Impact of the Metro Line 1 on Surrounding Rental Property Prices

May 16th, 2023

Abstract

This paper evaluates the impact of the introduction of Metro Line 1 in Mumbai, India on the rental prices of surrounding residential properties. Using household surveys conducted in 2004 and 2019, these effects are estimated using a difference-in-difference approach while controlling for housing characteristics. Two treatment groups are used, one consisting of houses within half of a kilometer of the nearest station, and another for houses within one kilometer. These treatment groups are contrasted with control houses between half of a kilometer to three kilometers from the line and those between one kilometer and three kilometers from the line, respectively. I find that, for the first group, proximity to the new line has a positive impact on the property's rental value.

I. Introduction

Public transportation has been integral to the development of the modern economy. It has provided individuals with higher employment opportunities while simultaneously allowing shops and businesses to have a wider audience of consumers. In particular, public transportation has played a major role in connecting lower population density regions with cities and areas of high economic activity. In India, a country where only a limited fraction of the population own personal vehicles, public transportation affords lower income individuals greater mobility[1].While older railways, trams, and trains were already in place, in 1984, the first metro line opened in Kolkata, India, ushering in a new era of modern rapid transit. Since then, 15 more metro lines have become operational and metro infrastructure is set to expand even further.

The primary purpose of this research is to understand the impact of a transport policy, in this case, the opening of Line 1 of the Mumbai Metro, on residential property values in a city. The Greater Mumbai Region (GMR) is home to over 12 million people and is one of the most densely populated regions in the world. Mumbai holds the title of the second most populous city in India, a country in which the urban population is already growing at an astounding rate (*Mumbai Population*, 2023). The benefits of improvements in housing amenities are known to be capitalized in property values (Bartik, 1988). Improvements in public transportation should similarly be reflected in housing prices. The construction of a subway can provide greater employment accessibility to workers. In 2005, it was measured that two-thirds of low-income commuters in Mumbai either walk or bike to their place of employment and the average one-way commute distance for low-income individuals is 3.9 km (Baker et. al, 2005). Moreover, metro

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[1] As of 2011, 21 percent of households in India own a two-wheeler such as a motorcycle and 4.7 percent of households own automobiles including cars, vans, and jeeps (Motor Vehicle Writeup, 2015).

lines allow more shopping opportunities and access to amenities that arise around public transportation, in addition to fostering agglomeration of activity that occurs near busy sites in a city. The effects of access to the increased number of shops and activities can be capitalized in the rental prices of homes. Additionally, as policymakers attempt to implement public transport for environmental reasons, the economic co-benefits of subway introduction can help fast-track these decisions.

Metro Line 1, spanning 11.4 km, is located centrally within the GMR, close to the airport. It began operating in 2014. What makes this line of particular importance is that it was the first East-West rail link constructed in Mumbai. By connecting the Central and Western rail lines, it greatly reduced commute times for many of the city's workers. Travel time along the corridor that Line 1 resides on reduced from over an hour to approximately 20 minutes. The metro now carries 400,000 passengers each day, establishing itself as an integral component of daily travel and commute.

I conjecture that the opening of Line 1 of the Mumbai Metro had a positive effect on surrounding housing prices because it facilitated access to other parts of the city and increased the number of businesses/shops in the area close to the line. While there may have been cost-benefit analyses done prior to the construction of the Metro Line 1, this project examines the change in residential property values, as measured by their rental prices, after the line was constructed. I use a difference-in-difference approach in order to determine the Metro Line's effect on housing rental prices, using two household surveys conducted by the World Bank before (2004) and after (2019) the opening of Line 1. Additionally, I measure the Euclidean distances from each house to the nearest of the 12 stations of the Metro Line 1 in order to calculate proximity to the Metro.

I investigate whether, following the introduction of Metro Line 1, the rental price of houses within one kilometer of the metro line increased by a statistically significant amount compared to houses located between one kilometer and three kilometers. This hypothesis remains the same for a treatment group of houses within half of a kilometer as well. Using control groups of houses between one kilometer and three kilometers from the Metro, as well as houses between half of a kilometer and three kilometers of the Metro, I test whether there are any notable differences in impacts between the two treatment groups. The reason I am choosing these definitions of treated houses is because one kilometer is a reasonable distance to walk to use the Metro or to shop at businesses that have opened near the Metro. The choice of control houses between one and three kilometers from the Metro avoids contaminating the control group with other projects that occurred at the same time as the opening of Line 1. In the future, I will conduct sensitivity tests with multiple buffers for the control group to deal with this issue. For instance, part of the Eastern Freeway was constructed within nine months of the Metro Line 1. I am focusing on the three kilometer boundaries so that my model does not capture the effects of the new highway. In my results, I find that there exists a positive and significant impact of proximity to Line 1 within half of a kilometer of the metro and residential property prices. While this relationship remains the same for houses within one kilometer as well, it is no longer statistically significant.

