What Are the Benefits of Metro Rail in Mumbai, India?*

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Abstract

We estimate the effects of the first metro rail line in Mumbai on property prices using administrative data on assessed property prices from 2011-18 for 723 sub-zones in the city. Comparing areas within 1 km of the metro with those beyond 1 km but within 3 km, we estimate the effects on property values for commercial, industrial, and residential properties. We find a significant and persistent increase in prices of 7-8% for residential and commercial land use categories in the treated areas relative to the control areas after Metro Line 1. We show that commute time savings and improvements in employment accessibility are plausible mechanisms underlying these effects.

JEL Codes: R4, R3, R1, O18

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1 Introduction

Public transit investment is an important tool to sustain growth and development in cities. Since transit projects are costly and infrastructure investments inherently risky, cost-benefit analysis of transport policies is of great interest. One way to measure the benefits of transit infrastructure is to estimate the impact of transit projects on property values, as future benefits are expected to be capitalized into property values. This also provides a measure of the impact of transport projects on property tax revenues, which can be used to finance transit projects or policies such as transit-oriented development.

Most of the literature evaluating the benefits of public transit projects is in the context of developed countries, whereas the majority of upcoming transit infrastructure projects are in developing world cities. We extend this literature by measuring the impact of the first line of the Mumbai Metro on property values. We then investigate the role of two mechanisms underlying the observed price effects: potential commute time savings and improvements in employment accessibility. Commute time savings are a first-order benefit of transport projects. Changes in employment accessibility or commuter market access have been shown to be an important force driving the spatial reorganization of cities following large infrastructure changes (Ahlfeldt et al. (2015), Redding and Turner (2015), Redding and Rossi-Hansberg (2017), Heblich et al. (2020), Kreindler and Miyauchi (2023), Tsivanidis (2019), Warnes (2020)). We test their importance in the context of Mumbai in a reduced-form way.

Line 1 of the Mumbai Metro opened in 2014. It is only 11.4 km in length but provided the first east-west rail link in a city with an extensive rail network. We measure its impact on property prices using administrative data on assessed values in 723 sub-zones of the city, from 2011 to 2018, for various land-use categories: residential, commercial shop, commercial office, industrial, and open-use land. Using difference-in-differences, we compare areas that are within 1 km of Line 1 with control areas that are beyond 1 km but within 3 km of Line 1, before and after the opening of Line 1. We find that two years before the opening of Line 1, the change in property prices in areas within 1 km of Line 1 was 5-6% higher than the change in areas between 1 and 3 km from Line 1, reflecting anticipatory effects of the policy. After 2014, prices for commercial and residential properties within 1 km of the Metro increased between 7% and 10% relative to the control group. Due to limited data in the pre-policy period and the possibility of price appreciation in anticipation, our results are likely an underestimate of the true property price appreciation after the opening of Line 1.

The assumption implicit in our analysis is that the change in prices over time would have been the same in sub-zones up to 3 km from Line 1 in the absence of Line 1. To test the sensitivity of our results, we repeat this analysis with different treatment and control group definitions. We also test the robustness of our results using a synthetic difference-in-differences identification strategy. We find that the magnitude of effects declines as the treatment area is expanded to include sub-zones further away from Line 1, suggesting that the influence of Line 1 is positively associated with spatial proximity to the line.

We then examine the source of these benefits. A first-order benefit is the time savings to commuters that Line 1 provides. Tsivanidis (2019) finds that time savings benefits account for about 40% of the overall general equilibrium welfare generated due to the introduction of Bus Rapid Transit in Bogota. Suri and Cropper (2024) study the magnitude of time savings in Mumbai using static commute mode choice and housing location choice models, assuming fixed job locations, to measure short run and long run welfare respectively. They estimate the annualized value of commute time savings due to Line 1 through improvements in travel time and household resorting to be 565 Million 2019 Int$. Twenty percent of these estimated benefits accrue to households living in our treatment area.

To explore the role of time savings benefits in this paper, we estimate the commute time savings by subzone that Line 1 has delivered, using household transportation surveys. Using a difference-in-differences design, we then estimate price appreciation in sub-zones with potential commute time reductions due to Line 1. We find that sub-zones with higher commute time reductions experienced increases in property prices due to the opening of Line 1. This is true for residential as well as commercial and industrial properties

Although the capitalized benefits provide a lower bound to the overall general equilibrium effects of Line 1 (Banzhaf (2021)), they do not directly inform us about the effects due to changes in job locations in Mumbai over time. We measure the impact of these changes on the benefits of Line 1 using a measure of improvement in employment accessibility from 2004 to 2019. This measure is similar to the measure of changes in commuter market access, which captures general equilibrium changes in access to wages across the city as households and firms re-sort in response to new infrastructure projects. Changes in commuter market access have been shown to be a major source of welfare in the context of the construction and removal of the Berlin wall (Ahlfeldt et al. (2015)), the introduction of the steam railway in London (Heblich et al. (2020)), the introduction of Bus Rapid Transit (BRT) in Bogota (Tsivanidis (2019)), and the introduction of BRT in Buenos Aires (Warnes (2020)). Our approach provides a reduced-form way to relate the spatial changes implied by spatial equilibrium models to the net benefits observed in property price appreciation.

Our measure of employment accessibility is a commuting-time weighted average of wages obtainable across the city from a given sub-zone. Lacking detailed information on wages, we follow the approach in Kreindler and Miyauchi (2023) to infer relative wages from commute flows. We obtain data on commute flows from two representative household surveys of travel demand conducted by the World Bank in 2004 and 2019.

We find that the capitalization effects of Line 1 were stronger in areas that have experienced greater improvements in employment accessibility between 2004 and 2019. Improvements in employment accessibility may reflect reductions in commuting times to high-wage locations and/or increases in effective wages in more accessible locations, holding commuting times constant. To the extent that changes in employment accessibility are due to factors unrelated to Metro Line 1, these results reflect the importance of the strategic placement of transport investments.

2 Context and Data

Mumbai is the financial capital of India and one of the most densely populated cities in the world. In the Greater Mumbai Region (GMR), 12.5 million people (Census, 2011) live in an area of 603.4 sqkm.[1] Mumbai faces enormous challenges with shortages of land, housing, infrastructure, and social services that have not kept up with the growing demands of the city. Some of Asia's largest slums, including Dharavi, with a population of over one million, are located in Mumbai. An estimated 42% of the city's population lives in slums, many located along railway tracks (Census 2011).

Mumbai has an extensive rail network. Mumbai Suburban Railway consists of 100 km of track in the Greater Mumbai Region and 465 km across the entire Mumbai Metropolitan Region (see Figure 1). It is one of the busiest commuter rail systems in the world. Suburban trains are, however, faced with an acute overcrowding problem—there are about 14-16 passengers per sqm of floor space during typical rush hour times (Hindustan Times (2017)). Although some air-conditioned trains have been introduced since December 2017, few of Mumbai's suburban trains are air-conditioned. Mumbai also has an extensive network of public buses that complements the rail system.

The 2011 Census reports that 50% of Mumbai's commuters used either rail or bus (Table 1); however, this share has been falling. As incomes have risen, commuters have switched to private vehicles. Between 2000 and 2017 the number of two-wheelers in Mumbai increased by 340%; the number of cars increased by 200%.[2] This has led to huge traffic

[1] The Greater Mumbai Region is the core of the larger Mumbai Metropolitan Region, which has a population of 22.88 million in an area of 6,355 sqkm.

[2] There were 407,306 two-wheelers and 303,108 cars in Mumbai in 2000. Their population increased to

congestion problems in the city, and a fall in bus ridership. Bus ridership declined from 4.2 million per day in 1997-98 (Korde (2018)) to 2 million in 2019 (DNA India (2019)).

An extensive metro rail project–300 km of metro lines—has been planned to alleviate Mumbai's congestion problems in an environmentally friendly way (Chacko (2018)). Metro Line 1 opened in 2014 and an additional 35 km of Metro opened in 2022-23. 167 km are currently under construction.[3] Metro Line 1, shown in Figure 1, is the first east-west rail link in the city. It is important to put this transit project in the context of Mumbai's development. Historically, both population and employment in the GMR have followed the Suburban Rail lines, with concentration in the south of the city, where the original central business district was located. Over time, both population and employment have moved northward, and there is a second business and industrial center in the middle of the GMR. Line 1 goes through this region. Appendix Figures B1 and B2 show the population and employment density in the GMR according to the 2011 Population Census and the 2013 Economic Census, respectively. There is high population and employment density near Line 1, suggesting the potential benefits of this location.

Property Prices: We measure the magnitude of realized benefits by estimating the capitalization of Line 1 into property values. Each year, the Municipal Council of Greater Mumbai (MCGM) uses information on property transactions conducted during the year to set assessed property prices for the following year for geographical sub-zones. The entire city is divided into over 723 sub-zones. Annual assessed values, also known as the Ready Reckoner Rates, are published in Rs. per sqm. for the following categories of properties, based on floor space use: open land, residential property, commercial office, commercial shop, and industrial property. In the absence of a consistent dataset on the market values of sale and rental prices of properties in Mumbai, Ready Reckoner rates are the best available proxy for property prices.

We obtained georeferenced administrative data on assessed property prices for each sub-zone in Mumbai for the period 2006-2018 to estimate the impact of Line 1 on property values. Maps of sub-zone boundaries were constructed manually based on published information from the MCGM.[4] We used this information to compile a panel dataset of property prices for 723 consistently defined sub-zones in the city for the period 2011-2018.[5] Sub-zone boundaries are drawn based on historical factors and regional policy

1,784,657 and 911,856 by 2017, respectively. (Source: Department of Motor Vehicles, Maharashtra)

[3]A monorail of 20 km has also been planned for the southeastern part of Mumbai. The first line of the Monorail, 8.9 km in length in Eastern Mumbai was opened to the public in 2014, four months before Metro Line 1. Pre-pandemic, the daily ridership of the Monorail was about 19,000, in contrast to 450,000 for Metro Line 1.

[4]Boundaries were digitized by AInsight Technologies Pvt. Ltd. https://www.ainsighttech.com

[5] Data for 2010 are not available. 2008-2009 have been excluded because the assessed prices were

requirements, which may differ each year. We harmonized the sub-zone boundaries over time manually starting with the boundaries in 2011 and matching boundaries in other years to them.[6]

A summary of inflation-adjusted assessed prices in the city for different property types is in Table 2. Typically, commercial shop is the most expensive floorspace category, followed by commercial office, industrial, residential, and open-use. The average nominal assessed price for residential land in GMR in 2015-18 was about $230 per sqft, while the highest price was about $990 per sqft.[7] The average nominal commercial shop price in the city during the same period was $358 per sqft, 56% higher than the average residential price. The increase in prices from 2011 and 2012 is higher for sub-zones within 1 km of Line 1 than for sub-zones at a greater distance. Yearly trends in nominal assessed prices are shown in Figure 2 for sub-zones within 1 km of Line 1 and those beyond 1 km but within 3 km of Line 1. The sharp price divergence after 2014 coincides with the opening of Line 1.

3 Effects of Metro Line 1 on Property Prices

We study the net benefits of Line 1 by estimating the effects of the opening of Line 1 on property prices. We also estimate the anticipatory price effects of Line 1. Following the current literature, we use a spatial difference-in-differences design as our primary estimation approach. To account for the potentially differential price trends between sub-zones close to Line 1 and those further away, we implement a synthetic difference-in-differences strategy, optimally weighting sub-zone-year observations to force common trends in the pre-period.

3.1 Empirical Strategy

We estimate the effects of Line 1 on property prices using a difference-in-differences framework that leverages the spatial and temporal variation in property prices across sub-zones. The benefits of Line 1 in terms of agglomeration economies and improved access to the rest of the city are likely to be greatest in areas close to the line.[8] To define our

artificially controlled to mitigate the influence of the global recession. Since these prices are administratively set, some areas were likely more protected than others. 2006 was the first year in which the current system of assessing prices was put in place and was therefore, more prone to errors.

