PROPERTY VALUE ASSESSMENT IN RIO DE JANEIRO: THE EFFECTS OF TRANSPORT INVESTMENTS

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ABSTRACT
This research assesses the effects of public transportation investments on property prices in Rio de Janeiro. 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 to this literature are threefold: first, we assess together two types of services, Subway and BRT. Second, we test other variables that represent accessibility as well as distance to the station. 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. 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.

RESUMO
Esta pesquisa avalia os efeitos dos investimentos do transporte público urbano sobre os preços dos imóveis no Rio de Janeiro. Nossa hipótese é que a abertura de uma nova estação de transporte aumenta o acesso à cidade para as propriedades em sua vizinhança. Quanto mais próximo da estação, e quanto maior a acessibilidade à empregos oferecidos pela estação, maior a probabilidade de valorização. Nossas contribuições para essa literatura são: primeiro, avaliamos dois tipos de serviços, Metrô e BRT. Segundo, testamos medidas alternativas de acessibilidade, além da variável mais comumente utilizada, que é distância até a estação. Em cidades com barreiras geográficas complexas, como o Rio de Janeiro, considerar apenas a distância até a estação pode subestimar os efeitos de capitalização. Terceiro, usamos dados de Airbnb como *proxy* para os preços de imóveis. Isso nos permite adotar uma variável de controle de efeito fixo para casas, ao invés de regressão hedônica.

1. INTRODUCTION

The impact of transportation investments on real estate values has received wide attention in academic studies (Gibbons and Machin (2005), McMillen and McDonald, 2004)). These studies have historically focused on housing and commercial property markets (Billings, 2011), and there is still great potential to explore how emerging markets such as Airbnb can help us better understand the linkages between transport and real estate values. Moreover, this literature generally tries to grasp the benefits of transportation investments using simple proximity measures based on Euclidian distance between real estate properties and the nearest transport station (Ingvardson and Nielsen, 2018). By doing so, these studies overlook transportation barriers created by physical geography, road network patterns and disordered urbanization commonly found in cities in the Global South. More importantly, these simple proximity measures overlook the frequency of transport services and network connectivity (Bowes and Ihlanfeldt (2001), Gibbons and Machin, (2005)), which will largely determine the extent to which a transportation investment will benefit a location by improving its accessibility to valued activities and amenities such as health services or employment opportunities.

This study examines how Airbnb prices respond to major investments in public transport infrastructure in a major city. The study uses the city of Rio de Janeiro (Brazil) as a case study. The city of Rio has one the worst traffic conditions in Brazil[1] and it has received substantial investments in its public transport infrastructure in the run-up to the 2014 FIFA World Cup and 2016 Olympic Games. Some of the most significant investments included the extension of a subway line and two Bus Rapid Transit (BRT) corridors that together stretch approximately 81 kilometers across the city. In this study we measure the benefits of these transportation projects by looking at how they increased between 2014 and 2017 the number of job opportunities that could be reached via public transport from each Airbnb listing location.

This work uses home-sharing data (Airbnb) as a proxy for property prices. Airbnb is the main short-term rental platform in Rio de Janeiro, and our database observes all short-term rental transactions (listings) for each property over the entire period of analysis (between oct 2014 and oct 2016). This allow us to use a panel model with property fixed effect in order to controls for every observable characteristic that can be part of a hedonic regression. Moreover, it controls for unobservable - time invariant - characteristics. Ignoring those unobservable can significantly bias the estimates if they are correlated with the treatment dummy.

Another advantage of using data from the short-term rental market in comparison with traditional properties is its liquidity. The general short-term rental length is a few days, whereas in traditional markets transaction duration takes years. This means that the anticipation effect, which is often identified as relevant in traditional markets in previous studies (McMillen and McDonald, 2004), has no direct effect on short-term rentals.

