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THE BENEFITS OF PUBLIC TRANSIT TO HOUSEHOLDS: EVIDENCE FROM INDIA

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ABSTRACT

We measure benefits to households from Mumbai's new Metro rail system. We estimate a commute mode choice model to value commute time savings in the short run and a housing choice model to value the improved commuting utility that households experience due to spatial sorting. Aggregate benefits from Metro rail are over 10 times higher when spatial sorting occurs. In the short run women, college-educated workers, and workers with above median incomes experience higher benefits than their opposites. In the long run, households with lower incomes and assets and less than college education benefit more than their wealthier counterparts.

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1 Introduction

The benefits of transport projects are often measured by the value of time savings they deliver. This approach underlies the World Bank's evaluation of transit projects and is also followed by cities in the United States (U.S. DOT (2016a)), the United Kingdom (U.K. DOT (2023)) and Canada (Alberta Transportation (2017)). The value of time savings can be estimated using a commute mode choice model, which assumes fixed residential and work locations. Due to this assumption, this approach is most appropriate for measuring short run benefits. Long run benefits are typically higher as mobility constraints are relaxed, but since politicians invest in infrastructure projects based on the salience of short run costs and benefits to the target voter base, this can lead to sub-optimal spending (Glaeser and Ponzetto (2018)). Due to weak institutions, cities in developing countries are even more susceptible to this.

In this paper, we leverage detailed household-level information and discrete choice models to contrast the short run and the long run benefits to households from Mumbai's new Metro system. We estimate the annual aggregate short run benefits from Mumbai's first Metro line to be \$51 million 2019 PPP dollars and aggregate long run benefits to equal \$591 million 2019 PPP dollars. Long run benefits exceed the construction cost of the Metro, but not the short run benefits. We compare this with a cost-benefit analysis of a more widely accessible Metro project that competes with the existing railway network in the city, and find that annualized long run benefits exceed the construction cost only at low discount rates. Our results validate the presence of discounted foreign bank loans for large infrastructure projects, without which such infrastructure projects may not exist. Lastly, we investigate the nature of spatial and demographic heterogeneity in benefits generated from these Metro projects, highlighting the labor market benefits along the intensive margin.

Mumbai, the financial capital of India, has had an extensive passenger rail network since the 19th century, but its transit infrastructure has struggled to keep up with the demands of the city's growing economy. Private vehicle ownership has increased four-fold in the last two decades, resulting in severe traffic congestion problems and constrained intracity commutes. To alleviate congestion and improve commuting conditions, over 300 km of Metro rail lines have been planned. The first part of the Metro network, an 11.4 km east-west link (Line 1), opened in 2014. An additional 92 km of the Metro network (Lines 2, 3 and 7) was scheduled to open in 2022, but is still only partly operational. We study the benefits to households from these two infrastructure projects. In doing so, we also inform transit policy by comparing benefits for two very different types of Metro projects.

We obtain data from a representative household survey conducted by the World Bank in 2019 with household locations, work locations, commute modes chosen by households' workers, vehicle ownership, and housing characteristics and costs. We supplement this with travel times from Google Maps, HERE, and a network algorithm and information on travel costs. We first estimate a discrete choice model in which workers select an optimal commute mode for residence-to-work commutes, assuming fixed residence and work locations. This yields estimates of commuter preferences for in-vehicle travel time, out-of-vehicle travel time, and income net of commuting costs. In doing so, we add to the literature on the value of time by providing preference estimates for travel time for a developing country. We use these estimates to compute expected compensating variation for commute time savings generated by Metro Line 1 and Lines 2, 3 and 7 (Small and Rosen (1981) and Kling and Thomson (1996)). This provides a measure of short run welfare.

In the long run, since households can move residential locations, welfare is likely higher. We therefore estimate a housing choice model: households select a house, assuming fixed work locations, based on the expected utility from the optimal commute mode decision and other housing and neighborhood characteristics including a measure of employment accessibility (similar to Barwick et al. (2024)). We use preference estimates from this model to compute a longer run welfare measure–the expected compensating variation for counterfactual improvements in commuting utility due to Metro projects, assuming inelastic housing supply.

The short run benefits implied by the commute mode choice model accrue to only those workers whose commute time between their residence and work location is reduced. This could be due to newly accessible Metro stations or more efficient transit routes. The mean expected compensating variation conditional on benefits being positive implies that the average beneficiary would be willing to pay 12-16% more than their current out-of-pocket expenditure for these time savings benefits. Long run welfare accrues to households experiencing improved commuting utility due to Metro projects linking workers' job locations and affordable houses in the city. At the same time, the welfare effect of changes in relative employment accessibility in the city and rental prices is ambiguous. The mean expected compensating variation implied by this model is 2% of average monthly rent for Line 1 and 6% of average monthly rent for lines 2, 3 and 7.

How benefits are distributed among various consumers is an important policy consideration. We examine the spatial heterogeneity in short run benefits by residence and work locations, and demographic heterogeneity by estimating commute mode choice models by gender, education, and income levels. In the long run, certain households may benefit more from re-sorting due to the geography of jobs. We therefore examine how long run benefits vary by work location and for different groups of households by vehicle ownership, income, and the education level of the primary worker of the household.

In the short run, women benefit more than men, workers with at least a college education benefit more than those with less than a college education, and workers with above-median incomes benefit more than those with below-median incomes. Travel time savings generated by the Metro projects are similar for different sub-groups of individuals in the sample. Therefore, the heterogeneity in benefits is due to differences in preferences. In the long run, households with lower incomes, less education, and no vehicles experience greater benefits. Their initial commuting constraint, relieved by Metro rail, is stronger than for economically advantaged households. In most of the existing literature on transit benefits, economically disadvantaged households benefit less than their counterparts, which is consistent with our short run results but opposite to our long run results.

Despite its smaller length, Line 1 yields average short run benefits per beneficiary that are 80% of the short run benefits per beneficiary due to Lines 2, 3 and 7, thus highlighting the importance of its strategic location. Line 1 provided the first east-west rail link in the city, while most of Lines 2, 3 and 7 run north-south, parallel to the existing Suburban Railway network. Lines 2, 3 and 7 are, however, much greater in length, and thus yield greater aggregate benefits, both in the short and the long run, than Line 1.

Our paper contributes to the growing literature on benefits of urban transit projects in developing world cities. We focus on a first order benefit, improved commute times and utilities, which is likely to be the most salient factor in policymakers' decisions.[1] A recent strand of literature has examined the general equilibrium welfare impacts of transit through quantitative spatial equilibrium models in London (Heblich et al. (2020)), Los Angeles (Severen (2021)), Bogotá (Tsivanidis (2023)), and Buenos Aires (Warnes (2020)). Similar to Barwick et al. (2024), our framework embeds the traditional commute mode choice model within the housing choice modeling framework introduced by Bayer et al. (2004). This allows us to benefit from carefully accounting for commuting preferences in modeling residential location decisions.

Our paper complements the existing literature in several ways. First, we examine the influence of heterogeneous preferences and the distribution of welfare generated from transit infrastructure in greater detail than the existing literature. Second, our approach

[1]Other types of benefits of urban transport projects include the impact on air pollution (reviewed in Li et al. (2020) and Cropper and Suri (2023)), population changes (Glaeser et al. (2008), Pathak et al. (2017), Gonzalez-Navarro and Turner (2018), Khanna et al. (2021), Balboni et al. (2025)), employment (Kwon and Lee (2022), Tyndall (2021), Zárate (2022)), innovation (Koh et al. (2025)), vehicle ownership (Mulalic and Rouwendal (2020)), congestion (Anderson (2014), Gu et al. (2021)), access to consumption amenities (Zheng et al. (2016), Lee and Tan (2024)), and trade and economic growth (Donaldson and Hornbeck (2016), Donaldson (2018), Banerjee et al. (2020)). See also Redding and Turner (2015) for a literature review.

allows us to separately estimate the value of direct commuting gains through both in-vehicle and access time savings in the short run and the long run. These values can be considered a conservative lower bound to the overall benefits of transit projects.[2] Data limitations prevent us from estimating a full quantitative spatial equilibrium model; however, we bridge the gap with the recent literature by modeling employment accessibility (or commuter market access) as a form of housing amenity affecting household sorting decisions.[3] While we don't explicitly model firm behavior, our approach allows us to incorporate the willingness to pay associated with changes in employment accessibility in estimating welfare. Lastly, the context of Mumbai is particularly interesting given its extensive network of public transit including the Suburban Railway and buses, in addition to the newly introduced Metro projects.[4]

The paper is organized as follows. Section 2 describes stylized facts about transportation in Mumbai. Section 3 describes the mode choices and characteristics of commuters in the household survey. The commute mode choice and housing location choice models are presented in Section 4 and the data used to estimate them in Section 5. The results of model estimations are reported in Section 6 and the welfare estimates that they imply in Section 7. Section 8 concludes.

2 Context

This paper is focused on the Greater Mumbai Region (henceforth, Mumbai), a subset of the Mumbai Metropolitan Region (MMR). With a population of over 20 million, MMR is one of the most populous metropolitan areas in the world. Mumbai is the core of the MMR, with a population of 12.5 million in the 2011 Census. It is located along the central-western coast of India, surrounded by the Arabian Sea on the east, west and south. The city's habitable areas and the existing road and rail network are shown in Figure 1.

Mumbai's 24 administrative wards are divided into 6 zones (Appendix Figure B1). The southern tip of the city (Zone 1) is the traditional city center. Zone 3 is a newly developed commercial and employment center. Zones 4, 5 and 6 constitute the suburban area. There has been a northward movement of employment and households in the city over time, made possible by public transit and lower property prices in the suburbs. Generally, population and employment are concentrated along the main rail lines. In the 2013 Employment

[2]In Tsivanidis (2023), direct commute time savings account for 57.5% of the general equilibrium welfare.

[3]Commuter market access and firm market access are the main channels through which welfare gains arise in quantitative spatial equilibrium models.

[4]See Kreindler et al. (2023) for a characterization of the optimal transit network based on commuting preferences.

Census, 80% of workers in formal jobs were concentrated in Zones 1-4. About 70% of individuals lived in Zones 1-4 according to the 2011 Census.

The Mumbai Suburban Railway, shown in black in Figure 1, is the heart of the city's public transit network; however, Suburban trains have severe overcrowding problems.[5] An extensive network of public buses complements the rail system, but its importance has been declining. Average daily bus ridership in 2019 was 2 million passengers (DNA India (2019)), compared to 4.2 million in 1997-98 (Korde (2018)). This is likely due to traffic congestion in the city and poor upkeep of public buses. Rising household incomes have also led to a sharp increase in private vehicle ownership. The two-wheeler and car population in the city increased by 340% and 200%, respectively, from 2000 to 2017, further contributing to traffic congestion.[6,7]

The Metro rail project was planned to alleviate Mumbai's congestion problems. The existing and planned lines are shown in Figure 1. Line 1 became operational in 2014. Lines 2, 3 and 7 were expected to become operational in 2021-22. Line 3 became fully operational in October 2025. Parts of Lines 2a (North-South part of the red line in Figure 1) and 7 became operational in 2022-2023, but the rest are still under construction. Line 2b will provide another east-west rail link, while the other parts of the network run parallel to the Mumbai local railway network.

3 Mode Choices and Individual Characteristics

This paper uses information on the residential location of households, household members' workplace locations and residence-to-work commute patterns from a survey conducted by the World Bank in January-March 2019 (Alam et al. (2021)).[8] 3,024 households were sampled in proportion to the population at the ward level. Two members were interviewed in each household, an adult male and female (ages 18-45) with priority given to primary earners and/or decision makers of the household. The location of sampled households is shown in Appendix Figure B2. While we do not know the exact work location of individuals in the survey, we denote the work location by a randomly selected

[5] There are about 14-16 passengers per sqm of floor space (Hindustan Times (2017)).

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

[7] In 2018, the average speed in the city during morning rush hours was 22 kmph, with a peak traffic speed of 7 kmph. Slow speeds and congestion in Mumbai are due to traffic as well as the city's road infrastructure (Akbar et al. (2023)). Its shape and coastal location also constraint its development (Harari (2020)).

[8] This survey was a sequel to one conducted by the World Bank in 2004 and follows the same sampling and questionnaire design (Baker et al. (2005)).

post office with the same pin code as the work location.[9] In this section, we describe the commuting patterns based on this survey, which form the basis for estimating the models in Sections 4.1 and 4.2.

The existing pattern of residential and employment locations in the city determines the extent of short run commute benefits from Metro rail. 72% of sampled workers work in Zones 1-4, while 68% live in Zones 1-4. Commute trips are generally short: 50% of commuters travel less than 2.5 km to get to their work location. 75% of all workers work in the same zone as their residence.[10]

The success of new transit projects depends not only on their placement but also on commute mode choices. In our sample, 8-10% of workers work from home. Table 1 shows the main commute modes for workers who commute to work. 33% travel by foot or bicycle. 24% use public transportation: 16% for train and 8% for bus. 10% use auto-rickshaws or taxis, and 34% use private two-wheelers or four-wheelers. Distances traveled by commuters are in the last row. These suggest that mobility is generally low in the city and that public transit facilitates longer commute distances, with train riders commuting over 10 km one-way (Table 2).

Vehicle ownership and income are important determinants of commute mode choices: 50% of workers live in households with at least one vehicle, an increase from 20% in 2004 (Baker et al. (2005)). Columns 6 and 7 of Table 1 show modal shares by vehicle ownership. 70% of workers with a vehicle use it as their main commute mode, while the rest are equally divided between walking, and public transit or auto-rickshaw.

The differences in commuting patterns for different sub-groups of sample in Table 1 reflect potential heterogeneity in the distributional effects of Metro rail. The difference in average commute distance between men and women is not statistically significant, but women are less likely to use private motorized transport than men. On average, workers without a college degree live closer to their work location (4 vs 5.7 km) and are more likely to walk to work than workers with a college education (41% vs 15%). College educated commuters are more likely to use train and private vehicles because of their higher incomes and greater commute distances. Workers earning above median incomes travel significantly greater distances (5 km) than those earning less (4.3 km). They are more likely to travel via private vehicle than walk or use public transit. The models discussed in the following sections use these observations to estimate the underlying preference parameters.

[9] There are 88 unique pin codes in Mumbai. The number of post offices per pin code ranges from 1 to 9, with the median being 4. Any measurement error due to this assumption is likely to be random.

[10] In 2004, the median commuter traveled 2.9 km to get to work (Baker et al. (2005))

4 Models

In this section, we develop models to value the time savings benefits of Metro rail in the short and long run. We begin with a model which characterizes commute mode choice as a function of in-vehicle travel time, out-of-vehicle travel time, and income net of travel costs similar to McFadden (1974). The commute mode choice model allows us to estimate individual preferences for time and costs, accounting for tastes for mode types such as public transit or private vehicles. Using these preferences, we estimate how much each individual would pay for the potential time savings due to Metro rail, holding their utility constant at the pre-policy level, i.e., we estimate their expected compensating variation. This is our measure of short run benefits due to Metro rail.

To measure long run benefits we estimate a model of residential location choice in which expected utility from the commute mode choice model enters the household's utility function, in addition to other housing amenities and housing cost (Barwick et al. (2024)). Households choose the house that maximizes their utility, holding work location fixed. We use this model to estimate households' compensating variation for Metro rail, which alters the maximum utility from commuting for each house in the household's choice set.

Our modeling approach allows us to separately measure the benefits that can be strictly attributed to commute time savings affecting individuals' optimal commute mode decisions (short run welfare) and those that arise due to household re-sorting in response to the potential time savings arising at different locations, conditional on their optimal commute mode decisions (long run welfare).

4.1 Commute Mode Choice

The motorized commute modes in Mumbai include bus and train, auto-rickshaw and taxi, and two-wheeler and car. Non-motorized modes (biking or walking) constitute one-third of commutes (see Table 1). We classify similar modes in categories to account for tastes for commute mode types. For example, individuals may have a preference for private vehicles or a distaste for public transit or walking.