[6] We use the one-to-many match feature in QGIS 3.20.3 and select as a unique match the sub-zone whose centroid has the least geodetic distance from the sub-zone centroid being matched. We choose 2011 as our base year because it produces the smallest average distance between centroids of matched sub-zones, suggesting good quality matches.

[7] The exchange rate used for this calculation: $1=Rs. 67 which is the average for 2015-18.

[8] Suri and Cropper (2024) note that most of the time savings benefits of Line 1 in the short run accrue through improvements in access times.

treatment and control sub-zones, we compute the shortest distance via the road network between each sub-zone centroid and Line 1 using network analysis in ArcGIS.[9] In our main analysis, sub-zones with a distance less than 1 km are defined as treated while those beyond 1 km and within 3 km are defined as controlled. We believe that these sub-zones are most likely to be similar and satisfy the common trends assumption, but we perform various robustness checks to validate our main results. We estimate the following two-way fixed effects regression.

$$\log\mathrm{P}_{st} = \alpha_s + \tau_t + \zeta * \mathrm{Treated}_s * \mathrm{Year\ 2013/2014}_t + \delta * \mathrm{Treated}_s * \mathrm{Post\text{-}2014}_t + \epsilon_{st} \quad (1)$$

where $\log\mathrm{P}_{st}$ indicates the property price in sub-zone s and year t. α_s and τ_t represent sub-zone and year fixed effects, accounting for aggregate shocks at the sub-zone and year levels, respectively. Since the assessed prices in year t reflect market conditions in year t-1, we choose the years 2011 and 2012 as our reference period, years 2013 and 2014 as the period for measuring anticipatory effects, and years 2015-18 as the period for measuring the effects of Line 1 becoming operational. ζ is the estimate of changes between treatment and control areas up to two years before the opening of Line 1 relative to 2011-12 and indicates the anticipatory effects of Line 1 on property prices. Anticipatory effects are restricted to two years because of evidence in the literature that anticipatory effects generally do not show up more than two years before a transit project (Diao et al. (2017), Gupta et al. (2020)) and because of the observed trends in price changes (shown in Figure 3, discussed in the following subsection). δ is the main coefficient of interest representing the effect of the opening of Line 1 on prices. It captures the cumulative effects on prices after Line 1 became operational. If anticipatory effects started materializing before the period for which we have data, δ will be an underestimate of the true impact of Line 1 on property prices. ϵ_{st} represents idiosyncratic shocks at the sub-zone-year level. Standard errors are clustered at the sub-zone and year levels following the recommendation in Cameron et al. (2011).[10]

A spatial difference-in-differences analysis based on proximity to the metro cannot estimate changes in property prices that may have occurred due to improved commute times and market access in areas beyond 1 km of the metro. But this empirical approach has the advantage of satisfying the identification assumptions more convincingly compared to an analysis of citywide properties based on stronger identifying assumptions. With this in mind, we repeat the analysis with other proximity-based treatment and control group definitions to learn more about the gradient of the effects on property prices. We use an alternative treatment definition based on commute time savings in the Section 4.1.

[9]For distance calculation, Line 1 is converted into nodes to calculate distance between two points.

[10]Results are robust to clustering at a more aggregated neighborhood level than the sub-zone level.

Other proximity-based definitions of treatment and control groups in our analysis include sub-zones within 1 km vs those between 2 and 3 km, sub-zones within 1 km vs those between 1 and 5 km, and sub-zones within 1 km vs all other sub-zones in the city beyond 1 km. We note that the possibility of general equilibrium effects in property markets in the vicinity of Line 1 implies a possible violation of the stable unit treatment value assumption (SUTVA). While it is not possible to completely address this in a reduced-form spatial difference-in-differences framework, we believe that limiting the geographical scope of our analysis reduces the likelihood of this problem. Additionally, using different treatment-control group definitions helps us understand the influence of spatial spillovers.

In the presence of spillovers affecting control group sub-zones or differential trends, synthetic difference-in-differences is likely to reduce the severity of bias of the two-way fixed effects estimator (equation 1) due to the inclusion of both sub-zone and time weights (Arkhangelsky et al. (2021)). More weight is assigned to pre-treatment periods where control group outcomes more closely resemble post-treatment control group outcomes and more weight is assigned to control units where the growth in pre-period outcomes is similar to that of treated units.[11] We compute this estimator using the method in Clarke et al. (2023), which estimates a weighted version of equation 1. The weight for each observation is a product of unit and time weight optimally computed using the procedure in Arkhangelsky et al. (2021). Our preferred method for computing standard errors is bootstrapping keeping weights fixed, but we also verify robustness using the placebo method. The former is more appropriate for a larger number of treated units, while the latter is better for a small number of treated units.

We use four treatment definitions in the synthetic difference-in-differences analysis: sub-zones within 1 km of Line 1 post-2014, sub-zones within 2 km of Line 1 post-2014; sub-zones within 3 km of Line 1 post-2014; and sub-zones within 1 km of Line 1 post-2012. The first treatment definition serves as a direct robustness check for our main results from the difference-in-differences analysis. The second and third definitions help us investigate spillover effects. The fourth definition helps us compute the combined effects due to the anticipation of the opening of Line 1 and the actual opening. Since this procedure weights observations in a data-driven way, we also repeat this analysis using all of the data that was obtained on assessed prices. We add data for 2006-09 to our primary sample, 2011-18. We had earlier excluded these data due to the likelihood of unknown measurement error in price setting and due to measurement error in harmonizing sub-zone boundaries across the years.

[11]Note that to the extent that the entire donor pool for the control group is contaminated, the same issues as before would apply.

3.2 Results

We first examine changes in property prices in treatment and control groups over time compared to the difference in 2011 (shown in Figures 3-6). Each point on these graphs shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following dynamic variant of equation 1,

$$\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st} \tag{2}$$

where logP_{st} is the property price in sub-zone s and year t. α_s and τ_t represent sub-zone and year fixed effects as before. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). Treated_s is an indicator for treated sub-zones. β_t is the main coefficient of interest reflecting the difference between treated and control sub-zones in the year t relative to this difference in 2011. A plot of β_t is in Figure 3. We see that in 2012, the average difference in prices in sub-zones within 1 km and those beyond 1 km but within 3 km was no different than in 2011. In 2013-14, prices in treatment areas were 5-6% higher and post-2014, prices were 8-10% higher, with the price increase being persistent over time. The price increase in 2013-14 represents the anticipatory effects of Line 1 and the increase post-2014 is the effect of opening of Line 1.

We also examine these trends for other control group definitions. Comparing sub-zones within 1 km of Line 1 with those beyond 1 km but within 5 km of Line 1, Figure 4 shows that the magnitude of changes are somewhat smaller, suggesting the possibility of spillover effects. Figure 5 compares sub-zones within 1 km with all the remaining sub-zones in the city and shows slightly lower appreciation, as before. This suggests that other parts of the city not close to Line 1 were also experiencing increases in property prices, likely not due to Line 1. This also suggests that sub-zones closer to Line 1 are more appropriate controls for sub-zones within 1 km of Line 1.

Since our treatment definition is based on the proximity of sub-zone centroids to the nearest point on Line 1 via the road network, measurement error is likely to be present. Sub-zones that we classify as being within 3 km but just beyond 1 km may, in reality, be treated. Figure 6 compares changes in property prices between sub-zones within 1 km and sub-zones beyond 2 km but within 3 km. We find similar price effects in this case to those in Figure 3.

Our main estimates of the anticipatory effects and effects of the opening of Line 1 are in Table 3. We find that two years before the opening of Line 1, property prices in sub-zones within 1 km of Line 1 increased by 5-6% relative to sub-zones beyond 1 km but within 3 km of Line 1. Due to the opening of Line 1, property prices increased by 7-10% depending on the land-use classification. The difference in magnitude of anticipatory effects and the effects of the opening of Line 1 is especially interesting given the delays in the completion and opening of infrastructure projects in India. It could be due to limited forward-looking behavior on the demand side, insufficient flexibility in the credit market, or a general mistrust of government announcements.

We show the robustness of these capitalization effects by estimating equation 1 for various control group definitions. Comparing sub-zones within 1 km with those beyond 1 km but within 5 km of Line 1, we find anticipatory effects ranging from 3.5-4.5% and the effects of the opening of Line 1 ranging from 4.5 to 5.5%, depending on the property type (Table 4). Comparing sub-zones within 1 km with the rest of the city, we find robust anticipatory effects but significant increases in prices due to the opening of Line 1 only for residential, commercial office, and industrial land-use properties. The average effect size is 3.1-3.8% for anticipatory effects, similar to other specifications. However, the effects of the opening of Line 1 are smaller, lying in the range of 5.8-6.5% (Table 5).[12]

To observe the influence of possible spillover effects, we also estimate equation 1 considering sub-zones within 1 km of Line 1 as treated and those beyond 2 km but within 3 km as controls. Table 6 shows roughly similar estimates as when sub-zones between 1-2 km were included in the control group. In this case, we note about a 1 percentage point deviation from the previous estimates for commercial shop and open-use floorspace types. This is likely a reflection of transit-oriented development, which would in principle be less constrained due to distance from Line 1, and therefore, more susceptible to spillover effects.

To account for the possible differential trends between treated and control sub-zones, we also obtain synthetic difference-in-differences estimates for different treatment and control groups. Results are in Table 7. The first panel shows the estimated effect of the opening of Line 1 on property prices in sub-zones within 1 km of Line 1 relative to a synthetic control group drawn from all sub-zones in Mumbai whose outcomes are parallel to the treatment group outcomes during 2011-14. These estimates of price appreciation, ranging from 2-4.4% are smaller than the difference-in-differences estimates, but are similar to the percentage point difference between the anticipatory effects and the effects of opening of Line 1. This is reasonable given that the anticipatory period is a part of the control group in this analysis. The last panel of this table shows estimates of price appreciation during the anticipatory period and the post-opening period combined. The combined

[12]We also use a distance measure as a continuous treatment variable in equation 1 and find similar results. We do not emphasize this analysis since it requires stronger identifying assumptions.

price appreciation ranges from 4.1-5.3% and is closer to the estimates obtained previously.[13]

To further test the robustness of the magnitude of price appreciation estimates, we exclude the years 2013 and 2014 from our sample and obtain the synthetic difference-in-differences estimates for different treatment definitions. Results are in Table 8. We observe 4.7-6% increase in property prices in sub-zones within 1 km of Line 1. These magnitudes are close to the spatial difference-in-differences estimates reported above. This also confirms that the reason for lower estimates in Table 7 was indeed the inclusion of the anticipatory effects period in the control group.[14]

The magnitude of effects we find for the impact of Line 1 is similar to the existing literature. McMillen and McDonald (2004) estimate a 7% increase in housing values in the vicinity of Chicago's Midway Line in 1993. Billings (2011) estimates a 4-11% increase in residential property values in response to a light transit line in Charlotte, North Carolina within 1 mile of the line, and no effects on commercial property values. In the context of Singapore, Diao et al. (2017) estimate that a mass rapid transit line that opened in phases in 2009-11 raised housing values in the vicinity of the transit line by 8.6%. Zhou et al. (2019) find price appreciation close to 4% in response to Line 6 of the Chinese metro. Gupta et al. (2020) estimate a 10% increase in property values in the vicinity of the Second Avenue Subway line that opened in New York City in 2017.

The estimated price effects of Metro Line 1 could reflect the direct effects of Line 1 as well as agglomeration effects. In the following section we investigate the influence of commute time savings, a direct first-order benefit of Line 1, and changes in employment accessibility, a proxy for agglomeration economies, on property price appreciation. Although the length of time required for agglomeration effects to materialize is uncertain, we believe that price changes due to direct short-term benefits likely show up before the agglomeration effects. Figures 3 - 6 show that relative to 2011, the estimated effects during the initial post-treatment periods are similar to the average for the entire period across property types. This suggests that our results more likely reflect direct benefits, including time savings, rather than agglomeration benefits.

