Urban Transit Infrastructure and Inequality*

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Abstract

We propose a quantitative spatial model featuring heterogeneous worker groups and their travel to consume non-tradable goods and services. We consider the opening of the Downtown Line (DTL) in Singapore, which connected regions where high-income households have residential amenities to where non-traded sectors are productive. Leveraging transit farecard data, we show that high-income workers saw large welfare gains but low-income workers gained little. Everyone enjoyed improved access to consumption opportunities, but low-income jobs in non-tradables moved to less attractive workplaces. Abstracting from consumption travel understates the disparate impact across worker groups three-fold.

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1 Introduction

With 68% of the world's population projected to live in urban areas by 2050, governments will continue to spend vast sums to alleviate congestion by expanding mass transit (United Nations 2018). As with any large public investment, it is important to consider how the economic benefits are shared between low- and high-income workers. If the economic benefits of transit are not shared, urban inequality may be exacerbated.[1] Urban inequality undermines social cohesion and may entrench accumulated advantages, thus threatening intergenerational mobility (see, e.g., Chetty et al. 2014).[2]

Existing research has highlighted differential access to employment opportunities across worker groups, emphasizing that poor workers face much larger commuting costs than the better-off. However, many transit trips are unrelated to work. For instance, transit users visit restaurants, retail stores, and hair salons.[3] Since low-income workers are overwhelmingly employed in these non-tradable sectors, changes in consumption travel lead to a spatial re-organization of low-income jobs in the city, possibly leading to disparate impacts of transit expansion by income stratum.[4]

[1]Public transit systems can disproportionately serve higher income workers. For instance, they are more likely to live in public-transit-accessible neighborhoods (McKenzie 2015). See, e.g., Couture et al. (2019) for references on urban inequality more generally.

[2]In Singapore, real household income for the bottom 10% increased 18.0% between 2001 and 2023, against 52.3% and 50.9% for the top two deciles (Singapore Department of Statistics 2024).

[3]According to the US National Household Travel Survey, as of 2017, 31% of travel miles are made for work purposes, while 33% of travel miles are made for shopping or meals, and another 26% for social or recreational purposes. See Appendix Figure A2 (Department of Transportation 2017). Additionally, in 2018, non-tradable consumption accounted for over 50% of total household expenditure in Singapore (Department of Statistics 2019). See Appendix Figure A3.

[4]Disparate impacts do not necessarily invalidate the value of transit expansion, especially if no one is strictly worse off. After all, high-income workers are net payers into most social support systems. Nonetheless, governments aim to reduce social disparities through transit investments.

In this paper, we ask: do the poor and other workers benefit alike from transit expansion, and what role does consumption travel play in this analysis? We exploit the universe of transit farecard trips from Singapore during the opening of the Downtown Line (DTL), described in Section 2. These farecard data are combined with administrative spatial data on land use, rents, expenditures and employment. The data inform a quantitative spatial model with heterogeneous worker types and travel to consume non-tradable goods. We shed light on the interplay between three pieces of the puzzle: consumption travel, inequality, and the spatial re-organization of economic activity.

Our core message is: Since low-income workers are overwhelmingly employed in non-tradable sectors, changes in consumption travel induced a spatial re-organization of low-income jobs in the city, with important distributional implications.[5] The DTL connected regions in which high-income households have residential amenities to regions in which non-traded sectors are productive. In contrast to our approach, prior work on disparate impacts of system expansions in Bogota (Tsivanidis 2019) and Tanzania (Balboni et al. 2020) focus on commuting. Similar to our predecessors, when we abstract from consumption trips, we find the DTL has little disparate impacts by income. However, factoring in consumption travel leads to the opposite conclusion.[6]

Constructed at a cost of US$15.5 billion, the DTL is the longest underground mass rapid transit line in Singapore, and is the city-state's most ambitious public transit project to date (The Straits Times 2017). In Section 3, we present evidence that, when a section of the DTL opened in December 2015, low- and high-income workers adjusted their travel patterns differently, both in the short run and up to a year after the line opened. Additionally, shortly after the sites of DTL stations were announced in 2008, the announcement was followed by higher price appreciation for apartments

[5]In Singapore, low-income workers are defined as those earning a monthly salary below the 25th percentile. They are targeted for transit subsidies and income support.

[6]For more papers on the impact of transportation infrastructure within cities, see, e.g., McDonald et al. (1995); Gibbons and Machin (2005); Baum-Snow and Kahn (2005); Glaeser, Kahn, and Rappaport 2008; Billings (2011); Donaldson (2018); Brooks and Lutz 2019; Gupta, Van Nieuwerburgh, and Kontokosta (2022); Heblich, S. Redding, and D. Sturm (2020); and Severen (2023).

near each DTL station, compared to those farther away.

Motivated by the descriptive evidence, in Subsection 5.1, we use gravity regressions to assess how responsive each type of worker is to travel time. We find that low-income workers have larger travel elasticities than high-income workers, and elasticities are larger for consumption than for work travel across both types.[7] Before the DTL opened, low-income workers had shorter commutes than high-income workers did, but traveled equally far to consume non-tradables.

To interpret these empirical findings, we develop a quantitative spatial model in Section 4 that nests several others.[8] In addition to incorporating heterogeneous worker types by income (low/high), we model travel to consume non-tradable goods in a manner that is informed by the data and admits tractable counterfactuals using exact-hat algebra (Dekle, Eaton, and Kortum 2008).[9] In the model, workers travel to work and to consume non-tradable goods and services. The city in which they reside is modeled as a set of neighborhoods, with a transportation network characterized by bilateral travel times between locations. Worker groups differ in their preferences over residences and consumption locations, productivities over workplaces and sectors, consumption patterns, and travel costs and elasticities. Workers first choose where to live, then where to work, and finally where to consume non-tradables. When choosing where to live, each worker trades off rents against residential amenities, access to employment, and consumption opportunities. When choosing where to work, each worker evaluates their type-specific wages, match-specific produc-

[7] These findings are robust to a differences-in-differences analysis comparing origin-destination pairs treated by the line opening (Severen 2023), and accounting for sparsity in the matrix of said origin-destination pairs (Dingel and Tintelnot 2020).

[8] For more papers on quantitative spatial models, see, e.g., Ahlfeldt et al. (2015); S. Redding (2016); Allen, Arkolakis, and Li (2016); Monte, S. J. Redding, and Rossi-Hansberg (2018); and Allen and Arkolakis (2022). While dynamic effects matter (Kleinman, Liu, and S. J. Redding 2023), our paper compares the pre- and post-DTL steady states; thus, a static model suffices.

[9] We contrast our paper from that of Miyauchi, Nakajima, and S. Redding (2022), which uses sophisticated computational tools to study trip chaining and consumption externalities in Tokyo.

tivities and commute distances. Finally, when choosing where to consume non-tradables, they consider prices, type-specific idiosyncratic consumption amenities, and travel distances. On the production side, the non-tradable and tradable sectors have different input requirements over commercial floor space and labor provided by each worker group, with the non-traded sector being much more intensive in low-income labor. Market clearing in the non-traded sector implies that, in each location, consumption travel patterns drive the demand for non-traded production, and thus the demand for low-income workers.

With the model in hand, we estimate and calibrate several other key parameters in Section 5.[10] Then, using exact-hat algebra, we quantify the welfare and inequality effects of the DTL in Section 6. We find that the DTL improves welfare for high-income workers by 1.8%. However, low income workers experience almost no net benefits.[11] Although both groups can better access consumption opportunities, low-income workers see their jobs in the non-tradable sector moving to places they deem less attractive, offsetting their gains from the consumption channel. This disparity between high- and low-income workers is driven by two mechanisms. First, the DTL disproportionately improves access for many high-income areas served directly by the line. Second, more consumers consume non-tradables near the city center because the DTL has made it easier for them to go

[10]Through the lens of the model, the fixed effects in our gravity regressions can be interpreted as measures of location attractiveness. These measures are validated against external data on associated amenities. Model-implied average wages by worker type and residence are also highly correlated with those observed in administrative data. Finally, using changes in travel times as observed in the farecard data before and after the opening of the line, we find that the model predicts well post-DTL travel flows, residential patterns and the entry of firms in the non-tradable sector. For more work on quantifying the value of urban amenities, see Roback (1982); Glaeser, Kolko, et al. (2001); Bayer, Keohane, et al. (2009), Diamond (2016); S. J. Redding and D. M. Sturm (2016); and Almagro and Domínguez-Iino (2020).