Assuming fixed residence and work locations, individual i chooses a travel mode $m \in$ M={Walk, Bus, Train, Auto-rickshaw, Two-wheeler, Car} to maximize their utility. These modes can be classified into mutually exclusive categories or nests denoted by B_k. Our preferred nesting structure has B_1={Walk, Auto-rickshaw} , B_2 = {Bus, Train}, B_3={Two-wheeler}, B_4={Car}.

Utility U_{imB_k} is assumed to be a function of in-vehicle and out-of-vehicle travel times, income minus out-of-pocket travel costs, scaled to the per-trip level, an unobserved nest-specific preference, and an individual-specific idiosyncratic random shock.[11] We assume a linear additive random utility function,

$$\begin{aligned} U_{imB_k} &= V_{imB_k} + \epsilon_{imB_k} \\ V_{imB_k} &= \alpha_1 * t^{ivt}_{imB_k} + \alpha_2 * t^{ovt}_{imB_k} + \alpha_3 * (w_i - c_{imB_k}) + \delta_{B_k} \end{aligned} \tag{1}$$

where $t^{ivt}_{imB_k}$ and $t^{ovt}_{imB_k}$ denote the in-vehicle and out-of-vehicle travel times in minutes for individual i's commute trip taken via mode $m \in B_k$. c_{imB_k} denotes the per trip out-of-pocket cost, w_i the individual wage scaled to the per trip level and δ_{B_k} the mean utility for nest B_k. V_{imB_k} is the deterministic portion of utility. $w - c$ enters the model linearly for computational simplicity.[12] ϵ_{imB_k} is an i.i.d. random utility shock assumed to follow a generalized extreme value distribution.

$$\epsilon_{imB_k} \sim exp\bigg(\sum_{k}^{K} \big(\sum_{m \in B_k} -e^{\epsilon_{imB_k}/\lambda_{B_k}} \big)^{\lambda_{B_k}} \bigg) \tag{2}$$

In this specification, we assume that for any two alternatives m_1 and m_2 in nest B_k , $\epsilon_{im_1B_k}$ is correlated with $\epsilon_{im_2B_k}$.[13] Any two alternatives across nests are assumed to be uncorrelated, i.e., $Cov(\epsilon_{imB_k}, \epsilon_{im'B_l}) = 0$ for $m \in B_k$ and $m' \in B_l$. The parameter λ_{B_k} represents the degree of independence among the alternatives in nest B_k. The probability of an individual choosing alternative $m \in B_k$ is given by

$$\mathcal{P}_{im} = \frac{e^{V_{im}/\lambda_{B_k}} \big(\sum_{j \in B_k} e^{V_{ij}/\lambda_{B_k}} \big)^{\lambda_{B_k}-1}}{\sum_{l=1}^{K} \big(\sum_{j \in B_l} e^{V_{ij}/\lambda_{B_l}} \big)^{\lambda_{B_l}}} \tag{3}$$

Identification of preferences relies on the cross-sectional variation in travel times and Hicksian bundles across feasible alternatives and individuals. Conditional on a worker's residence and work locations, different modes imply different time and money costs. Mode choices made by commuters in response to these trade-offs drive the marginal utilities

[11] We assume 22 working days and 2 trips per day, so the value of the monthly Hicksian bundle is divided by 44 to scale it to the per trip level.

[12] Allowing it to enter non-linearly as Cost/Wage lowers the estimated preferences for travel time slightly, but the model fit is similar. We discuss robustness in Section 6.1.

[13] For sensitivity analysis, we also consider a model where there is only one nest $K = 1$, and unobserved heterogeneity in preferences for in-vehicle and out-of-vehicle travel time that maybe correlated. We allow the parameters α_1 and α_2 to vary by individual and follow a joint Gaussian distribution. Nested logit is the preferred model because of the unrealistic substitution patterns implied by the conditional logit model, and because empirically, it fits the data better than a mixed logit model (discussed in Section 6.1). A conditional logit model with all mode-specific intercepts is not preferred because of insufficient statistical power to identify preferences from the variation in in-vehicle travel times that remains after accounting for mean preferences for modes.

of time and money. The implicit assumption is that this variation is uncorrelated with unobserved mode preferences conditional on mean utility differences across nests. Nest intercepts ensure that nest-level differences in reliability, convenience, or flexibility, do not drive our estimates. A common identification concern in commute mode choice models is differential transport availability across locations. Most households in the survey have access to a bus stop and train and feasible sets do not include private vehicles when the household doesn't own them. Nevertheless, we test the robustness of our estimates to the inclusion of residence location indicators interacted with nest indicators, in addition to interactions between demographic and nest indicators.

The average monetary value of time is the marginal rate of substitution between time and cost. Therefore, the average value of in-vehicle time is $\frac{\alpha_1}{\alpha_3}$ and the value of out-of-vehicle time is $\frac{\alpha_2}{\alpha_3}$. This is the value of time savings (VTTS) measure commonly used in the literature (Koppelman and Bhat (2006), Small et al. (2007), Tsivanidis (2023), Craig (2019), Akbar (2024), Buchholz et al. (2025)). A rough estimate of the VTTS associated with an infrastructure project is computed by multiplying the changes in in-vehicle and out-of-vehicle times by the respective marginal value of travel times for users affected by the project. This measures the value of small changes in travel time reasonably well, but not large changes such as those brought about by new infrastructure projects since it does not allow modal shares to change in response to the policy (Train (2009)).

Welfare: To measure the value of changes in travel times in the commute mode choice model we compute expected compensating variation, CV_i (Small and Rosen (1981), Varian (1992), Small et al. (2007)). CV_i measures the willingness to pay for travel time changes induced by Metro rail, holding utility constant at the pre-policy level.

$$E\big[\max_m U(t^{ivt,0}_{imB_k}, t^{ovt,0}_{imB_k}, w^0_i - c^0_{imB_k}, \delta^0_{B_k})\big] = E\big[\max_m U(t^{ivt,1}_{imB_k}, t^{ovt,1}_{imB_k}, w^0_i - c^0_{imB_k} - CV_i, \delta^0_{B_k})\big] \tag{4}$$

The superscript 0 indicates baseline variable values and the superscript 1 indicates variables changed by the policy. Due to the linear-in-parameters additive random specification with income also entering linearly, expected compensating variation has an exact formula (Kling and Thomson (1996)),

$$\frac{1}{\alpha_3}\Bigg[ln\big[\sum_k \big(\sum_m e^{(V^1_{imB_k}/\lambda_{B_k})}\big)^{(\lambda_{B_k})}\big] - ln\big[\sum_k \big(\sum_m e^{(V^0_{imB_k}/\lambda_{B_k})}\big)^{(\lambda_{B_k})}\big]\Bigg] \tag{5}$$

The short run benefits implied by the commute mode choice model accrue to only those workers whose commute time between their existing residence and work location is reduced. This could be due to newly accessible Metro stations, or more efficient transit routes. In Section 7.1, we estimate the commute mode choice model and short run benefits for all sampled commuters and also for sub-groups of commuters (women, college-educated workers, workers with above-median incomes).

4.2 Housing Location Choice

Assuming a fixed work location, household i chooses a house h from the set of feasible housing alternatives, based on various housing amenities, including the expected utility of commuting, and housing cost.[14]

$$\begin{aligned} U_{ih} &= V_{ih} + \epsilon_{ih} \\ V_{ih} &= \beta_K * K_{ih} + \beta_Z * Z_{ih} + \alpha_p * \mathrm{P}_h + \alpha_x * X_h + \nu_h \end{aligned} \tag{6}$$

V_{ih} refers to the deterministic portion of the utility function. ϵ_{ih} is the household-specific idiosyncratic shock component assumed to follow an i.i.d. Type I extreme value distribution. K_{ih} represents the attractiveness of house h to household i in terms of the ease and comfort of its workers' commute. It is the expected utility from commuting between house h and the fixed work locations of each worker of household i via the optimal commuting mode. This expected maximized commuting utility is derived using preference parameters from equation 1 for each worker i_g and is combined to obtain a household-level expected commuting utility as given below.[15]

$$K_{ih} = \mathbb{E}_g\Bigg[ln \sum_k \bigg(\sum_m e^{(\hat{V}_{i_g hmB_k}/\hat{\lambda}_{B_k})}\bigg)^{\hat{\lambda}_{B_k}}\Bigg] \tag{7}$$

$$\text{where } \hat{V}_{i_g hmB_k} = \hat{\alpha}_1 * t^{ivt}_{i_g hmB_k} + \hat{\alpha}_2 * t^{ovt}_{i_g hmB_k} + \hat{\alpha}_3 * (w_{i_g} - c_{i_g hmB_k}) + \hat{\delta}_{B_k}$$

Z_{ih} denotes housing attributes that vary by household such as the proportion of households within 2 km of house h that have the same religion or language as household i. P_h is the monthly rental price of housing h. X_h denotes housing characteristics other than rental price that do not vary across households, such as floor space, condition of roof, presence of an indoor toilet, and neighborhood characteristics such as employment accessibility, prevalence of crimes against women, whether the neighborhood is a slum area, and distance to the coast. ν_h captures unobserved preferences for housing h.

[14] Each house is assumed to represent a housing type.

[15] The functional form is due to the idiosyncratic shock being GEV distributed. Expectation is taken across workers within the household to obtain household-level average expected commuting utility. Employment location information is available for two workers of the household.

β_Z and β_K capture average preferences for attributes in Z_{ih} and K_{ih}. In some specifications, we use household characteristics such as education of the primary worker, income level, and vehicle ownership as taste shifters. In those cases, β is composed of two components, one that is constant across all households, and one that is constant across all households within a specific income or education category but varies across categories. For example, $\beta_Z = \bar{\beta_Z} + \beta_Z^{edu}$. This heterogeneity in preferences captures sorting based on income, education, and vehicle ownership. α_p and α_x capture average preferences for rental price and housing-specific characteristics in X_h.

Welfare: Long run welfare is given by the expected compensating variation for improved utility due to the addition of Metro rail. For a conditional logit model with income entering the utility function linearly, the exact formula for expected compensating variation is given below (Small and Rosen (1981)).

$$\frac{1}{|\alpha_p|}\left[ln\Big(\sum_h e^{V_{ih}^1}\Big) - ln\Big(\sum_h e^{V_{ih}^0}\Big)\right] \tag{8}$$

Superscript 0 denotes baseline values of the indirect utility function under the existing rail network, while 1 denotes the utility after the policy change.

In the housing choice model, time savings due to the Metro can affect utility through three channels: direct commuting utility, employment accessibility, and rental prices. Time savings improve commuting utility between the household's workers' existing work location and any house that the household has a positive probability of selecting. Commuting utility increases whenever the transit time is reduced between a house-work location pair. Additionally, relative changes in employment accessibility change the amenity value of certain houses. This changes the expected demand for each house and rental prices adjust to clear the market.

We compute welfare under two assumptions about housing supply elasticity. To observe welfare change due solely to improved commuting utilities and changes in employment accessibility, we assume supply to be infinitely elastic. In this case, housing supply fully adjusts to clear the market and rental prices remain the same. For comparison, we also assume housing supply elasticity to be 0.5 (following Saiz (2010) and Baum-Snow and Han (2024)).[16,17]

[16]We assume a simple upward sloping constant elasticity supply function: $S_h = A_h * P_h^{\eta}$, where S_h represents the supply of housing type h, P_h is the price, η the elasticity, and A_h is a normalization constant calibrated using baseline equilibrium shares.

[17]Gechter and Tsivanidis (2023) assumes a supply elasticity of 0.6 for Mumbai.

5 Data

Commute Mode Choice Model: The 2019 World Bank household survey has information on up to three modes for a typical residence-work commute, along with time spent in each mode. The chosen travel mode in the commute mode choice model is the 'main commute mode' defined as the motorized mode with maximum duration, or the non-motorized mode with maximum duration if that is the only reported travel mode.

To estimate preferences for travel time, we need travel time and costs between residential and work locations for all feasible travel modes, in addition to the chosen mode. We compile this information using multiple sources. The computation of in-vehicle and out-of-vehicle travel times for each mode and each origin-destination pair is described in Appendix Section A.2.

Out-of-pocket costs for bus, train and auto-rickshaw are calculated using the per km official fare rules relevant for a single-trip in 2019.[18] For two-wheeler and car, assuming a mileage of 26 kilometer per liter (kmpl) and 12 kmpl, we calculate the cost per trip km using the prevailing petrol price in Mumbai at the time (Rs. 86.16 per liter). We multiply the commute distances by the cost per km to calculate out-of-pocket costs.

Table 2 presents data on travel time, out-of-pocket cost, distance to work location, and the average monthly commuter income by the main commute mode chosen. Both average travel time and distance are the greatest for train commuters, while the cost per trip is the lowest for train commuters. On average, individuals commuting via two-wheeler and car have a higher income than the remaining sample. The distribution of average monthly incomes for train users indicates that train users include both low and high income commuters.

Housing Choice Model: The housing choice model is estimated using a sample of 2,170 households for whom complete information is available on relevant household characteristics and neighborhood and housing amenities. These are presented in Table 3. The average monthly household income is Rs. 30,939 ($1,454 PPP) with an average imputed monthly rent equal to 32% of household income. There is some clustering in households' chosen locations by religion and language. The two main religions in the sampled households are Hinduism (79%) and Islam (17%). 53% of households state Hindi as their mother tongue, while 36% state Marathi. On average, within a 2 km radius around each household, 45% of households have the same language, and 68% of households have the same religion. To identify household preferences for living close to other households with same language

[18]Our conclusions are robust to using fares for commuters with a monthly or quarterly pass for bus and train.

and religion, we compute, for each house in the sample, the proportion of households within a 2 km radius with a given religion and language.

To obtain maximum expected commuting utility for each household-house pair, we compute the household average value of K_{ih} (equation 7) for all commutes between the work locations of workers of household i and houses in household i's choice set. Household expected commuting utility is the main housing amenity through which we measure households' long run welfare due to Metro rail.

Housing characteristics common to all households are summarized in the second panel of Table 3. The average floorspace is 263 sqft, with the median house having only a single room. 59% of the houses have a separate kitchen space. Many houses do not have a toilet or bathroom inside the house; households living in these houses must rely on communal facilities. Access to public transit is good. Mean distance to the nearest railway station is 1.5 km, which is an 18-minute walk assuming a walking speed of 5 kmph. The nearest bus stop for most houses in the sample is within a 5-minute walk. We estimate preferences for a general employment accessibility index as well.

We control for employment accessibility as an amenity by constructing an index in the spirit of Hansen (1959) which is a commuting-cost-weighted average of the attractiveness of pin codes as employment locations. Let j index work locations in the city. The employment accessibility index for house h is defined as

$$\mathrm{EA}_h = \sum_j \left(\frac{w_j}{d_{hj}}\right) \tag{9}$$

where w_j is the wage obtainable at location j and $d_{hj} = exp(\kappa * t_{hj})$ is the iceberg commuting cost from house h to location j. t_{hj} is the travel time between h and j. $\kappa > 0$ is the semi-elasticity of commuting costs d_{hj} to commuting times t_{hj}. In the absence of data on wages, we use the method in Kreindler and Miyauchi (2023) to construct a proxy for w_j. We estimate a reduced-form gravity equation of aggregate commute flows between pairs of pin codes as a function of the fastest travel time between the two pin codes and fixed effects for origin and destination pin codes. Parameter estimates of destination fixed effects represent the relative attractiveness of locations for employment and serve as a proxy for w_j. The elasticity of commute flows to commute time obtained as the parameter on travel time and the relationship between estimated destination fixed effects and aggregate wages by pin code is used to estimate κ.[19] The estimation is discussed in Appendix Section A.3.

[19] We estimate $\kappa = 0.0107$. Ahlfeldt et al. (2015) estimates $\kappa = 0.01$ and Tsivanidis (2023) estimates $\kappa = 0.012$.