Previous studies have also found evidence that proximity to certain transport modes often come with noise and pollution externalities with negative capitalization effects (Ahlfeldt et al. 2019). In order to take this disamenities into account, we analyze how the effects of transport investments on Airbnb prices varied across space and by type of transport investment, whether subway or BRT. 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. Moreover, this research also 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 on cities in developed countries (Debrezion et al., 2007). There is lack of studies concerning Latin American cities, despite the recent rise in new transportation projects.

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. In general, the empirical studies conducted 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 estimation, but with differed methods. Others 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).

[1] TomTom Traffic Index

Our contributions to 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 duration of a home sharing contract 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 come at the expense of a large decrease in sample size and possible selection bias, because almost all contracts have a duration of a few days. 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 it possible to compare the real estate prices change in postcodes that experienced changes in rail access with the change in real estate prices in postcodes that did not, using a difference-in-differences estimation. In our case, as the 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.

Another advantage of this data set is that we do not expect an anticipated effect on short-term rents. McMillen and McDonald (2004) produce 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 the opening day, but house price does rise in anticipation of the increase in housing rent, which is caused by the improvement in accessibility. Housing rental contracts that begin 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 for 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), four factors may account for the effects of the open of new 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 use 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 provided to outsiders to the neighborhood.

We argue that estimate price gradients are insufficient to identify the impacts of transit investments in a context of heterogeneous neighborhoods. Billings (2011) findings suggest that the 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 measure 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 services, Subway and BRT, which allows us to take into account the differences of quality that each type provides on the perspective of property prices. This is possible because both types of service opened at almost the same time. Gibbons and Machin (2005) have a similar approach, considering differences between the Subway style of the London Underground/Docklands Light Railway services and the scheduled, limited stop services provided on the main-line Network Rail system.

Also, to our knowledge, this work is one of the first ex-post effects evaluation of transport improvements in a Brazilian city. A few studies elaborate models to assess land value using accessibility as an explanation variable. Andrade and Maia (2009) compare hedonics regression before and after the Recife Metro system, but not with a quasi-experimental methodological approach. This research stands out for using an innovative database accompanied by a more appropriate methodology for public policy impact assessment.

Rio de Janeiro is one of the largest and richest cities in the global south, and with the most expensive property prices in Brazil. In addition, the city's transportation investment was part of the preparation to host the 2016 Olympic Summer Games. Hence, 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 Subway 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 these mega-events to leverage urban development and to improve the city's transport conditions.

Concerning mobility conditions, Cariocas (the people who live in the city of Rio de Janeiro) are, in general, heavy public transit users. Public transit ridership represents about 50% of commute trips in the Rio de Janeiro metropolitan area. Despite this, the majority of the population of Rio de Janeiro 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 de Janeiro 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, the year the new stations opened. This is the worst commuting time in Brazil. Therefore, it is likely that new stations that offer commute saving time will succeed in attracting new users.

Rio de Janeiro, with over 12 million inhabitants, is one of the largest and richest urban areas in the Global South. 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), as well as having historical spatial segregation (Ribeiro et al., 2010). Most of the population of Rio de Janeiro also faces extremely poor transport conditions. The large income inequality is usually related to spatial inequality, and, consequently, heterogeneous effects on property prices.

Regarding physical geography, Rio de Janeiro is marked by the presence of three mountainous structures the shape the city. Although this feature offers city dwellers lush natural beauty, it also poses challenges to the transportation infrastructure and hampers travel in the urban space. The east side of the city, where the City Center and the South Zone are located, is squeezed between the sea and the Tijuca mountain structure. This region is home to 58% of jobs in only 8% of the territory. Not surprisingly, commuters to this region suffer with traffic congestion.

3.1 Rio de Janeiro's Transportation Infrastructure

Between 2010 and 2016 Rio de Janeiro 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 kilometers of extension and 5 stations: Jardim Oceânico, São Conrado, Antero de Quental, Jardim de Alah and Nossa Senhora da Paz. Jardim Oceânico station connects the Barra da Tijuca neighborhood (West Zone) to the Ipanema neighborhood, where the subway system was already in operation. The West Zone has 41% of the city's population.

