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Palak Suri
Maureen L. Cropper

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ABSTRACT

We estimate the effects of the first metro rail line in Mumbai using administrative data on assessed property prices from 2011-18 for 723 subzones 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 6-8%for residential and commercial land use categories in treated areas relative to control areas after Metro Line 1 opens. We show that commute time savings and improvements in employment accessibility are plausible mechanisms underlying these effects.

Palak Suri
West Virginia University
palak.suri@mail.wvu.edu

Maureen L. Cropper
University of Maryland, College Park
Department of Economics
and Resources for the Future
and also NBER
mcropper@umd.edu

1 Introduction

For decades economists have valued spatial amenities by estimating their impact on property values (Rosen (1974), Polinsky and Shavell (1976), Harrison Jr and Rubinfeld (1978), Smith and Huang (1995)). Hedonic methods have also been used to value proximity to public transit. Indeed, a meta-analysis by Rennert (2022) cites 200 studies of the impact of rail stations on property values, dating back to 1970. The recent literature, which relies on quasi experimental methods to value public transit, has estimated the impact of rail transit in both developed country cities (McMillen and McDonald (2004), Billings (2011), Diao et al. (2017), Gupta et al. (2022), Keeler and Stephens (2023)) and developing country cities (Li et al. (2016), Zhou et al. (2019)). We add to this literature by estimating the impact of the first line of the Mumbai Metro on property values near the Metro using a spatial difference-in-differences approach. We then extend the reduced-form literature by measuring the impact of commute time savings associated with the Metro on property prices throughout the city. We also examine the impact of changes in employment accessibility on price changes associated with the Metro, thus joining the hedonic literature with quantitative spatial equilibrium models of urban transit in a reduced-form way.

Time savings are among the most important benefits generated by public transit. Tsivanidis (2023) finds that time savings benefits account for about 54% of the overall general equilibrium welfare generated due to the introduction of Bus Rapid Transit in Bogotá. Gupta et al. (2022) measure the impact of the Second Avenue subway in New York City on average commute times, but do not directly relate commute time savings to property values. In this paper we use geographically referenced data on commute patterns from two World Bank surveys to measure potential commute time savings due to the first metro line and then use the magnitude of these savings in difference-in-differences models to estimate the impact on property prices throughout the city.

Transit infrastructure also facilitates improved employment accessibility or commuter market access by promoting agglomeration economies and worker access to them. 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 Bogotá (Tsivanidis (2023)), and the introduction of BRT in Buenos Aires (Warnes (2020)). We calculate employment accessibility as a commuting-time weighted average of wages obtainable across the city from a given residential location in 2004 and 2019. Lacking detailed information on wages, we follow the approach in Kreindler and Miyauchi (2023) to infer relative wages from commute flows. We then examine whether price appreciation due to Line 1 of the Mumbai Metro was higher in areas that experienced greater changes in employment accessibility.

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 subzones 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 subzones 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. This approach yields a conservative estimate, 5-6%, of price appreciation after the opening of Line 1. The magnitude of effects declines as the treatment area is expanded to include subzones 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. To explore the role of time savings benefits in this paper, we compute commute time savings by subzone due to Line 1 using information from two household surveys. We estimate the effect of time savings on property prices. We find that subzones with higher commute time reductions experienced increases in property prices due to the opening of Line 1. Subzones with time savings above the 75^{th} percentile experience a 5% price appreciation.

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 spatial changes in job locations and agglomeration economies. Therefore, we examine how the capitalization effects vary by changes in employment accessibility. Our approach provides a reduced-form way to relate the spatial restructuring implied by spatial equilibrium models to the net benefits observed in property price appreciation.

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, suggesting the presence of agglomeration effects in the neighborhood of Line 1. Improvements in employment accessibility are driven by reductions in commuting times to high-wage locations and 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. Zheng and Kahn (2013) also document the presence of a multiplier effect of place-based policies including the Beijing subway due to gentrification and opening of new restaurants, while Severen (2021) finds little role for non-commuting benefits of the Los Angeles Metro between 1990 and 2000. Our focus on employment access in a city like Mumbai, with its expansive network of suburban railway, makes for an interesting context.[1]

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.[2] 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]Other citywide benefits due to transit improvements in developing countries include the reallocation of workers from the informal to formal sector in Mexico (Zárate (2024)) and a reduction in local crime in Medellin accompanied by a pattern of dispersion in crime consistent with the transit network (Khanna et al. (2021)).

[2]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.

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%.[3] This has led to huge traffic 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 68.9 km of Metro opened in 2022-25. 133 km are currently under construction and an additional 141 km has been proposed.[4] 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 subzones.[5] The entire city is divided into 723 subzones. 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.

Assessment values are used to calculate transaction and property taxes, and are corre-

[3]There were 407,306 two-wheelers and 303,108 cars in Mumbai in 2000. Their population increased to 1,784,657 and 911,856 by 2017, respectively. (Source: Department of Motor Vehicles, Maharashtra)

[4]There is also a monorail of 20 km in 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. An additional 11.3 km opened in 2019. Pre-pandemic, the daily ridership of the Monorail was about 19,000, in contrast to 450,000 for Metro Line 1.

[5]Based on Point 7 in a public letter from the Maharashtra Chamber of Housing Industries, it seems that the median transaction is used.
Source: https://mchi.net/wp-content/uploads/2022/07/52271bfdec52d7a708f1c9e8d7cc94d6.pdf

lated with market prices.[6] Anagol et al. (2024) show a high correlation between reported transaction values and assessed values on all real estate transactions between 2013 and 2022. Using proprietary data on market prices of new real estate projects with potential revenues over 10 million rupees (roughly US$200,000), the authors find evidence of underreporting of transaction prices, but also high correlation with assessment prices. This implies that our estimated price impacts may underestimate the true impact of Line 1 on market prices. To the best of our knowledge, transaction-level data can no longer be collected without detailed information on property identifiers, making Ready Reckoner Rates the best available proxy for property prices for this time period.

We use georeferenced administrative data on assessed property prices for each subzone in Mumbai for the period 2011-2018 to estimate the impact of Line 1 on property values.[7] Maps of subzone boundaries were constructed manually based on published information from the MCGM.[8] We used this information to compile a panel dataset of property prices for 723 consistently defined subzones in the city for the period 2011-2018. Subzone boundaries are drawn based on historical factors and regional policy requirements, which may differ each year. We harmonized the subzone boundaries over time manually starting with the boundaries in 2011 and matching boundaries in other years to them.[9]

To further validate the assessment prices, we follow Banzhaf and Farooque (2013) and examine their correlation with housing characteristics from a household survey conducted by the World Bank in 2019. Results from an aggregate subzone-level hedonic regression are presented in Appendix Table B1. We find that 29% of the spatial variation in assessment prices is explained by subzone averages of floorspace area, distance to the nearest rail transit stop, distance to the coast, the rate of crimes against women, and indices reflecting access to medical services and housing amenities. Given that there is substantial within-subzone variation in amenities and limited sample overlap, the results indicate a meaningful relationship between assessment prices and location-specific amenities. In addition, the correlation between log residential assessment prices and subzone median self-reported rental values is 0.4. The correlation with self-reported sale values is 0.2.[10]

[6] To minimize tax revenue losses, the MCGM sets assessment prices close to observed market prices, but avoids exceeding the usual market price to err on the side of fairness for taxpayers (Anagol et al. (2024)).

[7] Data for 2010 are not available. We have excluded 2008-2009 to remove any influence of the global recession. A previous version of the paper made use of some of the data before 2008 but suffered from poor comparability over time.

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

[9] We use the one-to-many match feature in QGIS 3.20.3 and select as a unique match the subzone whose centroid has the least geodetic distance from the subzone centroid being matched. To improve match quality, we allow for multiple centroids and visually verify the results. We choose 2011 as our base year because it produces the smallest average distance between centroids of matched subzones, suggesting good quality matches. Our results are robust to harmonization based on matching maximum overlapping subzones.

[10] The corresponding correlations using mean values are 0.3 and 0.2, respectively.

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.[11] 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 subzones within 1 km of Line 1 than for subzones at a greater distance. Yearly trends in nominal assessed prices are shown in Figure 2 for subzones 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.

While most literature estimating the capitalization benefits of transit shows positive effects, in the context of Mumbai, it has been suggested that stringent regulatory environment and market distortions can be an impediment to capitalization (Gandhi et al. (2014)) due to limited development potential. Agarwal et al. (2024) find that Delhi Metro stations lead to lower mortgage defaults, but rule out an increase in property values as a major channel. On the other hand, Sharma and Newman (2018) find suggestive evidence of capitalization of the Bangalore Metro. Therefore, it is important to empirically examine whether the Mumbai Metro generated significant benefits and if they were capitalized into property values.

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 subzones close to Line 1 and those further away, we implement a synthetic difference-in-differences strategy, optimally weighting subzone-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 subzones. The benefits of Line 1 in terms of agglomeration economies and improved access

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

to the rest of the city are likely to be greatest in areas close to the line.[12] To define our treatment and control subzones, we compute the shortest distance via the road network between each subzone centroid and Line 1 using network analysis in ArcGIS.[13] In our main analysis, subzones 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 subzones 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.

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

where logP_{st} indicates the property price in subzone s and year t. α_s and τ_t represent subzone and year fixed effects, accounting for aggregate shocks at the subzone 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 net of negative effects due to construction. Net 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. (2022)) 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 effect 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.[14] ϵ_{st} represents idiosyncratic shocks

[12] 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.

[13] For distance calculation, Line 1 is converted into nodes to calculate distance between two points. Our analysis is at the subzone level and a subzone represents an aggregate neighborhood. Therefore, taking the shortest distance between subzones and Line 1 nodes produces better classification of treatment and control subzones as confirmed through visual inspection and a smoother gradient in terms of time savings.