We use the standardized values of EA_h as a housing amenity.[20]

6 Estimation and Results

6.1 Commute Mode Choice

We estimate the nested logit model in equations 1 and 2 using maximum likelihood estimation. We classify commute modes into nests based on similarity in scheduling flexibility or general accessibility and autonomy, as measured by the private or public nature of the travel mode. Bus and train are the least flexible of the publicly available options because of their fixed schedules. Auto-rickshaw and walking are less flexible than using a two-wheeler or a car because of their logistical infeasibility in certain locations or for longer distances.[21] But they are more flexible than bus or train due to the absence of a fixed schedule. Commuters are also more likely to choose train for longer commute distances (Table 2) which could indicate an absence or unreliability of buses on certain routes.

Due to arbitrariness in classifications, we present estimated parameters for three different nesting structures in Table 4: Column 1 {(Walk, Auto-rickshaw), (Bus, Train), (Two-wheeler), (Car)}, Column 2 {(Walk, Auto-rickshaw), (Bus, Train), (Two-wheeler, Car)}, and Column 3 {(Walk, Auto-rickshaw), (Train), (Bus), (Car, Two-wheeler)}. Model 1 is our preferred specification: it is consistent with our beliefs about mode substitution behavior in Mumbai and fits the data well. Empirically, Model 2 also performs well, therefore, Models 1 and 2 are the focus of our analysis. The only difference between the two models is that Model 1 assumes independence between idiosyncratic preference shocks for Car and Two-wheeler, whereas Model 2 does not. Model 3 assumes that idiosyncratic preference shocks for bus and train are independent, which is less likely to be true. The modal share predictions generated by the three models are in Table 5.[22]

Results in Table 4 indicate a distaste for longer commute times. The distaste for out-of-vehicle time is greater than the distaste for in-vehicle time, a common finding in the literature (Small et al. (2007), Chapman et al. (2006), Koppelman and Bhat (2006), Buchholz et al. (2025)). Estimated nest-intercepts indicate that mean utility for private and flexible modes is higher than for bus or train. On average, the value of in-vehicle time

[20]Results are robust to using an employment accessibility index which is a travel-time-weighted average of effective wages across the city, with time t_{hj} in the denominator instead of equation 9.

[21]For example, auto-rickshaws are not allowed in South Mumbai. Auto-rickshaws are more expensive than other modes and may sometimes be feasible only for shorter distances (see Table 2 for a cost comparison).

[22]Degenerate nests have a dissimilarity parameter of 1. To obtain predictions of modal shares consistent with equation 3, we constraint the dissimilarity parameters to 1 whenever they exceed 1 by a significant magnitude.

is Rs 0.77-0.82 per minute, and the value of out-of-vehicle time Rs. 1.41-1.45 per minute, about 40-42% and 73-74% of the mean wage, respectively.[23] We find similar estimates upon including interactions of nests with demographics (gender, income category, education category, age categories) and with residence ward fixed effects (Appendix Table B1).

The estimated preference parameters lie in the range of estimates commonly used for transport policy analysis. The U.S. Department of Transportation recommends setting the value of time equal to the median gross wage (U.S. DOT (2016a), U.S. DOT (2016b)), or at 80-120% of the wage rate to allow for uncertainty. Small et al. (2007) and Concas and Kolpakov (2009) report a range of estimates from the literature ranging from 20% to over 100% of the average wage across countries. Craig (2019) estimates the value of time in British Columbia to be 58% of the mean wage. Buchholz et al. (2025) estimates the value of waiting time in Prague to equal the mean wage.

These estimates are robust to different measures of in-vehicle and out-of-vehicle travel time. We estimate Models 1 and 2 using transit time information from HERE so that transfer times for bus and rail are included in out-of-vehicle time. We also use out-of-vehicle time exclusively from the household survey assuming households behave according to their perceptions of travel time, and not necessarily the actual time. Results for Models 1 and 2 are in Appendix Tables B2 and Table B3, respectively. The values of time implied by these alternative definitions are similar to Table 4.

For comparison, we estimate a nested logit model with income entering non-linearly as cost/wage and a mixed logit model allowing correlated heterogeneity in preferences for time. Correlated taste heterogeneity captures the possibility that individuals who have a greater distaste for in-vehicle travel time may also have a greater distaste for out-of-vehicle time and a lower marginal utility of money. Appendix Table B5 compares modal shares predicted by the nested logit models in Table 5 with the nested logit models with income entering non-linearly, and the mixed logit model.[24] The nested logit models perform better than the mixed logit specification in terms of predictions. Predictions from the preferred model specification with income entering linearly are similar to those from the model with income entering non-linearly.

[23] In the context of Jakarta, Kreindler et al. (2023) also finds the value of out-of-vehicle time to be twice the value of in-vehicle time.

[24] Preference parameters from the model with income entering non-linearly are in Appendix Table B4. Parameter estimates for the mixed logit model are not shown for brevity.

6.2 Housing Choice

We estimate the housing choice model following the two-step approach of Berry et al. (1995), Bayer et al. (2004), and Bayer et al. (2007). In the first stage, we estimate the parameters of equation 10 using maximum likelihood estimation.

$$U_{ih} = \beta_K * K_{ih} + \beta_Z * Z_{ih} + \delta_h + \epsilon_{ih} \tag{10}$$

The housing-specific variables in equation 6 are subsumed in δ_h, the housing specific constant that captures the mean utility for house h. Each house observed in the survey is assumed to represent a housing type. House (housing type) h is feasible for a household i if the survey-reported monthly rental cost of h is lower than the monthly income of household i. The estimation sample has 2,170 households choosing among 2,170 houses. Since the number of alternatives available per household is large, for computational reasons, we take a random sample of the feasible set in estimating the model (McFadden (1978)).[25]

In the second stage, $\hat{\delta}_h$ is decomposed using a linear model with random errors to estimate preferences for house-specific attributes that do not vary by household.

$$\hat{\delta}_h = \alpha_p * \mathrm{P}_h + \alpha_x * X_h + \nu_h \tag{11}$$

We use the estimated housing-specific intercepts from the first stage to estimate equation 11 using two-stage least squares. Unobserved housing attributes omitted from this equation contained in ν_h are likely correlated with rental price. Therefore, we instrument for rental price using the log of assessed value of properties in the neighborhood of h from the year 2017.[26] Neighborhoods for the purposes of value assessments, called sub-zones, are defined by the municipal government based on historical boundaries, land regulations, and market values. The formula for setting these values is unknown. However, it is known that each year the municipal government sets the assessed value for a given year based on transactions in that sub-zone in the previous year.[27] Assessments are used for collecting transaction and property taxes, and may differ from the market price of houses, but are correlated with market prices (Anagol et al. (2024)). For house h in sub-zone s_h, rental

[25]This simplification leads to a slight loss in precision in the first-stage estimates but not enough to outweigh the computational gains.

[26]Our results are robust to using the 2011 assessment values.

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

price can be written as a function of assessed values in sub-zone s_h.

$$\mathrm{P}_h = \omega * \mathrm{Log}(\text{Assessed value})_{s_h} + \alpha_x * X_h + \zeta_h \tag{12}$$

This instrument is valid as long as it is not correlated with ν_h. This is likely to be satisfied given the heterogeneity in housing types within a sub-zone s. This is also likely to be true given the pattern of raw correlation between observed amenities and assessed values (-0.2 - 0.09 for most amenities, and $\sim$ -0.37 for proximity to coast and employment accessibility). Consequently, the price coefficient is robust to controlling for amenities observed in the survey. The same argument, however, suggests that the instrument may be weak. We show robustness to the weak instrument problem using the inference criteria suggested in Lee et al. (2022).

Preference parameters in equation 10 estimated using a conditional logit specification are presented in Table 6. Households have a preference for houses that offer a higher commuting utility and for living close to other households with the same religion and language. Parameter estimates are robust to whether expected commuting utility is computed using commute mode choice Model 1 or Model 2. To test the sensitivity of commuting utility preference parameters to the first-stage specification, we estimate specifications allowing for the preferences for commuting utility and proximity to households with similar language and religion to vary by income, education and vehicle ownership. Preferences for expected commuting utility from the first-stage of these models are in Table 7.

Preferences for commuting utility are heterogeneous, i.e., some household types place a higher value on the possible commuting utility when selecting a house (Table 7). Households with a primary worker without a college degree have a stronger preference for houses with higher commuting utility than households whose primary worker has a college degree. Households with below median incomes have a stronger preference for commuting utility than their higher-income counterparts. In contrast, households that own a vehicle have a stronger preference for commuting utility than their counterparts. This is likely due to the fact that most households with a vehicle own a two-wheeler, which is more convenient for shorter distances.[28]

In the second stage, estimated house-specific intercepts from Model 1 in Table 6 are regressed on housing-specific characteristics using two-stage least squares, with the log of assessed values for residential properties used as an instrument for monthly rental price. Table 8 presents these regressions for different sets of control variables. With standard

[28]These comparisons are made in monetary terms using the marginal rate of substitution obtained by dividing the coefficient on travel time by the coefficient on rental price from the second stage.

errors clustered at the level of sub-zones, the first-stage F-statistic is ∼40.[29] Given the possibility of this instrument being weak, we use an adjusted critical t-value for inference at the 95% confidence level following Lee et al. (2022). These are reported in the last row of Table 8. The coefficient on rental price has the expected sign, and is significant and robust across these specifications. The corresponding first-stage estimates for these two-stage least square regressions are in Appendix Table B8.[30]

Table 8 indicates that households have a preference for lower rents, better housing infrastructure, proximity to the coast, areas with less crime, places further away from railway stations, and houses with a higher accessibility to potentially attractive work locations. While the consistency of parameters estimated in the first stage is independent of the second stage specification, examining the sensitivity of the coefficient on rental price is important to understand the sensitivity of the value of benefits of Metro rail implied by the model. Column 1 contains a housing amenity index which is the first principal component of the housing amenities available in the survey.[31] Columns 2-5 add additional amenities: distance to coast, distance to the nearest railway station, slum classification of the residential area, number of reported crimes against women, an index of employment accessibility, and an index for proximity to doctor and hospitals.[32] The coefficient on distance to the nearest railway station captures the average disamenity associated with being close to a congested transit access point. The fact that access to a transit stop reduces the travel time needed to reach an employment location is captured by the employment accessibility index.[33] Column 4 is our preferred specification: it allows the greatest number of controls without the loss of sample size due to missing observations.

7 Welfare Estimates

7.1 Short run Commuter Welfare

In 2019, the rail network in Mumbai consisted of the Suburban Railway and Metro Line 1. We compute counterfactual in-vehicle and out-of-vehicle travel times via rail by (i)

[29] According to Lee et al. (2022), first stage F-statistic below 100 may indicate a weak instrument problem.

[30] The second-stage results for Model 2 in Table 6 and the models in Table 7 are similar, therefore, we report only the results for the main specification.

[31] These include floorspace, number of rooms and dummy variables for good roof, separate kitchen, separate toilet, bathroom inside the house, and access to piped water. Factor loading of each of these variables in shown in Appendix Table B6.

[32] The index of proximity to health services is the first principal component of related variables from the survey, including categorical variables for walk time to the nearest private doctor, private hospital, government hospital. Factor loadings indicating the importance of each of these variables in the constructed index are in Appendix Table B7.

[33] Note that travel time used in this index is the lesser of drive and rail time.

removing Line 1 from the 2019 rail network, and (ii) adding Lines 2, 3 and 7 to the 2019 rail network. Line 1 reduces the in-vehicle commute time for 9% of commuters, while Lines 2, 3 and 7 reduce it for 30% of commuters. Conditional on positive time savings, the average time savings is 13 minutes for Line 1 and 9 minutes for Lines 2, 3 and 7. Line 1 reduces the out-of-vehicle travel time for 14% of commuters, while Lines 2, 3 and 7 reduce it for 41% of commuters. Average out-of-vehicle time savings conditional on positive savings is 21 minutes for Line 1, and 12 minutes for Lines 2, 3 and 7.

We compute expected compensating variation to value the time savings benefits due to Line 1 and the upcoming Lines, using parameters from Models 1 and 2 in Table 4. Since the models do not account for preferences for infrastructure quality, these benefits do not capture the improved utility from a more comfortable Metro rail infrastructure relative to the Suburban Railway. The estimates, therefore, likely understate benefits.

The monetary benefits of travel time savings are presented in Table 9. 25% of commuters have a positive willingness to pay for benefits due to Line 1, while 57% have a positive valuation of benefits due to Lines 2, 3 and 7. Conditional on the value of time savings being positive, the mean value of time savings implied by Model 1 is Rs. 77 per month for Line 1 and Rs. 98 per month for Lines 2, 3 and 7. The value of benefits as a proportion of average out-of-pocket commuting cost is 12% for Line 1 and an 14% for Lines 2, 3 and 7. The corresponding values implied by Model 2 are similar (second panel of Table 9).

The spatial distribution of expected compensating variation highlights the nature of travel time benefits. Figure 2 shows benefits from the two Metro projects by household location. Many more commuters benefit from Lines 2, 3 and 7 due to the wider accessibility of the network (92 km). Commuters in the vicinity of Metro stations experience the highest benefits, mainly due to reductions in out-of-vehicle access times. But commuters in other parts of the city also experience benefits due to improved transit connections. This is especially so for Line 1, which provided the first east-west rail link in the city.

Benefits aggregated to the level of work locations highlight which parts of the city benefit in the short run due to improved transit availability. Figure 3 shows the share of short run welfare by pin code of work location. Roughly 70% of the benefits are concentrated in pin codes within 5 km of Line 1. Benefits from Lines 2, 3 and 7 are much more dispersed across the city. These patterns confirm that benefits from a widely distributed transit network are much more spatially dispersed than those from a small, geographically restricted network.

Equity is an important consideration in transit infrastructure planning. Depending on the demographic concentration of workers across residences and pin codes and the spatial concentration of jobs and housing types, certain groups are ex ante more likely to benefit due to improved transit infrastructure (Baum-Snow and Kahn (2000), Glaeser et al. (2008), Akbar (2024)). To understand which groups receive greater benefits due to Metro rail, we estimate the commute mode choice model (equation 1) for various subgroups of individuals distinguished by gender, education and income level. Table 9 shows the value of in-vehicle and out-of-vehicle travel times for each group and the value of travel time benefits due to Line 1 and Lines 2, 3 and 7.

Conditional on benefits being positive, women experience 33% greater benefits than men due to Line 1 and 11% greater benefits due to Lines 2, 3 and 7.[34] The reduction in both in-vehicle and out-of-vehicle times is similar for men and women under both Metro projects. However, women have a greater distaste for travel time, especially out-of-vehicle time, compared to men, as implied by their marginal rate of substitution. On average, women also have a lower distaste for public transit compared to men. This is reflected in the fact that a greater proportion of women use publicly available modes despite traveling similar distances as men (Table 1).[35]

Transport infrastructure projects have strategic importance in enabling certain sub-groups of the population to participate in economic activity. For example, the presence of high-speed Metro rail has been linked to an increase in women's workforce participation in South Korea (Kwon and Lee (2022)). In the context of Mumbai, transport availability may not be the biggest factor constraining women's labor force participation (Alam et al. (2021)), but Table 9 indicates that the marginal benefits of Metro rail received by women workers are greater than those received by men, suggesting a potential effect along the intensive margin.

Reductions in travel times for workers with and without a college degree are similar. However, workers with a college degree experience higher benefits under both Metro projects because they have a stronger distaste for both in-vehicle and out-of-vehicle travel times. They also commute longer distances compared to individuals with less than a college education (Table 1). Their monthly expected compensating variation, conditional on positive benefits, is 67-96% higher than for workers below college education for Line 1 and 47-72% higher for Lines 2, 3 and 7.[36] College educated workers in the sample are also more likely to have above median incomes.

[34]The difference in benefits due to Line 1 is significant at the 95% confidence level, while the difference for Lines 2, 3 and 7 is significant at 80-85% confidence level.

[35]Difference in the value of time are due to differences in preferences for time and for mode category. Gender differences in preferences for mode categories might reflect access to household vehicles, preference for traveling in groups, or safety concerns. Women's preferences for public transit may reflect the availability of women-only coaches in trains and reserved seating for women on buses.

[36]Differences for both projects are significant at the 99% confidence level.