The BRT was implemented from June 6, 2012 through August 1, 2016 in the city of Rio and currently at a cost of R$ 4.7 billion. It has three bus corridors: TransOeste, TransCarioca and TransOlímpica. There is also an expansion of the BRT Transoeste, called Lote Zero, which connects Alvorada Terminal with Jardim Oceânico Subway Station. Transoeste was the first express corridor in operation with its first phase of 52 kilometers inaugurated in 2012, connecting the Alvorada Terminal in Barra da Tijuca, Santa Cruz and Campo Grande. This resulted in an almost 50% reduction in travel time as well as integration with other expresses modes and corridors. The TransCarioca, with almost 39 kilometers, connects the Alvorada Terminal in Barra da Tijuca to Tom Jobim International Airport. The implementation reduced travel time by 60% and carries up to 500,000 passengers per day. The TransOlímpica has an extension of 26 kilometers and its estimated capacity is 400,000 passengers per day.

4. METHODOLOGY

Our hypothesis is that opening a new transportation station increases access for properties in their vicinity to the city, and that then influences 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.

In order to ensure that any price change post transport intervention is likely attributable to the intervention, we use a quasi-experimental approach. In other words, we interpret the open of new stations similar to a natural experiment that heterogeneously affected rental prices. We divide the properties into two groups, one affected by the experiment (treatment group) and the other unaffected (control group). The variable that determines the group that each property will belong is distance to station.

We adopt as quasi-experimental designs the difference-in-differences methodology with a continuous treatment variable. This means that the intensity of the treatment varies with the distance from a property to the new station. We compare property prices before (untreated) and after (treated) the Subway Line 4 (treatment) open, at August 2016. As the Line 4 connected BRT lines to the Subway, BRT is also considered as suffering the treatment.

Each property is linked to its closest station, considering station impacts up to a maximum distance of 2.5 kilometers. We consider a distance cap of 0.5 kilometers for the continuous treatment variable. This means that beyond this distance the treatment remains fixed at 0.5 kilometers. In other words, we assume that there are no capitalization losses (or gains) 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 kilometers in Euclidean distance represents 0.8 kilometers in walking distance. It is also important to note that Rio de Janeiro’s warm and humid weather, mainly during the summer, may influence the willingness to walk to the station.

We drop the sample from the time of the Olympic Games, August 2016, as during this period the demand was extraordinarily high. We chose to include only the first two months after the treatment. We think this 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 emerge.

The quasi-experimental methodological strategy uses a pricing method framework as baseline in order to control for other variables that affect short-range rental prices.

4.1 Standard Hedonic Regression

We follow two approaches to assess short-range rental prices. The starting point is the standard hedonic pricing method using observed home characteristics (Sheppard, 1999). The Hedonic Regression is used here to build a pricing function that consider the price of a rental contract as a combination of characteristics that the property possesses, given that properties with better qualities demand higher prices as compared to properties with lower qualities.

To represent property characteristics, we use property information available on database, and the property location, represented here by its closest station.

We estimate the effects on short-range rental prices (with data at the home level) through the following equation.

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

where Y_{ist}: property price of property *i* and the closest transport station *s* in year-month *t*,
$Dist_{ist}$: Euclidean distance from the property to the closest urban transportation station
X_{ist}: vector of observed home characteristics,

T_s: vector of observed transport station characteristics and
W_t: fixed effects for month-year.

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 in all treatment period:

4.2 Fixed-Effect Panel Model

Hedonic regressions in housing market suffer from the impossibility to observe several product attributes. If these omitted attributes are correlated with the observed attributes, ordinary least squares estimates will be biased. When correlated unobservable are time-invariant and panel data are available, the unobservable can be accounted for with fixed-effects (Bajari, 2012).