[13] As previously mentioned, we repeat the synthetic difference-in-differences estimation using all of the data that we have (from 2006-18). Results are in Appendix Table B1. The magnitude of the estimates are the same as before. But there is more evidence of spillover effects across sub-zones as reflected in significant effects for sub-zones within 2 km and 3 km of Line 1.

[14] We also run these regressions on the entire 2006-18 sample excluding the years 2013 and 2014 and find similar effects. Results are reported in Appendix Table B2.

4 Sources of Benefits

Estimated price effects could reflect a variety of different factors. Our aim in this section is to investigate the influence of two sources of benefits of Line 1 on property prices: time savings and improvements in employment accessibility. In Section 4.1, we examine the role of time savings in explaining price changes directly by using alternative treatment definitions based on time savings due to Line 1.

We then examine spatial changes in employment accessibility in Section 4.2. Employment accessibility changes reflect changes in access to areas in the city with high economic activity and could reflect factors unrelated to the introduction of Line 1. The spatial pattern of changes can be leveraged to understand the benefits of the strategic location of Line 1. We examine the heterogeneity in spatial difference-in-differences estimates by levels of changes in employment accessibility to test the influence of improvements in employment accessibility in the vicinity of Line 1.

4.1 Time Savings

The first-order effect of transport projects is on the travel time of individuals. Transport projects such as metro rail provide benefits to commuters by reducing commute times from home to work. Suri and Cropper (2024) measure the value of improved commuting utility due to the reduction in commute time associated with Line 1 using a housing location choice model. The annual time-saving benefits of Line 1 when households can adjust their residential location are approximately 565 Million 2019 Int$. About 20% of these benefits accrue to households living in our treatment area.

In this section, we explore the role of time savings on residential property prices in a reduced-form way. We construct measures of commute time savings due to the opening of Line 1 using two representative surveys of travel demand conducted by the World Bank. Using information on commuter residential and workplace locations, we estimate the travel time savings due to the opening of Line 1 for each commuter and then calculate average savings by sub-zone. We then estimate the impact of time savings on property prices.

Data: We construct measures of time savings using two transportation surveys conducted by the World Bank in 2004 and 2019, administered to 6000 and 3000 households in the city, respectively. These data have information on geocoded household locations and the pincode (zipcode) of workers' work locations, which we use to describe a worker's usual commuting trip. We use a randomly chosen post office in each pincode to proxy work locations. We use the transport network map from OpenStreetMap and a network algorithm to compute travel time via rail along the shortest duration travel path for each worker's residence-to-work commute.

For individuals in the 2004 survey, we supplement the rail network with Metro Line 1 and compute the potential reduction in travel time. For individuals in the 2019 survey, we remove Metro Line 1 from the rail network to compute the reduction in travel time that could be attributed to it. We then average these for each sub-zone and each survey separately. Neither of the surveys has workers in every sub-zone, therefore, to improve spatial coverage, we average travel time savings for households in the two surveys and end up with information for 473 sub-zones.[15] 51% of these sub-zones have positive commute time savings. These savings can be from improved access to railway stations or more efficient rail transit connections. The mean distance of a sub-zone with positive time savings from Line 1 is 8.6 km.

Empirical Approach: We construct alternative treatment and control group definitions based on the level of time savings and estimate our difference-in-differences equation to understand their role in property price appreciation. Treatment definitions based on time savings rather than distance also limit the influence of anticipatory behavior since investment in property based on physical distance from an amenity is less risky. We use three criteria to define treated sub-zones: (i) sub-zones with any time savings based on the existing commuting patterns in the city, (ii) sub-zones with time savings above the median, conditional on positive savings, and (iii) sub-zones with time savings above the 75th percentile, conditional on positive savings. Figure 7 shows sub-zones with zero potential time savings and quartiles conditional on positive savings. Many sub-zones across the city experienced time savings benefits due to Line 1.

We begin by examining the dynamic difference-in-differences coefficients from estimating equation 2 using treatment definitions based on time savings. Figure 8 shows a clear pattern of price appreciation in sub-zones that experienced commute time savings after the opening of Line 1. The absence of any anticipatory effects lends further credibility to the nature of effects observed. Before the opening of Line 1, there are no significant differences in residential prices in sub-zones with positive time savings. There is a gradual increase in price appreciation in treatment sub-zones after the opening of Line 1. There is an immediate price appreciation of 2.3% in sub-zones with commute time savings over the 75th percentile of positive savings experienced, which increases to 7% in two years.

We also examine the impact of time savings on other property types because of Mumbai's mixed land-use policy and the likelihood of greater commercial activity in high-

[15]Our results are robust to using time savings implied by either survey.

demand residential neighborhoods. Dynamic event study estimates for all property types are similar to those for residential properties (shown in Appendix Figures B3-B5). These results show that benefits from transit infrastructure are larger than those implied by residential property price appreciation alone.

Regression estimates of price appreciation based on equation 1 and treatment definitions based on time savings are in Table 9. Residential property prices appreciated by 3% in sub-zones with above median time savings conditional on positive savings and by 5% in sub-zones with positive time savings above the 75^{th} percentile. Effects for other property types are of a similar size, albeit statistically weaker. These effects are slightly lower than our primary difference-in-differences results likely because price appreciation within 1 km of Line 1 encompasses time savings as well as benefits from transit-oriented development and agglomeration.

4.2 Employment Accessibility

Improvement in access to jobs is another important channel through which transport projects improve welfare and raise output (Heblich et al. (2020), Tsivanidis (2019), Warnes (2020)). Empirically, the access of a worker in location i to jobs can be measured by an employment accessibility index. For each residential location (e.g. sub-zone) in the city, the index measures employment opportunities in every employment location in the city, weighted by the cost to travel to that location. Transport projects can raise employment accessibility through agglomeration economies, which raise wages, and/or by making high-paying jobs more accessible through lower travel times.

We parameterize an employment accessibility index for each of the 723 sub-zones in Mumbai for 2004 and 2019 using information on commute flows from the two household surveys used in Section 4.1. We measure changes in employment accessibility for each sub-zone over this period and use it to study the heterogeneity in the impact of Line 1 on property values.

Our employment accessibility index is a commuting time weighted average of effective wages obtainable in various locations across the city accessible from a given residential location. Effective wages reflect the attractiveness of locations as employment locations after accounting for commuting time and average commuting preferences. Let j index possible work locations in the city. The employment accessibility index for residential location i is

$$\mathrm{EA}_i = \sum_j \left(\frac{W_j}{t_{ij}} \right) \tag{3}$$

W_j is the wage obtainable at location j. Similar to Kreindler and Miyauchi (2023), W_j is inferred from commute flows to potential destination work locations adjusted using an estimate of dispersion in individual decisions to locate in i and commute to j. t_{ij} is the travel time from house i to location j.[16] The estimation is discussed in Appendix Section A.

We look at changes in two employment accessibility indices across the city from 2004 to 2019 in Figure 9: the first one uses income information from household survey data to calibrate the dispersion parameter used to infer wages, and the second one calibrates the dispersion parameter using an estimate of the value of time from a commute mode choice model (Appendix Section A).[17] Both measures of employment accessibility produce a similar pattern of results. The correlation between the two measures is over 0.9, and therefore, we report results based only on the first measure. The largest improvements occurred in areas in the center of the city and in the north. Improvements in employment accessibility are smallest in the southernmost part of the city, which is the location of the traditional business district. This is consistent with the population and employment density in the city moving northward since the 90s (latest Census figures are in Figure B1).

We also look at changes in employment accessibility constructed separately for workers by college education level (Appendix Figure 10). There is some overlap in areas that experienced an improvement in employment accessibility for workers with college educations and those without. However, there are many sub-zones for which we could not compute a measure of change in employment accessibility for college-educated workers. This is because in the 2004 survey, only 21% of the workers had a college degree, and in the 2019 survey, only 32% had a college degree. Broadly, these maps mimic the pattern in overall improvements in employment accessibility.

Influence of Improvements in Employment Accessibility: Since changes in employment accessibility may not necessarily be caused by Metro Line 1, we test for the influence of employment accessibility by examining the heterogeneity in the main difference-in-differences estimates by improvements in employment accessibility. We restrict this analysis to sub-zones within 5 km of Line 1 to avoid areas with improvements in employment accessibility due to reasons clearly unrelated to the Metro. A similar pattern of results

[16]Our results are robust to using iceberg commuting costs instead of travel time t_{ij}.
[17]We compute the second index to test for robustness to the computational method.

holds with the analysis restricted to within 3 km of Line 1. We define indicator variables for relative improvements in employment accessibility within 5 km of Line 1 being above the median for all workers and for workers by education level. We estimate equation 4 to test for the differential effect on price appreciation in sub-zones with greater improvements in employment accessibility.

$$\begin{aligned} \log \mathrm{P}_{st} &= \alpha_s + \tau_t + \zeta * \text{Treated}_s * \text{Year 2013/2014}_t + \delta * \text{Within 1 km}_s * \text{Post-2014}_t \\ &+ \omega_1 * \mathbb{1}(\text{Improvements above K}^{th} \text{ percentile}) * \text{Within 1 km}_s * \text{Year 2013/2014}_t \\ &+ \omega_2 * \mathbb{1}(\text{Improvements above K}^{th} \text{ percentile}) * \text{Within 1 km}_s * \text{Post-2014}_t + \epsilon_{st} \end{aligned} \tag{4}$$

Results are in Table 10 for employment accessibility changes estimated for all workers. Compared to our difference-in-differences estimates, both the anticipatory effects and the effects of opening of Line 1 are significantly higher in areas with greater improvements in employment accessibility. This shows that the estimated capitalized benefits of Metro Line 1 are greater in areas where the improvement in employment accessibility is higher. In Appendix Table B4, we repeat this analysis using improvements in employment accessibility for workers with and without a college education. While some coefficients are only weakly statistically significant, these results suggest that improvements in employment accessibility for both types of workers influenced property price appreciation in the vicinity of Line 1. From Columns 2 and 3, it can be inferred that improvements in employment accessibility for college-educated workers, in particular, are highly correlated with price appreciation of commercial properties. Results are similar when the control group is restricted to areas beyond 1 km, but within 3 km on Line 1.

5 Conclusion

The use of reduced-form methods to examine the benefits of urban transport projects complements structural models which estimate households' compensating variation for transport projects (Barwick et al. (2021); Suri and Cropper (2024)) and quantitative spatial equilibrium models (Heblich et al. (2020); Tsivanidis (2019); Warnes (2020)) which simulate the impacts of transport projects on city output. In this paper, we have used reduced-form methods to answer three questions: (1) What is the impact of Line 1 of the Mumbai Metro on property prices near Line 1 for different land-use categories? (2) What is the impact of commute time savings generated by Line 1 on property prices throughout the city? (3) Was the price appreciation near Line 1 greater in areas where there have been greater increases in employment accessibility between 2004 and 2019?

Line 1 opened in June 2014, serving as the first east-west rail link in Mumbai. Our spatial difference-in-differences analysis shows that prices within one km of the line began to increase in 2013-2014, relative to 2011, in anticipation of the Metro opening. Compared to properties between 1 and 3 km of Line 1 (our main control group), properties within 1 km of the Metro (our main treatment group) appreciated by 5-6% in anticipation. After the opening of Line 1, between 2015-18, property price appreciation in treatment areas was 7-8% higher than in 2011. This is true for residential, commercial, and industrial properties and open land. Property price appreciation persists when other control groups are used—although its magnitude falls to 2-4% when synthetic difference-in-differences are used. These price increases reflect reductions in travel times for commuters living near the Metro and improved access to jobs across the city. They may also reflect agglomeration economies that firms enjoy by locating near the line.