[14] δ may also be overestimated if our base period of 2011-12 experienced strong negative effects due to construction. While it is not possible to confirm either over- or under-estimation, we believe that anticipatory effects are more likely to be the dominant force in our setting, similar to Gupta et al. (2022) in the context of Second Ave Subway in New York City and Ghosh et al. (2024) in the context of a road improvement project in Bangalore, India. Line 1 was inaugurated in 2006, and construction began in 2008, expected to be completed by early 2012. By 2011, 85% of major construction work was complete and the objective of becoming operational by 2012 was emphasized following a Right to Information inquiry on the project timeline (Jore and Shaikh (2011)). Negative effects of the construction are also likely to be more limited

at the subzone-year level. Standard errors are clustered at the subzone and year levels following the recommendation in Cameron et al. (2011).[15] Due to the nature of treatment in our context, most of the problems discussed in the recent difference-in-differences literature on staggered adoption do not apply to this setting (Roth et al. (2023),De Chaisemartin and d'Haultfoeuille (2023)). Nevertheless, we validate our two-way fixed effects panel estimates by comparing them with a long difference OLS estimate of the difference in log price changes in 2018 relative to 2011-12 average in treatment and control areas.

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 Section 4.1.[16]

Other proximity-based definitions of treatment and control groups in our analysis include subzones within 1 km vs those between 2 and 3 km, subzones within 1 km vs those between 1 and 5 km, and subzones within 1 km vs all other subzones 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, examining the gradient in treatment effects by distance (similar to Butts (2023))and using different treatment-control group definitions help us understand the influence of spatial spillovers.

In the presence of spillovers affecting control group subzones 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 subzone and time weights (Arkhangelsky et al. (2021)).[17] More weight is assigned to pre-treatment periods where

in their geographic scope. Furthermore, since anticipatory effects are more likely to outweigh construction effects closer to the opening date, our synthetic difference-in-differences estimates provide a conservative lower bound to our main estimates.

[15]Results are robust to clustering at a more aggregated neighborhood level than the subzone level.

[16]Another limitation of our analysis is that any other events correlated with the location and timing of Line 1 including any major road improvement projects can confound our results. The Andheri-Ghatkopar Link Road, which runs parallel to Line 1, was supposed to have been improved during 2014, but repairs were not completed until 2016. Since the analysis in Section 4.1 is based on potential rail commute time savings, it is less susceptible to this limitation.

[17]Consider an abbreviated version of equation 1: $\log \mathrm{P}_{st} = \alpha_s + \tau_t + \zeta * \mathrm{Treated}_{st} + \epsilon_{st}$. Difference-in-

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.[18] 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 weights optimally computed using the procedure in Arkhangelsky et al. (2021).[19] 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: subzones within 1 km of Line 1 post-2014, subzones within 2 km of Line 1 post-2014, subzones within 3 km of Line 1 post-2014, and subzones 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, and provides a conservative lower bound to our estimates of price appreciation. 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.

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 subzones relative to the difference in 2011. This is the coefficient vector β in the

difference estimates using this simple two-way fixed estimator are obtained by minimizing

$$\sum_s \sum_t (\log \mathrm{P}_{st} - \alpha_s - \tau_t - \zeta * \mathrm{Treated}_{st})^2$$

The synthetic difference-in-differences estimator instead minimizes

$$\sum_s \sum_t (\log \mathrm{P}_{st} - \alpha_s - \tau_t - \zeta * \mathrm{Treated}_{st})^2 \hat{\nu_s}^{sdid} \hat{\mu_t}^{sdid}$$

where $\hat{\nu_s}^{sdid}$ and $\hat{\mu_t}^{sdid}$ represent unit and time weights respectively.

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

[19]Simply put, synthetic difference-in-differences reweights the unexposed control units to make their time trend parallel to the average of the treated units pre-treatment, then applies a difference-in-differences analysis to this reweighted panel. Time weights ensure that those time periods are included which make the the weighted average of historical outcomes close to the average treatment period outcomes for control units, up to a constant.

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 subzone s and year t. α_s and τ_t represent subzone and year fixed effects as before. Year_t is a vector of indicator variables for the years 2012 to 2018 (2011 is the base year). Treated_s is an indicator for treated subzones. β_t is the main coefficient of interest reflecting the difference between treated and control subzones in 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 subzones 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 subzones 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 subzones within 1 km with all the remaining subzones 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 subzones closer to Line 1 are more appropriate controls for subzones within 1 km of Line 1.

Since our treatment definition is based on the proximity of subzone centroids to the nearest point on Line 1 via the road network, measurement error is likely to be present. Subzones 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 subzones within 1 km and subzones beyond 2 km but within 3 km. We find similar price effects in this case to those in Figure 3.

Our main difference-in-differences estimates of the anticipatory effects and effects of the opening of Line 1 are in Table 3.[20] We find that two years before the opening of Line 1, property prices in subzones within 1 km of Line 1 increased by 5-6% relative to subzones 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.[21] The estimated price effects of the opening of Line 1 are similar across land-use categories. This is likely due

[20]Estimates are similar when subzone boundaries are harmonized using the maximum overlap method in Python (Appendix Table B2).

[21]Long difference estimates comparing 2018 with 2011-12 average are similar (see Appendix Table B3).

to Mumbai's mixed land-use zoning, leading to a high correlation in markets for different land-use categories. The effects on open land are slightly higher due to their development potential.[22]

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. To assess the sensitivity of our results to potential deviations from parallel trends, we apply the method proposed by Oster (2019), estimating separate regressions for the anticipatory and post-opening periods. We find comparable bias-adjusted effect sizes across most land-use types, ranging from 3.5% to 5.7%, except for industrial land, where the effect declines to 1.6% (Appendix Table B4).[23]

We show the robustness of the difference-in-differences capitalization effects by estimating equation 1 for various control group definitions. Comparing subzones 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 subzones 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. The average effect size is 3.1-3.8% for anticipatory effects, similar to other specifications. The effects of the opening of Line 1 lie in the range of 5.8-6.5% (Table 5).[24]

To observe the influence of possible spillover effects, we also estimate equation 1 considering subzones 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 subzones between 1-2 km were included in the control group (see Table 3). 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. A complete heterogeneity analysis examining treatment effects in 0.5 km distance bins from the metro in the spirit of Butts (2023) is in Appendix Figure B3. The effect is strongest in subzones closest to the metro and gradually dissipates with distance, confirming that our results are not overestimated because of spatial spillovers.

[22]The open land-use category includes vacant lots and demolished and under construction buildings. The higher effects may be a result of new real estate projects in the treatment area.

[23]For all land-use types other than industrial, the degree of selection on unobservables would need to be between 1.7 and 2 times that of the observables to drive the estimated effect to zero; for industrial land, the required selection ratio is 1.2.

[24]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.

To account for the possible differential trends between treated and control subzones, 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 subzones within 1 km of Line 1 relative to a synthetic control group drawn from all subzones 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 price appreciation ranges from 4.1-5.3% and is closer to the estimates obtained previously.

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 subzones 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.

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. (2022) estimate a 10% increase in property values in the vicinity of the Second Avenue Subway line that opened in New York City in 2017. Keeler and Stephens (2023) estimate a 6.9% increase in property values within 0.25 miles of Phase 1 of the Gold Line that opened in 2003 in Los Angeles. However, the authors also report negative to no significant price effects due to the Expo Line and the Eastside Extension of the Gold Line, highlighting the heterogeneity in benefits generated by different transit projects.

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 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.

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 occur through two channels: changes in relative effective wages across the city, and reductions in transit commute times to high-wage job locations due to Metro Line 1. They represent longer-term benefits that may have been facilitated by the Metro. We examine the heterogeneity in spatial difference-in-differences estimates by magnitudes of changes in employment accessibility to test the influence of improvements in employment accessibility in the vicinity of Line 1.

Section 4.1 provides a causal estimate of the impact of time savings reductions due to the metro, while the analysis in Section 4.2 investigates how general equilibrium changes in employment accessibility—driven by both network-induced commute time savings and changes in effective wage gradients—influence the capitalized price effects estimated in Section 3.2.

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. Traditionally, the benefits of transportation projects in terms of the value of time savings has been measured using structural models of commute mode choice (Small et al. (2007)). Most reduced-form studies focus on geographically local effects of transit infrastructure, and only indirectly capture the value of time savings. For example, Gupta et al. (2022) estimate an average 3-minute reduction in commute time in the neighborhood directly served by the Second Ave Subway extension, and a 14 minute reduction for subway users. Time savings benefits, however, are typically more widespread. For example, in the context of Metro Line 1 in Mumbai, Suri and Cropper (2024) estimate that Line 1 reduced access to the nearest rail transit stop for 14% of commuters in the city by an average 21 minutes.[25]

In this section, we explore the role of citywide rail transit 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 subzone. 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 subzone and each survey separately. Neither of the surveys has workers in every subzone, therefore, to improve spatial coverage, we average travel time savings for households in the two surveys and end up with information for 473 subzones.[26] 51% of these subzones have positive commute time savings. These savings can be from improved access to railway stations or more efficient rail transit connections. The mean distance from Line 1 of a subzone with positive time savings 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

[25]The potential in-vehicle time savings for transit commutes across the city were also substantial, averaged at 13 minutes.

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

understand their role in property price appreciation. Treatment definitions based on time savings rather than distance also limit the influence of anticipatory behavior. We use three criteria to define treated subzones: (i) subzones with any time savings based on existing commuting patterns in the city, (ii) subzones with time savings above the median, conditional on positive savings, and (iii) subzones with time savings above the 75th percentile, conditional on positive savings. Figure 7 shows subzones with zero potential time savings and quartiles conditional on positive savings. Many subzones 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 subzones 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 subzones with positive time savings. There is a gradual increase in price appreciation in treatment subzones after the opening of Line 1. There is an immediate price appreciation of 2.3% in subzones 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-demand residential neighborhoods. Dynamic event study estimates for all property types are similar to those for residential properties (shown in Appendix Figures B4-B6). 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 subzones with above median time savings conditional on positive savings and by 5% in subzones 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 (2023), 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. subzone) 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 first descriptively examine the impact of changes in employment accessibility on residential prices. We then examine how the magnitude of changes in employment accessibility affects the impact of Metro Line 1 on property prices.

We parameterize an employment accessibility index for each of the 723 subzones 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 subzone 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 j adjusted for the dispersion in individual decisions to live in location i and work in location j. Following Tsivanidis (2023), the dispersion parameter is estimated from the value of time, which is derived using a structural model of commute mode choice for individuals located in i and working in j.[27] t_{ij} is the travel time from house i to location j.[28] The estimation is discussed in Appendix Section A.[29]

[27] This parameter is estimated in Suri and Cropper (2024) for Mumbai using the 2019 household survey data and in Takeuchi et al. (2007) using the 2004 household survey data.