[11]In Subsection 6.3, we show that our inequality implications are robust to equalizing, between worker groups, expenditure shares; travel costs; travel elasticities; and residential elasticities.

downtown. Thus, low-income jobs in the non-tradable sector move to the city center, yet low-income workers still live away from the center. Average commute times increased about 1% for low income workers, while high income workers saw a reduction.

Abstracting away from travel to consume non-tradables, we find a three-fold underestimation of the disparate impact of the DTL across worker groups. We find that both worker groups benefit from greater access to employment opportunities but a slightly larger share of the gains go to high-income workers. Absent non-tradable consumption, the model misses the spatial re-organization of low-income non-tradable sector jobs. Additionally, because workers value access to consumption opportunities, failing to account for consumption travel will understate the aggregate welfare effects of the DTL. In particular, this restricted model fails to capture the disproportionate gains in consumption access for high-income workers.[12]

2 Background and Data

2.1 Context: Singapore and the Downtown Line

Singapore is an island city-state in Southeast Asia. With a population of about 6 million inhabitants, Singapore is among the densest cities in the world.[13] Inequality is high; with a Gini coefficient of 37.8 as of 2022, Singapore ranks between the United States and Chile among high-income countries.[14] Of late, inequality has been of concern because conspicuous consumption has eroded the social fabric (Teo 2022). When pressed to redistribute via higher taxes and social spending, the

[12]Line placement also matters for the welfare and distributional impacts of transit expansion. In Online Appendix Section F.2, we simulate the removal of the North-South Line (NSL), a trunk line primarily serving more diverse neighborhoods. Welfare falls for both low and high types, by 4.2% and 2.0% respectively. Both types experience reductions in consumption and employment access.

[13]Singapore has highly restrictive immigration policies (Ministry of Manpower 2020). Yet its spatial distribution of non-tradables mirrors that of other major cities (see Figure A4).

[14]This Gini coefficient is based on household income from work per household member, after adjusting for government taxes and transfers. See `https://www.singstat.gov.sg/-/media/files/news/press09022023.ashx` for details.

government has demurred, pointing to the need to maintain the city's attractiveness as a place to do business.[15]

The population in Singapore is heavily reliant on public transportation, comprising buses, light-rail and mass-rail networks. These networks carry over 4 million passengers per day.[16] Approximately 60% of trips are made on buses. One reason for high transit use is that the city government imposes a Vehicle Quota System for private cars. As of February 2024, the price of a Volkswagen Golf is about US$150,000, six times that of the United States (US$25,000). As a result, only 28% of households in Singapore own a car, and far fewer drive to work.

The Downtown Line is the longest underground and mass rapid transit line in Singapore. At 41.9 kilometres (26.0 miles) and with 34 stations, the line runs from Bukit Panjang station in the north-west to Expo station in the east through the CBD. See Online Appendix Figure A5 for an illustration. The line was first announced on 23 October 2001 and was built in three phases.[17] The first phase opened in December 2013, comprising 6 stations from Bugis to Chinatown station within the Downtown area. The second phase, from Bukit Panjang to Rochor station, which linked the north-west to the center of the city, opened in December 2015. The final phase, from Fort Canning to Expo station, connecting the east to the city, opened in October 2017. The line, at a cost of US$15.5 billion, is considered the government's most ambitious public transit project to

[15]Academic and popular discourse in Singapore highlights a culture of "neoliberal morality" (e.g., Teo 2022). In Singaporean society, as opposed to a broad-based welfare system, income taxes are kept low, and the family is elevated as the main social safety net.

[16]Appendix Table A1 provides a summary of the mass-rail lines in Singapore.

[17]At the opening of Dover Station on the East-West Line, the then Minister for Communications and Information Technology Yeo Cheow Tong announced that Stage 2 of the Downtown Line "will serve the Bukit Panjang, Upper Bukit Timah and Bukit Timah regions... [relieving congestion] in the Upper Bukit Timah/Bukit Timah/Dunearn Road corridor." He did not mention other details on line alignment or where stations would be. On 15 July 2008, in a press release by the Land Transport Authority of Singapore, the precise location of stations on the line was revealed.

date (The Straits Times 2017). The line served to provide the north-west and east a direct link to the center of the city, and to alleviate congestion on various other rail and bus routes.

2.2 Data

Our primary source of data is public transit fare card data (EZ-Link) from the Land Transport Authority of Singapore.[18] We observe all trips made by public transit (mass rail, light rail or bus) linked to an individual's "EZ-Link" card. Our data set covers one week every quarter between June 2015 and June 2018, and three full months between December 2015 and February 2016. The longer quarterly data set allows us to observe changes in transit patterns from before the opening of Phase 2 of the Downtown Line to after the opening of Phase 3. The full three months of data captures the period directly before and after the opening of Phase 2 of the Downtown Line. In total, we observe over a billion trips. For each trip, we observe the origin, destination, and start and end time of the trip. Each individual in our data set is categorized into commuter groups. In our analysis, we focus on the Adult and Low-Income Worker categories. Low-Income Workers are those who earn a monthly salary below the 25th percentile (S$2,000 prior to 2020, against a median of S$4,534).[19]

Our unit of analysis is the *subzone*, the smallest administrative planning unit in our data sets, delineated by the Urban Redevelopment Authority of Singapore. Singapore is divided into 323 subzones with a median size of 1,229,894 square meters. These subzones are contained within larger spatial units, namely 55 planning areas and 5 planning regions. We link all bus and train stops to subzones.

We use our fare card data to generate work and consumption travel probabilities conditional

[18]A heat map visualization of the data is presented in Appendix Figure A7. For data construction and auxiliary data sets, see Online Appendix Section A.

[19]Low Income Workers receive up to a 25% subsidy on their fare costs. The Central Provident Fund automatically determines eligibility based on tax filings and sends an individual application package informing workers of their eligibility, details of the scheme, and how to apply for the subsidized card (Ministry of Transport 2014).

on residential subzone. We identify each individual's residence as the modal first origin and last destination of the day. We identify each individual's workplace as the modal destination during the morning rush hour (5am to 11 am) and origin during evening rush hour (3pm to 11pm).[20] Finally, we classify all remaining trips as consumption trips.

We also use data from several other administrative sources and spatial data on amenities from the government data portal (Open Government Products 2019). See Online Appendix Section A for details on these data sets and their construction.

3 Descriptive Analysis

In this section, we present descriptive results on the impact of the Downtown Line and motivating facts that guide our empirical analysis. In our analysis, we define low-income workers as those earning below the 25th percentile ($2,000 SGD or $1,500 USD per month, less than half of median earnings). All others are high-income workers, consistent with our farecard data. Our unit of analysis is the subzone, which we will henceforth call a neighborhood.

3.1 Residential, Employment, Consumption, and Travel Patterns

First, low- and high-income groups have different residential patterns across the city. Figure 1a plots the share of high-income workers that live in each neighborhood in 2015. High-income workers primarily cluster near the center of the city (e.g., Bukit Timah, Tanglin) with only some concentration in certain neighborhoods near the coasts of the island (e.g., East Coast Park). On the other hand, low income workers live farther from the city center, with many living closer to the north. Figure 1a also shows that the Downtown Line runs through some of the neighborhoods with the highest concentration of high-income workers in Singapore, clustered in or just west of the city center. The many low income residents in the north are not directly served by the Downtown Line. Hence, high-income workers may disproportionately benefit from the DTL.

[20]Modal morning destination/evening origin locations match 71% of the time and we validate that these identified residences and workplaces match well their corresponding shares in administrative data (Figure A15). See Online Appendix Section A for details.