Due to its centralized location, Line 1 also reduced commute times for individuals living in other parts of Mumbai. When we use two World Bank surveys covering 9,000 households to estimate the savings in commute times due to Line 1, we find that areas with higher average commute time savings experienced greater increases in residential property prices in 2015-2018 relative to areas with smaller time savings. Areas above the 75th percentile of positive commute time savings experienced increases in residential property prices of $\sim$7% relative to 2011. We view this as further evidence of the benefits of Metro Line 1.

To enrich our understanding of where Line 1 raised property prices we develop an index of employment accessibility. This measures, for any location, an average of wages in other locations in Mumbai, weighted by the inverse of commute times to each location. We compute this index in 2004 and 2019 and examine the spatial distribution of improvements in employment accessibility. The biggest increases in employment accessibility have occurred in central and northern Mumbai.

We then examine the influence of improvements in employment accessibility from 2004 to 2019 on property price appreciation within 1 km of Line 1 relative to that beyond 1 km but within 5 km. We find that price increases among the treated areas were greater in locations that experienced greater improvements in employment accessibility. Increases in employment accessibility did not necessarily occur because of the Metro, and therefore, we do not estimate the direct impact of improvements in employment accessibility. The fact that property price increases associated with the Metro have occurred in areas where employment accessibility increased highlights the importance of the strategic placement of transport investments.

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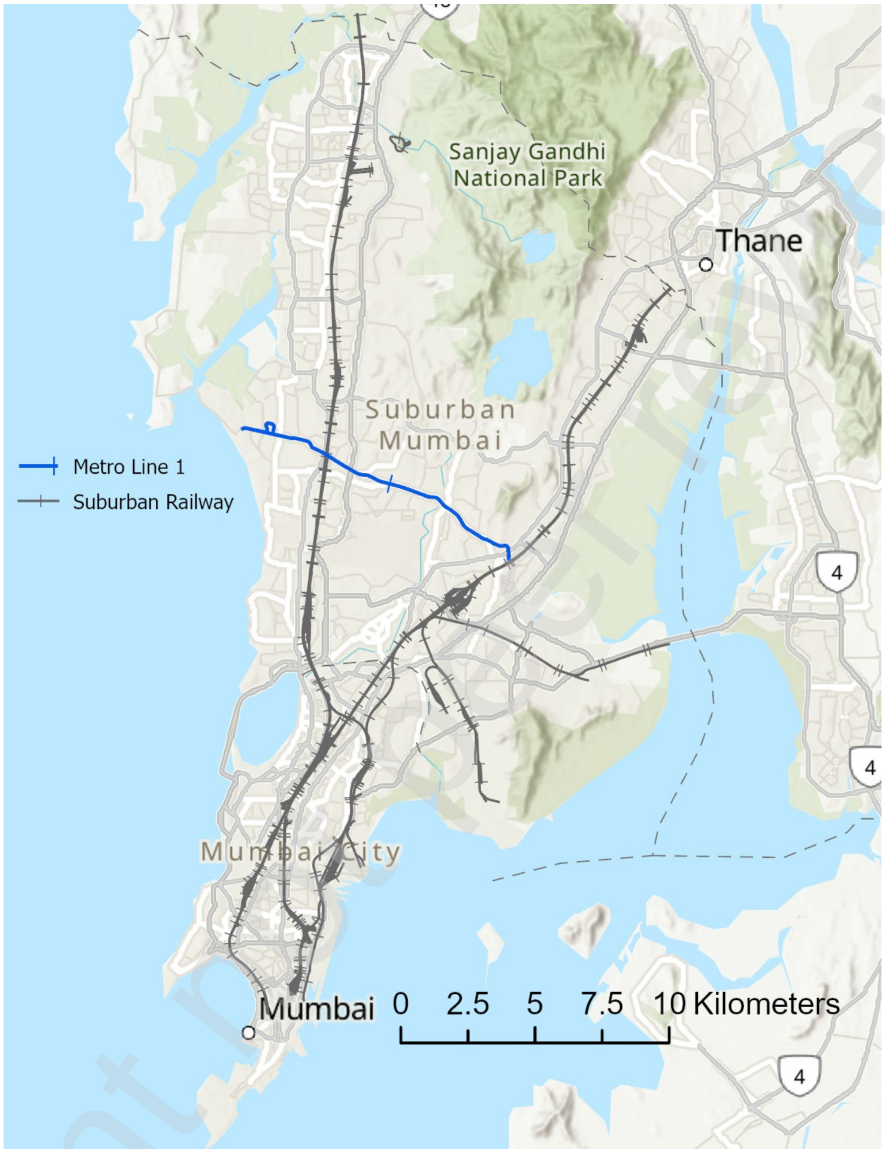
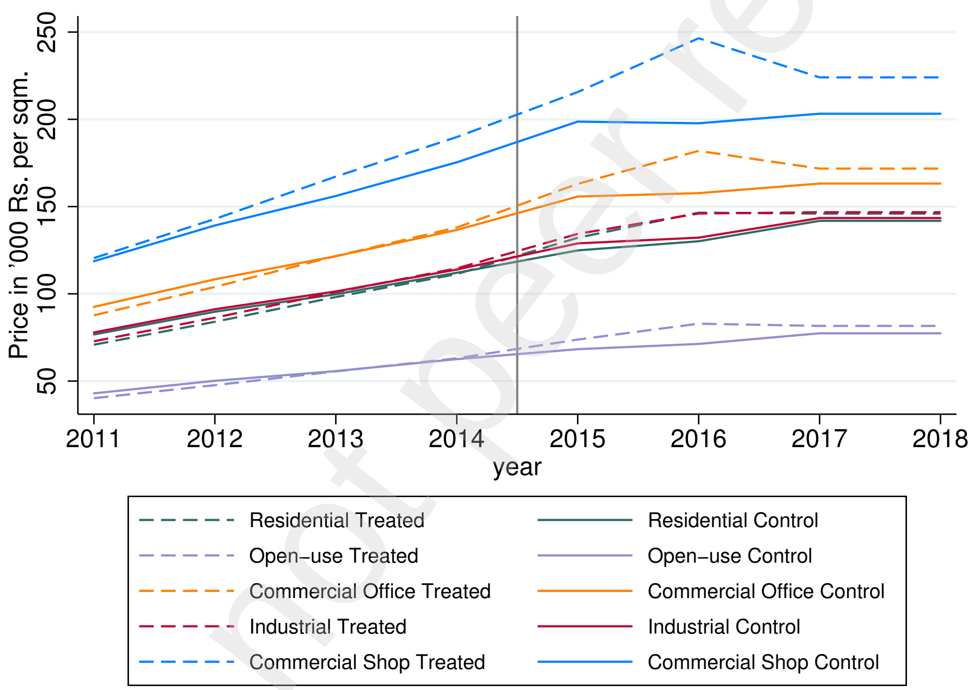
6 Figures and Tables

Figure 1: Mumbai's Rail Network



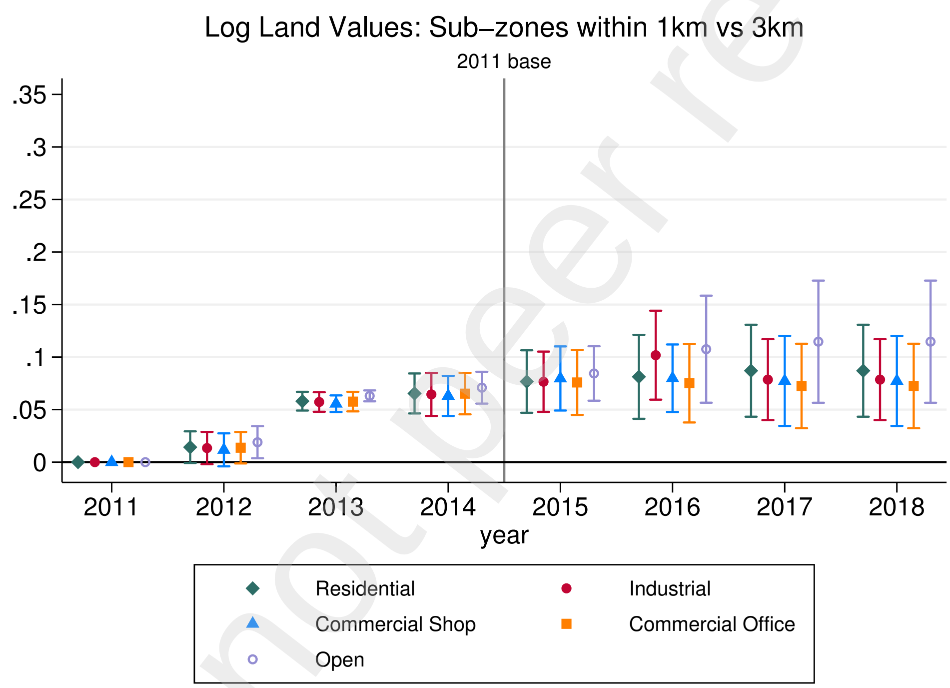
This map shows the Suburban railway network of Mumbai in grey, along with Metro Line 1 (11.4 km) in blue.

Figure 2: Trends in Nominal Assessed Property Prices in Sub-zones within 1 km and those beyond 1 km but within 3 km of Metro Line 1



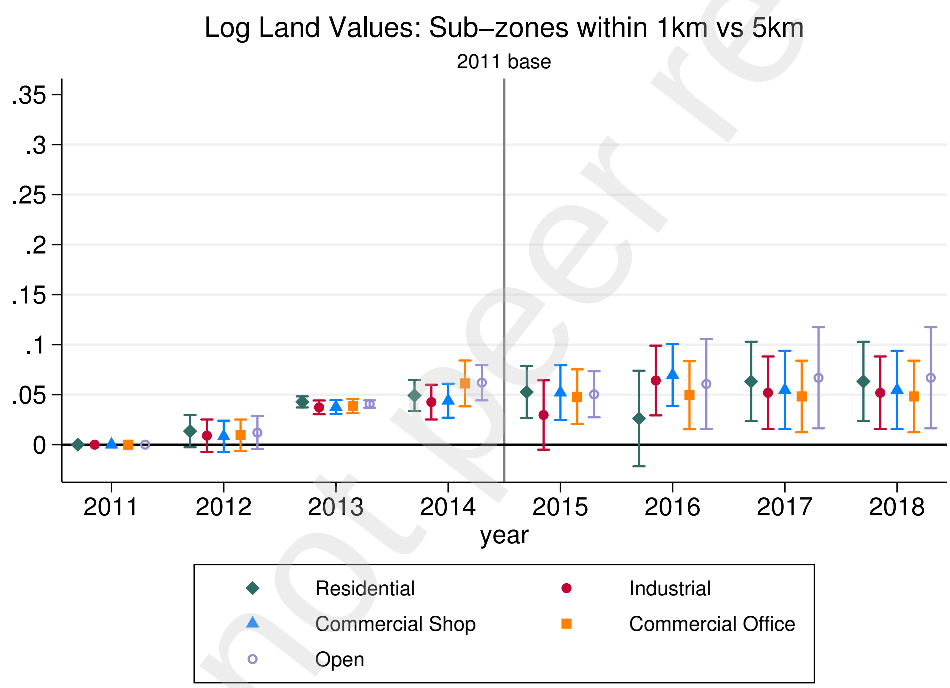
This figure shows trends in average property prices in sub-zones within 1 km of Line 1 (treated group), represented by dashed lines and those beyond 1 km but within 3 km of Line 1 (control group), represented by solid lines. Line 1 started in 2014 and the effects of its opening would show up 2015 onward, because assessed prices are based on previous year's market conditions.