[28] Our results are robust to using iceberg commuting costs instead of travel time t_{ij}.

[29] We use two indices in our analysis to assess the influence of different computational methods: the first one uses income information from the 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. We present results using the latter method in the text due to lower measurement error in commuting data relative to income data. A complete comparison of the two indices is

We look at changes in the employment accessibility index across the city from 2004 to 2019 in Figure 9. Improvements in employment accessibility are smallest in the southernmost part of the city, which is the location of the traditional business district. Similar to time savings (Figure 7), the largest improvements occurred in areas in central and northern parts of the city. This is consistent with the population and employment density in the city moving northward since the 90s. The latest Census figures are in Appendix Figure B1.

We also look at changes in employment accessibility constructed separately for workers by college education level (Appendix Figure B8). 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 subzones 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: To understand the importance of employment accessibility in predicting price changes, we begin with a simple linear regression of log changes in residential prices from 2011 to 2018 on changes in employment accessibility from 2004 to 2019. Employment accessibility improvements are associated with a 7.9% increase in residential property values (Appendix Table B6). We additionally use distance from the Metro as an instrument for changes in employment accessibility in Column 2, which increases the estimate to 10.2%.[30] Due to potential violations of the exclusion restriction, these results should be treated as descriptive.

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 subzones 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 holds with the analysis restricted to subzones 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 subzones

in Appendix Section A.

[30]These effects maybe underestimated and are smaller than those reported in Table 2 of Tsivanidis (2023), in part due to the misalignment of treatment and outcome time periods. Changes in employment accessibility are measured from 2004 to 2019, while prices are measured from 2011-2018, implying that baseline prices may already include capitalized value of some of the changes in employment accessibility.

with greater improvements in employment accessibility.

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

Table 10 reports the results of 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. This suggests that employment accessibility changes capture meaningful improvements associated with Line 1 that are capitalized into property prices.

In Appendix Table B9, 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.[31] From the magnitude of coefficients in the two panels, it can be inferred that improvements in employment accessibility for college-educated workers, in particular, are highly correlated with price appreciation of commercial properties.

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. (2024); Suri and Cropper (2024)) and quantitative spatial equilibrium models (Heblich et al. (2020); Tsivanidis (2023); 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

[31] Appendix Table B10 presents the results for our alternative measure and confirms this findings.

increase in 2013-2014, relative to 2011, in anticipation of Line 1 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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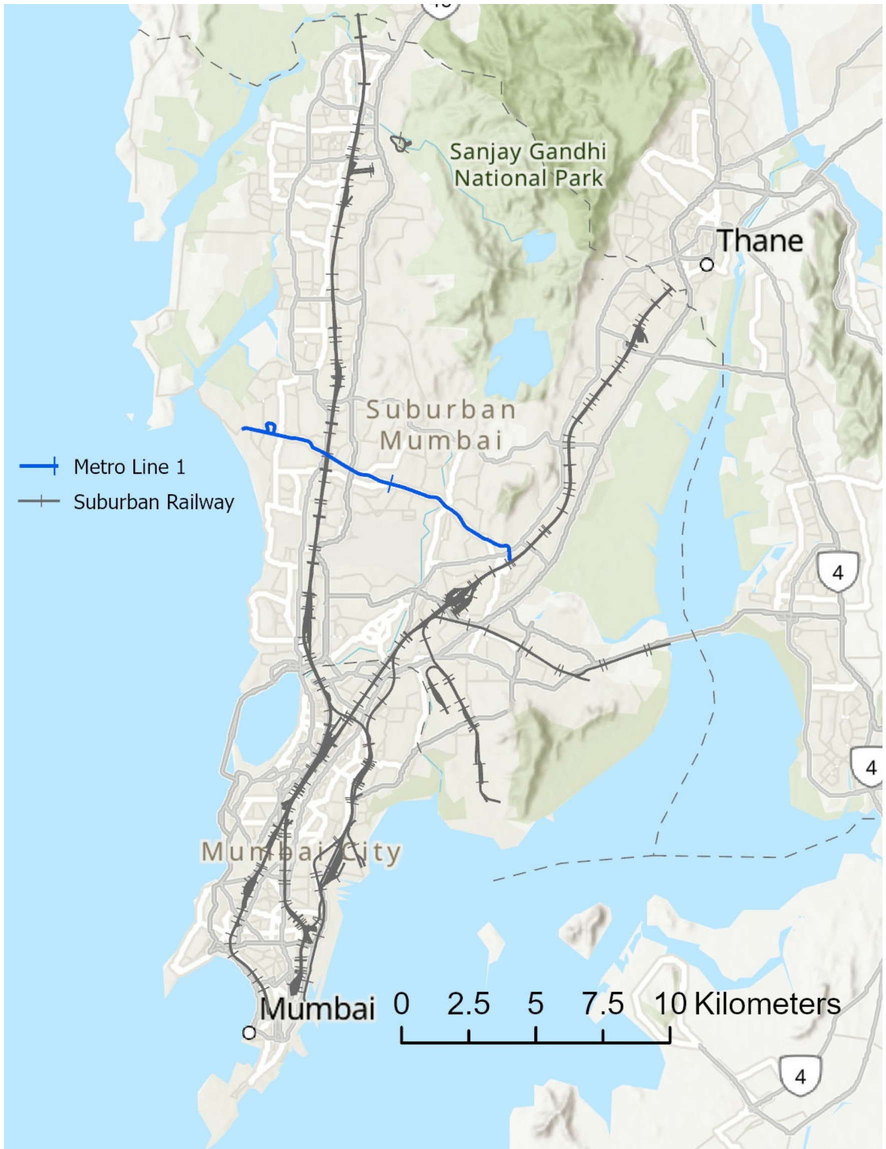
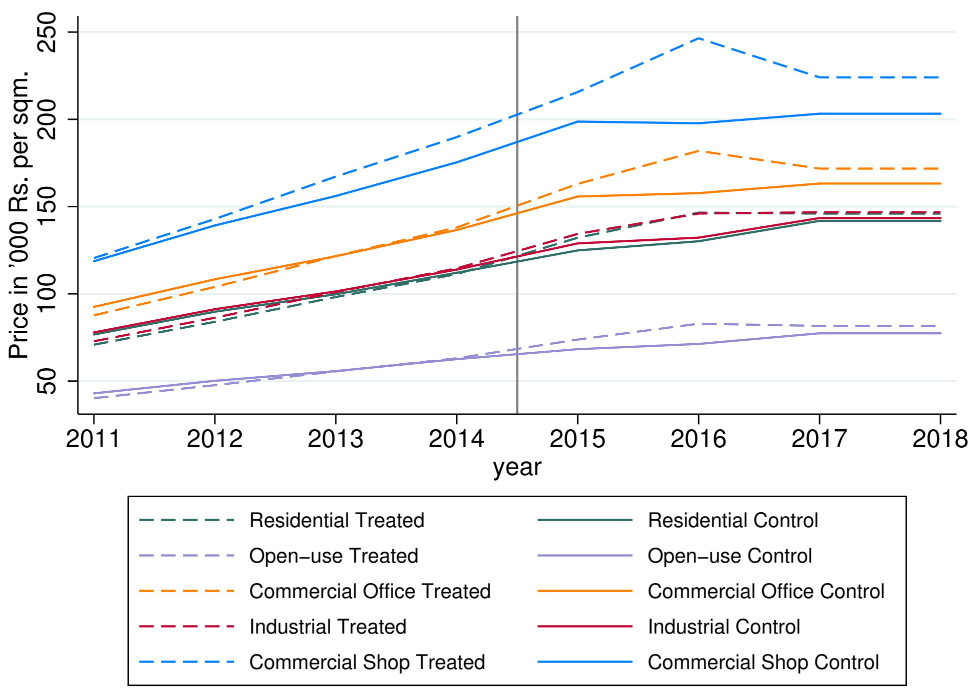
6 Figures and Tables

Figure 1: Mumbai's Rail Network



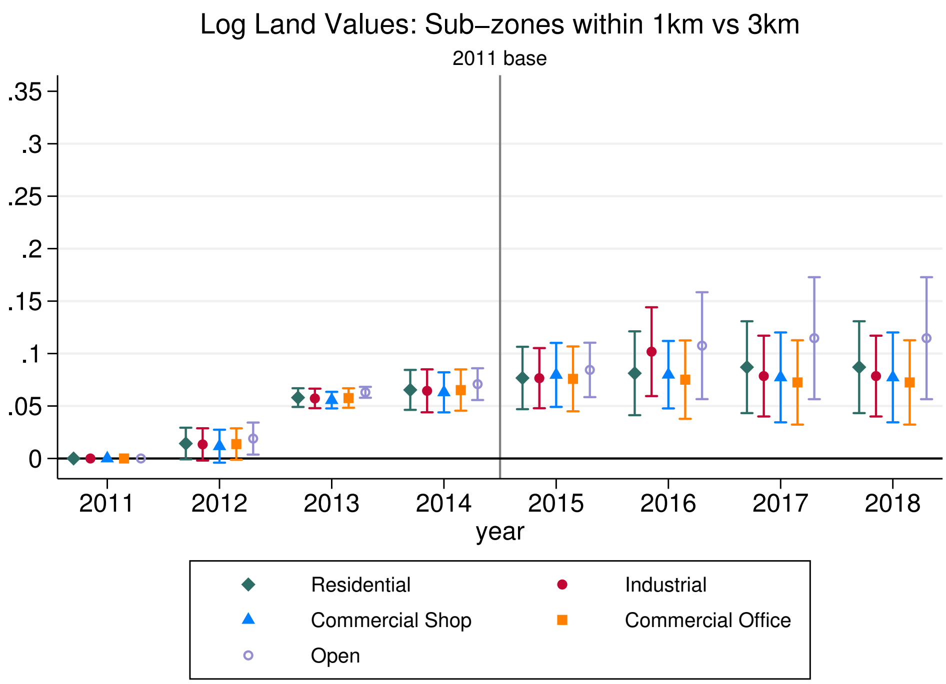
This map shows the Suburban railway network of Mumbai in grey, along with Metro Line 1 (11.4 km) in blue.