Second, neighborhoods with a high concentration of low-income workers are associated with a high share of non-tradable sector production. Figure A11 shows a strong positive correlation between the share of commercial land used by the non-tradable sector and the share of workers that are low-income. This finding is in line with the Labor Force Survey data, which indicates that 51% of workers in the non-tradable sector are low income, compared to only 14% in the tradable sector, as shown in Table A2.[21] These findings highlight the importance of the spatial distribution of non-tradable jobs for low-income workers.

Third, using itemized Household Expenditure Survey data broken down by income group, we find that high-income workers spend more on non-tradable goods and services than low-income workers. Figure A12 shows that high-income workers spend 40% of their income on non-tradable goods and services, 41% on tradables, and the remaining on housing. In contrast, low-income workers spend 34% of their income on non-tradable goods and services, 43% on tradables, and the remaining on housing. These findings suggest that improving access to consumption opportunities will raise welfare more for high-income than low-income workers, as the former spend a larger share of their income on non-tradables.

Fourth, low income workers make shorter commutes, at a median of 25 minutes, compared to 30 minutes for high income workers. However, for consumption trips, travel times are more similar across income groups and are shorter than workplace trips, at around 23 minutes for high-income workers and 22 minutes for low-income workers respectively. Figure A8 plots the travel time distributions by worker group and type of travel. Low-income workers make 5% more trips on average than high-income workers. Consumers travel more on weekends than weekdays. Figure A13 presents the average number of daily trips by worker group and weekday vs weekend travel.

3.2 The Downtown Line and Housing Prices

The precise locations of stations on the Downtown Line (DTL) were suddenly announced on July 15, 2008. We show that the announcement coincided with large changes in residential prices for

[21] 61% of employees in food and accommodation, 49% in retail, and 41% in personal services are low-income. Low-income workers comprise 25% of the labor force in Singapore.

houses near each DTL station. Our empirical design is an event study across time and space.[22] We compare "treated" apartments within one kilometer of a DTL station, relative to "control" apartments between one and five kilometers from any such station.[23] "Treated" apartments are more likely (than "control" apartments) to directly benefit from access by foot to a DTL station, in addition to the entry of non-tradable services in the vicinity of the station.[24]

Over 4 years, relative to apartments in the outer ring, residential prices increase by 4.84% for apartments in the inner ring. See Figure 2a.[25] We also estimate the relationship, over time, between housing prices and distance from the DTL. Regression coefficients are plotted in Figure 2b. Post-announcement, closer apartments see higher prices, all else equal.

Increased property prices suggest that residents value improved access granted by the DTL to both work and consumption locations.[26] These price effects increase over time, suggesting a longer-run re-organization of economic activity.

3.3 Impact of the Downtown Line on Travel

When Stage 2 of the Downtown Line (DTL) opened, we saw a sharp uptick in travel to DTL subzones. We conduct an event study around the opening of Phase 2 of the DTL (DTL2), which took place on December 27th, 2015.[27] We compare daily trips taken, by income type, to DTL and

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[22]For details on the precise specification and analysis, see Online Appendix B.1.

[23]Our results are robust to shrinking the outer limit of the control ring to 3km. See Table A5.

[24]We do not claim causality. See Online Appendix B.1 and Donaldson and Hornbeck (2016).

[25]Similarly, apartments that were closer to a DTL2 station than expected (assuming that stations are randomly uniformly distributed along DTL2) saw higher prices post-announcement, relative to apartments farther than expected. See Appendix Section B.1, Table A5, and Figure A14.

[26]Much of the housing stock (80%) in Singapore is government housing (see, e.g., Ferdowsian, Lee, and Yap 2023 and Lee et al. 2024), bought and sold on long leases. Regulation in this market is kept light-touch to facilitate price discovery and asset appreciation for existing owner-occupiers.

[27]The immediate pre-period, from December 1 to 26, forms the relevant short-run counterfactual because any disruptive road works would have been completed months before the opening of the

non-DTL subzones, before and after DTL2 opened.

Figure 3a plots the main results. We observe about a 20% increase in trips after DTL2 opened. Over all subzones, the volume of low-income trips increases by a smaller percentage than high-income trips. This finding suggests that high-income workers are taking greater advantage of the new DTL than low-income workers.

We also find that low- and high-income workers adjust their travel patterns differently across neighborhoods. In Figure 3b and 3c, we plot the travel patterns by income group for two of the major locations on the DTL line separately, Bukit Panjang and Upper Bukit Timah. High-income workers increase their travel to and from Bukit Panjang by about 40% on average, while low-income workers increase their travel volume by about 20%. On the other hand, both worker groups increase their travel to and from Upper Bukit Timah by the same amount. This disparity suggests that our model should account for differential travel responses when evaluating welfare across worker groups.

Lastly, we plot changes in travel patterns over a longer time horizon in Figure A16. We find that the responses in travel flow grow over time, stabilizing about a year after the line opened. Therefore, we should account for the long-run re-organization of economic activity in Singapore.[28]

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line. The time immediately preceding the opening of train lines is spent on train testing. For instance, Phase 3 of the DTL opened in October 2017, and was tested extensively by its operator from May 2017 to August 2017. See this link for details:

`https://www.todayonline.com/singapore/downtown-line-start-later-every-sunday-may-august`

[28]Additionally, using two cross-sections of food establishment license data between 2015 (before the opening of Phase 2 and 3 of the DTL) and 2018 (after the opening), we find that, in subzones with a DTL station, relatively more food establishments entered between 2015 and 2018. The number of food establishments in DTL locations increased by about 15% relative to non-DTL locations. See Appendix Table A4.

4 Quantitative Model

To guide our empirical analysis, we model a closed city with heterogenous workers and travel choice over workplace and consumption locations. The city has $n \in \mathbb{N}$ neighborhoods.[29] Neighborhoods differ in their exogenous amenities, productivities, residential and commercial floor space, as well as bilateral commute times.

High- and low-income workers decide where to live, where to consume non-tradable goods and services, and where and in which sector to work. Each worker type has different preferences, productivities, wages, travel costs, and consumption shares. Utility is derived from the consumption of a tradable good, a non-tradable good, and residential floor space.

In the production side of the model, there are two sectors: tradable goods $(j = 1)$ and non-tradable goods $(j = 0)$. Firms in both sectors are located across the city and use labor and commercial floor space as inputs. The demand for different worker types differs across sectors, with the non-tradable sector relying more on low-income workers, while the tradable sector relies more on high-income workers. The demand for non-tradable goods depends on where consumers choose to travel to consume them, while tradable goods can be costlessly traded across the city. The demand for labor by worker type varies across the city, depending on the productivity of each sector in each location, commercial rents, and demand for production. Perfectly competitive developers supply floor space using land and capital with constant returns to scale technology. In equilibrium, wages and the prices of floor space and goods adjust to clear markets in labor, land, and goods in the city.

4.1 Workers Choose Where to Live, Work, and Consume Non-Tradables

The city is populated by different worker groups indexed by $\theta \in \{+,-\}$, denoting high- and low-income workers respectively. Each type of worker has a fixed population $R(\theta)$.[30] High- and low-

[29] The population of each worker group is determined exogenously. Singapore is a small city-state with tightly regulated in- and out-migration.

[30] We abstract from tourists. Firstly, according to the Singapore Tourism Board, total tourist receipts made up 5.1% of total spending in the economy in 2015. If we remove accommodation receipts and expenditures on airfares/travel, this figure drops to 2.7%. This share is relatively small.

income workers have different expenditure shares over the three goods they consume: housing, of share $\gamma(\theta)$; non-tradables, of share $\alpha(\theta)$; and finally tradables, of share $1-\alpha(\theta)-\gamma(\theta)$. These shares measure the relative importance of housing, tradable and non-tradable consumption for utility for people of type θ.[31] The traded good can be frictionlessly transported within the city and is taken as numeraire. Non-traded goods must be consumed where they are supplied. If supplied in location l, a non-traded good is sold at price p_l.