Commuters with above median-incomes experience greater benefits than commuters with below-median incomes. The value of time savings due to Line 1 is 41% higher for above-median income commuters, while the value of time savings is 14% higher for Lines 2, 3 and 7.[37] Both groups experience similar time savings, indicating that this pattern is due to differences in preferences. We also test for heterogeneity in benefits by vehicle ownership using the main specification and summarizing the value of benefits separately by vehicle ownership. Those without a vehicle experience benefits that are three times the value of benefits experienced by vehicle owners.[38] The dispersion in monetized benefits accruing to different sub-groups is higher under the upcoming network than under Line 1, which accords with the greater length of the upcoming lines.[39]

7.2 Long run Household Welfare

The above estimates capture benefits to commuters if their residence and work locations are fixed. We also compute long run benefits, allowing households to choose a house that offers higher utility for its workers' commute. We begin by examining the sensitivity of welfare effects to various modeling decisions when housing supply is assumed to be infinitely elastic. In this case, rents stay the same, so all welfare effects occur solely due to changes in commuting utility and relative employment accessibility. We then discuss relative changes in rents and welfare in the inelastic housing supply case.

We find that average value of welfare due to Line 1, when households are allowed to re-sort and the supply is perfectly elastic, is about 1.4-2% of monthly rent or about Rs. 137-194 per month. These results, shown in Table 10, are stable across the various second-stage specifications. In comparison, the corresponding value of improved commuting utility due to Lines 2, 3 and 7 is 4-5.6% of monthly rent or Rs. 389-545 per month.[40] The larger mean expected compensating variation for lines 2,3 and 7 is not surprising, given the much larger extent of these lines relative to Line 1.[41] For the remainder of this section, we therefore, focus on the specification in Table 10 Model 1 Column 4.

When housing supply is inelastic, the average welfare is similar to the case of perfectly

[37]The differences are significant only for Model 2: for Line 1 at 95% confidence levels and for Lines 2, 3 and 7 at 90% confidence levels.

[38]There is limited statistical power to separately estimate the model for these subsamples.

[39]This is based on a two-sample variance comparison test.

[40]Previous versions of this paper featured a model where households chose commute mode and housing location simultaneously and were not constrained by their baseline status of vehicle ownership, and produced similar results (Suri (2022)).

[41]These welfare estimates are also robust to assumptions of preference heterogeneity in the first-stage (Appendix Table B9).

elastic supply (Table 11), however, the distributional implications are different.[42,43] Changes in commuting utility and relative employment accessibility lead to changes in rental prices across the city, creating negative welfare for some households. Even under the perfectly elastic case, relative changes in employment accessibility can generate negative welfare effects. Due to this, allowing rental price changes can soften the negative effects of worsening relative employment accessibility, as well as the positive effects of direct commuting utility improvements. The net impact is, therefore, ex-ante ambiguous.

The average rental price change in the city is roughly zero for both Metro projects. The spatial distribution of price changes in the city are consistent with theory (Figure 4). Prices increase in areas around Line 1 and in the northeast parts of the city due to the introduction of Line 1. Lines 2, 3 and 7 increase prices in the northern part of the city and around the East-West part of the network. Despite the changes in rental prices, most households experience positive benefits in the long run, whereas short run benefits accrue only to those whose current residence-work commute would benefit from the Metro.

Given the geography of existing jobs, neighborhood sorting in response to the Metro means that work locations accessible via Metro rail should experience the greatest benefits. This is seen in Figure 5, which shows the share of long run welfare by pin code of work location. The share of long run benefits to workers from Line 1 is higher for workers in the middle of the city. Long run benefits from Lines 2, 3 and 7 are more pronounced for workers employed along Lines 2, 3 and 7, although large shares of benefits accrue to workers in the very north and south of the city.

Long run benefits are more likely to accrue to those demographic groups who can move to a better house to take advantage of the Metro network. This depends on households' workers' work locations as well as the distribution of housing amenities and rents across locations. To examine the distribution of benefits across groups, we estimate the main specification for the entire sample, and compute the expected compensating variation assuming a 0.5 housing supply elasticity. Table 12 summarizes the expected compensating variation for different sub-samples.

Households without a vehicle experience significantly greater benefits from both Metro projects relative to households owning a vehicle. This is partly due to the improved commuting utility that accrues disproportionately more to households without a vehicle. Households where the primary worker has less than college education and lower income house-

[42] Assuming elasticity of supply=0 or 1 produces similar results.

[43] We do not allow demographic composition to adjust in equilibrium since our objective is to document benefits of transit infrastructure solely through the channel of commuting gains. In this context, allowing an adjustment in Z_{ih} increases average welfare. Therefore, our results provide a conservative lower bound.

holds benefit significantly more than their counterparts, in contrast to the short run distribution of benefits. Households with greater incomes and assets have fewer commuting constraints to begin with, and most of the benefits accrue to households for whom Metro rail relaxed a significant constraint.

Few other papers in the literature have examined heterogeneity in the benefits from transit project. In the context of Bogotá, Tsivanidis (2023) finds that the introduction of Bus Rapid Transit (BRT) generated greater general equilibrium welfare gains for high-skilled workers. This is consistent with our short run results, however, we find that households with less educated workers experience greater long run benefits. In Buenos Aires, Warnes (2020) finds that the BRT benefited high-skilled and low-skilled workers similarly. In U.S., Akbar (2024) finds that rail transit speed improvements lead to greater benefits for higher-income groups in cities with relatively high baseline transit speeds, and for lower-income groups in cities with relatively slower baseline transit speeds. This is weakly consistent with our short run results but not with our long run results. In the context of consumption-related travel in Singapore, high-income workers are found to benefit more due to the 41.9 km long Downtown Metro rail Line (Tan and Lee (2020)).

7.3 Benefits Cost Analysis

The short run benefits of Metro rail accrue to only a fraction of commuters– 25% for Line 1 and 57% for Lines 2, 3 and 7. When households are allowed to adjust their housing location, assuming a housing supply elasticity of 0.5, more than 90% of households experience positive benefits. Conditional on benefits being positive, the average long run benefits are more than twice the short run benefits for Line 1 and more than five times the short run benefits for Lines 2, 3 and 7. Relaxing the assumption of fixed housing location has a larger impact on the benefits of Lines 2, 3 and 7 because they extend the Metro network more than Line 1.

To estimate aggregate benefits of each Metro project, we scale household-level mean expected compensating variation using ward-level sample weights to obtain annual aggregate benefits at the city level. Total annual short run benefits of Line 1, which accrue to only one-quarter of the city's commuters are \$51 million (PPP), while the long run benefits, which accrue in expectation to all households, are 11 times this value (\$591 million PPP).[44]

[44] Households in the sample were chosen such that there was at least one working member, and one male and one female respondent available. Since each chosen household has at least one working member, we scale household-level expected compensating variation with a factor measuring the relative proportion of worker population in a ward to the number of households in the sample from that ward to obtain population-level benefits. We compute these benefits at the annual level. It is assumed that households that drop out of the sample due to missing information are randomly spatially distributed.

Total annual short run benefits due to Lines 2, 3 and 7 are $170 million (PPP), and their long run benefits are 9 times the short run value ($1,549 million PPP). Despite the much smaller length of Line 1, its aggregate benefits are 36% of those from Lines 2, 3 and 7, highlighting the consequences of its strategic placement. The benefits per km generated by Line 1 are higher than those generated by Lines 2, 3 and 7.

In Table 13, we compare both short run and long run aggregate benefits of each Metro project with the equivalent annualized capital cost of construction (EACC) based on various assumptions about the discount rate and asset life. One option is to use the interest rate on the original and refinanced loan borrowings of the construction company, 12% (Prasad (2015)).[45] Interest rates on loans for other parts of the Mumbai Metro network have been more favorable at 1-2% (CareEdge Ratings (2023)). Another option is to use an interest rate that is closer to the long run yield on government bonds, rates of 10% and 8%. The construction cost of Line 1 is $ 2.03 billion (PPP), and its EACC ranges from $200-$300 million (PPP). The *projected* construction cost of Lines 2, 3 and 7 is $ 22 billion (PPP), and the EACC ranges from $ 1.9-3 billion (PPP).

Under no set of assumptions do the short run benefits of either Line 1 or Lines 2, 3 and 7 cover the construction costs of the lines; however, the long run benefits of Line 1 do exceed the annualized construction cost. This is true of Lines 2, 3 and 7 only at a discount rate of 2 percent or lower. Table 13 illustrates the difficult choices facing decisionmakers: short run benefits rarely cover costs (even construction costs) and certainly not construction and operating costs. We note, however, that these benefits are due only to improvements in commute time and commuting utility and therefore, capture only the first-order direct benefits to households. Metro rail may reduce congestion (Anderson (2014), Gu et al. (2021)), lead to agglomeration benefits (Heblich et al. (2020), Severen (2021), Tsivanidis (2023), Warnes (2020)), and increase employment (Kwon and Lee (2022), Tyndall (2021)), benefits that we have not measured.

8 Conclusion

In this paper, we estimate structural models of commute mode choice and housing choice using data from a 2019 household survey in Mumbai. We use these estimates to compute short run and long run benefits to households from two Metro rail projects in Mumbai. Metro Line 1 (11.4 km) started operations in June 2014 and provided the first east-west rail link in the city. The upcoming network evaluated here consists of Lines 2, 3 and 7 (92 km), which was scheduled to open in 2022, but is only partly operational. The

[45] Metro Line 1 is operated by a Public Private Partnership.

reason for building Metro rail was to alleviate overcrowding problems facing the historic Suburban Railway network and road traffic congestion by moving commuters towards Metro rail. This is expected to improve intracity commuting accessibility. The benefits of Lines 2, 3 and 7 are greater than those of Line 1 because of the greater extent of the network. But the benefits per km are higher for Line 1.

To compute short run benefits, we use estimated preferences of commuters for in-vehicle travel time, out-of-vehicle travel time, travel costs and commute modes while assuming fixed residence and work locations. We compute long run benefits using estimated preferences of households for commuting utility in addition to other housing amenities and housing cost while assuming fixed work location. Household sorting leads to the aggregate value of long run benefits being substantially higher than short run benefits.

There are important spatial and demographic heterogeneities in benefits. Consistent with findings in the limited literature evaluating heterogeneity, we find that workers living close to Metro stations, women, workers with a college education or with above-median incomes receive disproportionately greater short run benefits than their opposites. This is due to difference in preferences as each Metro project generates similar travel time reductions for each group. In the long run, however, households with lower incomes and assets experience greater benefits.

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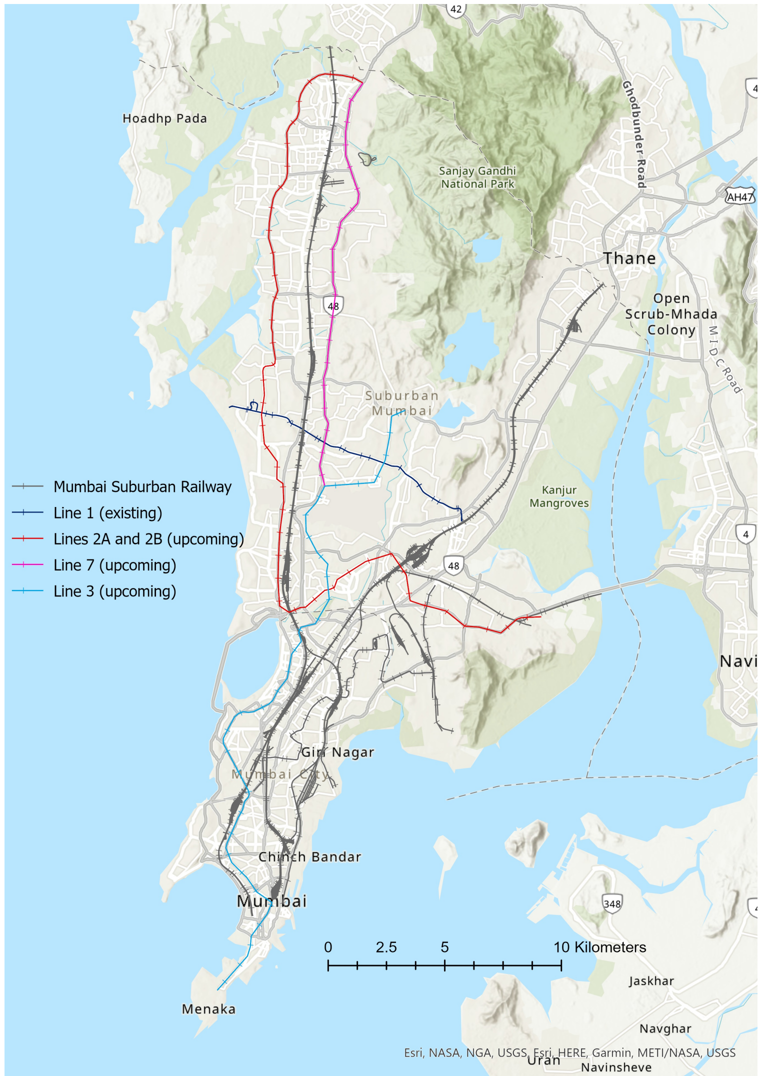
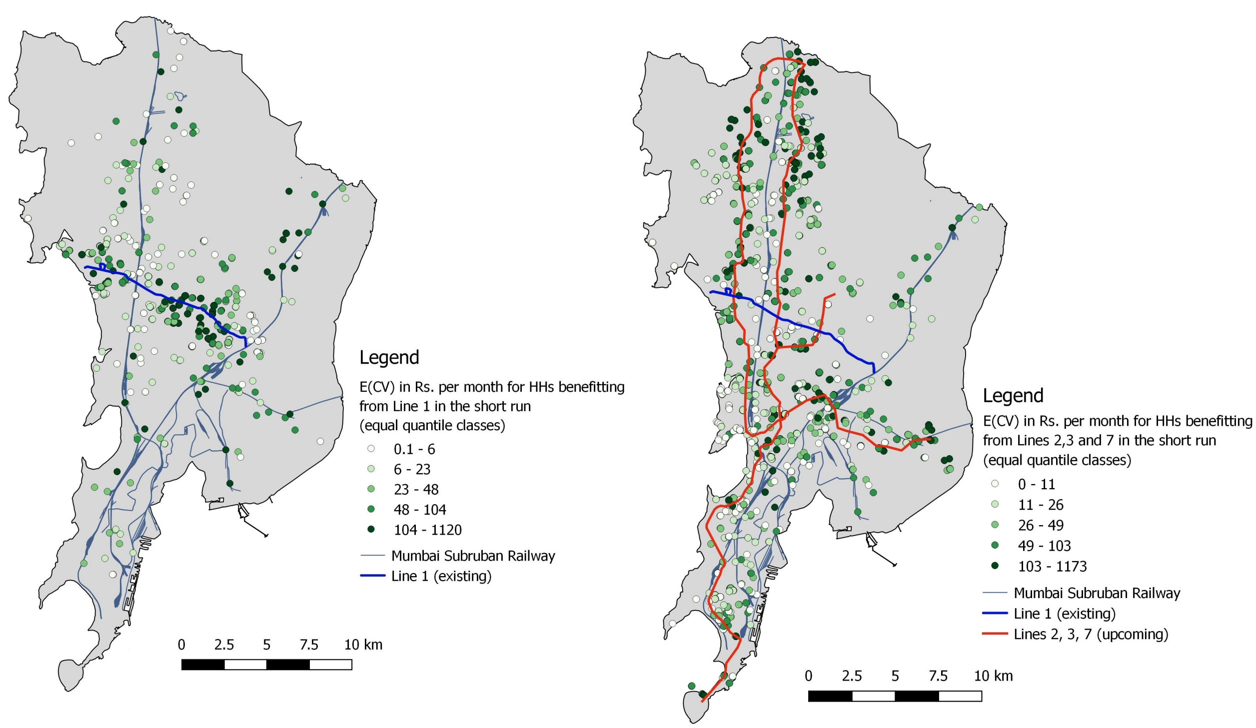
9 Figures and Tables