II. Literature Review

There exists a large body of literature that explores the positive and negative impacts of subways, including their impacts on commuting times, housing values, air pollution and local traffic. Some of these studies are conducted ex-ante, as necessitated for the undertaking of any large-scale transportation project. However, ex-post studies are just as critical in evaluating whether a project was successful, or even detrimental, to its stated purpose.

Cropper and Suri (2022) extend this literature by focusing on the impact of the Mumbai Metro Line 1 on land use prices. The study uses a difference-in-differences approach in an event study framework to assess the change in residential, commercial, and industrial property prices after the introduction of Line 1 using assessed property values. They observe the anticipatory effects of the Metro Line 1's construction as approximately a 5-6% growth in property prices in 2012-13, compared to values in 2011. Following the opening of the metro line, property values increased by 7% to 9% for commercial and residential properties, respectively, compared 2011 values. My research differs from theirs by using the rental prices of residential properties, rather than assess values, and by controlling for characteristics of the property such as location, interior space, and housing amenities (e.g. bathroom, kitchen). One concern about the use of assessed property values is that they do not necessarily reflect market transactions. Values for properties in 2013 are estimated in 2012. When anticipating a major infrastructure project, such as Line 1, assessors may incorporate their own views about the likely impact of the project into their assessments.

There have been no other studies of the impact of the Mumbai Metro on property values using modern econometric methods. In "Real Estate Prices in Mumbai; Does the Metro Rail Have an Impact?", Gandhi et al. (2014) examine the effect of various factors on assessed property values in Mumbai, using a single cross-section of data for the 2013. They find that proximity to a rail station increases assessed values, when controlling for other variables including distance from central business district to sub-zone center, built up area of amenities, dummy variables for sub-zones to the west of the western railway line and contiguous to the western coast, the proportion of area occupies by slums in the sub-zone, built up area of residences and commercial activity, respectively, to total build up of the subzone, the area of open spaces to the area od sub-zones, and the distance from sub-zone center to the nearest railway station. They were however unable to evaluate the impact of Metro Line 1.

Patil and Mithe (2018) examine changes in assessed property prices near individual stations along Metro Line 1 between 2013 and 2017. This is a descriptive analysis in which averages of assessed values are graphed. It is unclear for what land uses assessed value are measured, and no control group is used in their analysis.

Studies of the impacts of rapid transit on property values have been conducted in other cities. "Spatial Difference-in-Difference Models for Impact of New Mass Rapid Transit Line on Private Housing Values" by Diao et al. (2017) examines the impact of the Circle Line in Singapore. The authors find that housing prices increase by 7.8% in treated neighborhoods as compared to control neighborhoods. In their calculations, they defined neighborhoods that were within 600 meters of the Circle Line as treated and those outside of that buffer zone to be untreated. One result that the authors found was that as the opening date of the new line approached, housing prices near the line began to decrease, compared to the value one year prior to the opening.

Unlike the aforementioned study, in "The Effect of a Subway on House Prices: Evidence from Shanghai", Zhou et al. (2018) study the impact of the time savings associated with a new rail line on housing prices, rather than the impact of the distance of houses from the rail line on prices. They find that, in fact, residential properties that experience a greater time savings from construction of a new Metro line experienced the highest increase in property prices. The analysis was conducted on Line 6 of the Pudong district of Shanghai, China. The paper focuses on the distance to the central business district of Pudong in its calculation of how commute time was decreased to popular employment locations. The authors find that the average residential property price appreciation was 3.75%. Moreover, areas that initially had little access to the central business district, mainly suburbs, saw the greatest increase in housing values. This is likely due to the greater increase in commute time savings in these areas. In a future version of this paper, I would also like to include a neighborhood characteristic of distance to the central business district to incorporate the impacts of proximity to a major economic hub.