Figure 3: Differences in Log Prices in Sub-zones within 1 km of Metro Line 1 vs Sub-zones within 1-3 km of Line 1



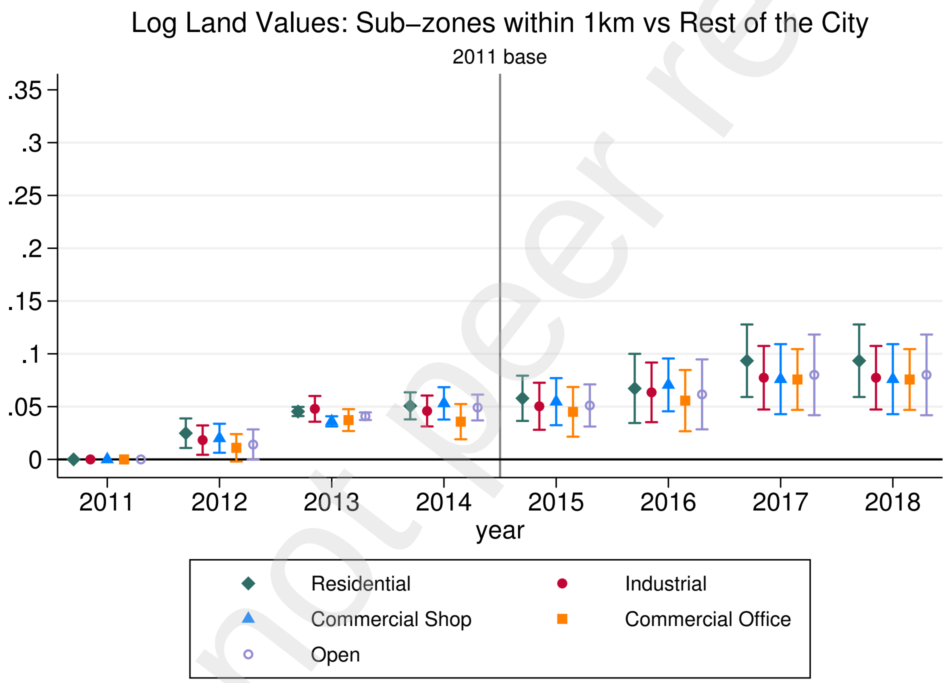
Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels.

Figure 4: Differences in Log Prices in Sub-zones within 1 km of Metro Line 1 vs Sub-zones within 1-5 km of Line 1



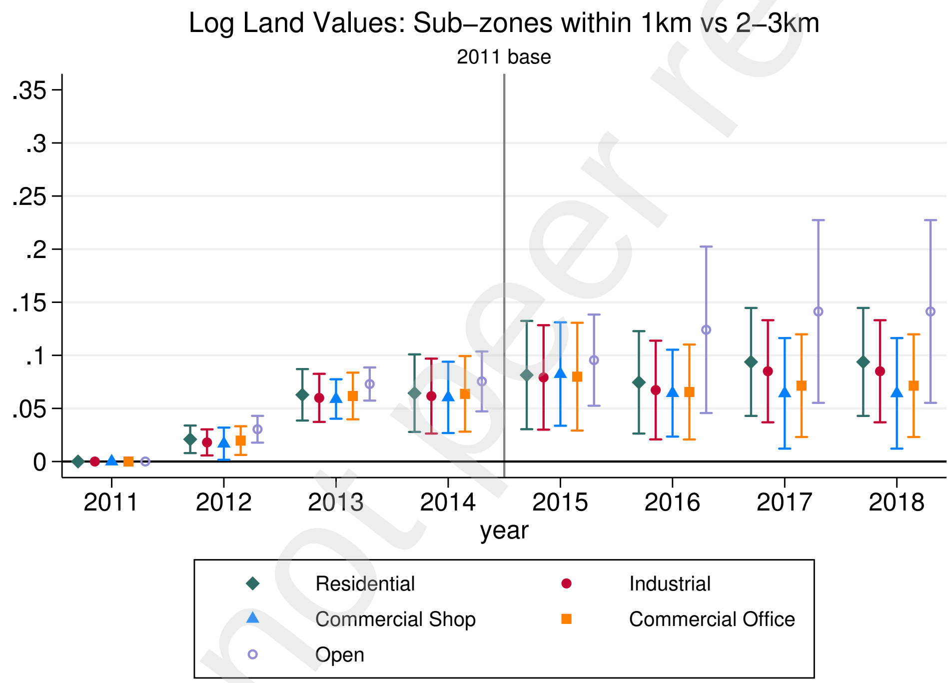
Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log\mathrm{P}_{st} = \alpha_s + \tau_t * \mathrm{Year}_t + \beta_t * \mathrm{Treated}_s * \mathrm{Year}_t + \epsilon_{st}$. $\log\mathrm{P}_{st}$ is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels.

Figure 5: Differences in Log Prices in Sub-zones within 1 km of Metro Line 1 vs Rest of the City



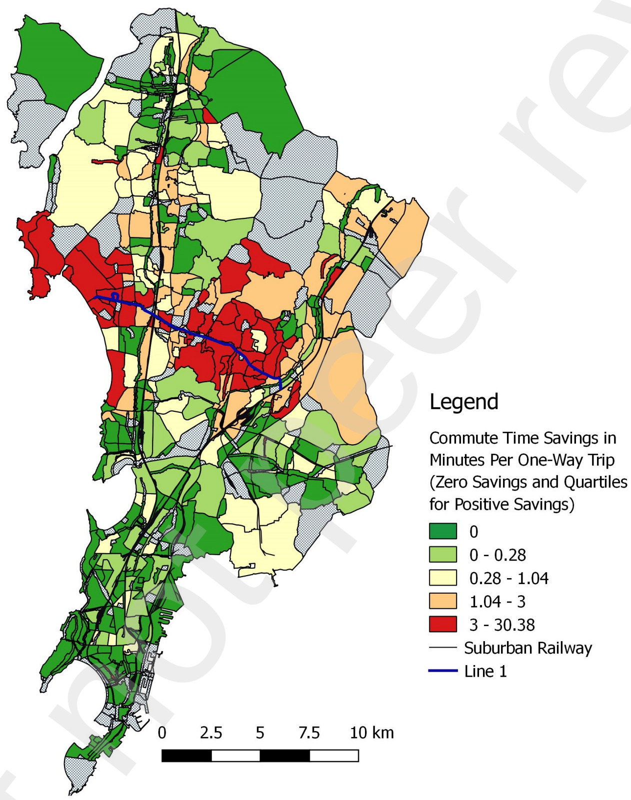
Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log\text{P}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. $\log\text{P}_{st}$ is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels.

Figure 6: Differences in Log Prices in Sub-zones within 1 km of Metro Line 1 vs Sub-zones within 2-3 km of Line 1



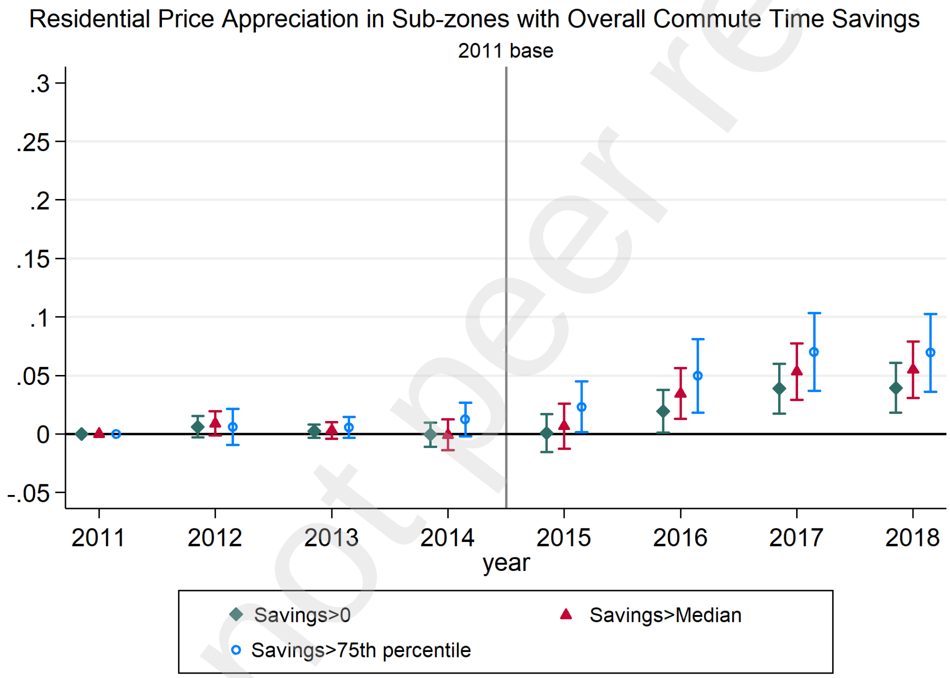
Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels.

Figure 7: Spatial Distribution of Potential Commute Time Savings using 2004 and 2019 Household Surveys



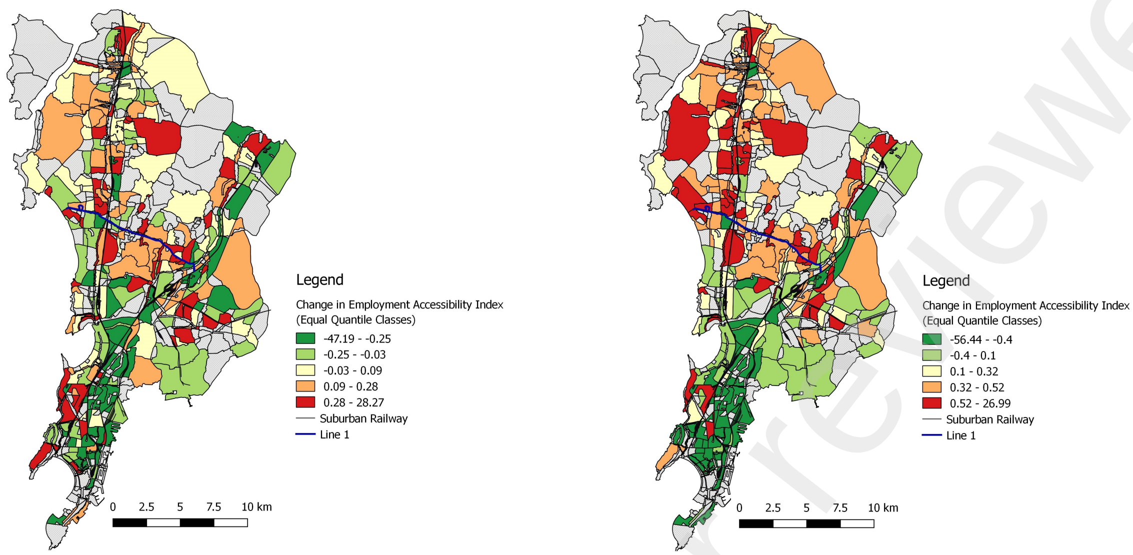
The graph shows average potential time savings due to Line 1 (in minutes per one-way trip) averaged for each sub-zone using 2004 and 2019 household survey data. Sub-zones with zero potential savings are in dark green. The remaining colors represent quartiles conditional on positive potential time savings: light green indicates sub-zones below the 25^{th} percentile savings, light yellow indicates 25^{th} to 50^{th} percentile savings, light orange indicates 50^{th} to 75^{th} percentile savings, red indicates those above the 75^{th} percentile. Sub-zones in gray are those for which we do not have any commuting individual in either survey round.

Figure 8: Differences in Log Residential Prices in Sub-zones with different levels of Time Savings



Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log\mathrm{P}_{st} = \alpha_s + \tau_t * \mathrm{Year}_t + \beta_t * \mathrm{Treated}_s * \mathrm{Year}_t + \epsilon_{st}$. $\log\mathrm{P}_{st}$ is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels. Treatment definition is based on the level of time savings.