Timing. Workers first choose where to live; then, in a second step, they choose where to work and where to consume non-tradables.[32] First, workers ω of type θ observe their idiosyncratic residential amenity draws for all neighborhoods and choose to live in some neighborhood n. Second, individuals observe their idiosyncratic productivities for all workplaces and idiosyncratic consumption preferences in all neighborhoods, then choose to work in some neighborhood i and sector j, and to consume non-tradables in some neighborhood l. With some abuse of notation, let R denote variables associated with a worker's residence choice; L her workplace and sector choice; and C her non-tradable consumption choice.

Second, the travel patterns of tourists are unlikely to be affected by the changes in transit access from the opening of DTL. Airbnb is only available for long stays; furthermore, hotels and tourist attractions are concentrated downtown.

[31]Larger consumption shares on housing imply larger implications of changes in rents for welfare. Larger consumption shares on non-tradables imply larger implications of access to consumption opportunities for welfare.

[32]Currently we assume the sequence of choices is (live, work, consume). This choice mirrors the decision process of most residents in Singapore, given the larger frictions to moving one's house (see, e.g., Bayer, McMillan, et al. 2016), than to change one's job, let alone change where one shops. Furthermore, this sequence of choices is standard in the literature (see, e.g., Miyauchi, Nakajima, and S. Redding 2022). Given the nesting structure in Equation (11), switching the choice sequence to (live, consume, work) is without loss. However, any other permutation may be with loss (e.g., work, live, consume).

Preferences. We assume indirect utility is Cobb-Douglas. It is the product of three terms, one for each choice the worker is called to make:

$$u^j_{nil}(\omega;\theta) = \mathbb{B}_n(\omega;\theta) \times \mathbb{W}^j_{ni}(\omega;\theta) \times \mathbb{C}_{nl}(\omega;\theta). \tag{1}$$

The first term $\mathbb{B}_n(\omega;\theta)$ covers the utility factors specific to the worker's residence. Then, conditional on living in neighborhood n, the second term $\mathbb{W}^j_{ni}(\omega;\theta)$ corresponds to utility from work; and lastly $\mathbb{C}_{nl}(\omega;\theta)$ corresponds to utility from consumption travel. In the next subsections, we define measures of workplace access $\mathbb{W}_n(\theta)$ and consumption access $\mathbb{C}_n(\theta)$, which are the ex ante (expected) versions of the utility realizations above, given the worker's residence: $\mathbb{E}_\omega[\mathbb{W}^j_{ni}(\omega;\theta)] = \mathbb{W}_n(\theta)$; and $\mathbb{E}_\omega[\mathbb{C}_{nl}(\omega;\theta)] = \mathbb{C}_n(\theta)$. These expectations are taken over idiosyncratic draws ω for residential amenities in neighborhood n, $b_n(\omega;\theta)$; efficiency units of labor (productivity) in neighborhood i and sector j, $a^j_i(\omega;\theta)$; and consumption amenities in neighborhood l, $c_l(\omega;\theta)$. We assume that these shocks are drawn from the following independent Fréchet distributions:

$$\begin{aligned} &F_n(b;R,\theta) = \exp[-b^{-\varepsilon(R,\theta)}]; \quad F^j_i(a;L,\theta) = \exp[-T_i(\theta)T^j(\theta)a^{-\varepsilon(L,\theta)}]; \\ &F_l(c;C,\theta) = \exp[-T_l(C,\theta)c^{-\varepsilon(C,\theta)}], \end{aligned} \tag{2}$$

where all the shape parameters, ε, are greater than 1; and all the scale parameters, $T_i(\theta), T^j(\theta), T_l(C,\theta)$, are greater than zero. These scale parameters control the overall level of the draws for residential preferences, work location productivity, sector productivity, and consumption preferences respectively. We allow scale parameters to vary across worker groups, to capture differences in preferences and productivities over locations across types. We also allow shape parameters, $\varepsilon(R,\theta), \varepsilon(L,\theta), \varepsilon(C,\theta)$, which control the dispersion of the distributions, to differ across groups. A higher ε corresponds to a smaller dispersion of idiosyncratic taste shocks.[33]

[33] The sensitivity of choices to other variables such as travel costs is governed by the dispersion of preferences or productivity. When workers have similar matches in different locations (high ε), their choices are more sensitive to these other variables. Differences in heterogeneity across groups

We proceed by backwards induction. First, we solve the worker's employment/sector choice subproblem; then her consumption travel subproblem; and finally her residence choice problem.

4.1.1 Employment is Driven by Productivity and Net Wages

Having chosen a neighborhood n in which to live, workers of type θ draw a vector of match-productivities with firms across the city as in Equation (2). With these draws in hand, workers choose to work in the neighborhood that offers the highest income net of their type-specific commuting costs:

$$\max_{i \in \mathbb{N}, j \in \{0,1\}} \mathbb{W}_{ni}^{j}(\omega;\theta) = \frac{w_i^j(\theta) a_i^j(\omega;\theta)}{\exp(\kappa(\theta)\tau_{ni})}. \tag{3}$$

The worker earns a wage $w_i^j(\theta)$ per efficiency unit in neighborhood i and sector j. She likes locations where she is more (idiosyncratically) productive $a_i^j(\omega;\theta)$. However, she dislikes a longer travel time τ_{ni} between her home and work. The parameter $\kappa(\theta)$ controls the size of travel costs by worker group.[34]

Fix a worker type θ who has made the choice to live in neighborhood n. Since idiosyncratic productivities are distributed according to a Fréchet distribution, the probability she decides to work in neighborhood i and sector j is given by the following gravity equation:

$$\lambda_{ni}^{j}(L,\theta) = \frac{T_i(\theta) T^j(\theta) [w_i^j(\theta) \exp(-\kappa(\theta)\tau_{ni})]^{\varepsilon(L,\theta)}}{\sum_{i' \in \mathbb{N}} \sum_{j'=0}^{1} T_{i'}(\theta) T^{j'}(\theta) [w_{i'}^{j'}(\theta) \exp(-\kappa(\theta)\tau_{ni'})]^{\varepsilon(L,\theta)}} \tag{4}$$

Individuals are more likely to travel to work in a neighborhood that pays a high wage net of travel costs, as in the numerator, relative to those in all other locations, as in the denominator. Differences in productivity heterogeneity across worker types is important in determining the incidence of travel costs, controlling the extent to which workers are willing to bear high commute costs to work in a neighborhood. Differences in productivity across neighborhoods and commute

will be important in determining the incidence of travel costs, since these differences control the extent to which individuals are willing to bear high travel costs to work or consume in a location.

[34] We expect differences in travel costs since low-income workers receive subsidies on travel. Higher travel costs imply larger gains from reductions in travel time.

costs by type drive differences in work travel patterns across worker groups.

Expected income prior to drawing the vector of match productivities is directly related to the denominator in Equation (4) through

$$\mathbb{W}_n(\theta) = \Gamma\left(\frac{\varepsilon(L,\theta)-1}{\varepsilon(L,\theta)}\right)\left[\sum_{i\in\mathbb{N}}\sum_{j=0}^{1} T_i(\theta)T^j(\theta)[w_i^j(\theta)\exp(-\kappa(\theta)\tau_{ni})]^{\varepsilon(L,\theta)}\right]^{1/\varepsilon(L,\theta)} \tag{5}$$

where $\Gamma(.)$ is the Gamma function. Intuitively, in locations with better *access to employment* $\mathbb{W}_n(\theta)$, or access to locations with high expected income by type, workers are better off.