Figure 1: Existing and Planned Rail Transit Network in Mumbai



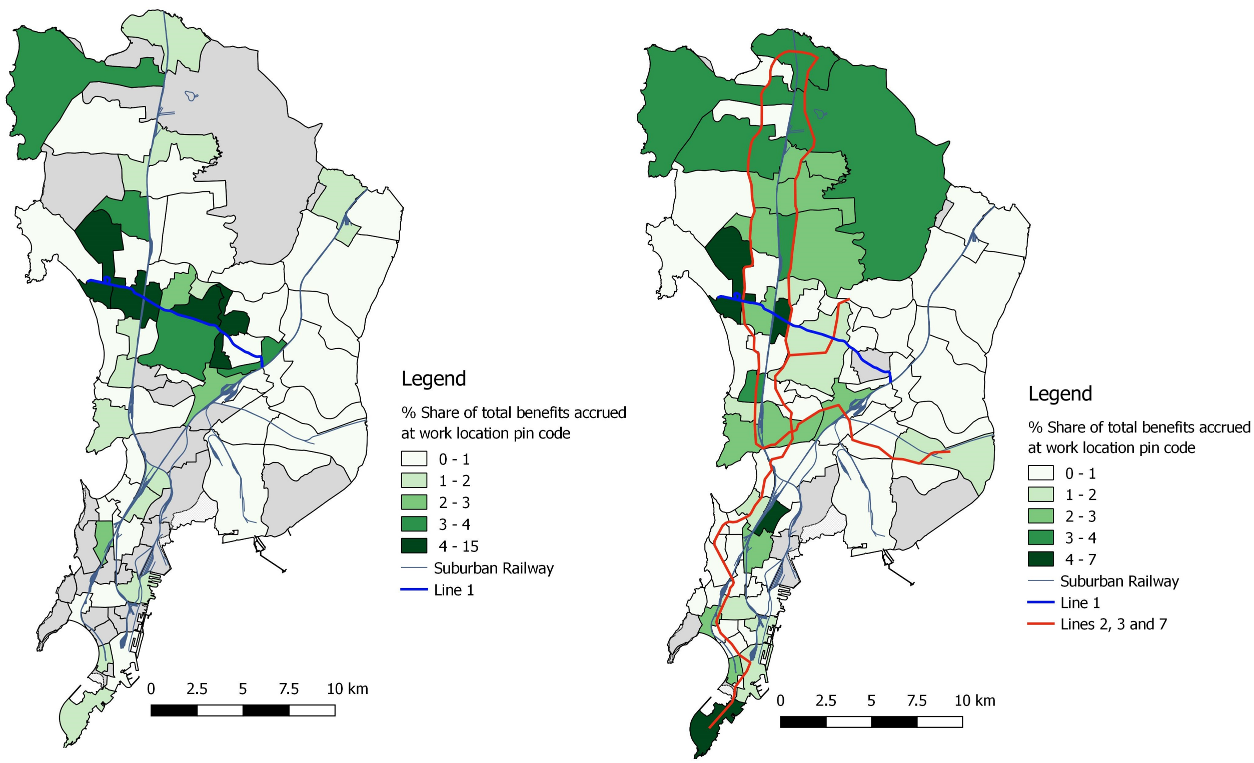
This map shows the existing Suburban railway network of Mumbai in gray, along with the existing Metro Line 1 in blue, and the three upcoming Metro Lines 2, 3 and 7 that are the focus of this paper in red, aqua and magenta, respectively. Parts of the upcoming network are operational as of October 2025.

Figure 2: Spatial Variation in the Value of Short Run Benefits from the Mode Choice Model in Rs. per month for HHs with positive benefits– Line 1 (left) and Lines 2, 3 and 7 (right)



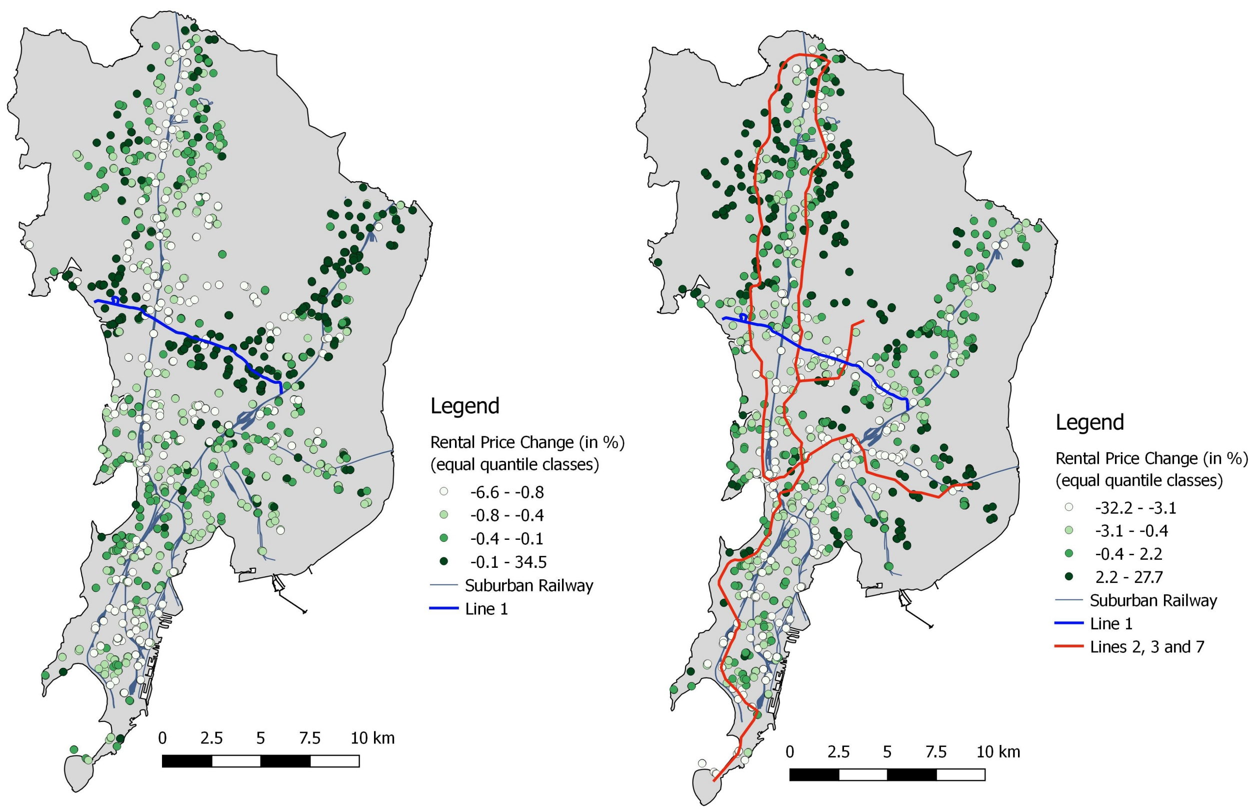
These maps show the sampled households with positive expected compensating variation computed using the formula in equation 5.

Figure 3: Spatial Variation in the Share of Short Run Benefits (in %) by Work Location Pin Code– Line 1 (left) and Lines 2, 3 and 7 (right)



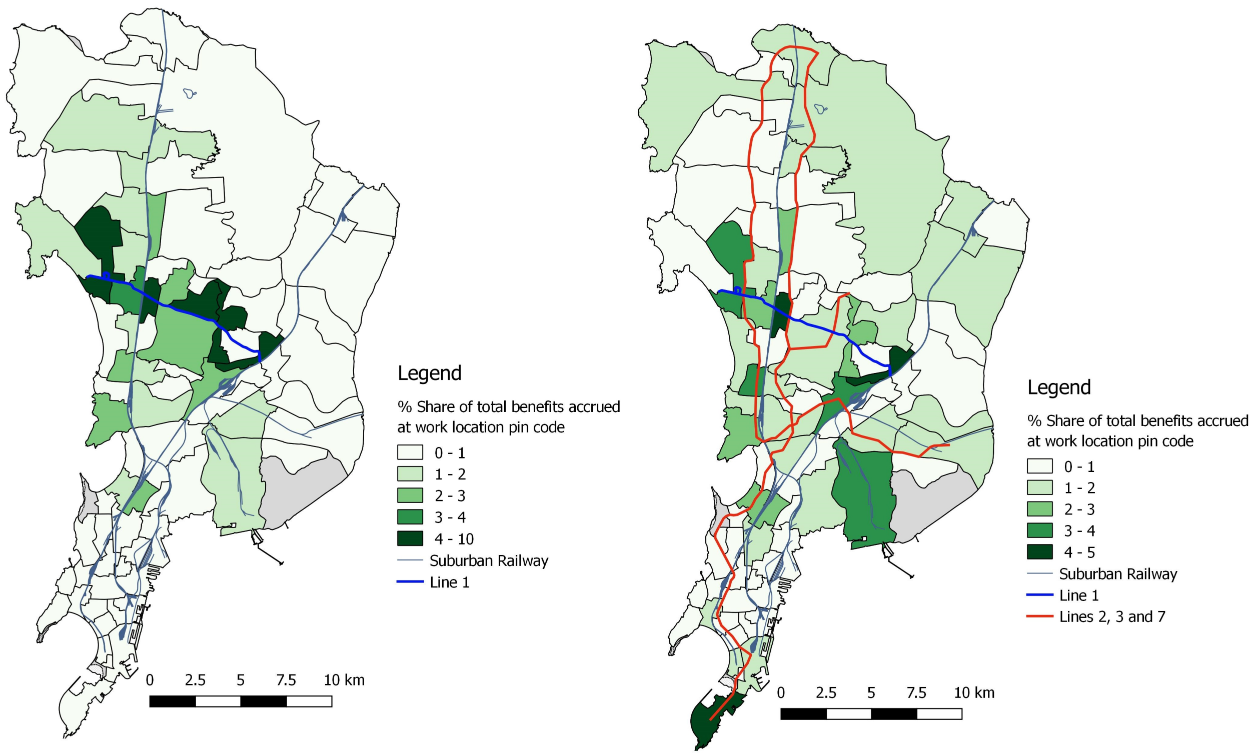
These maps show the share of total benefits accruing to different work location pin codes. Individual benefits were calculated using the formula in equation 5. Gray spaces indicate pin codes where no individual had positive benefits, including pin codes where no individual in the sample worked.

Figure 4: Spatial Variation in Rental Price Changes Implied by the Housing Choice Model in % from Line 1 (left) and Lines 2, 3 and 7 (right)



These maps show implied changes in rental prices for different houses in the city. The left graph shows negative of price changes due to the removal of Line 1 from the baseline rail network. The right graph shows price changes due to adding Lines 2, 3 and 7 to the baseline network assuming a housing supply elasticity of 0.5.

Figure 5: Spatial Variation in the Share of Long Run Benefits (in %) by Primary Worker's Work Location Pin Code– Line 1 (left) and Lines 2, 3 and 7 (right)



These maps show the share of total benefits accruing to different work location pin codes. Household benefits were calculated using the formula in equation 8 assuming a housing supply elasticity of 0.5. Gray spaces indicate pin codes where no primary worker of households in our sample worked.

Table 1: Main Mode Chosen for Work Commutes– Shares in %

	Full sample	By worker gender		By worker's educ level		HH's vehicle ownership		By worker income	
		Men	Women	Below College	College	Does not own	Owns	$\leq$ median	$>$ median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Walk	32.6	30.8	42.6	40.6	14.5	49.0	15.3	38.2	16.1
Train	16.0	15.7	17.8	14.2	20.0	24.1	7.5	16.8	13.7
Bus	8.4	7.7	12.3	9.3	6.3	14.1	2.4	10.5	2.5
Auto-rickshaw	9.1	8.1	15.3	9.3	8.7	12.8	5.3	10.7	4.6
Own two-wheeler	29.5	33.0	9.3	25.1	39.4		60.3	22.7	49.2
Car	4.5	4.8	2.8	1.5	11.1		9.1	1.2	13.9
Observations	2,876	2,444	432	1,992	884	1,472	1,404	2,144	732
Mean Distance (in km)	4.5	4.5	4.2	4.0	5.7	4.4	4.6	4.3	5.0

This Table shows the commute mode shares for different sub-groups of individuals in the commute mode choice estimation sample. Mean distance reported here is the distance along the shortest path from commuter residence to a randomly chosen post office in the survey-reported pin code of their work location. It is computed using the network program and the map of road network. The mode 'bicycle' is included in the category 'walk' because of the small share of individuals whose main commute mode is 'bicycle'.

Table 2: Summary Statistics by Chosen Travel Mode for Commute Mode Choice Models' Estimation Sample

Chosen travel mode	Mean	Std. Dev.	Min	Max
Road distance from residence to work location in km.				
Walk	1.78	1.18	0.07	7.82
Train	10.36	7.69	0.23	38.27
Bus	4.79	4.06	0.16	31.20
Auto-rickshaw	3.67	4.65	0.07	30.36
Own two-wheeler	4.25	4.63	0	31.32
Car	6.08	5.73	0.12	36.10
Full Sample	**4.50**	**5.39**	**0**	**38.27**
In-vehicle time (IVT) in minutes				
Walk	0	0	0	0
Train	34.76	20.02	0.70	110
Bus	37.27	22.39	5.00	134
Auto-rickshaw	16.24	14.05	2.62	95.2
Own two-wheeler	17.95	13.13	2.50	83.35
Car	21.31	16.46	2.95	74.55
Full Sample	**16.42**	**19.15**	**0**	**134**
Out-of-vehicle time (OVT) in minutes				
Walk	21.31	14.14	0.88	93.85
Train	15.55	9.23	0.63	49.22
Bus	4.12	2.73	0.30	14.44
Auto-rickshaw	6.86	3.32	5	20
Own two-wheeler	0	0	0	0
Car	0	0	0	0
Full Sample	**10.4**	**12.82**	**0**	**93.85**
Cost of one-way trip (c) in Rs.				
Walk	0	0	0	0
Train	6	2	5	10
Bus	14	5	8	42
Auto-rickshaw	60	62	18	395
Own two-wheeler	14	13	2	85
Car	53.57	47.09	6.92	259.20
Full Sample	**14.13**	**28.88**	**0**	**394.7**
Average monthly income in Rs.				
Walk	18,630	10,475	2,500	75,000
Train	21,310	11,937	2,500	75,000
Bus	17,417	6,801	2,500	37,500
Auto-rickshaw	18,973	8,568	7,500	75,000
Own two-wheeler	28,288	16,032	7,500	125,000
Car	47,129	26,823	7,500	125,000
Full Sample	**23,101**	**14,878**	**2,500**	**125,000**
Cost per minute wage (c/w)				
Walk	0	0	0	0
Train	4.18	2.55	0.79	23.76
Bus	11.74	7.75	2.53	66.53
Auto-rickshaw	43.30	44.74	5.70	267.90
Own two-wheeler	7.35	7.80	0.38	67.57
Car	17.84	19.94	1.15	147.10
Full Sample	**8.58**	**19.14**	**0.00**	**267.90**

This Table presents summary statistics of variables used in the estimation of mode choice model in Section 4.1 for the estimation sample with 2,876 workers. Bicycle is included in the category 'walk' since the share of commuters who bicycle is very small. Road distance is computed using network program. In-vehicle and out-of-vehicle times are described in Appendix Section A.2. Cost is computed using 2019 fare rules. The income variable in the survey is a categorical variable (Alam et al. (2021)); average income is computed using the median value of each category.