III. Data & Methodology

For this project, I use data from two World Bank household surveys, one from 2004 and one from 2019, which were conducted from before and after the introduction of Line 1 of the Mumbai Metro. Moreover, the 2004 survey was conducted before there were even discussions of building a new subway. This is important because I will not face the endogeneity issue of preemptive housing price increases from expectations of the metro line being built in the area. The households interviewed in these surveys were chosen at random, in proportion to population. The 2004 survey contains 4981 households and the 2019 survey contains 3024. Figure 1 provides a map of the entirety of Mumbai and outlines the stations along Line 1. The households surveyed in 2004 are shown in blue, and the households surveyed in 2019 are shown in red. The survey questionnaire was conducted for the purpose of understanding people's transportation behavior and included travel diaries. Some of the questions asked included information on religion, caste, mother tongue, how long they have been living there, square footage, amenities, mortgage, rent, neighborhood perception, and household assets. They also included detailed information on housing characteristics such as the roof material, floor material, wall material, amenities such as a kitchen, bathroom, toilet, and piped water, and whether or not there is a footpath in the neighborhood. Not all of these housing characteristics were asked about in the

2019 survey however, so only the characteristics in common between the two surveys were used in my model. While surveys such as these sometimes experience bias, as people try to inflate the value of their home to make it sound more expensive, I do not believe this was prevalent in these surveys. Instead of asking the respondent how much they pay for their property, the question asks “What would a house like yours rent for?” which is a less personal question.

I am controlling for housing amenities in my analysis – something not taken into account in Cropper and Suri (2022) – in order to better understand the effects that the Metro had on property prices. In an article in Land Economics, Bartik concludes that amenities are important to control for because if the amenities of a certain house does not improve over time, especially relative to other houses in the area, the rent of the house will decline. Furthermore, numerous ex-post studies have found that amenities are a significant indicator of housing prices. Table 1 demonstrates the similarities and differences between housing characteristics in the two years. The slum flag, better roof, number of rooms, separate kitchen, toilet inside, separate bathroom, piped water, and footpath in neighborhood variables are all coded as binary variables within the dataset. The better roof variable in particular, refers to whether the roof material used for the house provides sufficient protection and is sustainable, as determined in Cropper and Suri’s paper. Certain amenities such as house size (log of space) and having a separate kitchen did not change much over the years, whereas having a footpath within the neighborhood or a toilet inside the home was much more common in 2019 than it was in 2004. Other amenities that similarly increased in prevalence include having a better roof and having a separate bathroom. In both years, the average number of rooms was somewhere between one and two rooms. The proportion of houses characterized as a slum in the sample increased slightly from 2004 to 2019.

Access to piped water within the home also increased slightly from 2004 to 2019. The increases in the prevalence of housing amenities demonstrates relative improvement in quality of life.

I used the ArcGIS application to find the Euclidean distance between each of the houses in the dataset and Metro Line 1[2]. After simple tabulations to differentiate households that were within half a kilometer, one kilometer, between half and three kilometers, and between one and three kilometers, I was able to use these data in my analysis. By these definitions, pooling the two surveys, there are 251 households within half a kilometer of the nearest station, 687 within one kilometer, 1557 within half a kilometer and three kilometers, and 1121 within one kilometer and three kilometers. In total, this encompasses 1808 households for each regression.

This paper uses a difference-in-difference model to estimate the effects of the opening of Metro Line 1. If P, N, F, B, A refer to the rental price, near (Line 1), far (from Line 1), before (Line 1), and after (Line1), average treatment effect = $(P_{N,A} - P_{F,A}) - (P_{N,B} - P_{F,B})$. A difference-in-difference approach requires three key assumptions. The first of these is the Stable Unit Treatment Variable Assumption, also known as SUTVA, which mandates that there should be no influence of the treatment on components of the model beyond the treatment itself. This assumption cannot be proven but it is reasonable to expect that the majority of households would not elect to move within a three-kilometer radius. Another assumption is the common trends assumption that requires that the groups used in the model were following the same trends before the treatment was introduced. I do not have housing rents for houses in the years between 2004 and 2014, so I cannot conduct a parallel trends test, given the nature of the data. Lastly, because

[2] I first used the longitudinal and latitudinal household location data from the two World Bank surveys and converted it into points on a map. After using the same technique for the data on all 12 stations on Metro Line 1, I used the Near tool to calculate the planar distance from each of the households to the nearest station.

we want to capture the effects of the treatment exclusively, I cannot have any of our controls be correlated with our treatment. In other words, we wish to see exogeneity between our treatment and controls. None of the housing characteristics used in the model have any correlation to the construction of the Metro Line 1, so this assumption is met.

The difference-in-difference equation I use to estimate the effects of the line is as follows:

$lnRent = \beta + \delta * hhdummy + \beta * nearline + \delta * nearline * hhdummy + \Gamma X + \varepsilon$ where δ measures average treatment effect and δ measures the general impact of time on housing values. X represents housing covariates and ε refers to the error term. The variable "hhdummy" is a dummy variable that equals 1 if the household is from the 2019 survey and 0 if the household is from the 2004 survey. Γ is a vector of coefficients for housing covariates. The subscript "i" represents each of the houses used for this calculation. The variable "nearline" yields the benefits of being near the line. In the dataset, the "nearline" variable is a dummy variable listed either as "underhalfkm" or "under1km" depending on whether the house is within half of a kilometer or 1 kilometer of the nearest station, respectively. The housing covariates used are all those in Table 1. For all of the dummy variables used in the dataset, a 1 indicates that the household has the characteristic, and a zero if not.