4.1.2 Consumption is Driven by Tastes and Net Prices

Having chosen to live in neighborhood n, workers of type θ draw a vector of idiosyncratic preference shocks with consumption locations across the city as in Equation (2). With these draws in hand, workers choose to consume non-tradables in the neighborhood with the best consumption amenities, accounting for travel costs and the price of non-tradables.

$$\max_{l\in\mathbb{N}} \mathbb{C}_{nl}(\omega;\theta) = \frac{c_l(\omega;\theta)}{p_l{}^{\alpha(\theta)}\exp(\kappa(\theta)\tau_{nl})} \tag{6}$$

Workers have idiosyncratic preferences over consumption locations $c_l(\omega;\theta)$. They prefer lower non-tradable prices p_l and a shorter travel time τ_{nl} between their origin and their destination. Because idiosyncratic tastes $c_l(\omega;\theta)$ are distributed according to a Fréchet distribution, the probability this worker decides to consume non-tradables in location l is given by the following gravity equation:

$$\lambda_{nl}(C,\theta) = \frac{T_l(C,\theta)[p_l{}^{\alpha(\theta)}\exp(\kappa(\theta)\tau_{nl})]^{-\varepsilon(C,\theta)}}{\sum_{l'\in\mathbb{N}} T_{l'}(C,\theta)[p_{l'}{}^{\alpha(\theta)}\exp(\kappa(\theta)\tau_{nl'})]^{-\varepsilon(C,\theta)}} \tag{7}$$

Individuals are more likely to travel to consume in neighborhoods with high consumption amenities net of the price of non-tradables and travel costs, as in the numerator, relative to those in all other locations, as in the denominator. Differences in preference heterogeneity across worker types is important in determining the incidence of travel costs, controlling the extent to which workers are willing to bear high travel costs to consume non-tradables in a neighborhood. Differences in preferences across neighborhoods and travel costs by type drive differences in consumption travel patterns across worker groups.

Expected utility from non-tradable consumption prior to drawing the vector of idiosyncratic preferences is directly related to the denominator in Equation (7) through

$$\mathbb{C}_n(\theta) = \Gamma\left(\frac{\varepsilon(C,\theta)-1}{\varepsilon(C,\theta)}\right)\left[\sum_{l\in\mathbb{N}} T_l(C,\theta)[p_l{}^{\alpha(\theta)}\exp(\kappa(\theta)\tau_{nl})]^{-\varepsilon(C,\theta)}\right]^{\alpha(\theta)/\varepsilon(C,\theta)} \tag{8}$$

where $\Gamma(.)$ is the Gamma function. Intuitively, in locations with better *access to consumption* $\mathbb{C}_n(\theta)$, or access to locations with low prices and high consumption amenities by type, workers are better off.

4.1.3 Residences are Driven by Employment and Consumption Access Net of Rents

In the first stage, individuals choose where to live to maximize their expected indirect utility after observing their idiosyncratic residential amenity draws across all neighborhoods. Workers of type θ solve the following problem:

$$\max_{n\in\mathbb{N}} U_n(\omega;\theta) = \max_{n\in\mathbb{N}} \mathbb{B}_n(\omega;\theta)\mathbb{W}_n(\theta)\mathbb{C}_n(\theta) = \max_{n\in\mathbb{N}} B_n(\theta)b_n(\omega;\theta)Q_n{}^{-\gamma(\theta)}\mathbb{W}_n(\theta)\mathbb{C}_n(\theta). \tag{9}$$

Workers are attracted to locations with high (endogenous) residential amenities of their type $B_n(\theta)$, high idiosyncratic residential amenities $b_n(\omega;\theta)$, low housing prices Q_n, high net incomes $\mathbb{W}_n(\theta)$, and high utility from consumption of non-tradables $\mathbb{C}_n(\theta)$.

Since idiosyncratic residence amenity draws are Fréchet distributed, the share of type-θ workers who live in neighborhood n is

$$\lambda_n(R,\theta) = \frac{B_n(\theta)[Q_n^{-\gamma(\theta)}\mathbb{W}_n(\theta)\mathbb{C}_n(\theta)]^{\varepsilon(R,\theta)}}{\sum_{n'\in\mathbb{N}} B_{n'}(\theta)[Q_{n'}^{-\gamma(\theta)}\mathbb{W}_{n'}(\theta)\mathbb{C}_{n'}(\theta)]^{\varepsilon(R,\theta)}} \tag{10}$$

Similar residential amenities across neighborhoods (high ε) imply that choices are more sensitive to changes in access to employment, access to consumption, and rents. Differences in preferences across neighborhoods by type drive differences in residential patterns in the city across worker groups.

4.1.4 Expected Utility

Since we consider a "closed city", expected utility from living in the city prior to drawing the vector of idiosyncratic preferences is directly related to the denominator in Equation (10) through

$$\bar{U}(\theta) = \Gamma\left(\frac{\varepsilon(R,\theta)-1}{\varepsilon(R,\theta)}\right)\left[\sum_{n\in\mathbb{N}} B_n(\theta)[Q_n^{-\gamma(\theta)}\mathbb{W}_n(\theta)\mathbb{C}_n(\theta)]^{\varepsilon(R,\theta)}\right]^{1/\varepsilon(R,\theta)}. \tag{11}$$

4.2 Firms in Tradable and Non-Tradable Sectors Maximize Profits

4.2.1 Production Locates Where Floor Space and Labor Are Relatively Cheap

In each location $i \in \mathbb{N}$, firms operate in both non-tradable and tradable sectors, $j \in \{0,1\}$. Sectoral productivity differs across locations. Firms produce under perfect competition and with a constant returns to scale technology. We specify firm production as being a Cobb-Douglas aggregate over labor and commercial floor space. Output is thus

$$Y_i^j = A_i^j (L_i^j)^{\beta^j} (H_i^j)^{1-\beta^j} \tag{12}$$

where $\beta^j \in [0,1]$ and H_i^j is commercial floor space. Labor input L_i^j is a Cobb-Douglas aggregate over each worker group's effective units of labor, $\tilde{N}_i^j(\theta)$:

$$L_i^j = \tilde{N}_i^j(+)^{\beta^j(+)} \tilde{N}_i^j(-)^{1-\beta^j(+)} \tag{13}$$

where $\beta^j(+) \in [0,1]$ represents the intensity with which sector j uses high-type workers.[35] Each sector and neighborhood also has different productivities A_i^j.

In location i and sector j, let p_i^j be the price of the good and W_i^j the cost of labor.[36] We write

[35] The tradable sector relies on high-income workers, while the non-tradable sector depends on low-income workers. Thus, the spatial distribution of non-tradable versus tradable production relates strongly to that of low-income versus high-income jobs. Hence, different worker types living in the same neighborhood may have different levels of employment access.

[36] Because the traded good is numeraire, where no confusion exists, we write p_i for the price of the non-traded good. See Online Appendix C.1 for derivations.

the demand for labor, in quantities and in efficiency units, as well as that for commercial floor space. Solving the firm's profit maximization problem, we find

$$L_i^j = \beta^j p_i^j Y_i^j / W_i^j \tag{14}$$

$$\tilde{N}_i^j(\theta) = \beta^j(\theta) L_i^j W_i^j / w_i^{(j)}(\theta) \tag{15}$$

$$H_i^j = (1-\beta^j) p_i^j Y_i^j / q_i, \tag{16}$$

where q_i is the price of commercial floor space in location i.

4.3 Floor Space Is Produced Using Land and Imported Construction Materials

Following Combes, Duranton, and Gobillon (2019) and Epple, Gordon, and Sieg (2010), floor space is supplied by perfectly competitive developers; these developers are absentee landlords to whom land rents accrue.[37] Land supply M_i in each location i is taken as exogenous. Floor space is produced using land M_i and construction materials K_i, using a constant returns to scale technology:

$$\mathbb{H}_i = K_i^{\varphi} M_i^{1-\varphi} \tag{17}$$

where $\mathbb{H}_i$ is total floor space and φ is the share of land in floor space production. As Singapore is a small, open economy that imports its construction materials, we assume these materials K_i are supplied perfectly elastically. Cost minimization implies that

$$Q_i = P^{(K)} M_i^{\frac{\varphi-1}{\varphi}} \mathbb{H}_i^{\frac{1-\varphi}{\varphi}} \varphi^{-1}, \tag{18}$$

where $P^{(K)}$ is the common price for construction materials across all neighborhoods.[38] As the production of non-tradable goods and the demand for floor space rise in response to increased

[37]Singapore's housing subsidies are broad-based and over 80% of the population is eligible. These subsidies are standardized across the country.