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



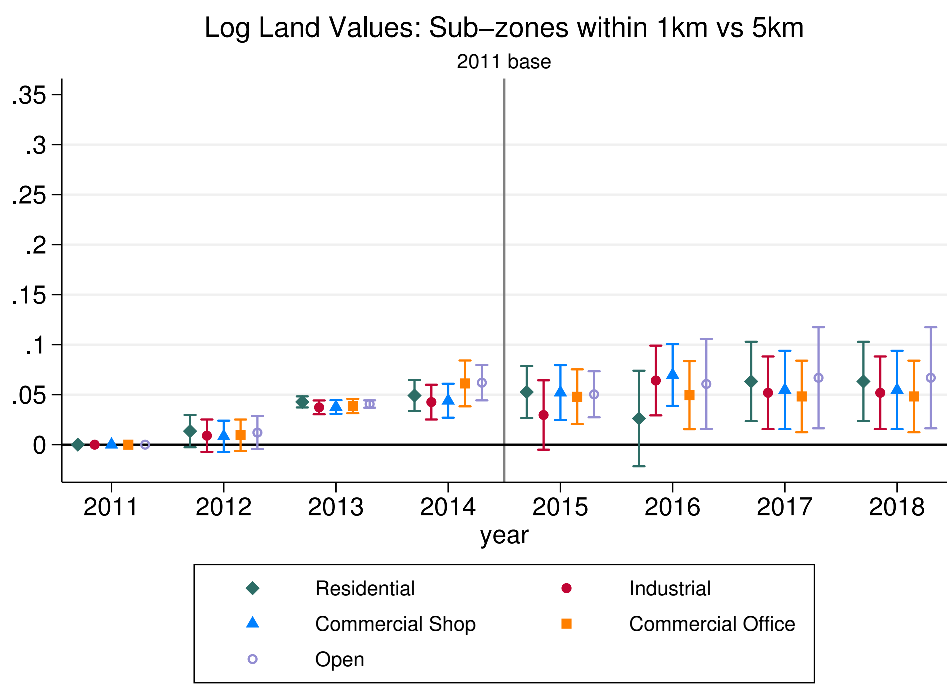
This figure shows trends in average property prices in subzones within 1 km of Line 1 (treated group), represented by dashed lines and those beyond 1 km but within 3 km of Line 1 (control group), represented by solid lines. Line 1 started in 2014 and the effects of its opening would show up 2015 onward,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

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



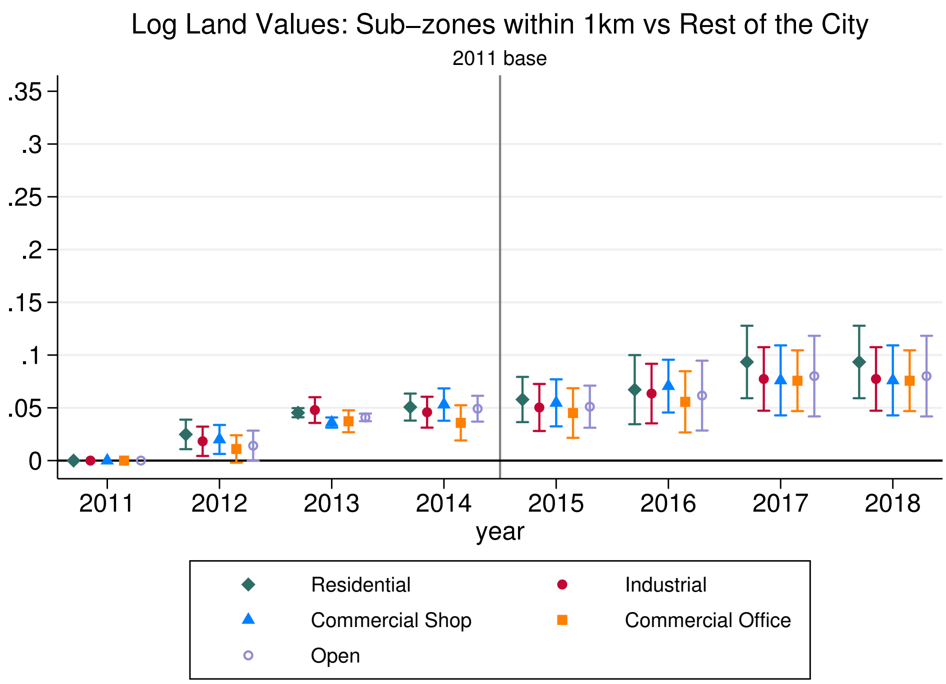
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels.

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



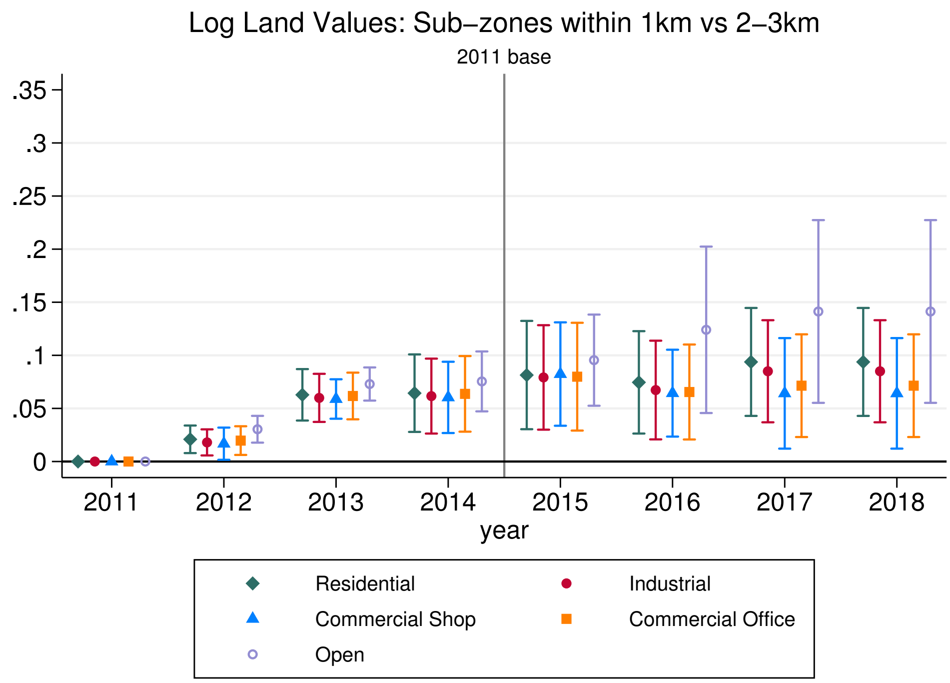
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels.

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



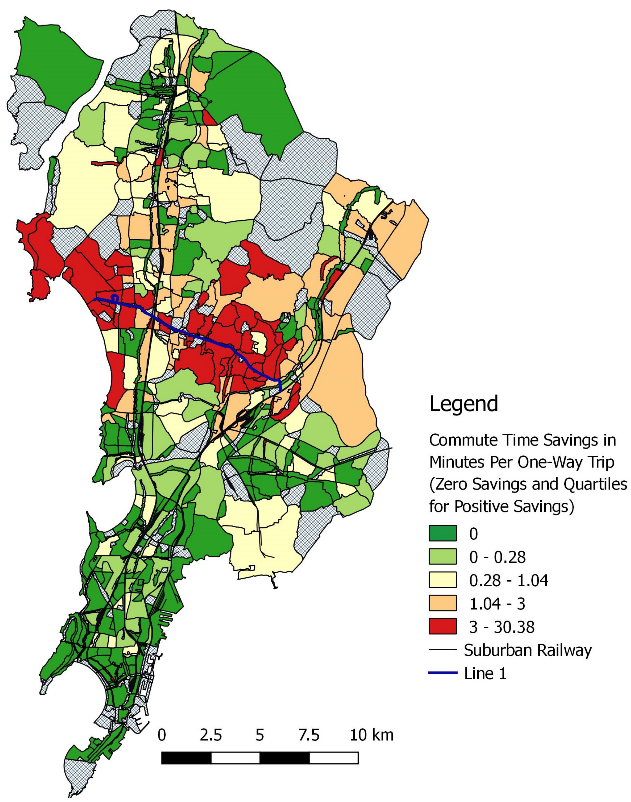
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels.

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



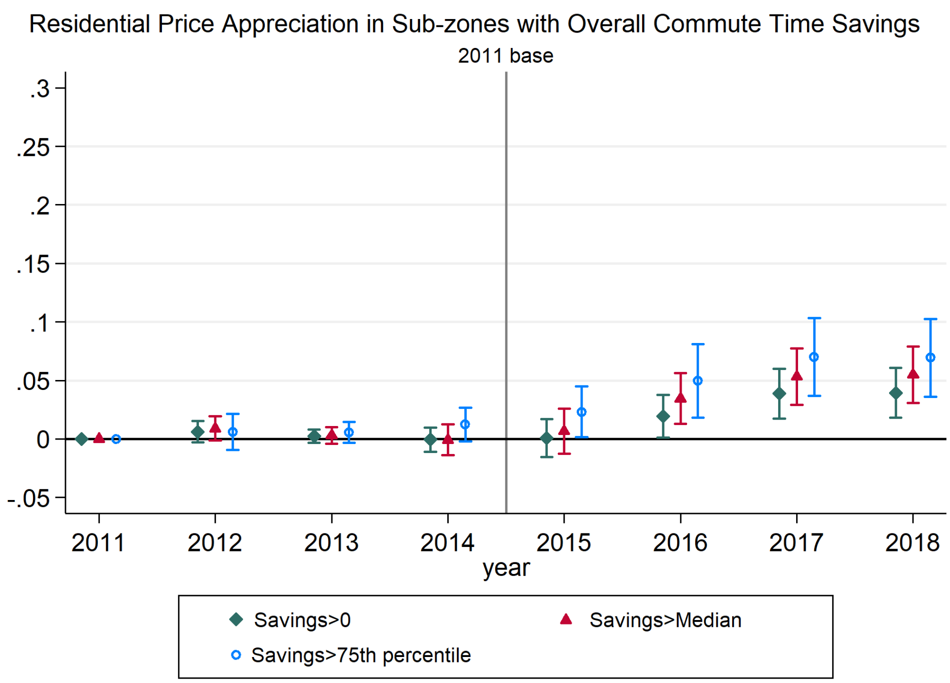
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log P_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. $\log P_{st}$ is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels.