When compiling the data from the two World Bank surveys into one dataset, the rental prices for the 2004 households were converted into 2019 rupees for consistency. To calculate the difference-in-difference estimator, the logarithm of the rental price in 2019 rupees was regressed upon the treatment variable, the dummy variable indicating the year of the survey, and the interaction term between the treatment and time variable, in addition to all of the specified housing characteristics.

In an attempt to better specify the model, two additional neighborhood characteristics are included in the regression along with the aforementioned housing characteristics. Coast-side properties tend to be areas of bustling business and happenings so it follows that these areas may be more highly coveted and therefore more expensive. Given that the west coast of Mumbai is much more affluent than the eastern parts that are close to wetlands and swamp regions, proximitiy to the west coast may be an amenity that is not factored into the current model. I calculate the houses' distance to the west coast and incorporate these into the model as a continuous variable. In addition to including a "distance to coast" variable, I also to introduce a "distance to central business district" variable into the model. This may be a highly motivating factor for the use of the Metro Line 1 because individuals who already live close to the central business district may not require the use of the Metro Line 1, whereas individuals who live further away from the central business district may rely on the metro to gain access to this part of the city. The central business district of Mumbai has slowly shifted upwards from a lower part of the city so this will have to be taken into account when calculating these distances. In 2004, the central business district was believed to be Colaba, home to the famous Gateway of India, located at the southern tip of the Mumbai peninsula (Shah, 2014). It has since shifted to the Bandra-Kurla Complex, higher up in the city, closer to Metro Line 1 (Das, 2019).

IV. Results

I begin by looking at simple cross-sections to explain any cross-sectional variations that occur within the data. In the simple hedonic regression of the 2004 logarithm of housing price on housing characteristics shown in Table 2, we find that all of the variables used are highly statistically significant, demonstrating that they are all appropriate indicators of housing rental price. Some of the indicators of rental price include the logarithm of interior space, access to piped water, and whether there was a toilet inside the household, all of which are highly statistically significant. In the 2019 regression (Table 3), we see very similar results with the exception of a negative coefficient for the separate kitchen and the better roof variables. Neither of these coefficients, however are statistically significant. The slum flag has a negative sign in both tables, which shows that a house being classified as located within a slum negatively affects the house's price.

To test whether we are seeing the effects of collinearity between some of the housing characteristic variables such as the ones for bathroom and toilet, I constructed a pairwise correlation matrix in Tables IV and V, between all of the housing characteristic variables. Houses located in slums are less likely to have the housing amenities controlled for in this paper, as such, the coefficients on the slum flag correlations are negative. While the footpath amenity and the number of rooms have a negative correlation in 2004, it is not statistically significant. Similarly, there are negative coefficients for the footpath amenity with the better roof, separate kitchen, and separate bathroom variables indicating potential multicollinearity issues. One potential source of the issue could be that by 2019, houses have more standardized amenities across income levels. I am running auxiliary regressions to examine collinearity issues among the explanatory variables, to be reported in a future version of the paper.

The distance to central business district variable is highly statistically significant. For both the under half kilometer and under one kilometer regressions, proximity to the central business district increases property rental pricing by almost four percent. However, the distance to coast variable in both regressions appears to be somewhat of a disamenity, as proximity to the west coast reduces the price of the home by 2 percent.

The results of the difference-in-difference estimation indicate that proximity to the Metro Line 1 does indeed have a positive impact on the house's rental price. Two coefficients of importance in Tables VI and VII are the interaction term between the house dummy variable and the time variable. For the regression that uses the half kilometer buffer, we see that being within that range after the metro was built increased property rental prices by 12.94%. This percentage drops to 7.46% for house within one kilometer of the subway, however the result is not statistically significant. The inclusion of neighborhood characteristics produce similar results, although there is less of a difference between the results of the regressions for the two definitions. For the treatment group defined as being within half of a kilometer of Line 1, these houses saw property prices increase by 11.79% due to their location [Table VIII]. For the regression including houses within one kilometer of their nearest station, being located in this region yields an 8% increase in the value of the home [Table IX]. This difference in impact indicates that houses within 500 meters of the Metro Line 1 – closer to the line – saw an increase in property values due to the construction of the subway while the impact beyond 500 meters is not statistically significant.