[38]For derivations, see Online Appendix C.3. We do not solve for the price for construction materials $P^{(K)}$ in the initial equilibrium because our counterfactual analysis uses exact-hat algebra. This price $P^{(K)}$ remains unchanged before and after the opening of DTL2.

consumption travel, increased rents may drive out tradable production and residents, shifting commercial and residential spatial patterns across the city.[39]

Following Ahlfeldt et al. (2015), after factoring in the tax equivalent of land use regulations, the land market equilibrium requires no arbitrage between the commercial and residential use of floor space. The commercial price of floor space for both the tradable and non-tradable sector is $q_i = \xi_i Q_i$, where ξ_i equals one plus the tax equivalent of land use regulations that restrict commercial land use relative to residential land use. We allow this wedge between commercial and residential floor prices to vary across neighborhoods.

4.4 Markets Clear in Land, Labor, and Non-Tradables

Land. Summing over housing expenditures for all residents, the expression for demand for residential floor space in neighborhood n is

$$H_n(R) = Q_n^{-1} \sum_{\theta \in \{+,-\}} \gamma(\theta) R(\theta) \lambda_n(R,\theta) \mathbb{W}_n(\theta) \tag{19}$$

Market clearing for floor space requires that the total supply of floor space equals the total floor space demanded from both residents and firms in each neighborhood i:

$$\mathbb{H}_i = H_i(R) + \sum_{j \in \{0,1\}} H_i^j. \tag{20}$$

Labor. Using the commuting probabilities from Equation (4), the supply of workers to any location is the sum over the number of commuters by origin that travel to that work location:

$$N_i^j(\theta) = \sum_{n \in \mathbb{N}} \lambda_{ni}^j(L,\theta) \lambda_n(R,\theta) R(\theta) \tag{21}$$

Labor supply in the model takes a log-linear form that depends on two forces. Firstly, more workers commute to destinations paying higher wages. Second, firms attract workers when they have better access to them through the commuting network. Ultimately, workers care about wages net of

[39]Assuming a perfectly price inelastic supply yields similar qualitative results (Section 6.2.1).

commute costs. Meanwhile, total effective labor supply to location i and sector j is given by

$$\tilde{N}_i^j(\theta) = \sum_{n \in \mathbb{N}} \bar{a}_{ni}^j(\theta)\lambda_{ni}^j(L,\theta)\lambda_n(R,\theta)R(\theta) \tag{22}$$

where $\bar{a}_{ni}^j(\theta)$ is the average productivity of type-θ workers who live in n and decide to work in i.[40]

In each neighborhood i and sector j, market clearing requires that the supply of effective labor, as in Equation (22), equals the demand for effective labor, as in Equation (14). Wages by worker type are endogenously determined by market clearing.

Non-tradables. In each neighborhood l, total receipts for non-tradables must equal total expenditures on non-tradables:

$$p_l A_l^{(0)} \left(L_l^{(0)}\right)^{\beta^{(0)}} \left(H_l^{(0)}\right)^{1-\beta^{(0)}} = \sum_{n \in \mathbb{N}} \sum_{\theta \in \{+,-\}} \alpha(\theta)\lambda_{nl}(C,\theta)\lambda_n(R,\theta)R(\theta)\mathbb{W}_n(\theta). \tag{23}$$

Prices of non-tradables are endogenously determined to clear the market. We sum over expenditures of non-tradables for all the workers who travel from some neighborhood n to consume in neighborhood l across worker groups.

4.5 Externalities

4.5.1 Productivities Depend on Employment Density

A location's productivity depends on both an exogenous component $\bar{A}_i^j$ that reflects features independent of economic activity (e.g. access to roads, slope of land) as well as the endogenous density of employment in that location:

$$A_i^j = \bar{A}_i^j \left[M_i^{-1}(N_i(+)+N_i(-))\right]^{\mu(A)}, \tag{24}$$

where M_i is the total amount of land in location i. The strength of agglomeration externalities is governed by the parameter $\mu(A)$.[41]

[40] Average productivity $\bar{a}_{ni}^j(\theta)$ follows from the Fréchet distribution of idiosyncratic worker productivities. See Online Appendix Section C.2.

[41] We permit spillovers in productivity by sector but disallow them from being type-specific. We collapse productivity spillovers by type for parsimony. Absent spillovers of any kind, our model

4.5.2 Amenities Depend on the Composition of Residents

Amenities in a neighborhood are a function of an exogenous component $\bar{B}_n(\theta)$ and a residential externality. This externality depends on the ratio of high-skilled to low-skilled residents:

$$B_n(\theta) = \bar{B}_n(\theta) \left(\frac{R_n(\theta)}{R_n(\text{not } \theta)} \right)^{\mu(U,\theta)} \tag{25}$$

In our model, instead of being a function of the total density of residents, endogenous amenities depend on the demographic composition of workers across income groups, similar to Tsivanidis (2019).[42] Workers are more willing to pay to live in neighborhoods that are high in amenities of their type. As workers locate in these neighborhoods, they increase these type-specific endogenous amenities even more, strengthening segregation.

4.6 Equilibrium

We now define the general equilibrium of our model.

Definition Given vectors of exogenous location characteristics $\{\bar{B}_n(\theta), \bar{A}_i^j, \tau_{ni}, \bar{H}_i, \psi_i, \xi_i\}$, city group-wise populations $R(\theta)$, and model parameters

$$\{\alpha, \beta, \gamma, \kappa(\theta), T_n(R,\theta), T_i(\theta), T^j(\theta), T_l(C,\theta), \varepsilon(R,\theta), \varepsilon(L,\theta), \varepsilon(C,\theta), \varphi, \mu(A), \mu(U,\theta)\},$$

an *equilibrium* is a vector of endogenous objects

$$\{q_i, w_i^j(\theta), H_i^j, \tilde{N}_i^j(\theta), \lambda_n(R,\theta), \lambda_{ni}^j(L,\theta), \lambda_{nl}(C,\theta), \bar{U}(\theta)\}$$

such that:

generates qualitatively similar counterfactual predictions. See Table 2. Type-specific productivity spillovers would lead workers of the same (income, sector) to concentrate in neighborhoods in which they are already abundant.

[42]In contrast to the United States (e.g., Guerrieri, Hartley, and Hurst 2013), in Singapore, residents prefer to live in neighborhoods with others of similar socioeconomic status. See Online Appendix C.4.

1. **Labor Market Clearing**: The supply of labor by individuals in Equation (22) is consistent with demand for labor by firms in Equation (14).

2. **Floor Space Market Clearing**: The market for floor space clears as in Equation (20), its price is consistent with residential populations (19) and commercial floor space use (16), and total floor space is consistent with land developer optimality (18).

3. **Goods Market Clearing**: Non-tradable consumption matches non-tradable production in each neighborhood, as in Equation (23).

4. **Closed City**: Populations add up to the city total.

We discuss equilibrium existence and uniqueness. In a version of the model without externalities, by similar arguments to those made in Ahlfeldt et al. (2015), the model's congestion forces — commuting costs, travel costs to consume non-traded goods, and an inelastic land supply — ensure that a unique equilibrium exists. In the full version of the model, by adapting arguments in Section 3.1 of Allen, Arkolakis, and Li (2022), uniqueness can be guaranteed when "agglomeration forces are small relative to congestion forces."[43]

4.7 Model Discussion

First of all, our model captures the direct distributional implications of changing access to consumption, in addition to changing employment access. Transit improvements affect how easily different worker types access consumption opportunities, and these effects also depend on where they live, work and consume. Suppose travel costs fell between low-income neighborhoods and locations in which non-tradable goods are high in quality (net of price). Then low-income workers would become better off. Access to consumption is more important to welfare for worker types with 1) larger expenditures on non-tradables, 2) larger dispersion of preferences over consumption locations (more inelastic demand), and 3) higher travel costs.