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



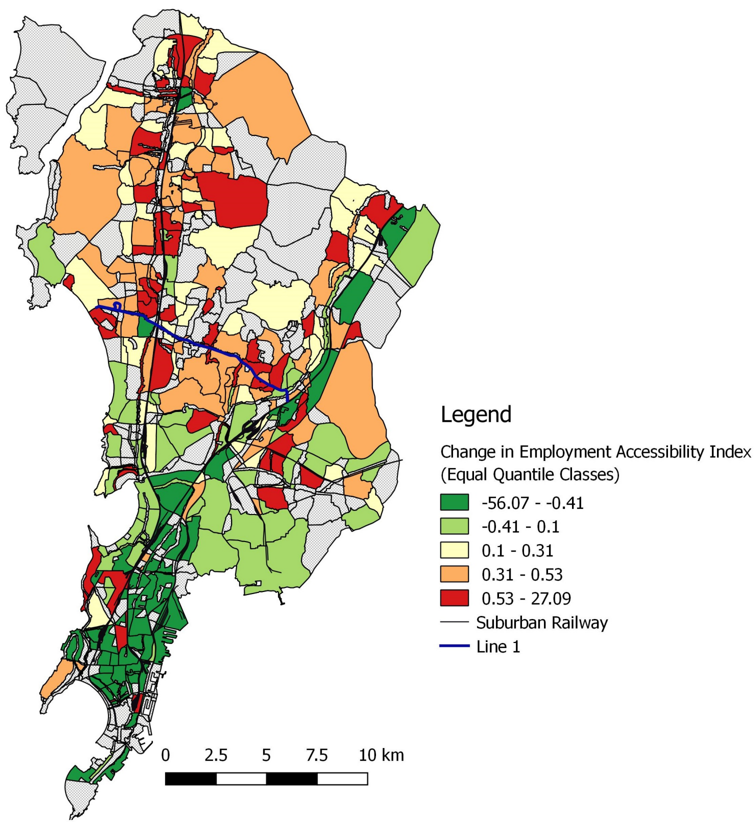
The graph shows average potential time savings due to Line 1 (in minutes per one-way trip) averaged for each subzone using 2004 and 2019 household survey data. Subzones with zero potential savings are in dark green. The remaining colors represent quartiles conditional on positive potential time savings: light green indicates subzones below the 25th percentile savings, light yellow indicates 25th to 50th percentile savings, light orange indicates 50th to 75th percentile savings, red indicates those above the 75th percentile. Subzones 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 Subzones 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 subzones 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 subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels. Treatment definition is based on the level of time savings.

Figure 9: Spatial Changes in Employment Accessibility at the Subzone level



This map shows changes in employment accessibility from 2004 to 2019 using house-specific indices aggregated at the subzone level. Subzones in grey are those for which we cannot compute employment accessibility in both years.

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 Subzones 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 subzones with centroid within 3 km of Metro Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone 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 Subzones 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 subzones with centroid within 5 km of Metro Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone 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 Subzones 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 subzones in the city. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone 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 Subzones 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 subzones in the city. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone 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: Subzones 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: Subzones 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: Subzones 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: Subzones 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 subzones in the city. Each specification has subzone 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)

	(1) Residential	(2) Commercial Office	(3) Commercial Shop	(4) Industrial	(5) Open Land
Treatment Definition: Subzones 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: Subzones 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: Subzones 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 subzones in the city. Years for which anticipatory effects were observed (2013 and 2014) are excluded from this sample. Each specification has subzone 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 subzones 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. subzones 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. subzones 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. subzones 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 subzones in the city that are not covered by the treatment group definition indicated above. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone 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 Subzones within 1 km vs 1-5 km by Changes in Employment Accessibility

	(1) Residential	(2) Comm. Office	(3) Comm. Shop	(4) Industrial	(5) Open Land
Within 1 km*Two years pre-2014	-0.040*	-0.042**	-0.043**	-0.040*	-0.038**
	(0.020)	(0.015)	(0.013)	(0.021)	(0.014)
Within 1 km*Post-2014	-0.027	-0.026	-0.021	-0.009	0.020
	(0.033)	(0.044)	(0.046)	(0.032)	(0.041)
Two years pre-2014*Above Median Change	-0.015	-0.018	-0.019	-0.016	-0.013*
	(0.013)	(0.012)	(0.013)	(0.012)	(0.007)
Post-2014*Above Median Change	-0.043	-0.046	-0.045	-0.056	-0.008
	(0.029)	(0.030)	(0.029)	(0.032)	(0.039)
Within 1 km*Two years pre-2014*Above Median Change	0.098**	0.099***	0.101***	0.097**	0.095***
	(0.029)	(0.027)	(0.025)	(0.030)	(0.024)
Within 1 km*Post-2014*Above Median Change	0.110*	0.112*	0.118*	0.092	0.063
	(0.052)	(0.058)	(0.062)	(0.051)	(0.059)
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 subzones with centroid within 5 km of Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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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 for the 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.

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

Similar to Kreindler and Miyauchi (2023), we estimate the following reduced-form gravity equation of commuter flows derived from equation 8 using a Poisson pseudo-maximum likelihood estimator.

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

N_{ij} represent aggregate commute flows between i and j. $\beta = \kappa * \theta$ captures the sensitivity of commuting decisions to commuting time, t_{ij}. 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 the 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 B5. 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, $\psi_j = \theta * log(W_j)$.[32] 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 $\hat{W}_j = exp(\hat{\psi}_j/\hat{\theta})$ 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.[33] We use two approaches to obtain $\hat{\theta}$, which is used to estimate wages separately for 2004 and 2019. We also estimate wages separately for workers with and without a college education to then construct separate group-specific measures of employment accessibility. For simplicity, we use the same year-specific parameter values of $\hat{\theta}$ when computing wages for workers with and without a college education.

First, 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. Our estimates imply $\hat{\theta} = 12.85$ for 2019 and 16.57 for 2004,

[32] 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.

[33] The corresponding correlation for 2004 is 0.27.

which is slightly higher than what others have estimated in the literature.[34] We, therefore, use an alternate approach to estimate $\hat{\theta}$ in which we first estimate κ using a commute mode choice model as in Tsivanidis (2023) and then compute $\hat{\theta} = \hat{\beta}/\hat{\kappa}$ using $\hat{\beta}$ from Columns 1 and 4 of Appendix Table B5 for years 2004 and 2019, respectively. For this measure, we use the value of $\kappa = 0.019$ for 2019 derived from the commute mode choice model in Suri and Cropper (2024) and $\kappa = 0.034$ for 2004 derived from a similar commute mode choice mode in Takeuchi et al. (2007).[35] This implies $\hat{\theta} = 3.43$ for 2004 and 7.26 for 2019, more similar to other contexts. We also note that the approach in Kreindler and Miyauchi (2023) implies $\kappa = 0.0107$ using 2019 data and $\kappa = 0.007$ using 2004 data, which is similar to estimates obtained in other contexts (0.01 in Ahlfeldt (2011) and 0.012 in Tsivanidis (2023)).

The main difference between the two measures is the use of commute mode choice information vs the use of household survey personal incomes. Although the quality of commute mode information is better than wage information, given the differences in parameter values, it is valuable to empirically assess the informational content of both measures. The correlation between the two measures is over 0.9, and both produce a similar pattern of results, but our primary measure is more highly correlated with time savings and with price changes.

We plot subzone level changes in employment accessibility in Figure 9 for the primary measure using κ estimated from commute mode choice models and in Appendix Figure B7 for the measure using θ estimated from the wage regression. The variation across subzones is more gradual in the primary measure.[36] This implies that it is driven more by proximity changes to the Metro, which by default vary gradually. The alternate measure could be driven by measurement errors or wage changes that are independent of the metro. The primary measure captures the benefits to the north relatively more than the alternate measure, and is more highly correlated with the time savings pattern in the city (Figure 7).

We next regress log changes in residential prices from 2011 to 2018 on changes in employment accessibility using OLS. To further isolate changes in employment accessibility driven by the metro, we also estimate 2SLS regressions with proximity to Metro Line 1 as the instrument.[37] While proximity may not fully satisfy the exclusion restriction necessary for instrument validity, it provides a descriptive check on our OLS estimates. Results

[34] Kreindler and Miyauchi (2023) estimates $\hat{\theta} = 8.3$ for Dhaka, Bangladesh. Ahlfeldt et al. (2015) estimates $\hat{\theta} = 6.83$ in the context of Berlin, Germany and Heblich et al. (2020) estimates $\hat{\theta} = 5.25$ in the context of London.

[35] The value of time in Rs./min. in Takeuchi et al. (2007) is Rs. 0.57/min., while in Suri and Cropper (2024) it is Rs. 0.77/min. We obtain similar results under the assumption that $\kappa = 0.019$ for both years.

[36] We thank an anonymous referee for pointing this out.

[37] We thank an anonymous referee for suggesting this.

are in Appendix Tables B6 and B7. The instrument is weak for the alternate measure, and the weak instrument bias is apparent in Appendix Table B7. We see that changes in employment accessibility predict residential price changes, especially when they are driven by proximity to the metro (Appendix Table B6). Since our objective is to capture employment accessibility changes related to the metro, this analysis validates our choice of the primary measure.

We next examine the heterogeneity in our difference-in-differences estimates by changes in the two employment accessibility measures. Both measures produce a similar pattern of results, but the heterogeneity coefficients using our primary measure are somewhat smaller as seen by comparing Table 10 and Appendix Table B8. Results point to a greater capitalization of proximity to the metro into property prices in subzones with greater improvements in employments accessibility. Small differences in coefficients can also be observed in results by worker education in Appendix Tables B9 and B10, but we advise caution in interpreting these results due to limited sample sizes of the two household surveys. This analysis highlight the implications of parametric assumptions that are often necessary to make in general equilibrium models.