Table 3: Summary Statistics for Housing Choice Models' Estimation Sample

Variables	Mean	Std. Dev.
Household characteristics		
Income in Rs.	30,939	19,207
Monthly rental price in Rs.	9,757	7,155
College-educated Primary Worker	0.30	
Vehicle Ownership	0.51	
Main religion: Hindu	0.79	
Main religion: Muslim	0.17	
Main religion: Other	0.04	
Main language: Hindi	0.53	
Main language: Marathi	0.36	
Main language: Gujarati	0.06	
Main language: Others	0.05	
Households in the neighborhood with same religion	0.68	
Households in the neighborhood with same language	0.45	
Housing characteristics		
Distance to nearest railway station in km	1.50	1.17
Standardized employment accessibility index	0.01	1
Floorspace in sqft.	262.76	165.91
Good Roof	0.71	
Number of rooms (Median)	1	0.59
Kitchen is separate	0.59	
Toilet inside the house	0.65	
Bathroom inside the house	0.75	
Piped water	0.76	
Footpath in the neighborhood	0.75	
Slum Classification	0.44	
Distance to coast (in km)	4.67	3.17
Reports of crimes against women (Median)	38.5	18.28
Walk time to the nearest pvt. doctor	8.05	6.00
Walk time to the nearest govt. hospital	19.96	8.86
Walk time to the nearest pvt. hospital	17.30	8.86

This Table presents summary statistics of variables used in the estimation of housing choice model in Section 4.2. Standard deviation is not shown for binary variables. 'Other' religions include Christianity, Sikhism, Jainism, Buddhism, and Zoroastrianism (Parsi). 'Other' languages include Tamil, Telugu, Marwari, Kannada, Konkani, Punjabi, Sindhi, English, Bengali, Bhojpuri, and Odia. Proportion of households with the same language and religion are defined within a 2 km radius around the household's location. Mean walk time to health facilities is calculated by averaging the median of categories with survey-reported times. Mean monthly household income Rs 30,939 = $1,454 (PPP); mean monthly rent Rs. 9,757 = $458.45 (PPP).

Table 4: Preference Parameters from Nested Logit Models of Commute Mode Choice for Different Nesting Structures

	Model 1	Model 2	Model 3
Income-Cost	0.025***	0.023***	0.024***
	(0.002)	(0.001)	(0.001)
IVT	-0.019***	-0.019***	-0.014***
	(0.003)	(0.003)	(0.003)
OVT	-0.035***	-0.034***	-0.035***
	(0.002)	(0.002)	(0.002)
Intercepts:			
(Walk, Auto-rickshaw)	Omitted	Omitted	Omitted
(Two-wheeler)	0.734***		
	(0.079)		
(Car)	1.190***		
	(0.147)		
(Train, Bus)	-1.289***	-1.270***	
	(0.095)	(0.093)	
(Car, Two-wheeler)		0.796***	0.710***
		(0.075)	(0.075)
(Train)			-1.296***
			(0.084)
(Bus)			-1.991***
			(0.109)
Dissimilarity Parameters:			
(Two-wheeler)	1		
(Car)	1		
(Train, Bus)	0.687***	0.681***	
	(0.104)	(0.103)	
(Walk, Auto-rickshaw)	0.626***	0.596***	0.555***
	(0.063)	(0.058)	(0.051)
(Car, Two-wheeler)		1	1
		(constrained)	(constrained)
(Train)			1
(Bus)			1
Individuals	2876.000	2876.000	2876.000
LR chi2	314.955	318.729	358.420
Log likelihood	-2982.274	-2987.271	-2955.539
IVT value (Rs. per minute)	0.772	0.824	0.575
OVT value (Rs. per minute)	1.412	1.446	1.460
Value of IVT (% wage)	39.7	42.4	29.6
Value of OVT (% wage)	72.6	74.4	75.1

This Table presents estimated preference parameters for the nested logit model in equation 1. Std. errors are in parentheses. IVT and OVT are per trip in-vehicle and out-of-vehicle times (in minutes), respectively. Income-Cost is the value of monthly Hicksian bundle scaled to per trip level. It is obtained by subtracting monthly out-of-pocket travel cost from monthly income and dividing by the number of working days in a month (22) and number of trips in a day (2). Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus); Model 3: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train), (Bus). Dissimilarity parameter is constrained to be $\leq$1 so that predictions are consistent with equation 3. 'Walk' also includes 'bicycle'.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Predicted Mode Shares of Nested Logit Models from Table 4

Travel modes	True shares	Model 1	Model 2	Model 3
Walk	32.55	29.08	28.99	28.39
Train	15.99	12.54	12.52	15.99
Bus	8.41	11.87	11.89	8.41
Auto-rickshaw	9.14	12.61	12.70	13.30
Own two-wheeler	29.45	29.45	30.21	30.23
Car	4.45	4.45	3.69	3.67

This Table compares the predicted mode shares under the three nested logit models in Table 4 with the true sample shares. Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus); Model 3: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train), (Bus).

Table 6: Preference Parameters from the First Stage of the Housing Choice Model

	Model 1 (1)	Model 2 (2)
Expected Commuting Utility	2.362***	2.409***
	(0.043)	(0.044)
Proportion of HHs with same language	2.182***	2.186***
	(0.250)	(0.250)
Proportion of HHs with same religion	2.668***	2.666***
	(0.393)	(0.393)
Households	2,170	2,170
Wald chi2	3556	3527
Log likelihood	-6910	-6918

This Table presents estimated preference parameters for the first-stage (equation 10) of the housing location choice model in Section 4.2. Estimates of $\hat{\delta}_h$ are not shown. Standard errors are in parentheses. Expected commuting utility is computed using equation 7. Proportion of HHs with the same language and religion as the chooser are defined within a 2 km neighborhood around the house. Columns 1 and 2 have expected commuting utility estimated using Models 1 and 2 in Table 4, respectively. Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Preferences for Commuting Utility from the Housing Choice Models with Taste Shifters

Taste shifter	(1) None	(2) Educ	(3) Income	(4) Vehicle ownership
Model 1:				
Base category	2.362***	2.542***	2.415***	2.207***
	(0.043)	(0.052)	(0.055)	(0.049)
$\geq$ college educ		1.996***		
		(0.065)		
Median HH income			2.385***	
			(0.068)	
$>$ Median HH income			2.038***	
			(0.109)	
HH owns vehicle				2.649***
				(0.069)
Households	2170	2170	2170	2170
Log Likelihood	-6910	-6883	-6901	-6891
Model 2:				
Base category	2.409***	2.587***	2.452***	2.235***
	(0.044)	(0.053)	(0.056)	(0.050)
$\geq$ college educ		2.045***		
		(0.066)		
Median HH income			2.438***	
			(0.070)	
$>$ Median HH income			2.108***	
			(0.113)	
HH owns vehicle				2.735***
				(0.071)
Households	2170	2170	2170	2170
Log Likelihood	-6918	-6893	-6910	-6896

This Table shows preferences for expected commuting utility estimated in the first-stage of the housing choice model using specifications with taste-shifters. Column (1) is the base model without any taste-shifters. Base category is households where the primary worker has below college education in Column (2); below median income household in Column (3); and households that do not own a vehicle in Column (4). These models also account for heterogeneous preferences for the proportion of HHs with the same language and religion within a 2 km radius of the feasible house.

Table 8: Mean Preferences for Housing Amenities from Second Stage Regressions

	(1)	(2)	(3)	(4)	(5)
Rental Price	-0.000169***	-0.000157***	-0.000123***	-0.000122***	-0.000137***
	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00003)
	[-4.330]	[-3.949]	[-3.693]	[-4.075]	[-4.304]
Housing Amenity Index	0.456600***	0.441438***	0.375659***	0.381520***	0.412724***
	(0.08352)	(0.08199)	(0.07028)	(0.06494)	(0.07055)
	[5.467]	[5.384]	[5.345]	[5.875]	[5.850]
Distance to coast (in km)		0.032555**	0.009907	-0.051829***	-0.040053***
		(0.01626)	(0.01242)	(0.01406)	(0.01407)
		[2.003]	[0.798]	[-3.686]	[-2.846]
Slum Classification Dummy		-0.177700**	-0.113486	-0.129261**	-0.121339*
		(0.09039)	(0.06997)	(0.06347)	(0.06699)
		[-1.966]	[-1.622]	[-2.037]	[-1.811]
No. of Reported Crimes Against Women		-0.004437	-0.008021***	-0.009455***	-0.005905**
		(0.00381)	(0.00283)	(0.00258)	(0.00289)
		[-1.166]	[-2.830]	[-3.669]	[-2.045]
Distance to the nearest railway station (in km)			0.342368***	0.151881***	0.119253**
			(0.03663)	(0.04914)	(0.05425)
			[9.346]	[3.091]	[2.198]
Standardized Employment Accessibility Index				0.435875***	0.421044***
				(0.05762)	(0.05935)
				[7.564]	[7.094]
Proximity to Health Services Index					0.007399
					(0.03130)
					[0.236]
F(excluded IV)	40.44	41.01	38.82	39.33	39.83
Observations	2,170	2,170	2,170	2,170	1,989
Critical Value for |t| at 95% level (Lee et al. (2022))	2.247	2.247	2.247	2.247	2.247

This Table presents 2SLS parameter estimates of the second stage of the housing choice model. Dependent variable is the vector of estimated intercepts from the first stage conditional logit model presented in Table 6). Log of assessed property value for residential land in the sub-zone of a house is used as an instrument for monthly rental price in Rs. 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 clustered at the sub-zone level are in parentheses. t-statistics are in brackets. Star marks reflect conventional inference values.

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

Table 9: The Value of Time Savings from the Commute Mode Choice Model

	Full sample	Men	Women	$<$ College education	$\geq$ College education	$\leq$median income	$>$ median income
Nested logit Model 1:							
Individuals	2876	2444	432	1992	884	2144	732
IVT Value (Rs./min)	0.77	0.83	0.59	0.66	1.15	0.59	1.60
IVT Value (% of wage)	39.72	40.46	45.14	40.53	43.26	44.17	43.37
OVT Value (Rs./min)	1.41	1.39	1.55	1.31	1.83	1.28	1.75
OVT Value (% of wage)	72.62	67.68	117.89	80.68	68.69	94.99	47.24
% sample with positive E(CV) Line 1	24.58	24.67	24.07	22.09	30.43	24.35	25.27
Mean E(CV) Line 1|Positive E(CV) (Rs./month)	77.27	74.56	98.30	66.17	110.47	70.84	84.07
% sample with positive E(CV) Lines 2,3,7	56.71	57.12	54.40	55.47	60.18	56.62	56.83
Mean E(CV) Lines 2,3,7|Positive E(CV) (Rs./month)	97.63	98.32	109.24	88.43	130.10	96.47	90.47
Nested logit Model 2:							
Individuals	2876	2444	432	1992	884	2144	732
IVT Value (Rs./min)	0.82	0.88	0.66	0.64	1.42	0.56	2.00
IVT Value (% of wage)	42.37	42.61	50.29	39.15	53.24	41.97	54.12
OVT Value (Rs./min)	1.45	1.42	1.59	1.30	2.02	1.25	1.92
OVT Value (% of wage)	74.36	69.09	121.32	79.74	75.75	92.72	51.88
% sample with positive E(CV) Line 1	24.58	24.67	24.07	22.09	30.54	24.35	25.41
Mean E(CV) Line 1|Positive E(CV) (Rs./month)	80.35	77.09	102.57	65.00	127.76	68.69	97.00
% sample with positive E(CV) Lines 2,3,7	56.71	57.12	54.40	55.47	60.41	56.62	56.83
Mean E(CV) Lines 2,3,7|Positive E(CV) (Rs./month)	101.32	101.39	115.65	86.88	149.63	93.76	106.78

This Table presents the marginal rate of substitution and the mean expected compensating variation for Line 1 and Lines 2, 3 and 7 computed using estimated parameters from a nested logit model (equation 1) estimated separately for the subsamples indicated in the columns. Preference parameters for the full sample are in Table 4. Individuals indicate the number of individuals in each of these estimation samples. Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus).

Table 10: The Value of Commuting Utility from the Housing Choice Model with Perfectly Elastic Housing Supply

	(1)	(2)	(3)	(4)	(5)
Mean E(CV) Line 1:					
Model 1 (in Rs. per month)	137.52	148.39	189.90	191.46	170.19
Model 1 (% Monthly Rent)	1.41	1.52	1.95	1.96	1.74
Model 2 (in Rs. per month)	138.63	150.22	192.37	193.97	172.37
Model 2 (% Monthly Rent)	1.42	1.54	1.97	1.99	1.77
Mean E(CV) Lines 2, 3 and 7:					
Model 1 (in Rs. per month)	389.51	420.29	537.87	542.30	482.04
Model 1 (% Monthly Rent)	3.99	4.31	5.51	5.56	4.94
Model 2 (in Rs. per month)	389.42	421.96	540.38	544.86	484.19
Model 2 (% Monthly Rent)	3.99	4.32	5.54	5.58	4.96
Controls:					
Housing amenities index	✓	✓	✓	✓	✓
Distance to coast in km	✗	✓	✓	✓	✓
Slum classification dummy	✗	✓	✓	✓	✓
Crimes against women (Reports)	✗	✓	✓	✓	✓
Distance to nearest station	✗	✗	✓	✓	✓
Employment accessibility index	✗	✗	✗	✓	✓
Proximity to Health Services	✗	✗	✗	✗	✓

This Table presents the mean expected compensating variation for Line 1 and Lines 2, 3 and 7 (equation 8) computed using the first stage estimates in Table 6 and various second-stage specifications (Table 8), the controls for which are indicated. The average monthly rent is Rs. 9757.147.

Table 11: The Distribution of Long Run Welfare (in Rs. per month) from the Housing Choice Model With Perfectly Elastic and Inelastic Housing Supply

	Line 1		Lines 2, 3 and 7	
	Perfectly Elastic	Elasticity=0.5	Perfectly Elastic	Elasticity=0.5
Mean	191.39	199.57	542.09	533.76
Min	-154.27	-314.72	-1341.88	-707.75
5th Percentile	-3.64	26.22	42.60	-110.12
25th Percentile	49.91	82.08	270.40	298.66
Median	83.49	107.97	461.28	463.77
75th Percentile	162.18	171.69	743.97	728.08
95th Percentile	935.35	807.90	1265.89	1261.98
Max	3391.40	3265.64	5411.37	5574.82

This Table presents the distribution of mean expected compensating variation (equation 8) under housing supply elasticity assumptions indicated in each column. The computation uses the first-stage estimates from Model 1 in Table 6 and the second-stage estimates from Column 4 in Table 8. The average monthly rent is Rs. 9757.147.

Table 12: Heterogeneity in the Value of Long Run Welfare from the Housing Choice Model (Housing Supply Elasticity=0.5)

	Line 1		Lines 2, 3, 7	
	in Rs.	% of Monthly Rent	in Rs.	% of Monthly Rent
Full Sample	199.57	2.05	533.76	5.47
Primary worker has $<$ college education	205.16	2.58	568.14	7.14
Primary worker has $\geq$ college education	186.31	1.33	452.30	3.23
Below median income HH	222.54	3.31	606.20	9.02
Median income HH	190.20	1.65	484.57	4.19
Above median income HH	116.60	0.62	337.70	1.79
HH does now own vehicle	310.72	4.24	829.82	11.33
HH owns a vehicle	90.65	0.75	243.64	2.01

This Table presents the mean expected compensating variation for Line 1 and Lines 2, 3 and 7 for sub-groups of households indicated in the rows. Expected compensating variation is computed using the first-stage specification of the housing choice model without taste-shifters (Model 1 in Table 6) and using the preferred second-stage specification (Column 4 of Table 8) for the full sample of households and averages are calculated for each sub-group. Housing supply elasticity is assumed to be 0.5. The average monthly rent is Rs. 9757.147.

Table 13: Aggregate Benefits of Metro Lines vs. the Equivalent Annualized Capital Costs (EACC) in $ Million (PPP)

	EACC				**Short Run**	**Long Run**
	(1)	(2)	(3)	(4)	**Benefits**	**Benefits**
Line 1	300	200	200	124	51.2	591.63
Lines 2, 3 and 7	3,000	2,300	1,900	1,344	169.6	1549.74
EACC assumptions:						
Life of asset (years)	20	30	35	20		
Interest rate (in %)	12	10	8	2		

This Table presents the equivalent annualized capital costs under three assumptions indicated in the second panel; and the annual aggregate short run and long run benefits of Metro Line 1 and Lines 2, 3 and 7 computed by scaling the individual-level estimates for Model 1. Total construction cost of Line 1 is $2.03 Billion (PPP). Total *projected* cost of Lines 2, 3 and 7 is $22 Billion (PPP). Exchange rate: $1 PPP = Rs. 21.283

A Appendix: Data

A.1 Household Survey Description

The individual and household data used in this paper are from a survey of 3,024 households representative of the Greater Mumbai Region (GMR) conducted by the World Bank in January-March 2019. Two members were interviewed in each household, an adult male and female (ages 18-45) with priority given to primary earners and decision makers of the household. The survey contains information on household members' education, occupation, income, household demographic composition, housing condition, household assets, pin codes of work locations and commute trips from residence to workplace. A travel diary was also filled out by each of the main respondents for a 24-hour period with the following information for all trips taken on the chosen day: origin, destination, purpose, duration, time of day trip originated, distance traveled, mode(s) chosen, and out-of-pocket cost. These data are described in Alam et al. (2021).