Next, consumption travel shapes the (type-specific) residential patterns of the city. Workers

[43] See Appendix Subsection C.5 for details.

trade off access to non-tradables against access to employment and higher rents when choosing where to live. Worker types with less dispersion in residential amenities can take advantage of both improved access to consumption and employment in other locations. Relative to Miyauchi, Nakajima, and S. Redding (2022), our specification of consumption travel preserves tractability while still permitting differences in how low- and high-income workers behave.

Lastly, incorporating travel to consume non-tradables also has distributional implications for access to employment across worker groups. Responding to changes in transit access, consumers change where they consume non-tradables, trading off travel costs and type-specific amenities and prices. Thus relative factor demand changes across locations. Since firms selling non-tradables hire more low-income workers, low-income jobs move to where residents are traveling more for consumption. High-income jobs in tradables may also move away from locations with greater consumption travel, since commercial rents will rise with greater production of non-tradables. In sum, where jobs move is an empirical question. Since commercial activity between tradable and non-tradable sectors reorganizes across space, each worker group faces differential changes in expected access to employment or expected income net of commuting. Hence, it is an empirical question whether inequality rises or falls.[44]

5 Estimation

This section estimates the model from Section 4. First, using gravity specifications from the model, we estimate workplace and consumption preferences and access across neighborhoods and worker groups. Second, we estimate type-specific work and consumption travel costs, as well as parameters governing the dispersion of idiosyncratic workplace productivities and consumption amenities. Third, we estimate parameters governing the dispersion of idiosyncratic residential amenities and residential spillovers by type. Fourth, we recover residential amenities across neighborhoods and across worker types. Finally, we calibrate the remaining parameters.[45]

[44]These reallocative predictions can be directly tested with data on exogenous shocks to demand for non-tradable goods.

[45]For model inversion, see Online Appendix D.

5.1 Estimating Workplace and Consumption Preferences and Access

First, we estimate workplace and consumption preferences and access using data from before the DTL opened. For each worker type $\theta \in \{+,-\}$, we combine the workplace travel flow Equation (4) with our specification of travel costs, $\phi(L,\theta) = \varepsilon(L,\theta)\kappa(\theta)$; as well as the consumption travel flow Equation (7) with our specification of travel costs $\phi(C,\theta) = \varepsilon(C,\theta)\kappa(\theta)$. The resulting gravity equations relate the variation in travel flows to the variation in travel times:

$$\ln \lambda_{ni}(L,\theta) = \eta_i(L,\theta) - \mu_n(L,\theta) - \phi(L,\theta)\tau_{ni} + u_{ni}(L,\theta) \tag{26}$$

$$\ln \lambda_{nl}(C,\theta) = \eta_l(C,\theta) - \mu_n(C,\theta) - \phi(C,\theta)\tau_{nl} + u_{nl}(C,\theta). \tag{27}$$

In these equations, the η's and the μ's correspond to destination and origin fixed effects; and the u's are unobserved shifters of travel propensities. We take the τ's as the average time taken to travel between origin and destination neighborhoods in the farecard data, and construct travel shares from identified residences and workplaces/consumption destinations in the farecard data.

We note that travel times τ may be correlated with the unobservable u. Endogeneity in this setting takes two forms. The first relates to the intensity of transit development: the widest roads may be precisely those used by the most commuters. To deal with this source of endogeneity, in our preferred specification, we instrument for τ with the straight-line distance between neighborhood centroids. Table 1 reports the results from the regressions associated with Equations (26) and (27). First, we estimate negative and statistically significant semi-elasticities of both work and consumption travel flows with respect to travel time. The commuting semi-elasticities are $\hat{\phi}(L,+) = -0.051$ for high-income workers and $\hat{\phi}(L,-) = -0.070$ for low-income workers; while the consumption travel semi-elasticities are $\hat{\phi}(C,+) = -0.053$ and $\hat{\phi}(C,-) = -0.094$ respectively. We note that the gravity coefficients for low-income workers are larger in magnitude than those for high-income workers ($p < 0.01$), indicating that low-income workers are more sensitive to changes in travel time. Comparing our estimates for work trips to those of consumption trips, we find smaller gravity coefficients for work travel than consumption travel across both groups.

The second source of endogeneity is from possible sorting and complementarities across (origin, destination) pairs (see, e.g., Dingel and Tintelnot 2020 and Severen 2023). To assess robustness of our preferred specification to such complementarities, we also estimate Equations (26) and (27) using a difference-in-differences framework:

$$\Delta \ln \lambda_{ni}(L,\theta) = \Delta \eta_i(L,\theta) - \Delta \mu_n(L,\theta) - \phi(L,\theta)\Delta\tau_{ni} + \Delta u_{ni}(L,\theta); \tag{28}$$

$$\Delta \ln \lambda_{nl}(C,\theta) = \Delta \eta_l(C,\theta) - \Delta \mu_n(C,\theta) - \phi(C,\theta)\Delta\tau_{nl} + \Delta u_{nl}(C,\theta), \tag{29}$$

where the differences are across trips taken before and after the line opening. Identification of ϕ then requires $\mathbb{E}[\Delta\tau_{ni} \times \Delta u_{ni}(L,\theta)] = 0$ and $\mathbb{E}[\Delta\tau_{nl} \times \Delta u_{nl}(C,\theta)] = 0$, i.e., that sorting patterns and flow correlations across distance are stable.

Instead of pooling across time, this difference-in-differences method enables us to leverage two "intermediate" control groups of origin-destination *pairs*, where one of the two "ends" is treated and the other is not. Consider workers living in Bishan, an origin neighborhood not sited on top of a DTL2 station. Workers consuming non-tradable goods in Beauty World (who benefit from DTL2) are compared with those who visit Orchard (who do not). Similarly, consider Orchard, a major shopping belt not served directly by DTL2. Shoppers who live in Bishan (not on DTL2) are compared with those who live in Bukit Panjang (a terminus of DTL2). These comparisons "control for many potential unobserved motives for changing travel behavior" (Severen 2023).[46]

In Table A6, we display the results from the regression associated with Equations (28) and (29). We find that the semi-elasticities recovered in this alternate procedure are quantitatively similar to those recovered when estimating the first equation (in levels).

Returning to our original specification (in levels), the destination fixed effects η from the first pair of regressions give us measures of workplace (resp. consumption) attractiveness across neigh-

[46]The exclusion restriction would be violated if, for instance, after DTL2 opened, shops in all neighborhoods served by DTL2 systematically favored demographic groups prevalent in the far west of Singapore (hence closer to DTL2 neighborhoods) relative to those in the east. Such a violation seems implausible because Singapore is highly racially and socioeconomically integrated.

borhoods:

$$\exp(\hat{\eta}_i(L,\theta)) = \sum_{j\in\{0,1\}} T_i(\theta)T^j(\theta)w_i^j(\theta)^{\varepsilon(L,\theta)};$$
$$\exp(\hat{\eta}_l(C,\theta)) = T_l(C,\theta)p_l^{-\alpha(\theta)\times\varepsilon(C,\theta)},$$

which captures average workplace (resp. consumption) amenities by type, as well as the type-specific averages, across sectors, of productivity and wages (resp. prices of non-tradables) in each destination neighborhood. These destination fixed effects differ starkly by income type. In Figures A17a and A17b, we display scatter plots of workplace and consumption preferences by high- and low-income workers. We observe substantial differences in where low and high income groups prefer to work and consume non-tradables.[47]

The residence fixed effect terms μ_n from the above regressions can be written

$$\exp(\hat{\mu}_n(L,\theta)) = \sum_{i\in\mathbb{N}}\sum_{j\in\{0,1\}} T_i(\theta)T^j(\theta)w_i^j(\theta)^{\varepsilon(L,\theta)}\exp(-\varepsilon(L,\theta)\times\kappa(\theta)\times\tau_{ni});$$
$$\exp(\hat{\mu}_n(C,\theta)) = \sum_{l\in\mathbb{N}} T_l(C,\theta)p_l^{-\alpha(\theta)\times\varepsilon(C,\theta)}\exp(-\varepsilon(C,\theta)\times\kappa(\theta)\times\tau_{nl})$$

which, for fixed shock parameters ε and an origin neighborhood n, allows us to recover our measures of employment access, $\mathbb{W}_n(\theta)$, and consumption access, $\mathbb{S}_n(\theta)$, across neighborhoods. The employment measure captures the expected wages net of commuting across neighborhoods i and sectors j, while the consumption measure reflects the expected utility from non-tradable consump-

[47] As a test of model fit, in Table A9, for each income group, we display regression coefficients of consumption attractiveness against various external measures of retail amenities. We find that our attractiveness measure is positively correlated with the density of food establishments, supermarkets and clinics in a neighborhood. Interestingly, we find that low-income workers prefer locations where low-cost options make up a larger share of food establishments, such as hawker stalls and food courts, while the corresponding coefficient is insignificant at the 5% level for high-income workers. This last finding corroborates our descriptive evidence that the rich and poor consume different non-tradable goods.

tion across destination neighborhoods l.