B Appendix Figures and Tables

Figure B1: Population density 2011
(People per sqkm)

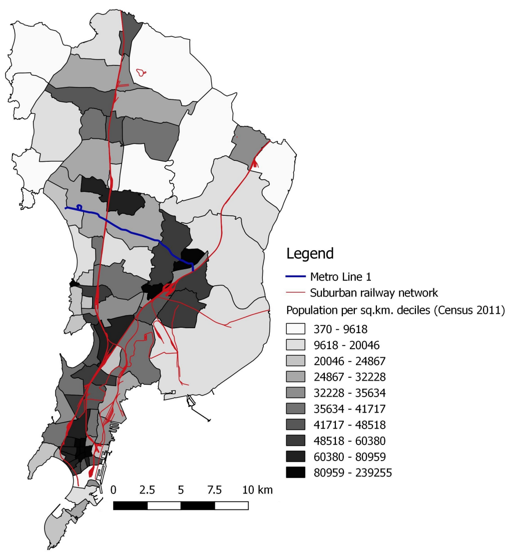
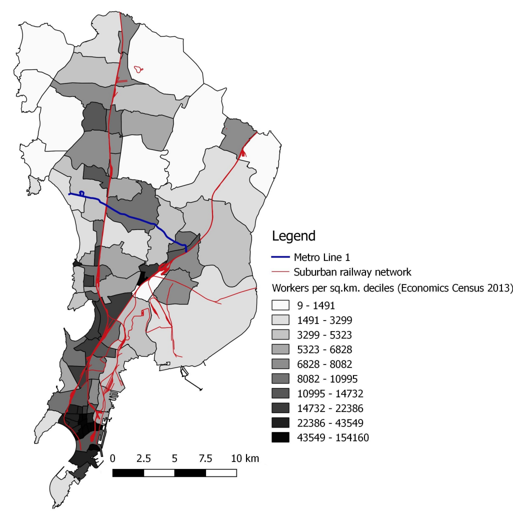
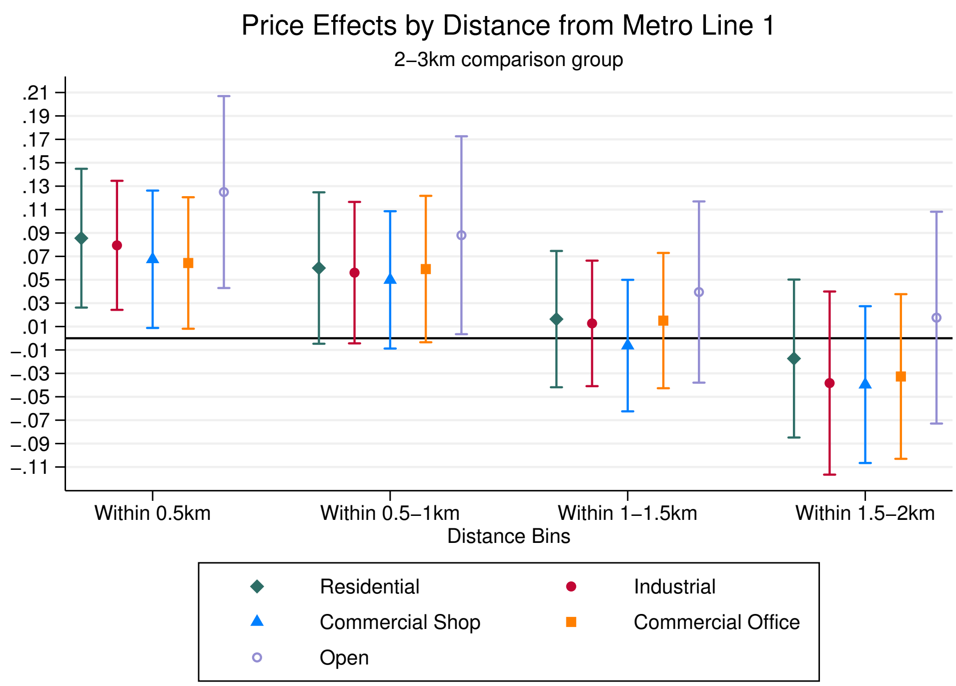


Figure B2: Employment density 2013
(Workers per sqkm)



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: Heterogeneity in DID Estimates by Various Distance Bins Relative to 2-3 km

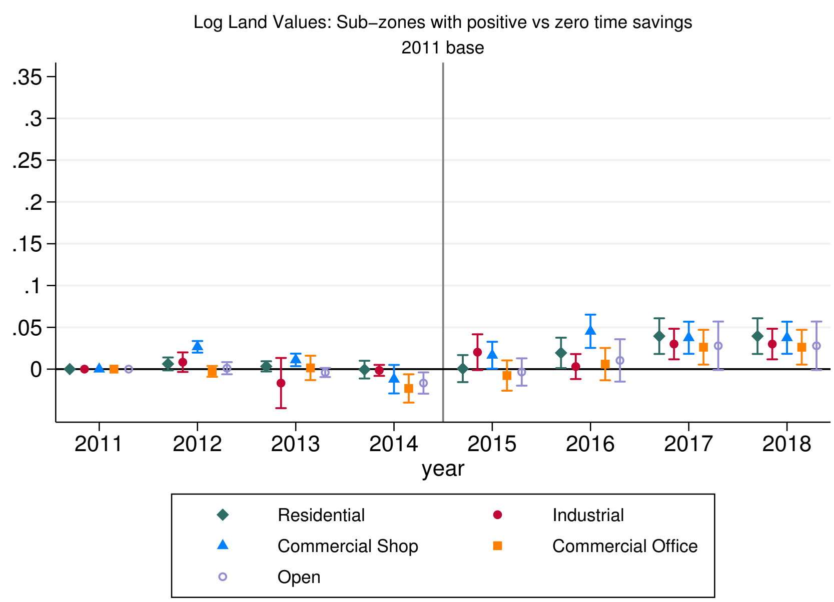


Each point on this graph shows DID estimates of the effects of the opening of Line 1 on property prices in subzones categorized by distance from Line 1 in 0.5 km bins (following Butts (2023)). This is the coefficient vector δ_k in the following equation.

$$\text{logP}_{st} = \alpha_s + \tau_t + \zeta * \text{Treated}_s * \text{Year 2013/2014}_t + \sum_{k=1}^{4} \delta_k * \text{Treated}_{ks} * \text{Post-2014}_t + \epsilon_{st}.$$

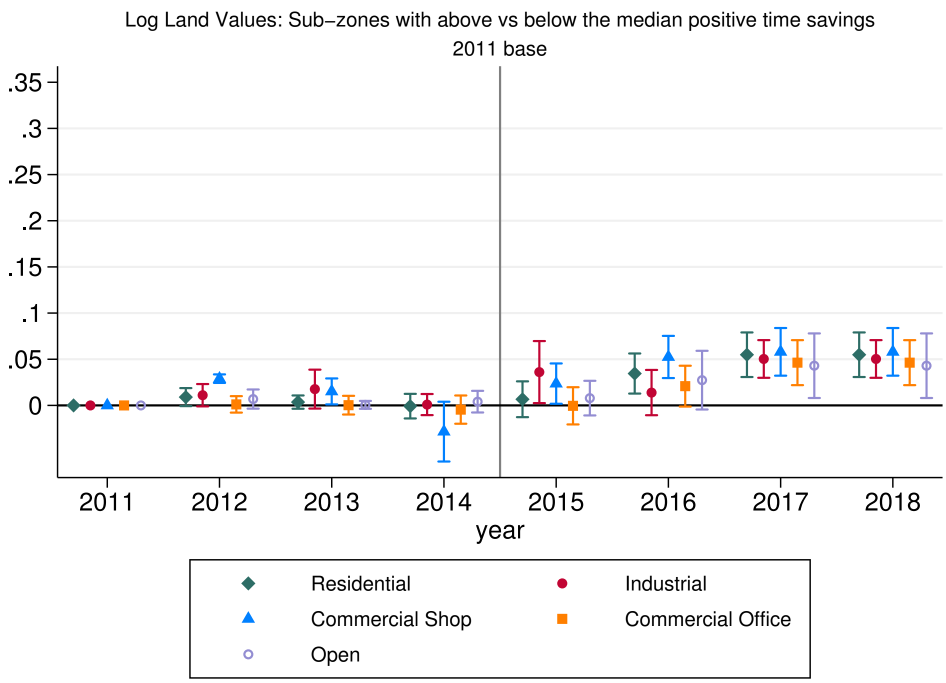
logP_{st} is the property price in subzone s and year t, Treated_{ks} indicates subzones in one of the four distance bins, α_s and τ_t represent subzone and year fixed effects, respectively. Sample is restricted to subzones within 3km of Line 1. S.e. are clustered at the subzone and year levels. This graph shows that the price appreciation effects of the opening of Line 1 are strongest in subzones closest to the metro and gradually dissipate with distance, confirming that our main results are not overestimated because of spatial spillovers.

Figure B4: Differences in Log Prices in Subzones with Positive vs Zero Time Savings



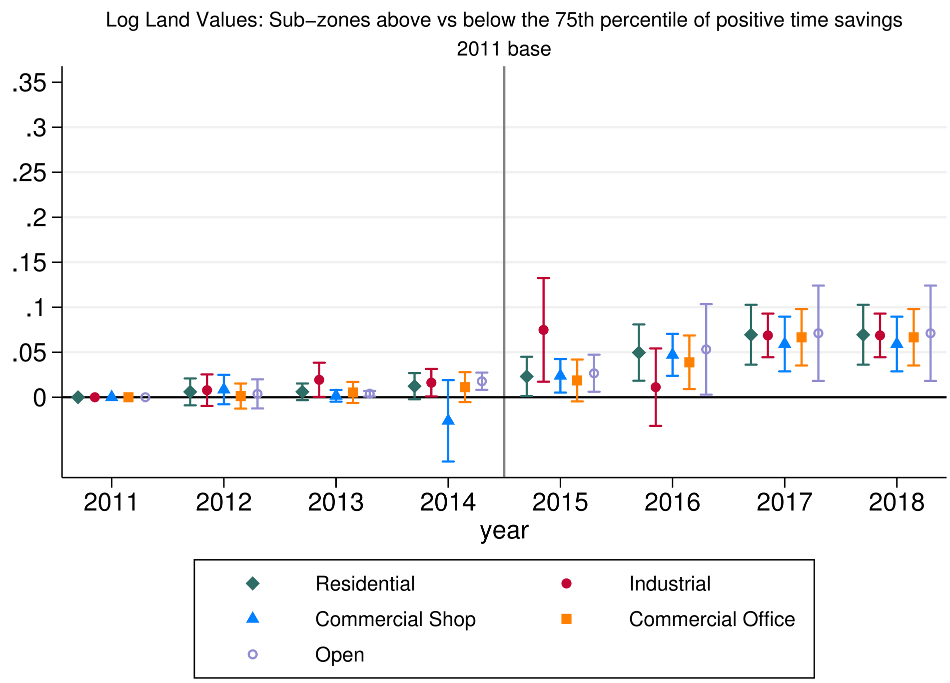
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels. Treatment definition is based on the level of time savings.