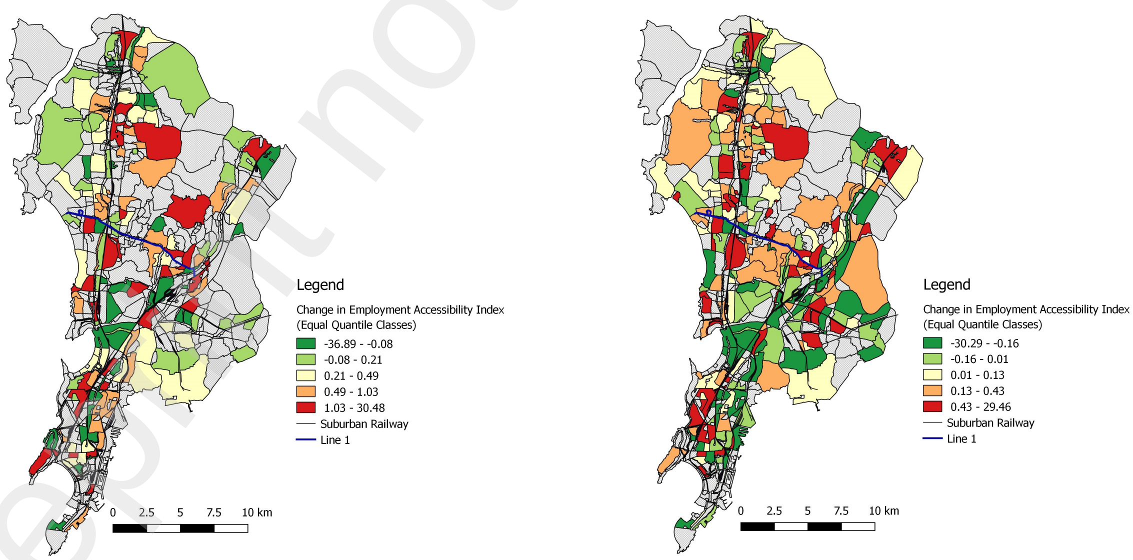
Figure 9: Spatial Changes in Employment Accessibility at the Sub-zone level



Preferred Measure **Alt. Measure**

These maps show changes in employment accessibility from 2004 to 2019 using indices aggregated at the sub-zone level. Alternative Measure is shown for robustness. Sub-zones in grey are those for which we cannot compute employment accessibility in both years.

Figure 10: Spatial Changes in Employment Accessibility by Worker College Education



Workers with College Education **Workers without a College Education**

These maps show changes in employment accessibility from 2004 to 2019 using indices aggregated at the sub-zone level constructed separately for the sample of workers by college education.

Table 1: Commute Mode Shares for Workers who Commute to Work (Census 2011)

Mode	Share (in %)
On foot	31.07
Bicycle	1.50
Moped/Scooter/Motor Cycle	5.55
Car/Jeep/Van	5.96
Tempo/Autorickshaw/Taxi	3.91
Bus	20.41
Train	30.79
Water transport	0.21
Any other	0.61
Total	**100.00**
Workers who don't commute	19.62

This Table presents commute mode shares from Census 2011 for workers who are not in the agriculture and allied sectors.

Table 2: Real Property Prices Before and After Line 1 (in 2001 Rs. per sqm)

	Pre-Line 1						Post-Line 1		
	Base 2011-2012			Anticipatory 2013-2014			Treatment 2015-2018		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Within 1 km of Line 1									
Residential	106	38,437	12,383	106	42,538	13,135	212	49,388	13,395
Commercial Office	106	47,589	13,926	106	52,743	14,941	212	58,554	14,526
Commercial Shop	106	65,257	18,480	106	72,345	20,271	212	79,332	20,394
Industrial	106	39,479	11,899	106	43,753	12,710	212	50,003	13,137
Open-use	106	21,822	8,924	106	24,103	9,549	212	28,122	10,009
Beyond 1 km but within 3 km of Line 1									
Residential	166	41,331	17,418	166	43,548	18,564	329	49,656	19,667
Commercial Office	166	49,821	20,189	166	52,446	21,151	329	57,698	22,058
Commercial Shop	166	64,027	25,187	166	67,435	26,092	329	72,651	26,310
Industrial	166	42,057	17,035	166	44,339	18,191	329	49,926	19,612
Open-use	168	22,805	12,126	168	23,971	12,837	336	27,157	13,804
Beyond 3km but within 5 km of Line 1									
Residential	124	39,596	15,668	124	43,551	17,531	251	56,525	65,932
Commercial Office	124	49,467	20,271	124	53,872	22,363	251	61,321	24,926
Commercial Shop	124	63,591	25,616	124	70,109	28,206	251	76,815	31,187
Industrial	126	40,514	15,384	126	44,848	17,213	252	54,760	53,484
Open-use	126	20,426	11,168	126	22,021	11,409	252	26,389	12,985
Entire City									
Residential	1,432	50,949	42,311	1,431	53,841	39,244	2,864	60,590	44,403
Commercial Office	1,422	64,318	46,884	1,422	70,471	68,074	2,844	73,956	48,530
Commercial Shop	1,432	81,448	57,940	1,432	87,718	62,715	2,864	92,134	57,959
Industrial	1,426	51,673	38,129	1,426	55,720	44,159	2,849	61,370	42,914
Open-use	1,446	26,141	20,731	1,446	27,823	21,294	2,892	31,564	22,608

This Table presents summary statistics of prices in Rs. per sqm. for different property types adjusted for inflation using the 2001 Consumer Price Index for Industrial Workers in the city of Mumbai published by the Government of India. Rs. 100 in 2001 is equivalent to Rs. 255 on average during the period 2011-2018. Categorization of years is consistent with the definitions of base period, anticipatory effects period, and the post-treatment period in our analysis.

Table 3: DID estimates of the Effects of Metro Line 1 on Assessed Property Prices in Sub-zones within 1 km vs 1-3 km

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Two years pre-2014*Within 1km	0.055***	0.055***	0.053***	0.054***	0.057***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.009)
Post-2014*Within 1km	0.076***	0.067**	0.073***	0.077***	0.096***
	(0.022)	(0.020)	(0.020)	(0.020)	(0.027)
Observations	1,085	1,085	1,085	1,085	1,096
R^2	0.97	0.97	0.97	0.94	0.96

This Table presents estimates of equation 1. Dependent variable is log of assessed property prices in Rs. per sqm. Sample restricted to sub-zones with centroid within 3 km of Metro Line 1. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: DID estimates of the Effects of Metro Line 1 on Assessed Property Prices in Sub-zones within 1 km vs 1-5 km

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Two years pre-2014*Within 1km	0.039***	0.045**	0.037***	0.035***	0.045***
	(0.010)	(0.013)	(0.009)	(0.009)	(0.011)
Post-2014*Within 1km	0.045*	0.044*	0.054**	0.045*	0.055*
	(0.022)	(0.019)	(0.019)	(0.020)	(0.024)
Observations	1,584	1,584	1,584	1,589	1,600
R^2	0.94	0.95	0.95	0.93	0.95

This Table presents estimates of equation 1. Dependent variable is log of assessed property prices in Rs. per sqm. Sample restricted to sub-zones with centroid within 5 km of Metro Line 1. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: DID estimates of the Effects of Metro Line 1 on Assessed Property Prices in Sub-zones within 1 km vs Rest of the City

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Two years pre-2014*Within 1km	0.036**	0.031**	0.035**	0.038***	0.038***
	(0.012)	(0.009)	(0.012)	(0.010)	(0.009)
Post-2014*Within 1km	0.065**	0.058**	0.059**	0.058**	0.061**
	(0.021)	(0.017)	(0.018)	(0.018)	(0.020)
Observations	5,727	5,688	5,728	5,701	5,784
R^2	0.97	0.97	0.97	0.96	0.98

This Table presents estimates of equation 1. Dependent variable is log of assessed property prices in Rs. per sqm. Sample includes all sub-zones in the city. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: DID estimates of the Effects of Metro Line 1 on Assessed Property Prices in Sub-zones within 1 km vs 2-3 km

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Two years pre-2014*Within 1km	0.053**	0.053**	0.051**	0.052**	0.059***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.014)
Post-2014*Within 1km	0.075**	0.062**	0.060*	0.070**	0.110**
	(0.026)	(0.026)	(0.026)	(0.025)	(0.038)
Observations	741	741	741	741	752
R^2	0.97	0.97	0.97	0.97	0.96

This Table presents estimates of equation 1. Dependent variable is log of assessed property prices in Rs. per sqm. Sample includes all sub-zones in the city. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Synthetic DID estimates of the Effects of Line 1 on Assessed Property Prices (2011-18 Sample)

	Residential	Commercial Office	Commercial Shop	Industrial	Open Land
Treatment Definition: Sub-zones within 1 km post-2014					
SDID ATT Estimate	0.026**	0.044***	0.035***	0.020**	0.019
	(0.010)	(0.010)	(0.006)	(0.011)	(0.012)
Treatment Definition: Sub-zones within 2 km post-2014					
SDID ATT Estimate	0.021	0.021	0.017	0.011	0.009
	(0.014)	(0.014)	(0.012)	(0.009)	(0.013)
Treatment Definition: Sub-zones within 3 km post-2014					
SDID ATT Estimate	0.018	0.017**	0.019	0.009	-0.003
	(0.011)	(0.008)	(0.012)	(0.011)	(0.012)
Treatment Definition: Sub-zones within 1 km post-2012 (Incl Anticipatory Effects)					
SDID ATT Estimate	0.046***	0.044***	0.044***	0.041***	0.053***
	(0.015)	(0.015)	(0.014)	(0.013)	(0.012)

Dependent variable is log of assessed property prices in Rs. per sqm. Sample includes all sub-zones in the city. Each specification has sub-zone and year fixed effects. Bootstrap standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Synthetic DID estimates of the Effects of Line 1 on Assessed Property Prices (2011-12 and 2015-18 Sample)

	Residential	Commercial Office	Commercial Shop	Industrial	Open Land
Treatment Definition: Sub-zones within 1 km post 2014					
SDID ATT Estimate	0.056***	0.053**	0.053***	0.047***	0.060***
	(0.019)	(0.023)	(0.013)	(0.014)	(0.018)
Treatment Definition: Sub-zones within 2 km post 2014					
SDID ATT Estimate	0.021	0.021*	0.014	0.010	0.024*
	(0.013)	(0.012)	(0.011)	(0.015)	(0.013)
Treatment Definition: Sub-zones within 3 km post 2014					
SDID ATT Estimate	0.013	0.014	0.010	0.001	-0.002
	(0.014)	(0.012)	(0.013)	(0.010)	(0.014)

Dependent variable is log of assessed property prices in Rs. per sqm. Sample includes all sub-zones in the city. Years for which anticipatory effects were observed (2013 and 2014) are excluded from this sample. Each specification has sub-zone and year fixed effects. Bootstrap standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: DID estimates of the effect of metro on assessed property prices in sub-zones that experienced commute time savings based on actual residence and work locations

	(1) Residential	(2) Comm. office	(3) Comm. shop	(4) Industrial	(5) Open Land
Panel A: Treatment group incl. sub-zones with positive time savings for a rail commute					
Savings>0 * Two years pre-2014	-0.002	-0.009	-0.014	-0.013	-0.011
	(0.006)	(0.011)	(0.015)	(0.011)	(0.007)
Savings>0 * Post-2014	0.022	0.014	0.021	0.017	0.015
	(0.014)	(0.013)	(0.015)	(0.012)	(0.015)
Observations	3,767	3,752	3,768	3,757	3,784
R^2	0.98	0.98	0.97	0.94	0.98
Panel B: Treatment group incl. sub-zones with above median positive time savings for a rail commute					
Savings>Median * Two years pre-2014	-0.003	-0.003	-0.021	0.004	-0.001
	(0.007)	(0.007)	(0.022)	(0.010)	(0.005)
Savings>Median * Post-2014	0.033*	0.028	0.034	0.032*	0.027
	(0.017)	(0.016)	(0.018)	(0.016)	(0.018)
Observations	3,767	3,752	3,768	3,757	3,784
R^2	0.98	0.98	0.97	0.94	0.98
Panel C: Treatment group incl. sub-zones with above 75th pctile positive time savings for a rail commute					
Savings>75th percentile * Two years pre-2014	0.006	0.008	-0.017	0.014	0.009
	(0.009)	(0.009)	(0.018)	(0.008)	(0.005)
Savings>75th percentile * Post-2014	0.050**	0.047**	0.043**	0.052*	0.054*
	(0.020)	(0.019)	(0.017)	(0.023)	(0.026)
Observations	3,767	3,752	3,768	3,757	3,784
R^2	0.98	0.98	0.97	0.94	0.98