V. Conclusion

This study investigates the change the property rental prices due to the introduction of the Metro Line 1 in Mumbai, India while accounting for housing characteristics. Similar studies on this topic have used less reliable sources of data which may have led to bias in the outcomes. Moreover, this study provides a contribution to existing work by controlling for characteristics of the home such as whether the household has a toilet inside, a separate kitchen, a separate bathroom, neighborhood footpaths, and more. Results from this study demonstrate a positive impact on household rental prices due to the introduction of the Metro Line 1, when treatment houses are considered to be ones within 0.5 kilometers from the Metro. Similar results are found when the neighborhood characteristics of distance to coast and distance to central business district are included in the model.

In the future, I would like to run the same regressions used in this paper keeping distance to the nearest metro station as a continuous variable instead. This would allow me to observe more accurately the point at which proximity to the line stops being statistically significant. Another variation in the methodology that could be done in future work is to measure the house's shortest distance to Line 1, as opposed to the distance to the nearest station. The differences, or lack thereof, between the results found in this paper and the results from this new method would be interesting to explore because as the metro gains popularity, there will also be shops and businesses that open up along the corridor of the metro which will attract consumers as well. In other words, the construction of Line 1 may not be appreciating property values because of ease of transportation exclusively, but rather due to a combination of its transportation benefits with the other services that are provided along the passageway.

Other additions that a future version of this paper will have are additional regressions run for the upper five stations and lower seven stations separately. The stations would be divided in this manner both due to their geographic proximity to one another as well as the relative wealth of the region. As mentioned above, the western part of Mumbai is generally regarded as wealthier so the upper five stations may opt to use personal vehicles over public transportation. The lower seven stations are much close to the mangroves and is less industrialized which could mean the individuals who live in this area may likely experience higher residential property prices from the increased access to more economically active parts of the city. For this reason, I am proposing to run the difference-in-difference regressions again controlling for housing and neighborhood characteristics for these two groupings of stations.

Additionally, I believe there is further work to be done in terms of controlling for the effects of the Eastern Freeway. The very last portion of the freeway, which happens to be the section closest to the line, was constructed the same year that the Metro Line 1 was built. While only one of the stations on Metro Line 1 is relatively close to the Eastern Freeway, this is still something that would be important to look into in future versions of this paper.

Retrospective analysis on the impact of a policy action can help guide future projects, as there may be unintended consequences from seemingly positive initiatives.[3] For example, even with ease of access to other parts of the city, the lack of last-mile connectivity is a common issue commuters face when using public transportation. While a higher income individual may be able to call a taxi or ride sharing service to make up the difference, lower income individuals may still need to walk great lengths to get to their final destination. While it was not the case for Metro Line 1, this, in addition to increased traffic and noise, may cause property prices near a metro to decrease in some cases.

One important policy implication to consider is that when high rates of economic activity begins to occur around newly implemented public transportation infrastructure – or is expected to occur – the new developments that are constructed in these areas as a result are generally marketed towards wealthier consumers. This could have detrimental effects in a city such as Mumbai, where many low-income individuals live near public transportation infrastructure. As such, the introduction of a new subway could drive out these low income individuals for whom the line was intended to aid in the first place. While residential property prices may indeed

[3] For instance, the construction of a metro line in Bangalore failed to decongest traffic in the city, illustrating the dangers of assuming that a particular initiative is equally effective in every circumstance in which it is used (Kidiyoor, 2022).

increase from the opening of a metro line, a potential unintended consequence is rapid gentrification of the surrounding area.

Another potential future area of study on this topic includes how the introduction of the Metro Line 1 has impacted traffic and air quality in the city of Mumbai. Many major cities in India tend to face traffic issues, Mumbai being one of the cities that has the greatest difficulties with this. Moreover, global climate change is a pressing issue in our world today that disproportionately affects developing nations. Increased traffic exacerbates the already poor air quality conditions in major cities like Mumbai and may also increase carbon dioxide emissions. In the past, Indian cities have taken to drastic measures in attempt to reduce the smog issue caused, in large part by traffic. For example, one solution taken in New Delhi was to mandate that only cars with even or odd license plates can be out on the roads on certain days (2015). It would be important to study the impacts of a public transportation project like the construction of the Metro Line on traffic and consequently, surrounding air quality.