The second approach to assess short-range rental prices uses the repeated observations per property to build a pricing function that consider property and time fixed-effects. While hedonic regressions uses property observable characteristics to infer it rental price, fixed effects models uses own past transaction time-invariant variables with time-invariant effects.

In the fixed effect panel model, we deploy dummy variable for each property (property fixed-effect) and each month-year (time fixed-effect):

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

Where α_i: dummy for each property i.

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

5. DATA

The study uses micro-level data for the entire city of Rio de Janeiro, rather than designated sample areas. For home characteristics, we use the property's available quantitative information. For vector of observed transport station characteristics, we use the station's accessibility data. Regarding transport infrastructure database, we have information about all the BRT and Subway stations, including the latitude – longitude, as well as the opening date. In regards to accessibility data, we use Pereira et al (2017), which considers the 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

Airbnb is the world's biggest online marketplace and hospitality service for people to lease or rent short-term lodging. Our data source is AirDNA analytics, which is based on Airbnb data gathered from information publicly available on the Airbnb website.

Our sample is composed of Rio de Janeiro city data, from October 2014 until October 2016. The data is composed by two databases. The first is property data, containing 65,647 properties, with location information (Neighborhood and latitude – longitude) and quantitative and qualitative information. The second database is the advertised listings, aggregated monthly and daily. We use the monthly data that contains 705,709 information, each one representing a property month report. More information

5.2 Accessibility

Rio de Janeiro's accessibility database from Pereira et al (2018), which considers geolocated timetables of Rio de Janeiro'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 de Janeiro's transport system in order to estimate the change in accessibility that resulted from policies implemented in Rio de Janeiro between 2014 and 2017.

They estimate accessibility in terms of how many job opportunities people could reach from their households within 60 minutes via public transport and walking. 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 shows the increase in job accessibility caused by the new transport infrastructure.

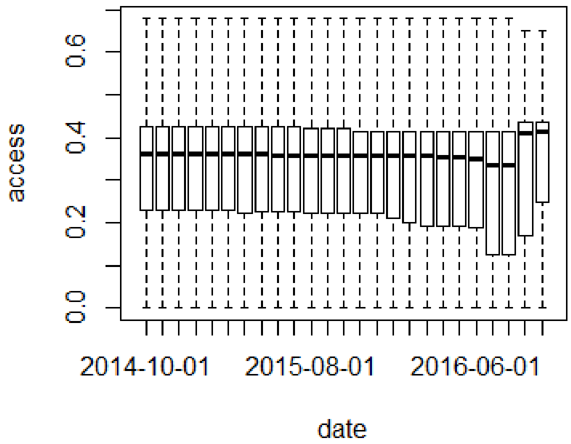

Figure 1: Histogram of job accessibility for the entire sample[2]

The summary statistics of Metro Line 4 and BRT, divided in treatment and control group are listed in Figure **2**:

Station name (Metro Line 4)	Group	Number of Listings	Average price	Average distance to closest station	Average job accessibility	Average number of Bedroom
Antero de Quintal	Control	35058	173	0.704	0.198	1.75
Antero de Quintal	Treatment	5284	173	0.698	0.323	1.79
General Osório	Control	71622	143	0.452	0.291	1.6
General Osório	Treatment	10018	120	0.454	0.431	1.62
Jardim de Alah	Control	17914	179	0.833	0.224	1.74
Jardim de Alah	Treatment	2662	153	0.851	0.398	1.79
Jardim Oceânico	Control	14598	228	1.08	0.097	2.11
Jardim Oceânico	Treatment	2665	222	1.03	0.184	2.12
Ns. da Paz	Control	25344	192	0.371	0.225	1.83
Ns. da Paz	Treatment	3706	184	0.371	0.424	1.87
São Conrado	Control	7312	256	1.33	0.106	2.06