Figure B5: Differences in Log Prices in Subzones with Above vs Below the Median level of Time Savings



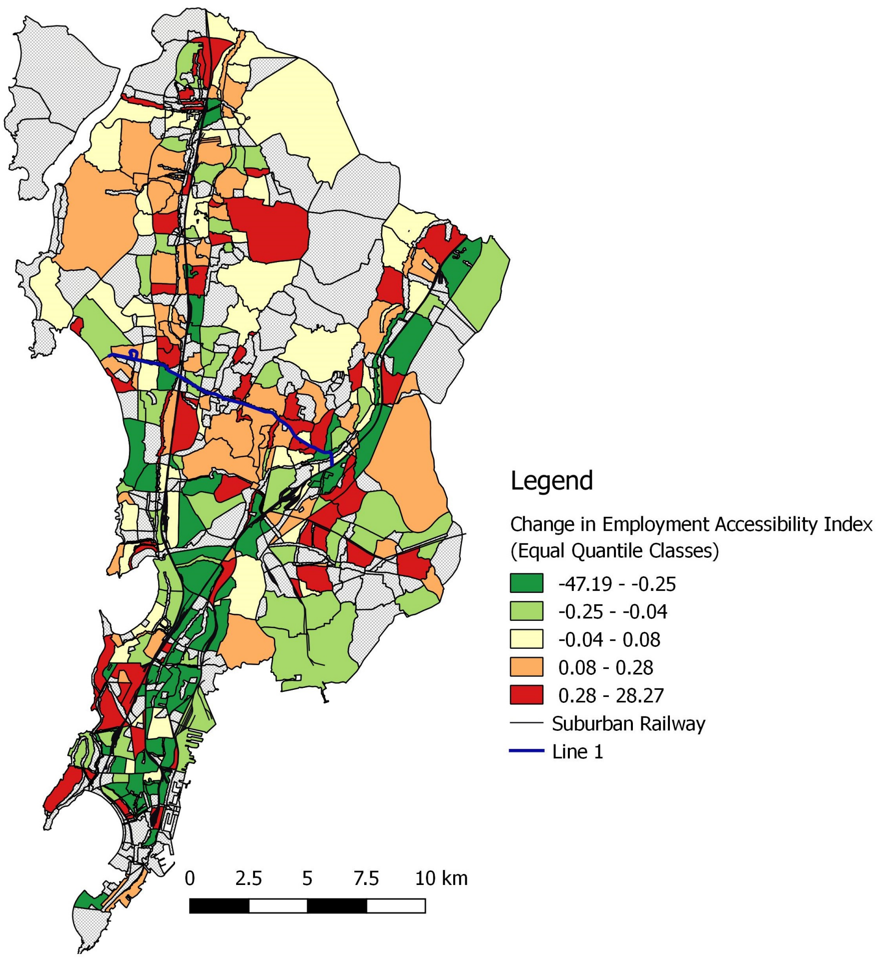
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\text{logP}_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. logP_{st} is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels. Treatment definition is based on the level of time savings.

Figure B6: Differences in Log Prices in Subzones with Above vs Below the 75th percentile level of Time Savings



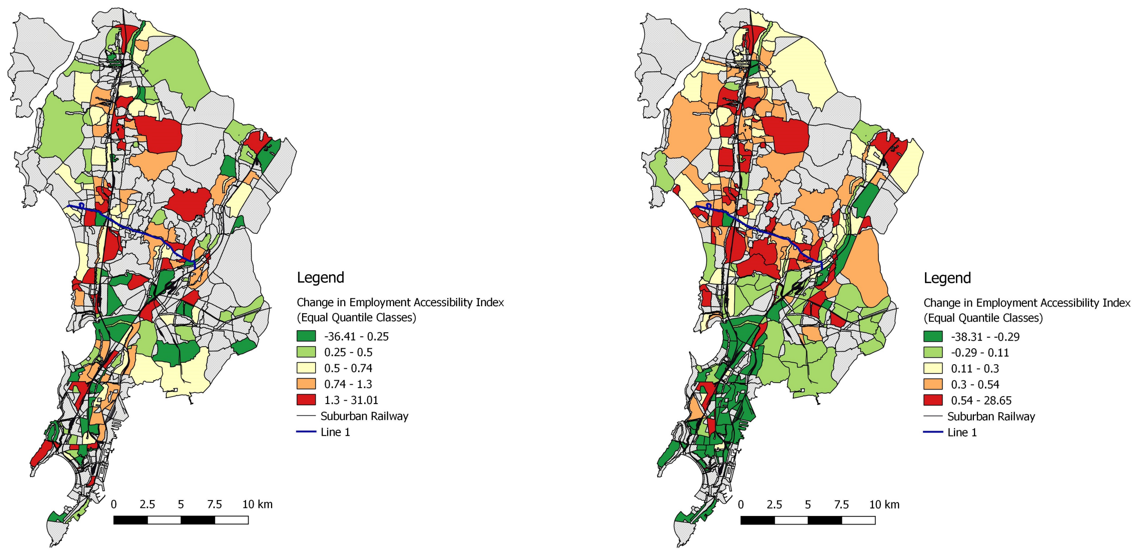
Each point on this graph shows the proportional change in the difference between average prices in treatment and control subzones relative to the difference in 2011. This is the coefficient vector β in the following equation estimated using OLS. $\log P_{st} = \alpha_s + \tau_t * \text{Year}_t + \beta_t * \text{Treated}_s * \text{Year}_t + \epsilon_{st}$. $\log P_{st}$ is the property price in subzone s and year t, α_s and τ_t represent subzone 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 subzone and year levels. Treatment definition is based on the level of time savings.

Figure B7: Spatial Changes in Employment Accessibility at the Subzone level (Alternative Measure)



This map shows changes in employment accessibility from 2004 to 2019 using house-specific indices aggregated at the subzone level. Subzones in grey are those for which we cannot compute employment accessibility in both years.

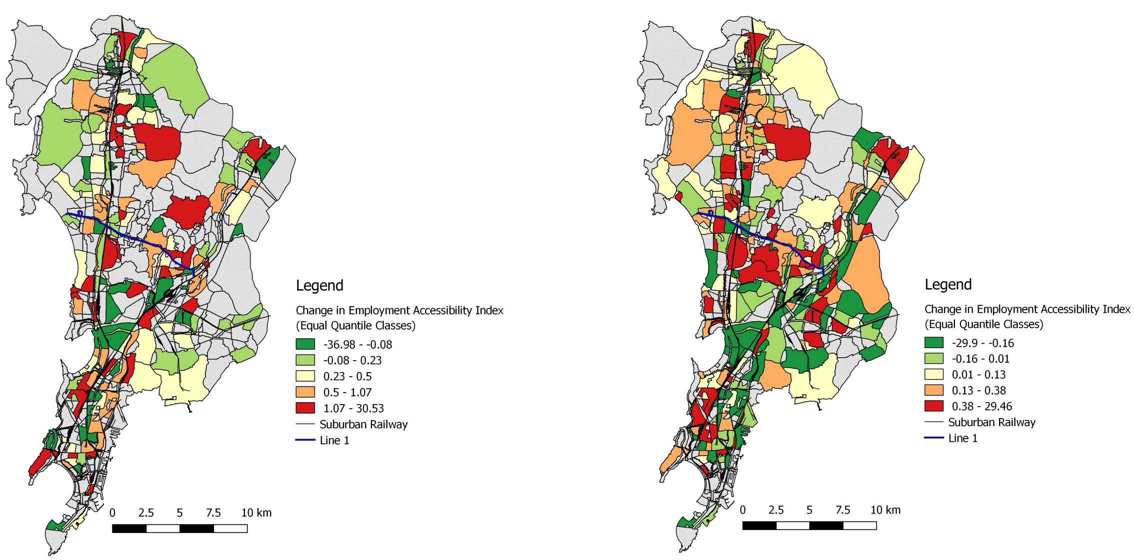
Figure B8: Spatial Changes in Employment Accessibility by Worker College Education (Primary Measure)



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 subzone level constructed separately for the sample of workers by college education.

Figure B9: Spatial Changes in Employment Accessibility by Worker College Education (Alt. Measure)



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 subzone level constructed separately for the sample of workers by college education.

Table B1: Determinants of the Spatial Variation in Assessment Prices

	Log(Assessment Prices)
Healthcare Amenity Index	0.068***
	(0.018)
Log(Floorspace Area)	0.257***
	(0.076)
Housing Amenity Index	-0.034**
	(0.016)
Distance to the Coast	-0.060***
	(0.009)
Proportion of Slum Households	-0.116**
	(0.056)
Log(Crimes Against Women)	-0.026
	(0.040)
Distance to the Nearest Railway Station	-0.016
	(0.026)
R^2	0.291
Observations	365

Dependent variable is the log of residential assessment prices in Rs. per sqm. of floorspace. This is a subzone level regression, hence, all housing characteristics are averaged at this level. Housing Amenity Index is the first principal component of housing amenities including number of rooms and dummy variables for good roof, separate kitchen, separate toilet, bathroom inside the house, and access to piped water. Healthcare Amenity Index is the first principal component of proximity to the nearest private and government health clinics and hospitals. The indices are created using subzone level mean values. Heteroskedasticity robust standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Robustness of Estimates in Table 3 to an Alternative Method of Subzone Boundaries Harmonization (Maximum Overlap Criterion)

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Two years pre-2014*Within 1km	0.055***	0.055***	0.053***	0.054***	0.057***
	(0.011)	(0.012)	(0.011)	(0.011)	(0.009)
Post-2014*Within 1km	0.069**	0.060**	0.068***	0.070***	0.088**
	(0.020)	(0.019)	(0.019)	(0.019)	(0.026)
Observations	1,084	1,084	1,084	1,084	1,096
R^2	0.97	0.97	0.98	0.95	0.97

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

Table B3: Long Difference Estimates of the Effects of Metro Line 1 on Assessed Property Prices in Subzones within 1 km vs 1-3 km