VI. References

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VI. Figures & Tables

Figure I

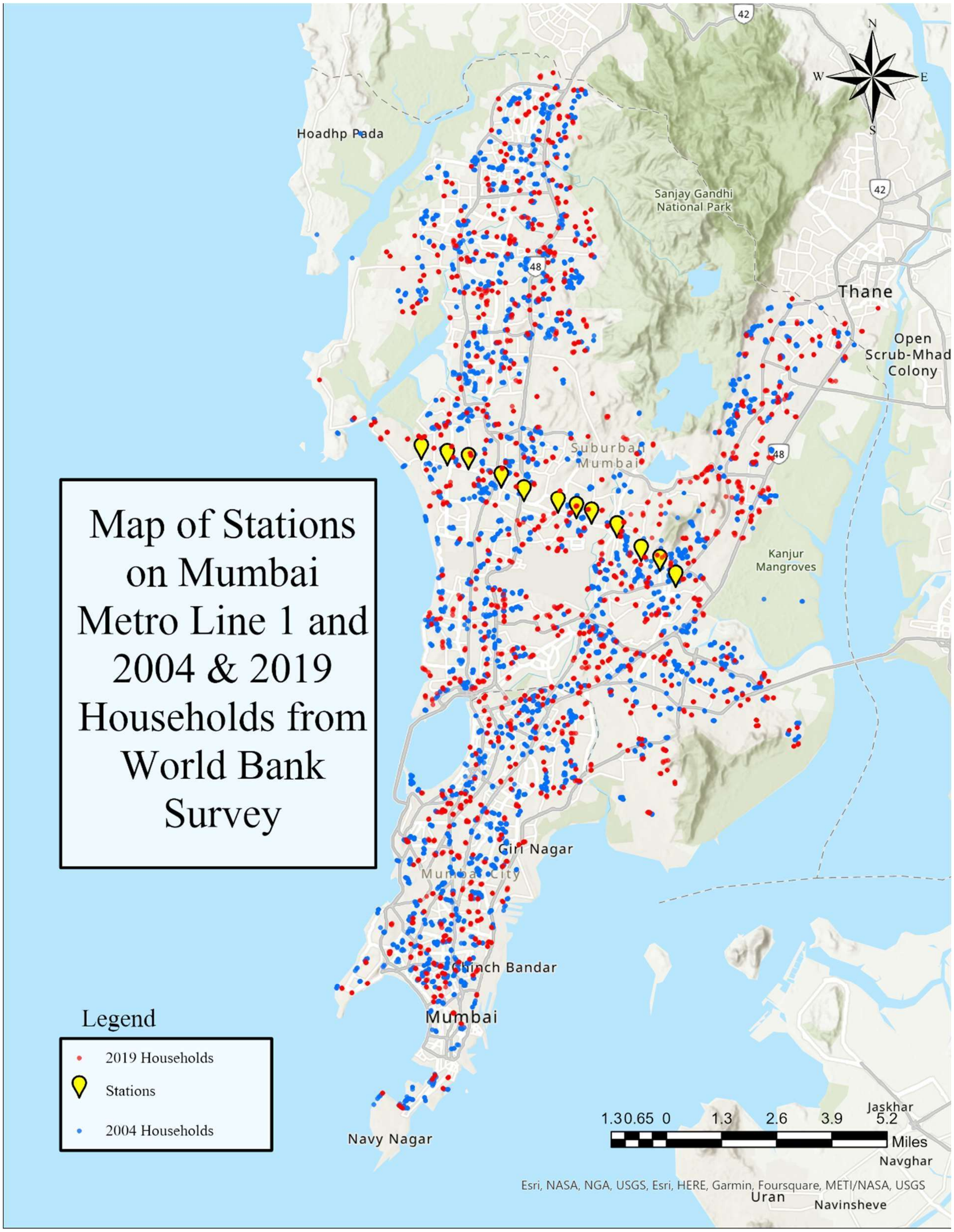

Table I – Summary Statistics of Housing Characteristic Variables

TABLE I

Variable	2004	2019
Slum Flag	0.375	0.435
	[0.484]	[0.496]
Better Roof	0.497	0.712
	[0.5]	[0.453]
Number of Rooms	1.461	1.37
	[0.979]	[0.591]
Seperate Kitchen	0.544	0.575
	[0.498]	[0.494]
Toilet Inside	0.32	0.635
	[0.466]	[0.482]
Seperate Bathroom	0.488	0.728
	[0.488]	[0.45]
Piped Water	0.69	0.765
	[0.462]	[0.424]
Log of Space	5.356	5.437
	[0.634]	[0.504]
Footpath in Neighborhood	0.303	0.771
	[0.459]	[0.42]

Note: The mean is listed first and the standard deviation is written below in the square brackets

Table II – Hedonic Regression of 2004 Household Prices on Housing Characteristics Adjusted to 2019 Rupees