Definition of main mode: For the commute mode choice model in the paper, household location is treated as the origin, and a randomly selected post office that has the same pin code as the individual's workplace as the destination. The number of post offices per pin code in Mumbai ranges from 1 to 9, with the median being 4. For workers who commute, the survey records up to three modes of transportation used and the time spent in each mode for a one-way trip. The chosen travel mode in the commute mode choice model is the main mode, defined as follows. When a mix of motorized and non-motorized transportation is used, the main mode is defined as the motorized mode on which the most time is spent. If a person spends 15 minutes walking, 5 minutes on a two-wheeler, and 10 minutes on a train, then train is the main mode. If two modes are being used for the same duration, then the underrepresented mode is defined as the main mode. This is, however, a rare instance in the data. The main mode is non-motorized (walk or bicycle) when that is the only reported travel mode. This definition is adopted from Takeuchi et al. (2007) which uses data from a similar survey conducted by the World Bank in Mumbai in 2004.

Definition of religion and language variables in Section 4.2: For each house, a 2 km neighborhood was defined using Euclidean distance. The median house has 117 neighbors. The proportion of neighbors with the same language and religion as household i in the housing choice model is calculated by matching household i's religion and language with that of the households in the neighborhood of each house in household i's choice set.

A.2 In-vehicle and Out-of-vehicle Time Variables

We implement a network program to compute travel time along the shortest duration path for each residence-work commute trip in the sample by rail and walking.[46] The program, implemented in Python, uses origin and destination locations, maps of the road and rail networks from Open Street Maps and speeds to compute the travel time along the shortest duration path between an origin-destination pair using Dijkstra's algorithm. It converts distance along a path into travel time by dividing paths into smaller segments of equal lengths, computing travel time for each segment using user-specified speed information and adding together travel times for each segment along a path. To compute walk times, we assume a speed of 5 kmph along the road network. For travel times by train, we assume a speed of 40 kmph for the Mumbai Suburban Railway network segments, 35 kmph for Metro rail network segments, and 5 kmph (walking speed) for the road segments connecting gaps in the train network.

In addition to computing travel times under the rail network that includes Suburban Railway and Metro Line 1, we also calculate travel times (a) with Lines 2, 3 and 7 added to the existing network and (b) without any Metro line, for short run welfare calculations.

Second, we obtain a dataset with travel times for shortest duration drive and transit trips for 500,000 and 250,000 randomly selected origin-destination pairs, respectively.[47] We match commute trips in our sample to a randomly chosen origin-destination pair from the set of trips in this dataset that are within 1 km of the survey households' origin-destination points. The median distance between survey households and the origin point of a matched trip in this dataset is 148 meters.[48] Google Maps API gives step-by-step detailed information for any trip, but this dataset has overall travel durations only. As a result, it is not possible to distinguish between train and bus trips in the transit data. The main advantage of these data is that travel times for driving trips account for traffic conditions and allow us to accurately model the tradeoff between rail and road transport, which is critical because of the traffic problems in Mumbai. For residence-work pairs for which Google Maps data is missing, we use the network program with road network to compute drive times at a flat speed of 20 kmph, which is the median and modal speed in Mumbai in a 2015 dataset of traffic speeds in the city constructed using Google Directions API by Sarath Guttikunda. The reason for assuming flat speeds is the low variation in speeds observed in this dataset.

[46]The program is implemented in Python using packages GOSTnets and NetworkX. Link for GOSTnets: https://github.com/worldbank/GOST_PublicGoods

[47]This dataset from 2018 was compiled and generously shared by researchers at the Asian Development Bank.

[48]The median distance between the post office and the destination of a matched trip is 717 meters; but, since the post office is not the exact work location, this is simply classical measurement error.

Third, we use HERE API to obtain detailed step-by-step information about transit trips by train or bus for each residence-commute trip. This information allows us to identify access time, transfer time and the in-vehicle travel time for transit options separately. Most of these trips are by bus, therefore, these data also allow us to identify travel time by bus separately from that by rail.

In constructing the in-vehicle time variable, travel time by train is always from the network program. Travel time by bus is from HERE data, whenever the information is available. In the absence of valid data from HERE, the maximum of Google Maps transit and Google Maps drive time is used.[49] This happens in 17% of cases (481 trips). While HERE data allows the identification of transfer time for transit, in the main analysis, out-of-vehicle time refers to the initial access time, and in-vehicle time includes transfer time unless otherwise stated.[50]

The out-of-vehicle time variable for train and bus is the walk time from a household to the nearest railway station or bus stop. This is computed using the network program assuming a walking speed of 5 kmph. For non-motorized trips, this is the walk time to the post office chosen as the work location. For auto-rickshaw, this value is taken from the survey data. In-vehicle time for non-motorized trips, and out-of-vehicle time for car and two-wheeler is always zero. We test the sensitivity of estimated preference parameters to these definitions.

A.3 Employment Accessibility Index

Our employment accessibility index is a commuting-cost-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 preferences for commuting. The index is similar in spirit to the accessibility index in Hansen (1959) and commuter market access in the recent quantitative spatial equilibrium literature (for example, see Ahlfeldt et al. (2015) and Tsivanidis (2023)). Let j index possible work locations in the city. The employment accessibility index for a house h is

$$\text{EA}_h = \sum_j \left(\frac{w_j}{d_{hj}}\right) \tag{13}$$

[49] Sometimes HERE queries resulted in valid trips but missing travel times, while sometimes they returned completely empty results.

[50] Since the exact work location is not known and the destination of a commute trip is a randomly chosen post office in the pin code of the work location, including last mile access time only introduces measurement error.

w_j is the effective wage obtainable at location j. $d_{hj} = exp(\kappa * t_{hj})$ is the iceberg commuting cost from house h to location j. t_{hj} is the travel time between h and j. κ is a decay parameter specifying the semi-elasticity of commuting costs d_{hj} to commuting times t_{hj}. We use the methodology in Kreindler and Miyauchi (2023) to obtain a proxy for w_j and estimate κ. The underlying model that allows identification of these parameters is one where commuters choose an origin and destination for commutes based on the characteristics of each location and commuting costs.

The utility that a worker living at location h receives from working at employment location j is given by

$$U_{hj}(\omega) = \frac{w_j * \epsilon_{hj}(\omega)}{d_{hj}} \tag{14}$$

w_j is the effective wage obtainable at j and each worker gets the same wage. $d_{hj} = exp(\kappa * t_{hj})$ is the iceberg commuting cost between h and j represented by an exponential function of commuting time t_{hj} times the semi-elasticity of commuting costs to time κ. $\epsilon_{hj}(\omega)$ is an idiosyncratic utility shock assumed to follow an i.i.d. Fréchet distribution with shape parameter θ and scale parameter normalized to one.[51] 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.

Equation 14 implies that the probability of a worker working in j conditional on living in h is given by

$$\pi_{hj|h} = \frac{(w_j/d_{hj})^{\theta}}{\sum_j (w_j/d_{hj})^{\theta}} \tag{15}$$

Equation 15 implies the following gravity equation of commute flow shares.

$$\log\pi_{hj|h} = -\kappa * \theta * t_{hj} + \theta * \log w_j - \log\Big(\sum_j (w_j/exp(\kappa * t_{hj}))^{\theta}\Big) \tag{16}$$

We estimate the following reduced-form gravity equation of commuter flows derived from

[51]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. Kreindler and Miyauchi (2023) shows that their model is robust to alternate assumptions, for example, in (Tsivanidis (2023)), θ represents the inverse of dispersion in worker productivity across locations.

16 using a Poisson pseudo-maximum likelihood estimator.

$$N_{hj} = -\beta * t_{hj} + \psi_j + \gamma_h + \nu_{hj} \tag{17}$$

N_{hj} represent aggregate commute flows between h and j.[52] β captures the sensitivity of commuting decisions to commuting time. γ_h and ψ_j are origin and destination fixed effects that reflect residence and workplace amenities, respectively. Workplace amenities are termed as 'effective wages' in our analysis. ν_{hj} is the random error.

To calculate the employment accessibility index in equation 13, we first estimate equation 17 using data on commute flows between residence and work location pin codes from each household survey. There are 85 unique residential pin codes and 88 unique work location pin codes in the data, implying a possible 7480 unique flows. Travel time is the pin code-pair-level mean of the minimum travel time via road or transit between each household in the survey and their work location. We estimate this equation using a Poisson pseudo-maximum likelihood estimator. Estimates of work location fixed effects, $\hat{\psi}_j$ are assumed to proxy the effective wage at each location, w_j.[53]

The parameter measuring the sensitivity of commuting decisions to commute time, β is composed of two components: the semi-elasticity of commuting shares to commute costs (θ) and the semi-elasticity of commuting costs to commuting time (κ). We find β=0.138 from estimating the gravity equation.

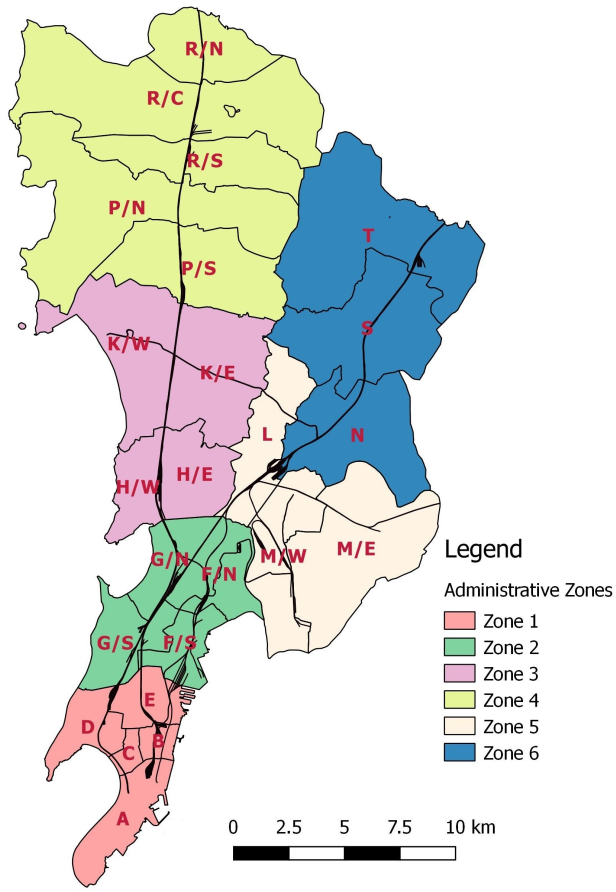
Following Kreindler and Miyauchi (2023), we obtain $\hat{\theta}$ by inverting the coefficient from an OLS regression of log of average incomes aggregated at the pin code level on $\hat{\psi}_j$. We then obtain $\hat{\kappa} = \frac{\hat{\beta}}{\hat{\theta}}$. Intuitively, $\hat{\psi}_j$ are model predicted wages and they deviate from actual wages in proportion to the variation in idiosyncratic shocks. We find $\hat{\theta}$=12.85 and therefore, $\hat{\kappa} = 0.0107$. Ahlfeldt et al. (2015) estimates $\kappa = 0.01$ and Tsivanidis (2023) estimates $\kappa = 0.012$. Note that $\hat{\psi}_j$ does not have a fixed scale, so we standardize EA_h to be mean 0 with variance 1 for the second stage of the housing choice model.

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

[53]The correlation between $\hat{\psi}_j$ and average income from the 2019 survey data at the level of work location pin code is 0.24.

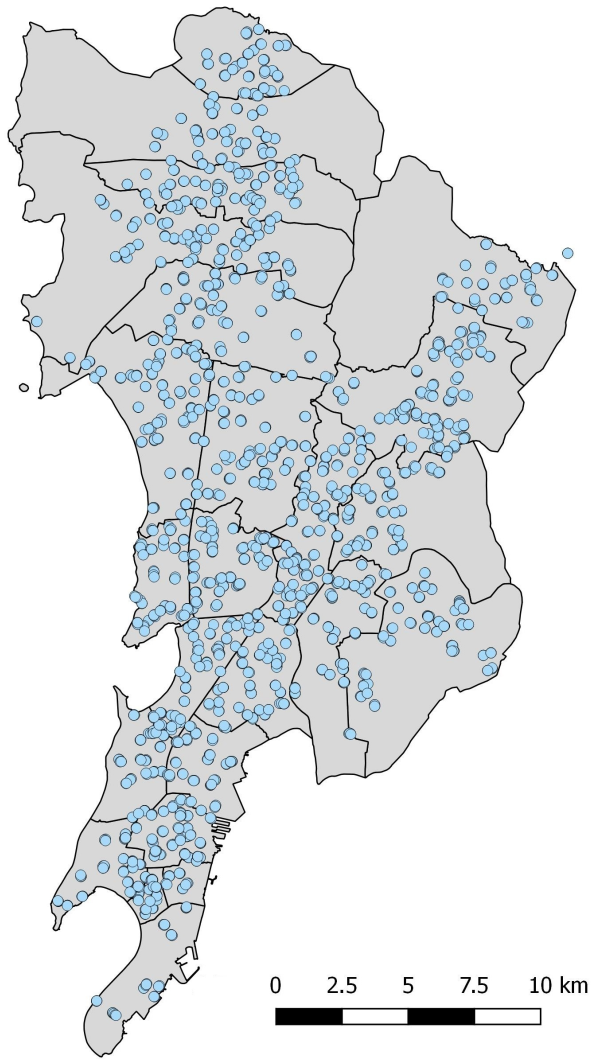
B Appendix: Figures and Tables

Figure B1: Administrative Wards and Zones in Mumbai



This map shows the 24 administrative wards in the Greater Mumbai Region. These wards are divided into six zones by the City for jurisdictional purposes indicated by the six colors. The existing rail lines (including Metro Line 1) are in black.

Figure B2: Sample of Households in the World Bank 2019 Survey



This map shows the locations of households sampled for the World Bank Survey. Sampling was done in proportion to population at the ward level. Sample is representative at the ward and city levels.