[2] 1 =100% of jobs reached within 60 minutes

São Conrado	Treatment	1183	220	1.24	0.209	2.15

Line name (BRT)	Group	Number of Listings	Average price	Average distance to closest station	Average job accessibility	Average number of Bedroom
Lote Zero	Control	27056	185	0.75	0.102	1.9
Lote Zero	Treatment	5404	163	0.729	0.132	1.96
TransCarioca	Control	19069	171	1.37	0.124	1.88
TransCarioca	Treatment	4625	178	1.2	0.166	1.94
TransOeste	Control	32498	217	0.927	0.051	2.27
TransOeste	Treatment	8241	203	0.946	0.051	2.3
TransOlimpica	Control	15534	187	0.535	0.083	2
TransOlimpica	Treatment	4303	173	0.551	0.104	1.99

Figure 2: Summary statistics

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 addition, we try other variables as measures of accessibility, rather than distance to station. We then 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 3 shows regression estimates of the model in equation (1) using the data described in the previous section. We estimate the effects of station accessibility and distance on average daily rate (ADR).

In this regression we use as observed house characteristics (X_{isct}): number of beds, maximum number of guests, listing type (entire home/apt, private room and shared room), property type (apartment, house, loft, etc.). In order to control for transport station characteristics (T_s), we use a dummy variable for each transport station. We also allow time fixed effects.

	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 transport station 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		

Figure 3: Hedonic Regression

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

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

In the 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 respect to accessibility to jobs, the estimation presents the opposite effects in Line 4 and BRT. The first showed an unexpected negative effect and the second, a positive effect. In all cases, the effects are statically significant.

6.2 Panel Regressions

Figure 4 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 groups as described in Figure **2**.

	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			

Figure 4: Aggregated Panel Regression

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

	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

Figure 5: Line 4 Panel Regression

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

These regressions disclose the different patterns in Line 4. Jardim Oceanico Station’s real estate prices are (weakly) related to distance and significantly related to the increase in accessibility to jobs opportunities. The remaining properties near Line 4 stations are not influenced by distance-to-station 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.

Note that the R-squared has different interpretation in hedonic and fixed-effect regressions. In the second, the property and time fixed-effects are omitted from the statistic calculation, so the R-squared represents the explanation power caused by the variables added, and not by the all fixed-effects variables. If, for example, we run the same fixed-effects regression, but creating the dummy variables for each the property and time, rather than the use of panel regression algorithm, all results would be the same, except the reported R-squared, that would be much higher.

DiscussionFigure 3, Figure 4 and Figure 5 presents 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.

Regarding the methodologies, there are slight differences in results. In both cases, we find the distance-to-station 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 entire Line 4, we find a negative coefficient for accessibility to jobs, while when we disaggregate the Jardim Oceanico station from Line 4, we obtained the expected results 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 as being one of the main tourist destinations. Regarding accessibility, the neighborhoods are well served by bus, taxi and bike paths.

On the other hand, the Barra da Tijuca neighborhood, where the Jardim Oceanico station is located, is mostly residential and received great real estate growth in recent years. This neighborhood's access to the majority of the city's best jobs is difficult, as most are located in the South Zone and City Center. Before the inauguration of Line 4, the commute was limited to a few routes that were congestion during rush hour. Buses were the only transit alternative, 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 at a property in Barra da Tijuca at a lower cost, yet still with access to the South Zone and without necessarily facing the traffic congestion. Boyce et al. (1972), has 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 station 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).

7. 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 distance to the station, the most commonly used explanatory variable. This enabled us to demonstrate that the result achieved is in line with the literature; that is, a statistically insignificant result was found for Subway and negative for BRT. This result can be explained by the high average income of the subway station's neighborhood and lower income in the BRT neighborhood.

Using fixed effects panel regression, we 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 connect to the 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 these features. The alternative accessibility variable was successful in capturing part of the heterogeneous valuation among residents of different regions.

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