TABLE II

logrent	Coefficient	Std. err.	t	P>t
slum flag	-0.1154	0.023	-5.02	0.000
better roof	0.2814	0.024	11.73	0.000
log space	0.3010	0.019	15.77	0.000
no. of rooms	0.0642	0.010	6.50	0.000
separate kitchen	0.1313	0.024	5.45	0.000
toilet inside	0.4006	0.027	14.96	0.000
separate bathroom	0.0766	0.024	3.15	0.002
piped water	0.1714	0.023	7.53	0.000
footpath	0.0665	0.020	3.26	0.001
_cons	6.1801	0.095	65.26	0.000
R-Squared = 0.4884				
Adj. R-Squared = 0.4875				
Total Observations = 4,924				

Note: the slum flag contains a negative coefficient indicating that being located in a region classified as a slum has a negative impact on property price. The log of the rent is being regressed.

Table III – Hedonic Regression of 2019 Household Prices on Housing Characteristics

TABLE III

logrental	Coefficient	Std. err.	t	P>t
slum flag	-0.0758	0.030	-2.53	0.012
better roof	-0.0493	0.035	-1.39	0.165
log space	0.5085	0.038	13.44	0.000
no. of rooms	0.0683	0.030	2.29	0.022
separate kitchen	-0.0253	0.040	-0.64	0.523
toilet inside	0.1998	0.042	4.81	0.000
separate bathroom	0.0381	0.040	0.96	0.335
piped water	0.2740	0.042	6.51	0.000
footpath	0.0235	0.036	0.65	0.518
_cons	5.7030	0.181	31.53	0.000

R-Squared = 0.1993

Adj. R-Squared = 0.1969

Total Observations = 3,016

Note: the slum flag contains a negative coefficient indicating that being located in a region classified as a slum has a negative impact on property price. The Log of the rent is being regressed.

Table IV – Pairwise correlation matrix for 2004 housing characteristic variables

TABLE IV

	slum flag	better roof	log of space	no. of rooms	seperate kitchen	toilet inside	separate bathroom	piped water	footpath
slum flag	1.0000								
better roof	-0.5798	1.0000							
	[0.0000]								
log of space	-0.3743	0.3820	1.0000						
	[0.0000]	[0.0000]							
no. of rooms	-0.1902	0.1935	0.4231	1.0000					
	[0.0000]	[0.0000]	[0.0000]						
separate kitchen	-0.2813	0.3074	0.5474	0.2797	1.0000				
	[0.0000]	[0.0000]	[0.0000]	[0.0000]					
toilet inside	-0.4658	0.5088	0.5820	0.3303	0.5289	1.0000			
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]				
separate bathroom	-0.3715	0.4725	0.4492	0.2043	0.5733	0.4971	1.0000		
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
piped water	-0.3472	0.4077	0.3803	0.1692	0.3775	0.4059	0.4412	1.0000	
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]		
footpath	-0.1564	0.2452	0.0660	-0.0208	0.0005	0.0328	0.1670	0.2513	1.0000
	[0.0000]	[0.0000]	[0.0000]	[0.1428]	[0.973]	[0.0206]	[0.0000]	[0.0000]	

Note: All variables have a negative coefficient when correlated with the slum flag because having a household in a region classified as a slum has a negative impact on property price.

Table V – Pairwise correlation matrix for 2019 housing characteristic variables

TABLE V

	slum flag	better roof	log of space	no. of rooms	seperate kitchen	toilet inside	separate bathroom	piped water	footpath
slum flag	1								
better roof	0.0066	1							
	[0.7177]								
log of space	-0.0569	0.296	1						
	[0.0018]	[0.0000]							
no. of rooms	-0.039	0.2184	0.5065	1					
	[0.0321]	[0.0000]	[0.0000]						
separate kitchen	-0.0544	0.3142	0.4543	0.4204	1				
	[0.0028]	[0.0000]	[0.0000]	[0.0000]					
toilet inside	-0.1135	0.1658	0.4406	0.2987	0.5082	1			
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]				
separate bathroom	-0.0823	0.1575	0.356	0.3085	0.4842	0.4285	1		
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
piped water	-0.0995	0.1291	0.364	0.2285	0.3441	0.5444	0.2397	1	
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]		
footpath	-0.0898	-0.1847	0.0529	0.0343	-0.0628	0.0466	-0.0758	0.0939	1
	[0.0000]	[0.0000]	[0.0036]	[0.0595]	[0.0006]	[0.0104]	[0.0000]	[0.0000]	

Note: Most variables have a negative coefficient when correlated with the slum flag because having a household in a region classified as a slum has a negative impact on property price.