Table B1: Robustness of Preference Parameters from Nested Logit Models of Commute Mode Choice to Demographics × Nest and Location × Nest Indicators

	Model 1	Model 2	Model 3
Income-Cost	0.026***	0.024***	0.024***
	(0.002)	(0.002)	(0.001)
IVT	-0.018***	-0.018***	-0.013***
	(0.003)	(0.003)	(0.004)
OVT	-0.035***	-0.033***	-0.035***
	(0.002)	(0.002)	(0.002)
See Next Page for Nest Parameters			
Dissimilarity Parameters:			
(Two-wheeler)	1		
(Car)	1		
(Train, Bus)	0.656***	0.645***	
	(0.098)	(0.097)	
(Walk, Auto-rickshaw)	0.665***	0.602***	0.559***
	(0.072)	(0.060)	(0.052)
(Car, Two-wheeler)		1	1
		(constrained)	(constrained)
(Train)			1
(Bus)			1
Individuals	2876.000	2876.000	2876.000
LR chi2	612.030	594.901	684.980
Log likelihood	-2708.111	-2750.444	-2685.150
IVT value (Rs. per minute)	0.704	0.781	0.529
OVT value (Rs. per minute)	1.355	1.415	1.441
Value of IVT (% wage)	36.2	40.2	27.2
Value of OVT (% wage)	69.7	72.8	74.1

This Table presents estimated preference parameters for the nested logit model in equation 1 with the addition of interactions of nest fixed effect with residence ward (suppressed) and demographics including gender (omitted category is Men), income category (omitted category is below median income), education category (omitted category is less than college-educated), age category (omitted category is 18-30 years old). Nest parameters are in Part B of the Table. Std. errors are in parentheses. IVT and OVT are per trip in-vehicle and out-of-vehicle times (in minutes), respectively. Income-Cost is the value of monthly Hicksian bundle scaled to per trip level. It is obtained by subtracting monthly out-of-pocket travel cost from monthly income and dividing by the number of working days in a month (22) and number of trips in a day (2). Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus); Model 3: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train), (Bus). Dissimilarity parameter is constrained to be ≤1 so that predictions are consistent with equation 3. 'Walk' also includes 'bicycle'.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Nest Parameters and Interactions for Table B1

	Model 1	Model 2	Model 3
(Walk, Auto-rickshaw)	Omitted	Omitted	Omitted
(Two-wheeler)			
Intercept	1.586***		
	(0.378)		
Woman	-2.733***		
	(0.238)		
> Median Income	0.443*		
	(0.191)		
≥College-educated	0.481*		
	(0.187)		
31-40 Years Old	-0.214		
	(0.185)		
41-55 Years Old	-0.846***		
	(0.206)		
(Car)			
Intercept	22.066		
	(9204.650)		
Woman	-1.311*		
	(0.550)		
> Median Income	1.758***		
	(0.469)		
≥College-educated	1.728***		
	(0.431)		
31-40 Years Old	0.498		
	(0.435)		
41-55 Years Old	0.810		
	(0.488)		
(Train, Bus)			
Intercept	-1.427***	-1.448***	
	(0.255)	(0.253)	
Woman	-0.251	-0.245	
	(0.152)	(0.150)	
> Median Income	-0.245	-0.265	
	(0.181)	(0.180)	
≥College-educated	0.646***	0.654***	
	(0.148)	(0.147)	
31-40 Years Old	0.041	0.034	
	(0.139)	(0.137)	
41-55 Years Old	-0.026	-0.022	
	(0.153)	(0.151)	
(Car, Two-wheeler)			
Intercept		1.509***	1.394***
		(0.371)	(0.372)
Woman		-2.487***	-2.519***
		(0.220)	(0.221)
> Median Income		0.613***	0.614***
		(0.183)	(0.184)
≥College-educated		0.651***	0.673***
		(0.180)	(0.181)
31-40 Years Old		-0.119	-0.120
		(0.176)	(0.176)
41-55 Years Old		-0.564**	-0.562**
		(0.195)	(0.195)
(Train)			
Intercept			-1.890***
			(0.309)
Woman			-0.466*
			(0.183)
> Median Income			-0.046
			(0.198)
≥College-educated			0.839***
			(0.166)
31-40 Years Old			0.010
			(0.162)
41-55 Years Old			-0.019
			(0.177)
(Bus)			
Intercept			-1.627***
			(0.316)
Woman			0.024
			(0.193)
> Median Income			-0.917**
			(0.295)
≥College-educated			0.266
			(0.203)
31-40 Years Old			0.028
			(0.184)
41-55 Years Old			-0.088
			(0.204)

Table B2: Sensitivity of the Commute Mode Choice Model Parameters to Different Definitions of IVT and OVT for Model 1 in Table 4

	(1)	(2)	(3)
OVT definition	Survey+NetworkX	Survey+HERE (includes transfer time)	Survey
IVT definition	GM+HERE +NetworkX	GM+HERE (excluding transfer time)	GM+HERE +NetworkX
Income-Cost	0.025***	0.025***	0.026***
	(0.002)	(0.002)	(0.002)
IVT	-0.019***	-0.021***	-0.015***
	(0.003)	(0.003)	(0.003)
OVT	-0.035***	-0.033***	-0.032***
	(0.002)	(0.002)	(0.002)
Intercepts:			
(Walk, Auto-rickshaw)	Omitted	Omitted	Omitted
(Two-wheeler)	0.734***	0.753***	0.748***
	(0.079)	(0.082)	(0.082)
(Car)	1.190***	1.202***	1.204***
	(0.147)	(0.152)	(0.154)
(Train, Bus)	-1.289***	-1.091***	-1.032***
	(0.095)	(0.078)	(0.077)
Dissimilarity Parameters:			
(Two-wheeler)	1	1	1
(Car)	1	1	1
(Train, Bus)	0.687***	0.545***	0.425***
	(0.104)	(0.066)	(0.054)
(Walk, Auto-rickshaw)	0.626***	0.665***	0.658***
	(0.063)	(0.073)	(0.075)
Individuals	2876.000	2854.000	2824.000
LR chi2	314.955	314.096	313.294
Log likelihood	-2982.274	-2943.460	-2904.154
IVT value (Rs. per minute)	0.772	0.823	0.592
OVT value (Rs. per minute)	1.412	1.314	1.233
Value of IVT (% wage)	39.7	42.5	30.6
Value of OVT (% wage)	72.6	67.8	63.8

This Table presents estimated preference parameters for the nested logit model in equation 1 for different definitions of in-vehicle time and out-of-vehicle time. In-vehicle time in Columns (1) and (3) for train is from the network program; for bus, it is from HERE Transit API and Google Maps API; and for the remaining options, it is from Google Maps API. In these two columns, out-of-vehicle time measures the first mile access. In Column (1), out-of-vehicle time for walk, train and bus are from the network program; for auto-rickshaw, it is from the survey. Column (2) is the same as Column (1) except that out-of-vehicle time includes transfer time for bus and train from HERE API, and the same is excluded from in-vehicle time. In Column (3), out-of-vehicle time is from the survey. Std. errors are in parentheses. Estimated parameters are based on the nesting structure in Model 1 of Table 4: (Walk, Auto-rickshaw) , (Car), (Two-wheeler), (Train, Bus). Estimated parameters based on Model 2 are in Table B3. Dissimilarity parameter is constrained to be ≤1 so that predictions are consistent with equation 3. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B3: Sensitivity of the Commute Mode Choice Model Parameters to Different Definitions of IVT and OVT for Model 2 in Table 4

	(1)	(2)	(3)
OVT definition	Survey+NetworkX	Survey+HERE (includes transfer time)	Survey
IVT definition	GM+HERE +NetworkX	GM+HERE (excluding transfer time)	GM+HERE +NetworkX
Income-Cost	0.023***	0.024***	0.024***
	(0.001)	(0.001)	(0.002)
IVT	-0.019***	-0.021***	-0.015***
	(0.003)	(0.003)	(0.003)
OVT	-0.034***	-0.032***	-0.031***
	(0.002)	(0.002)	(0.002)
Intercepts:			
(Walk, Auto-rickshaw)	Omitted	Omitted	Omitted
(Car, Two-wheeler)	0.796***	0.808***	0.802***
	(0.075)	(0.078)	(0.077)
(Train, Bus)	-1.270***	-1.083***	-1.023***
	(0.093)	(0.076)	(0.075)
Dissimilarity Parameters:			
(Car, Two-wheeler)	1	1	1
	(constrained)	(constrained)	(constrained)
(Train, Bus)	0.681***	0.535***	0.420***
	(0.103)	(0.066)	(0.054)
(Walk, Auto-rickshaw)	0.596***	0.628***	0.617***
	(0.058)	(0.065)	(0.066)
Individuals	2876.000	2854.000	2824.000
LR chi2	318.729	317.518	317.055
Log likelihood	-2987.271	-2948.212	-2908.934
IVT value (Rs. per minute)	0.824	0.865	0.634
OVT value (Rs. per minute)	1.446	1.345	1.268
Value of IVT (% wage)	42.4	44.7	32.8
Value of OVT (% wage)	74.4	69.4	65.6

This Table presents estimated preference parameters for the nested logit model in equation 1 for different definitions of in-vehicle time and out-of-vehicle time. In-vehicle time in Columns (1) and (3) for train is from the network program; for bus, it is from HERE Transit API and Google Maps API; and for the remaining options, it is from Google Maps API. In these two columns, out-of-vehicle time measures the first mile access. In Column (1), out-of-vehicle time for walk, train and bus are from the network program; for auto-rickshaw, it is from the survey. Column (2) is the same as Column (1) except that out-of-vehicle time includes transfer time for bus and train from HERE API, and the same is excluded from in-vehicle time. In Column (3), out-of-vehicle time is from the survey. Std. errors are in parentheses. Estimated parameters are based on the nesting structure in Model 2 of Table 4: (Car, Two-wheeler), (Walk, Auto-rickshaw), (Train, Bus). Estimated parameters based on Model 1 are in Appendix Table B2. Dissimilarity parameter is constrained to be ≤1 so that predictions are consistent with equation 3.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B4: Preference Parameters from Nested Logit Models of Commute Mode Choice With Income Entering Non-Linearly

	(1) Model 1	(2) Model 2	(3) Model 3
Cost/Wage	-0.042***	-0.041***	-0.042***
	(0.002)	(0.002)	(0.003)
IVT	-0.025***	-0.025***	-0.018***
	(0.004)	(0.004)	(0.004)
OVT	-0.038***	-0.038***	-0.038***
	(0.002)	(0.002)	(0.002)
Intercepts:			
(Walk, Auto-rickshaw)	Omitted	Omitted	Omitted
(Two-wheeler)	0.989***		
	(0.077)		
(Car)	1.244***		
	(0.140)		
(Train, Bus)	-1.120***	-1.108***	
	(0.108)	(0.108)	
(Car, Two-wheeler)		1.028***	0.983***
		(0.074)	(0.094)
(Train)			-0.989***
			(0.090)
(Bus)			-1.620***
			(0.118)
Dissimilarity Parameters:			
(Two-wheeler)	1		
(Car)	1		
(Train, Bus)	0.909***	0.910***	
	(0.135)	(0.135)	
(Walk, Auto-rickshaw)	1	1	1.044***
	(constrained)	(constrained)	(0.113)
(Car, Two-wheeler)		1	1
		(constrained)	(constrained)
(Train)			1
(Bus)			1
Individuals	2876.000	2876.000	2876.000
LR chi2	492.290	494.239	366.308
Log likelihood	-2995.816	-2997.480	-2969.753
IVT value (% wage)	58.4	60.2	42.3
OVT value (% wage)	89.7	90.7	90.6

This Table presents estimated preference parameters for in-vehicle time in minutes (IVT), out-of-vehicle time in minutes (OVT) and cost/wage, the ratio of out-of-pocket cost per trip (in Rs.) to wage (in Rs. per minute). Wage per minute is calculated by scaling the monthly income with number of working days (22), working hours per day (9), and minutes in an hour (60). Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus); Model 3: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train), (Bus). Dissimilarity parameter has been constrained to 1 so that predictions are consistent with equation 3. Walk also includes bicycle. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B5: Predicted mode shares of Nested Logit Models from Tables 4 (income entering linearly), B4 (income entering non-linearly), and a Mixed Logit Model (correlated random coefficients)

Travel modes	True shares	Income entering linearly Model 1	Model 2	Model 3	Income entering non-linearly Model 1	Model 2	Model 3	Mixed Logit
Walk	32.55	29.08	28.99	28.39	28.13	28.04	27.17	28.00
Train	15.99	12.54	12.52	15.99	12.94	12.94	15.99	20.71
Bus	8.41	11.87	11.89	8.41	11.46	11.47	8.41	16.47
Auto-rickshaw	9.14	12.61	12.70	13.30	13.56	13.65	14.52	14.66
Own two-wheeler	29.45	29.45	30.21	30.23	29.45	29.90	29.92	17.91
Car	4.45	4.45	3.69	3.67	4.45	4.00	3.98	2.24

This Table compares sample commute mode shares with predicted mode shares from nested logit models in Table 4 where income-cost enters linearly, models in Table B4 where income enters non-linearly to compare model fit, and those predicted under a mixed logit specification. Nesting structure in Model 1: (Walk, Auto-rickshaw), (Car), (Two-wheeler), (Train, Bus); Model 2: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train, Bus); Model 3: (Walk, Auto-rickshaw), (Car, Two-wheeler), (Train), (Bus). The utility function specification for mixed logit model is $U_{im} = \alpha_1^i * t_{im}^{ivt} + \alpha_2^i * t_{im}^{ovt} + \alpha_3^i * (w_i - c_{im}) + \epsilon_{im}$ with ϵ_{im} i.i.d. random error following Type I extreme value distribution $\epsilon_{im} \sim f(\epsilon_{im}) = e^{-\epsilon_{im}} e^{-e^{-\epsilon_{im}}}$ and $\alpha_1^i, \alpha_2^i, \alpha_3^i \sim N(\alpha, \mathbf{\Sigma})$.

Table B6: Factor Loading for Variables in Housing Amenities Index

Variable	Factor Loading
Good roof	0.2488
Floorspace (in sqft.)	0.3809
Number of rooms	0.3744
Separate Kitchen	0.4499
Toilet inside the house	0.4333
Bathroom inside the house	0.3720
Piped water	0.3526

This Table presents factor loadings for the Housing amenities index variable used in the second stage of the housing choice model (Table 8). These variables are summarized in Table 6.

Table B7: Factor Loading for Variables in Index for Proximity to Doctor/Hospital

Variable	Factor Loading
Pvt. Doctor/Clinic nearby	0.4071
Municipal Hospital nearby	0.6476
Pvt. Hospital/Nursing Home nearby	0.6441

This Table presents factor loadings for the proximity to doctor/hospital index variable used in the second stage of the housing choice model (Column (5), Table 6). Each of these variables have four categories increasing in order of proximity.

Table B8: First Stage for the 2SLS Regression in Table 8

	(1)	(2)	(3)	(4)	(5)
Log(Annual assessed sale value)	3637.496***	3594.764***	3593.144***	3601.963***	3154.939***
	(572.026)	(561.310)	(576.687)	(574.384)	(499.932)
Housing Amenity Index	2232.026***	2225.880***	2225.741***	2245.628***	2224.245***
	(141.948)	(147.204)	(147.750)	(148.090)	(147.637)
Distance to coast (in km)		42.429	42.707	-109.139	-55.038
		(58.631)	(61.772)	(74.866)	(73.166)
Slum Classification Dummy		-961.339***	-961.750***	-1002.938***	-854.924**
		(337.903)	(336.040)	(329.238)	(340.533)
No. of Reported Crimes Against Women		-1.777	-1.729	-5.263	10.162
		(13.360)	(13.688)	(13.698)	(14.189)
Distance to the nearest railway station (in km)			-4.499	-473.355*	-480.123*
			(202.728)	(264.479)	(277.323)
Standardized Employment Accessibility Index				1072.819***	831.095***
				(306.753)	(303.340)
Proximity to Health Services Index					401.972***
					(135.074)
R-squared	0.373	0.378	0.378	0.387	0.403
Observations	2,170	2,170	2,170	2,170	1,989

This Table presents the first-stage estimates of the 2SLS specifications in Table 8. These parameters are in equation 12. Dependent variable is the monthly rental price of houses in Rs. Robust std errors clustered at the sub-zone level are in parentheses.

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

Table B9: Sensitivity of Long Run Welfare to First Stage Specification (Perfectly Elastic Housing Supply Case)

Taste shifter	(1) **None**	(2) **Educ**	(3) **Income**	(4) **Vehicle ownership**
Mean E(CV) Line 1:				
Model 1 (in Rs. per month)	191.46	192.09	191.26	179.72
Model 1 (% Monthly Rent)	1.96	1.97	1.96	1.84
Model 2 (in Rs. per month)	193.97	197.82	192.46	183.20
Model 2 (% Monthly Rent)	1.99	2.03	1.97	1.88
Mean E(CV) Lines 2, 3 and 7:				
Model 1 (in Rs. per month)	542.30	557.36	533.83	524.10
Model 1 (% Monthly Rent)	5.56	5.71	5.47	5.37
Model 2 (in Rs. per month)	544.86	554.42	539.68	516.99
Model 2 (% Monthly Rent)	5.58	5.68	5.53	5.30

This Table shows expected compensating variation computed using specifications with various taste-shifters in the first stage. Column (1) is the base model without any taste-shifters. Taste-shifters in Columns 2, 3 and 4 are education, income, and vehicle ownership, respectively (corresponding to Table 7). The corresponding second stage specification for each model has the same controls as in Column (4), Table 8. The average monthly rent is Rs. 9757.147.