibility to jobs opportunities, while the others properties in the vicinity of Line 4 stations are not related to distance and significantly related to job accessibility, but with the unexpected sign.

It important to highlight that the introduction of job accessibility improved the assessment of the relationship between price capitalization and accessibility. The traditional distance-to-station variable was not able to explain real estate gains. This variable proved to be effective both as a substitute and as a complement to the distance-to-station.

7. Discussion

Figures 2 and 3 present coefficients of interest for standard Hedonic regression as well as additional fixed effect panel model specifications. Results are organized similarly for both transport types (Subway and BRT) and we only report the coefficient of interest based on separate regressions conducted for each column heading.

In regard to the methodologies, there are slightly difference in results. In both cases we find distance-to-stations coefficients statistically equal zero to Line 4 and negative to BRT. For job accessibility, results remain significantly negative for Line 4 and insignificant to BRT. This outcome may be explained by the difference in methods for controlling property characteristics. While hedonic regression uses observable variables of the real estate or region, in the fixed-effect model each property has a dummy variable, which makes it possible to control by observable and unobservable factors. This, in theory, controls by all factors, but the treatment.

Some results were the opposite of what was expected. In the case of the aggregate regression for the whole Line 4, we find a negative coefficient for accessibility to jobs, while when we disaggregate the Jardim Oceânico station from Line 4, we obtained the result as expected for this station. We also find a positive coefficient for job accessibility for BRT in Hedonic regression.

This result may be related to economic and geographic differences between regions. Ipanema and Leblon are located in the South Zone and are the richest neighborhoods of the city, with real estate prices among the most expensive in the world. The neighborhoods also stand out for offering good entertainment services, such as

restaurants and retail, and to be one of the main tourist destinations. Regarding accessibility, the neighborhoods are well served by bus, taxi and bike paths.

On the other hand, the neighborhood of Barra da Tijuca, where the Jardim Oceânico station is located, has received great real estate growth in recent years and is mostly residential. The access of this neighborhood to most of the city's best jobs, which are located in the South and Center Zone, is difficult. Before the inauguration of Line 4, the commute was limited to a few routes that were congestion in rush hours. The only transit alternative was buses, which shared the same congested streets with cars.

Therefore, the explanations for this unexpected result is a substitution effect. Accessibility is (imperfectly) symmetrical: increasing the accessibility of a region to the city also means that the city has greater access to that region. In this sense, the opening of Line 4 allowed the option to stay in a property in Barra da Tijuca at a lower cost and access the South Zone without necessarily facing the long congestion. Boyce et al. (1972), have concluded that increases in property values near a new transit line are accompanied by noticeable property value decreases in other locations.

Another explanation is the low adhesion of the inhabitants of Ipanema and Leblon to the Subway. The literature shows that impact of railway station on property value depends on demographic factors. Proximity to a railway stations is of higher value to low-income residential neighborhoods than to high-income residential neighborhoods (Bowes and Ihlanfeldt, 2001). The reason is that low-income residents tend to rely on public transit and thus attach higher value to living close to the station. Similarly, a decrease of 7% was found in San Diego, which was explained by a very low ridership in a corridor with generally very high average incomes. Thus, the residents in the corridor did not find the system attractive (Cervero & Duncan, 2002).

8. Conclusions

The present research presents the first ex-post effects evaluation of transport improvements for Brazil and one of the first for Latin America. Two regression methods were used. The first is a standard hedonic regression, including the most commonly used explanatory variable, the distance to the station. This enabled us to demonstrate that the result achieved is in line with the literature; that is, a statistically insignificant result was found for Metro and negative for BRT. This result can be explained by the average high income of the neighbor of the subway stations and lower income in the BRT neighborhood.

Using a more robust method of regression, fixed effects panel regression, it was identified that the results found for Line 4 are heterogeneous for their stations. The Jardim Oceanico station in Barra da Tijuca suffers a high gain from the point of view of accessibility because this neighborhood did not have access to good transit to access regions with jobs and leisure. Because of this, the introduction of a new variable that measures accessibility has proved to be effective.

Our main finding is that, in a city with high heterogeneity, such as Rio de Janeiro, consideration must be given to the potential differences of great magnitude between

the various regions of the city. In this sense, the distance to the station is not able to capture all this features. The accessibility variable was successful in capturing part of the heterogeneous valuation among residents of different regions

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