Table VI– Difference-in-Difference Result for Households Within Half a Kilometer of the Nearest Station

TABLE VI

logrent	Coefficient	Std. err.	t	P>|t|
underhalfkm	-0.0697	0.051	-1.38	0.168
hhdummy	0.1128	0.054	2.09	0.037
hhdummyXunderhalfkm	**0.1295**	0.059	2.19	0.028
slum flag	-0.1913	0.038	-5.02	0.000
better roof	0.0457	0.050	0.92	0.358
no. of rooms	0.0804	0.034	2.35	0.019
separate kitchen	-0.1060	0.049	-2.16	0.031
toilet inside	0.5820	0.053	10.92	0.000
separate bathroom	-0.0641	0.050	-1.29	0.197
piped water	0.1721	0.043	4.04	0.000
log of space	0.4384	0.047	9.29	0.000
footpath	0.0065	0.044	0.15	0.884
constant	5.7484	0.218	26.38	0.000

R-Squared = 0.4096

Adj. R-Squared = 0.4060

Total Observations = 1,800

Note: the number of observations have decreased from the original sample because I only use houses located within 3 kilometers of their respective nearest station

Table VII – Difference-in-Difference Result for Households Within One Kilometer of the Nearest Station

TABLE VII

logrent	Coefficient	Std. err.	t	P>|t|
under1km	-0.0143	0.036	-0.39	0.695
hhdummy	0.1527	0.051	3.01	0.003
hhdummyXunder1km	**0.0746**	0.095	0.79	0.431
slum flag	-0.1856	0.038	-4.87	0.000
better roof	0.0536	0.050	1.08	0.281
no. of rooms	0.0745	0.034	2.19	0.029
separate kitchen	-0.1037	0.049	-2.11	0.035
toilet inside	0.5852	0.053	10.97	0.000
separate bathroom	-0.0648	0.050	-1.30	0.193
piped water	0.1729	0.043	4.06	0.000
log of space	0.4425	0.047	9.36	0.000
footpath	0.0026	0.045	0.06	0.954
constant	5.7221	0.218	26.26	0.000

R-Squared = 0.4080

Adj. R-Squared = 0.4043

Total Observations = 1,800

Note: the number of observations have decreased from the original sample because I only use houses located within 3 kilometers of their respective nearest station

Table VII – Difference-in-Difference Result for Households Under Half of a Kilometer of the Nearest Station including Neighborhood Characteristics

TABLE VIII

logrent	Coefficient	Std. err.	t	P>|t|
hhdummy	0.7413	0.163	4.54	0.000
underhalfkm	-0.0602	0.051	-1.17	0.241
hhdummyXunderhalfkm	**0.1179**	0.060	1.96	0.050
slumflag	-0.1485	0.039	-3.79	0.000
better roof	0.1130	0.051	2.22	0.027
no. of rooms	0.2283	0.031	7.37	0.000
separate kitchen	-0.0109	0.048	-0.23	0.822
toilet inside	0.6263	0.054	11.66	0.000
separate bathroom	-0.0308	0.050	-0.61	0.539
piped water	0.1994	0.043	4.63	0.000
footpath	-0.0050	0.045	-0.11	0.912
dist. to west coast	-0.0186	0.008	-2.31	0.021
dist. to CBD	0.0388	0.010	4	0.000
_cons	6.9369	0.240	28.85	0.000
	R-Squared = 0.3942			
	Adj. R-Squared = 0.3898			
	Total Observations = 1,800			

Note: the number of observations have decreased from the original sample because I only use houses located within 3 kilometers of their respective nearest station

Table IX - Difference-in-Difference Result for Households Within One Kilometer of the Nearest Station including Neighborhood Characteristics

TABLE IX

Log of Rent	Coefficient	Std. err.	t	P>|t|
nearline2	-0.0102	0.037	-0.28	0.783
2019dummy	0.7716	0.163	4.75	0.000
2019dummyXnearline2	**0.0806**	0.096	0.84	0.401
slum flag	-0.1413	0.039	-3.61	0.000
better roof	0.1202	0.051	2.35	0.019
no. of rooms	0.2252	0.031	7.27	0.000
separate kitchen	-0.0080	0.049	-0.17	0.868
toilet inside	0.6281	0.054	11.69	0.000
separate bathroom	-0.0316	0.050	-0.63	0.528
piped water	0.1992	0.043	4.62	0.000
footpath	-0.0100	0.045	-0.22	0.825
dist. to west coast	-0.0208	0.008	-2.58	0.010
dist. to CBD	0.0385	0.010	3.95	0.000
constant	6.9475	0.242	28.71	0.000
R-Squared = 0.3930; Observations = 1,800				

Note: the number of observations have decreased from the original sample because I only use houses located within 3 kilometers of their respective nearest station