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Within 1km	0.081***	0.067***	0.072***	0.073***	0.107***
	(0.026)	(0.025)	(0.026)	(0.024)	(0.034)
Observations	135	135	135	135	137
R^2	0.064	0.046	0.052	0.059	0.058

Dependent variable is the difference in log residential price in 2018 relative to 2011-12 average. Sample restricted to subzones with centroid within 3 km of Metro Line 1. Each specification has subzone and year fixed effects. Robust s.e. are in parentheses. Estimates are similar to our main panel difference-in-differences results. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: DID Estimates of the Effects of Metro Line 1 on Assessed Property Prices in Subzones within 1 km vs 1-3 km with Adjusted Coefficients from Oster (2019)

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Anticipatory Effects Regression					
Estimated Coefficient	0.055**	0.055**	0.053**	0.054**	0.057**
	(0.016)	(0.016)	(0.015)	(0.015)	(0.017)
Adjusted Coefficient (Oster (2019))	0.047	0.045	0.042	0.045	0.050
Observations	544	544	544	544	548
R^2	0.98	0.98	0.98	0.98	0.98
Effects After Opening of Line 1					
Estimated Coefficient	0.076**	0.067**	0.073**	0.077**	0.096**
	(0.022)	(0.021)	(0.021)	(0.020)	(0.027)
Adjusted Coefficient (Oster (2019))	0.047	0.036	0.035	0.016	0.057
Observations	813	813	813	813	822
R^2	0.97	0.97	0.97	0.94	0.96

This Table presents the difference-in-difference estimates for the anticipatory effects period 2013-14 and post-opening period separately along with adjusted OLS coefficient from Oster (2019). This is for transparency in estimation; the results in the first row of each of the two panels are mathematically equivalent to equation 1. Dependent variable is log of assessed property prices in Rs. per sqm. Sample restricted to subzones with centroid within 3 km of Metro Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone and year levels are in parentheses. Adjusted coefficients provide a lower bound to our main estimates, and are similar to our synthetic difference-in-differences estimates, except for industrial land-use type. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5: 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	$\geq$College	$<$College	All	$\geq$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 B6: Association between Changes in Employment Accessibility and Changes in Residential Prices (Primary Measure)

	(1) OLS	(2) 2SLS
Changes in Employment Accessibility	0.079***	0.102***
	(0.015)	(0.030)
	[5.230]	[3.354]
Observations	252	252
First stage F-statistic		103.5
Critical Value for |t| at 95% level (Lee et al. (2022))		2.03

Dependent variable is the difference in log residential price in 2018 relative to 2011. Columns 1 and 2 are based on the preferred measure of employment accessibility, while Columns 3 and 4 are based on the alternative measure. Columns 2 and 4 show 2SLS regressions using distance from the Metro as an instrumental variable for for changes in employment accessibility. First stage F-statistic is indicated at the bottom. To provide evidence for instrument strength, critical t-values using adjusted standard errors are noted in the last row following Lee et al. (2022) for valid inference at the 95% level. Robust std. errors are in parentheses and t-statistics are in brackets. Stars reflect conventional inference values. We winsorize the EA changes variable by trimming the top and bottom 5% of observations to reduce the influence of outliers.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B7: Association between Changes in Employment Accessibility and Changes in Residential Prices (Alt. Measure)

	(1) OLS	(2) 2SLS
Changes in Employment Accessibility	0.052*	0.679*
	(0.031)	(0.358)
	[1.710]	[1.897]
Observations	252	252
First stage F-statistic		3.9
Critical Value for |t| at 95% level (Lee et al. (2022))		>18

Dependent variable is the difference in log residential price in 2018 relative to 2011. Columns 1 and 2 are based on the preferred measure of employment accessibility, while Columns 3 and 4 are based on the alternative measure. Columns 2 and 4 show 2SLS regressions using distance from the Metro as an instrumental variable for for changes in employment accessibility. First stage F-statistic is indicated at the bottom. To provide evidence for instrument strength, critical t-values using adjusted standard errors are noted in the last row following Lee et al. (2022) for valid inference at the 95% level. Robust std. errors are in parentheses and t-statistics are in brackets. Stars reflect conventional inference values. We winsorize the EA changes variable by trimming the top and bottom 5% of observations to reduce the influence of outliers.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B8: Heterogeneity in the Effects of Metro Line 1 on Assessed Property Prices in Subzones within 1 km vs 1-5 km by Changes in Employment Accessibility (Alt. Measure)

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Within 1 km*Two years pre-2014	-0.016	-0.018	-0.020	-0.016	-0.014
	(0.028)	(0.026)	(0.024)	(0.028)	(0.024)
Within 1 km*Post-2014	-0.021	-0.017	-0.009	-0.010	0.022
	(0.031)	(0.039)	(0.041)	(0.028)	(0.039)
Two years pre-2014*Above Median Change	-0.021	-0.023*	-0.025*	-0.021	-0.018**
	(0.012)	(0.011)	(0.012)	(0.012)	(0.006)
Post-2014*Above Median Change	-0.054	-0.052	-0.049	-0.066*	-0.021
	(0.029)	(0.030)	(0.029)	(0.031)	(0.039)
Within 1 km*Two years pre-2014*Above Median Change	0.071*	0.073*	0.075*	0.070*	0.069*
	(0.035)	(0.034)	(0.033)	(0.036)	(0.030)
Within 1 km*Post-2014*Above Median Change	0.109*	0.105*	0.106	0.098*	0.069
	(0.052)	(0.054)	(0.059)	(0.046)	(0.057)
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 subzones with centroid within 5 km of Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone and year levels are in parentheses. Results indicate that capitalization effects within 1 km of Line 1 are stronger in areas that experienced above median employment accessibility improvements. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B9: Heterogeneity in the Effects of Metro Line 1 on Assessed Property Prices in Subzones within 1 km vs 1-5 km by Changes in Employment Accessibility (Primary Measure)

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Improvement for College-educated Workers					
Within 1 km*Two years pre-2014	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.035)	(0.034)	(0.034)	(0.036)	(0.035)
Within 1 km*Post-2014	0.010	-0.011	-0.011	0.019	0.015
	(0.038)	(0.043)	(0.046)	(0.033)	(0.037)
Two years pre-2014*Above Median Change	-0.022	-0.022	-0.022	-0.022	-0.027
	(0.024)	(0.023)	(0.023)	(0.025)	(0.027)
Post-2014*Above Median Change	-0.026	-0.008	-0.012	-0.014	-0.006
	(0.043)	(0.044)	(0.044)	(0.042)	(0.048)
Within 1 km*Two years pre-2014*Above Median Change	0.111**	0.111*	0.112**	0.110*	0.117**
	(0.047)	(0.048)	(0.042)	(0.047)	(0.048)
Within 1 km*Post-2014*Above Median Change	0.101	0.127*	0.146	0.092	0.100
	(0.066)	(0.063)	(0.078)	(0.063)	(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					
Within 1 km*Two years pre-2014	0.001	-0.001	-0.003	0.001	0.003
	(0.027)	(0.027)	(0.026)	(0.030)	(0.024)
Within 1 km*Post-2014	0.006	0.025	0.045	0.007	0.054
	(0.052)	(0.049)	(0.051)	(0.043)	(0.057)
Two years pre-2014*Above Median Change	0.013	0.011	0.009	0.013	0.016
	(0.016)	(0.015)	(0.014)	(0.015)	(0.010)
Post-2014*Above Median Change	-0.005	0.004	0.023	-0.022	0.040
	(0.030)	(0.031)	(0.029)	(0.032)	(0.041)
Within 1 km*Two years pre-2014*Above Median Change	0.042	0.044	0.045	0.041	0.039
	(0.036)	(0.037)	(0.035)	(0.039)	(0.032)
Within 1 km*Post-2014*Above Median Change	0.053	0.028	0.009	0.057	0.002
	(0.064)	(0.060)	(0.064)	(0.056)	(0.068)
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 subzones with centroid within 5 km of Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone and year levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B10: Heterogeneity in the Effects of Metro Line 1 on Assessed Property Prices in Subzones within 1 km vs 1-5 km by Changes in Employment Accessibility (Alt. Measure)

	Residential	Comm. Office	Comm. Shop	Industrial	Open Land
Improvement for College-educated Workers					
Within 1 km*Two years pre-2014	-0.003	-0.002	-0.003	-0.003	-0.003
	(0.036)	(0.035)	(0.034)	(0.036)	(0.035)
Within 1 km*Post-2014	0.013	-0.007	-0.009	0.022	0.017
	(0.038)	(0.043)	(0.046)	(0.033)	(0.038)
Two years pre-2014*Above Median Change	-0.021	-0.022	-0.022	-0.022	-0.027
	(0.027)	(0.026)	(0.026)	(0.027)	(0.030)
Post-2014*Above Median Change	-0.020	0.001	-0.009	-0.008	-0.003
	(0.044)	(0.046)	(0.045)	(0.043)	(0.049)
Within 1 km*Two years pre-2014*Above Median Change	0.111*	0.111*	0.111**	0.110*	0.116*
	(0.049)	(0.049)	(0.044)	(0.049)	(0.050)
Within 1 km*Post-2014*Above Median Change	0.095	0.118	0.144	0.086	0.097
	(0.067)	(0.064)	(0.079)	(0.064)	(0.072)
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					
Within 1 km*Two years pre-2014	-0.020	-0.022	-0.024	-0.019	-0.018
	(0.024)	(0.023)	(0.023)	(0.025)	(0.020)
Within 1 km*Post-2014	-0.033	-0.010	0.013	-0.029	0.013
	(0.054)	(0.050)	(0.050)	(0.046)	(0.060)
Two years pre-2014*Above Median Change	-0.006	-0.008	-0.010	-0.006	-0.003
	(0.014)	(0.013)	(0.013)	(0.013)	(0.006)
Post-2014*Above Median Change	-0.021	-0.013	0.006	-0.036	0.023
	(0.029)	(0.030)	(0.029)	(0.031)	(0.042)
Within 1 km*Two years pre-2014*Above Median Change	0.084**	0.086**	0.088**	0.084**	0.082**
	(0.033)	(0.034)	(0.032)	(0.035)	(0.028)
Within 1 km*Post-2014*Above Median Change	0.122*	0.092	0.066	0.120*	0.075
	(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 subzones with centroid within 5 km of Line 1. Each specification has subzone and year fixed effects. Robust s.e. clustered at the subzone and year levels are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$