Dependent variable is log of assessed property prices in Rs. per sqm. Control group includes sub-zones based on potential time savings as indicated by the treatment group definition. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Heterogeneity in the Effects of Metro Line 1 on Assessed Property Prices in Sub-zones within 1 km vs 1-5 km by Changes in Employment Accessibility

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Two years pre-2014*Within 1 km	-0.024	-0.025	-0.027	-0.024	-0.022
	(0.029)	(0.029)	(0.029)	(0.029)	(0.026)
Post-2014*Within 1 km	-0.063	-0.065	-0.059	-0.052	-0.033
	(0.043)	(0.045)	(0.043)	(0.040)	(0.049)
Two years pre-2014*Above Median Change	-0.028*	-0.030**	-0.032**	-0.028**	-0.026***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.005)
Post-2014*Above Median Change	-0.065*	-0.069*	-0.071**	-0.077**	-0.036
	(0.028)	(0.029)	(0.027)	(0.030)	(0.039)
Two years pre-2014*Within 1 km*Above Median Change	0.084*	0.086*	0.088**	0.084*	0.082**
	(0.036)	(0.037)	(0.036)	(0.037)	(0.032)
Post-2014*Within 1 km*Above Median Change	0.173**	0.180**	0.185**	0.162**	0.153**
	(0.056)	(0.057)	(0.059)	(0.048)	(0.063)
Observations	709	709	709	709	712
R^2	0.98	0.97	0.97	0.94	0.97

This Table presents estimates of equation 4. Dependent variable is log of assessed property prices in Rs. per sqm. Sample restricted to sub-zones with centroid within 5 km of Line 1. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix Employment Accessibility Measurement

The employment accessibility index for residential location i is

$$\text{EA}_i = \sum_j \left(\frac{W_j}{t_{ij}} \right) \tag{5}$$

W_j is the wage obtainable at location j. t_{ij} is the travel time from location i to location j. We use the methodology in Kreindler and Miyauchi (2023) to obtain a proxy for W_j. W_j is inferred from commute flows to potential destination work locations adjusted using an estimate of dispersion in individual decisions to locate in i and commute to j. Our results are robust to using iceberg commuting costs, $d_{ij} = exp(\kappa * t_{ij})$ instead of travel time t_{ij}.

The rationale behind our approach comes from an urban location choice model. The utility that a worker living at location i receives from working at employment location j is given by

$$U_{ij}(\omega) = \frac{W_j * \epsilon_{ij}(\omega)}{d_{ij}} \tag{6}$$

W_j is the effective wage obtainable at j and each worker receives the same wage. $d_{ij} = exp(\kappa * t_{ij})$ is the iceberg commuting cost between i and j represented by an exponential function of commuting time t_{ij} times the semi-elasticity of commuting costs to time, κ. $\epsilon_{ij}(\omega)$ is an an idiosyncratic utility shock assumed to follow an i.i.d. Fréchet distribution with shape parameter θ and scale parameter normalized to one. Equation 6 implies that the probability of a worker working in j conditional on living in i is given by

$$\pi_{ij|i} = \frac{(W_j/d_{ij})^\theta}{\sum_j (W_j/d_{ij})^\theta} \tag{7}$$

Equation 7 implies the following gravity equation of commute flow shares.

$$\text{log}\pi_{ij|i} = -\kappa * \theta * t_{ij} + \theta * \text{log}W_j - \log\big(\sum_j (W_j/exp(\kappa * t_{ij}))^\theta\big) \tag{8}$$

We estimate the following reduced-form gravity equation of commuter flows derived from 8 using a Poisson pseudo-maximum likelihood estimator in a two-way fixed effects regression.

$$N_{ij} = -\beta * t_{ij} + \psi_j + \gamma_i \tag{9}$$

N_{ij} represent aggregate commute flows between i and j.[18] $\beta = \kappa * \theta$ captures the sensitivity of commuting decisions to commuting time. θ represents the semi-elasticity of commuting shares to commute costs and κ the semi-elasticity of commuting costs to commuting time. γ_i and ψ_j are origin and destination fixed effects that reflect residence and workplace amenities, respectively.

We estimate equation 9 using data on commute flows between residence and work location pincodes from each household survey. There are 85 unique residential pincodes and 88 unique work location pincodes in data, implying a possible 7480 unique flows. Travel time is the pincode-pair-level mean of the minimum travel time via road or transit between each household in the survey and their work location. Gravity equation estimates using 2019 and 2004 survey data for all workers and workers by education level are in Appendix Table B3. The reported coefficient is $\hat{\beta}$, representing the sensitivity of commute flows to time. Estimates for all commuters using 2004 and 2019 data are similar. Workers with below college education are more sensitive to commute time than those with at least a college education.

Work location fixed effects, ψ_j are proportional to effective wages with a factor θ, the parameter representing the inverse of the dispersion in random shocks to the utility function, i.e, $\psi_j = \theta * log(W_j)$.[19] A higher value of θ implies lower dispersion in random shocks across individuals that lead to the observed pattern of commute flows. That is, the higher the θ, the more likely that the pattern of commute flows came about as a result of individuals responding to the spatial distribution of wages, amenities, and commuting costs.

The estimated model-implied wages $\hat{W}_j$ represent effective wages obtainable in location j including monetary wages and all other amenities valued by workers. The correlation between $\hat{\psi}_j$ and average income from the 2019 survey data at the level of work location pincode is 0.32, despite the coarse scale of our survey measure of income. We infer $\hat{\theta}$ by inverting the coefficient from an OLS regression of log of average incomes across work locations on $\hat{\psi}_j$ following Kreindler and Miyauchi (2023) and use it to compute wage proxies, $\hat{W}_j = exp(\hat{\psi}_j / \hat{\theta})$. We also estimate wages separately for workers with and without a college education to then construct separate group-specific measures of employment accessibility.

Our estimates imply $\hat{\theta} = 12.85$ for 2019 and 16.56 for 2004, which is slightly higher than what others have estimated in the literature.[20] Therefore, we also use an alternate

[18] We use aggregate commute flows instead of shares or log of commute flows as the outcome variable because it provides a better model fit without changing the results.

[19] The random shock encompasses many different unaccounted for reasons that could be behind the observed spatial distribution, for example, proximity to family members or a cultural center.

[20] Kreindler and Miyauchi (2023) estimates $\hat{\theta} = 8.3$ for Dhaka, Bangladesh. Ahlfeldt et al. (2015) estimates

approach to estimate $\hat{\theta}$ in which we first estimate κ using a commute mode choice model as in Tsivanidis (2019) and then compute $\hat{\theta} = \hat{\beta}/\hat{\kappa}$ using $\hat{\beta}$ from Columns 1 and 3 of Appendix Table B3 for years 2004 and 2019, respectively. In our context, such an approach would yield $\kappa = 0.0129$ when computed using in-vehicle time and $\kappa = 0.035$ when computed using a combination of in-vehicle and access times (from Suri and Cropper (2024)). We prefer the value computed using a combination of in-vehicle and access times since access times are shown to be highly important in the context of Mumbai.We also note that the approach in Kreindler and Miyauchi (2023) implies $\kappa = 0.0107$ using 2019 data and $= 0.0178$ using 2004 data, which is equal to the estimates obtained in other contexts (0.01 in Ahlfeldt (2011) and 0.012 in Tsivanidis (2019)). Our results are robust to wages computed using either of these approaches.

B Appendix Figures and Tables

$\hat{\theta} = 6.83$ in the context of Berlin, Germany and Heblich et al. (2020) estimates $\hat{\theta} = 5.25$ in the context of London.

Figure B1: Population density (People per sqkm)

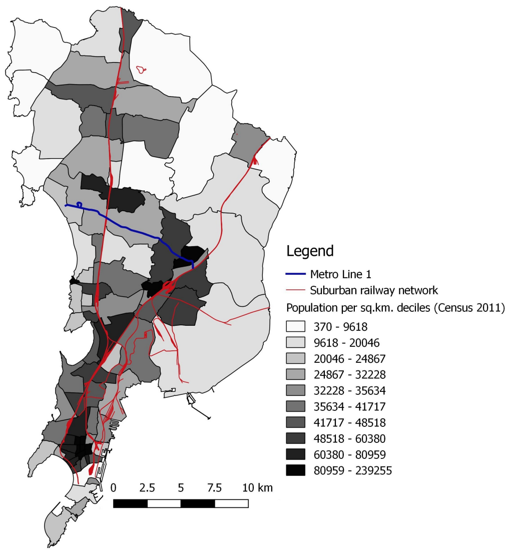
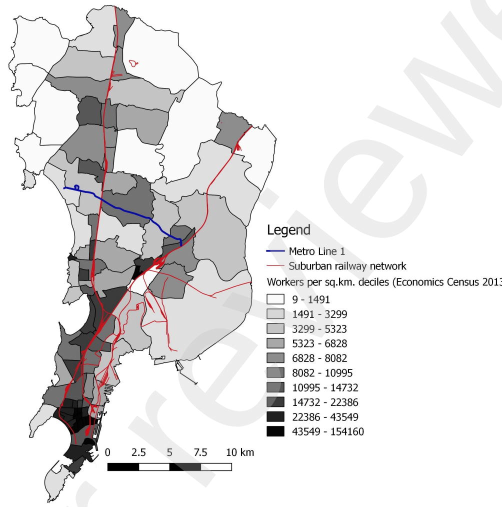
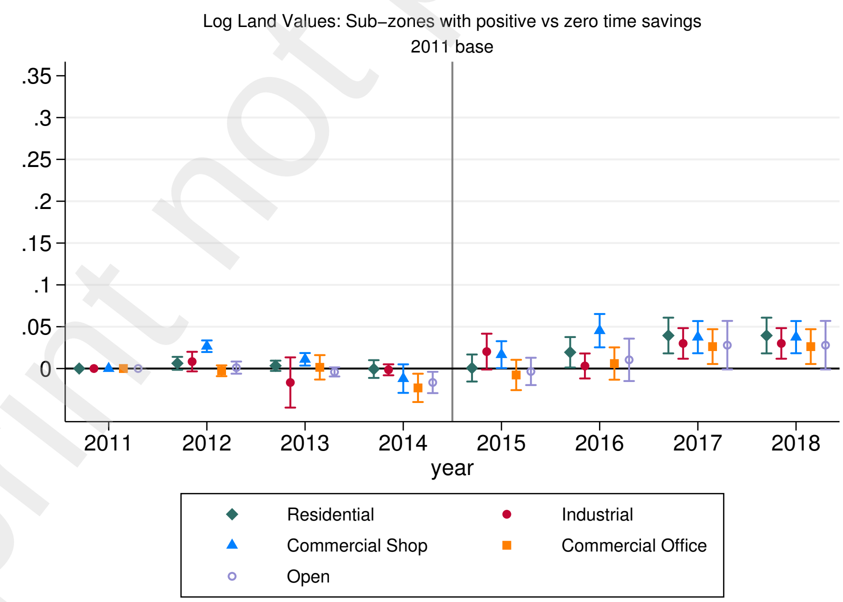


Figure B2: Employment density (Workers per sqkm)



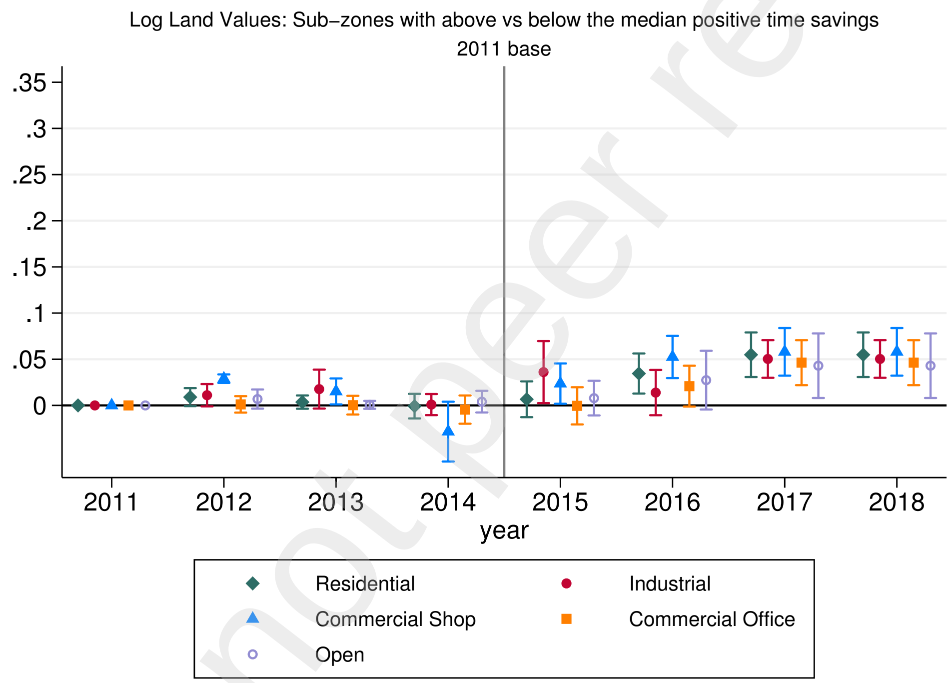
These maps show the 88 administrative sections in Mumbai shaded to reflect deciles of population per sqkm and workers per sqkm. Population density is calculated using population figures from Census 2011. Employment density is calculated using the number of workers employed in formal establishments from the Economic Census 2013. Area of each section is calculated using a digitized map of the city. The Suburban railway network of Mumbai is in red. Metro Line 1 is in blue.

Figure B3: Differences in Log Prices in Sub-zones with Positive vs Zero Time Savings



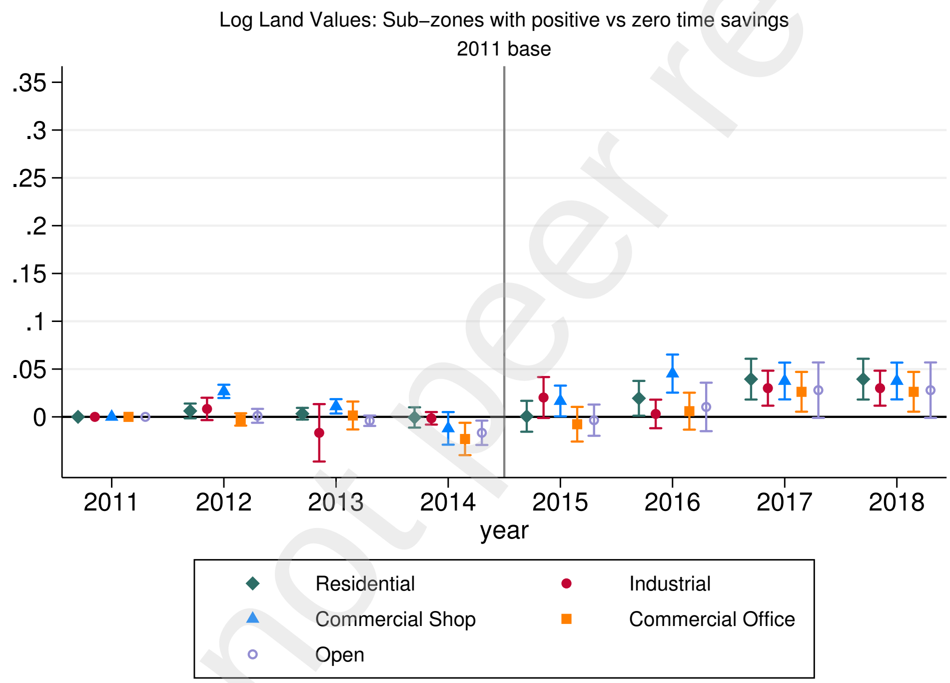
Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log\mathrm{P}_{st} = \alpha_s + \tau_t * \mathrm{Year}_t + \beta_t * \mathrm{Treated}_s * \mathrm{Year}_t + \epsilon_{st}$. $\log\mathrm{P}_{st}$ is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels. Treatment definition is based on the level of time savings.

Figure B4: Differences in Log Prices in Sub-zones with Above vs Below the Median level of Time Savings



Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log\mathrm{P}_{st} = \alpha_s + \tau_t * \mathrm{Year}_t + \beta_t * \mathrm{Treated}_s * \mathrm{Year}_t + \epsilon_{st}$. $\log\mathrm{P}_{st}$ is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels. Treatment definition is based on the level of time savings.

Figure B5: Differences in Log Prices in Sub-zones with Above vs Below the 75th percentile level of Time Savings



Each point on this graph shows the proportional change in the difference between average prices in treatment and control sub-zones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log\text{P}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. $\log\text{P}_{st}$ is the property price in sub-zone s and year t, α_s and τ_t represent sub-zone and year fixed effects, respectively. Year_t is a vector of indicator variables for the years 2012-2018 (2011 is the base year). S.e. are clustered at the sub-zone and year levels. Treatment definition is based on the level of time savings.

Table B1: Synthetic DID estimates of the Effects of Line 1 on Assessed Property Prices (2006-18 Sample)

	Residential	Commercial Office	Commercial Shop	Industrial	Open Land
Treatment Definition: Sub-zones within 1 km post 2014					
SDID ATT Estimate	0.026***	0.043***	0.027***	0.020*	0.025
	(0.009)	(0.016)	(0.011)	(0.012)	(0.015)
Treatment Definition: Sub-zones within 2 km post 2014					
SDID ATT Estimate	0.023*	0.021	0.013	0.014	0.018*
	(0.012)	(0.013)	(0.009)	(0.012)	(0.011)
Treatment Definition: Sub-zones within 3 km post 2014					
SDID ATT Estimate	0.019**	0.017**	0.016**	0.012*	0.006
	(0.009)	(0.009)	(0.008)	(0.007)	(0.012)
Treatment Definition: Sub-zones within 1 km post 2012 (Incl Anticipatory Effects)					
SDID ATT Estimate	0.045**	0.042***	0.042***	0.041***	0.046***
	(0.020)	(0.013)	(0.016)	(0.010)	(0.015)

Dependent variable is log of assessed property prices in Rs. per sqm. Sample includes all sub-zones in the city. Each specification has sub-zone and year fixed effects. Bootstrap standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Synthetic DID estimates of the Effects of Line 1 on Assessed Property Prices (2006-12 and 2015-2018 Sample)

	Residential	Commercial Office	Commercial Shop	Industrial	Open Land
Treatment Definition: Sub-zones within 1 km post 2014					
SDID ATT Estimate	0.055***	0.050**	0.049***	0.047**	0.054**
	(0.017)	(0.021)	(0.019)	(0.018)	(0.022)
Treatment Definition: Sub-zones within 2 km post 2014					
SDID ATT Estimate	0.026*	0.021**	0.014	0.015	0.022
	(0.014)	(0.010)	(0.017)	(0.013)	(0.015)
Treatment Definition: Sub-zones within 3 km post 2014					
SDID ATT Estimate	0.017	0.015	0.010	0.007	0.001
	(0.013)	(0.015)	(0.014)	(0.008)	(0.016)

Dependent variable is log of assessed property prices in Rs. per sqm. Sample includes all sub-zones in the city. Years for which anticipatory effects were observed (2014 and 2014) are excluded from this sample. Each specification has sub-zone and year fixed effects. Bootstrap standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Gravity Equation Estimates using 2004 and 2019 Commute Flows, by Worker Education Level

	(1)	(2)	(3)	(4)	(5)	(6)
Travel time (minutes)	-.138***	-.101***	-.168***	-.117***	-.063***	-.139***
	(.006)	(.006)	(.009)	(.007)	(.005)	(.008)
Survey Round	2019	2019	2019	2004	2004	2004
Worker type	All	≥College	<College	All	≥College	<College
Observations	7310	6560	7224	7656	6888	7569
Pseudo-R^2	0.56	0.45	0.58	0.50	0.38	0.53

This Table shows estimates of Poisson regression of commute flows between pincode pairs on travel time and origin and destination pincode f.e. Robust s.e. are in parentheses. Travel time is calculated between household location and a randomly chosen post-office in the pincode of the work location using a network program in Python and then averaged for each pincode pair. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B4: Heterogeneity in the Effects of Metro Line 1 on Assessed Property Prices in Sub-zones within 1 km vs 1-5 km by Changes in Employment Accessibility

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Improvement for College-educated Workers					
Two years pre-2014*Within 1 km	0.004	0.004	0.004	0.004	0.003
	(0.035)	(0.034)	(0.033)	(0.035)	(0.035)
Post-2014*Within 1 km	0.012	-0.009	-0.012	0.025	0.016
	(0.039)	(0.043)	(0.046)	(0.033)	(0.038)
Two years pre-2014*Above Median Change	-0.009	-0.009	-0.009	-0.009	-0.015
	(0.026)	(0.024)	(0.024)	(0.026)	(0.028)
Post-2014*Above Median Change	-0.021	-0.004	-0.015	-0.002	-0.005
	(0.043)	(0.045)	(0.045)	(0.042)	(0.049)
Two years pre-2014*Within 1 km*Above Median Change	0.099*	0.098*	0.099*	0.097*	0.104*
	(0.048)	(0.049)	(0.043)	(0.048)	(0.049)
Post-2014*Within 1 km*Above Median Change	0.096	0.123*	0.149	0.080	0.099
	(0.066)	(0.064)	(0.079)	(0.064)	(0.071)
Observations	360	360	360	360	360
R^2	0.98	0.97	0.97	0.97	0.98
Improvement for Workers Without a College Education					
Two years pre-2014*Within 1 km	-0.019	-0.021	-0.023	-0.019	-0.017
	(0.024)	(0.023)	(0.023)	(0.025)	(0.020)
Post-2014*Within 1 km	-0.034	-0.011	0.013	-0.030	0.012
	(0.054)	(0.050)	(0.050)	(0.046)	(0.060)
Two years pre-2014*Above Median Change	-0.004	-0.006	-0.008	-0.004	-0.002
	(0.014)	(0.013)	(0.013)	(0.013)	(0.006)
Post-2014*Above Median Change	-0.023	-0.016	0.006	-0.038	0.021
	(0.029)	(0.030)	(0.029)	(0.032)	(0.042)
Two years pre-2014*Within 1 km*Above Median Change	0.083**	0.085**	0.087**	0.082*	0.081**
	(0.033)	(0.034)	(0.032)	(0.035)	(0.028)
Post-2014*Within 1 km*Above Median Change	0.123*	0.094	0.067	0.122*	0.077
	(0.063)	(0.059)	(0.063)	(0.055)	(0.069)
Observations	669	669	669	669	672
R^2	0.98	0.97	0.97	0.94	0.96

This Table presents estimates of equation 4. Dependent variable is log of assessed property prices in Rs. per sqm. Sample restricted to sub-zones with centroid within 5 km of Line 1. Each specification has sub-zone and year fixed effects. Robust s.e. clustered at the sub-zone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$