5.2 Estimating Travel Elasticities and Costs

5.2.1 Dispersion of Workplace Idiosyncratic Productivity

Taking logs of the expression for expected income by worker type in Equation (5), we can estimate the workplace dispersion parameter, $\varepsilon(L,\theta)$, by regressing the estimated residence fixed effects, $\hat{\mu}_n(L,\theta)$, on the log of average residential income from observed administrative data by type. The parameter $\varepsilon(L,\theta)$ is thus identified off variation across neighborhoods in income and the estimated measure of residence attractiveness.[48]

$$\hat{\mu}_n(L,\theta) = \varepsilon(L,\theta)\ln(\text{Residential Income}_n) + e_n \tag{30}$$

The residual e_n accounts for estimation error in the residence fixed effects and any departures from model assumptions.

Appendix Table A8 presents our estimation results. We find a strong positive correlation between our model's estimate of expected income with that of non-targeted data. We show in Figure A18, similar to what Miyauchi, Nakajima, and S. Redding (2022) find, that residence fixed effects are generally log-linear in residential income. However, there are outliers in a few high-income neighborhoods, reflecting non-labor income at high income levels. In our preferred specification, we drop the four richest neighborhoods, estimating a workplace idiosyncratic dispersion of $\hat{\varepsilon}(L,+) = 2.912$ for high-income workers and $\hat{\varepsilon}(L,-) = 5.023$ for low-income workers respectively. Consistent with findings in Tsivanidis (2019), our point estimates suggest that high-income workers may have more inelastic work travel patterns than low-income workers.[49] Therefore, high-

[48]Since we have rich transit data, had we a panel of wages across neighborhoods, we would estimate a differenced version of Equation (30). Then, identification only requires stability of sorting patterns across neighborhoods. Unfortunately our wage data are from 2010 and 2015, with the former being before our sample period.

[49]In robustness exercises considered in Section 6.3, we consider how our inequality predictions change if both income groups had (1) the same travel costs; or (2) the same travel elasticities; or

income workers may benefit more from reductions in travel costs, being less able to substitute to more attractive work locations in equilibrium.

5.2.2 Dispersion of Idiosyncratic Consumption Amenities

Next, we can compute the consumption travel dispersion parameter by worker type, $\varepsilon(C,\theta)$, using the estimated semi-elasticities for consumption and work travel, $\phi(C,\theta)$ and $\phi(L,\theta)$: $\hat{\varepsilon}(C,\theta) = \hat{\varepsilon}(L,\theta)\hat{\phi}(C,\theta)/\hat{\phi}(L,\theta)$. We find a idiosyncratic consumption dispersion of $\hat{\varepsilon}(C,-) = 3.00$ for high-income workers and $\hat{\varepsilon}(C,-) = 5.81$ for low-income workers. See Appendix Table A10 for the estimated parameters. As in the previous section, our point estimates suggest that high-income workers have more inelastic consumption travel patterns than low-income workers. Thus, high-income workers could benefit more from reductions in travel costs as they are less able to substitute to more attractive consumption locations in equilibrium. Idiosyncratic dispersion in consumption appears slightly larger for consumption trips than workplace trips.

5.2.3 Travel Costs

Finally, we can back out the travel cost parameter by worker type: $\hat{\kappa}(\theta) = \hat{\phi}(C,\theta)/\hat{\varepsilon}(C,\theta)$. We estimate a travel cost parameter of $\hat{\kappa}(+) = 0.018$ for high-income workers and $\hat{\kappa}(-) = 0.014$ for low-income workers, as displayed in Appendix Table A10. Our point estimates suggest that low-income workers have slightly lower travel costs, with the wedge between travel costs consistent with the 25% subsidy low-income workers receive on transit fares.[50]

5.3 Estimating Residential Externalities and Dispersion of Amenities

To estimate spillovers in amenities and production, we exploit the fact that changes in market access induced by the Downtown Line result in a shock to the supply of labor and resident locations

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(3) the same residential elasticities. We find similar qualitative results.

More data can confirm a difference in workplace idiosyncratic dispersion between high- and low-income workers. For instance, one could link income *by worker* to their choice of residence and workplace using administrative data from, e.g., the Central Provident Fund of Singapore.

[50]The ratio of travel costs between low- and high-income workers is $0.014/0.018 = 0.778$.

across the city. To operationalize this fact, we estimate the model in 2015 and 2018 before and after the opening of the DTL.[51] By log-linearizing Equation (10) and substituting in Equation (25), we estimate $\mu(U,\theta)$ and $\varepsilon(R,\theta)$ with the following equation:

$$\begin{aligned}\Delta\ln\lambda_n(R,\theta) = \varepsilon(R,\theta)\Delta\ln Q_n^{-\gamma(\theta)}\mathbb{W}_n(\theta)\mathbb{C}_n(\theta) + \\ \varepsilon(R,\theta)\mu(U,\theta)\Delta\ln\left[\frac{R_n(\theta)}{R_n(\text{not }\theta)}\right] + \Delta\ln e_n(\theta),\end{aligned} \tag{31}$$

where Δ indicates the difference in estimated model unobservables (or data) before and after the line opening. Identification of $\varepsilon(R,\theta)$ and $\mu(U,\theta)$ requires that changes in local rents and access are orthogonal to changes in latent residential amenities, controlling for residential composition.[52]

We present the estimates from Equation (31) in Appendix Table A11. Our point estimates suggest that the dispersion of idiosyncratic residential amenities is slightly larger for high types at $\varepsilon(R,+) = 1.48$ than that of low types at $\varepsilon(R,-) = 1.38$. High-income workers may be better able to take advantage of improvements in access across neighborhoods by shifting where they live.[53] We find stronger externalities for low types ($\mu(U,-) = 0.45$) than high types ($\mu(U,+) = 0.22$), consistent with the findings from Tsivanidis (2019). This finding implies that there are stronger spillovers in endogenous amenities for low-income workers, and hence a stronger force towards clustering in the same neighborhoods.

[51]We use housing prices from 2008, just before the precise station locations on the DTL were announced. In our descriptive analysis (Subsection 3.2), we showed that price appreciation, between control apartments and treated apartments near the planned line, diverged after 2008, but not before. Prices from 2015 would have "priced in" much of the improved accessibility from DTL2.

[52]While our identification assumption is strong, our main results do not hinge on the dispersion of spillovers in amenities and production. In Table 2, we report our counterfactual estimates in a model without spillovers, finding no qualitative difference compared to our preferred specification.

[53]As with workplace productivity, better income data can confirm this difference.

5.4 Estimating Residential Amenities

Next, we recover composite residential amenities $B_n(\theta)$ using known parameters, observed land prices and travel shares, and estimated measures of work and consumption access:

$$B_n(\theta) = \frac{Q_n^{\gamma} \lambda_n(R,\theta)^{1/\varepsilon(R,\theta)} \bar{U}(\theta)}{\mathbb{W}_n(\theta)\mathbb{C}_n(\theta)} \times \Gamma\left(\frac{\varepsilon(R,\theta)-1}{\varepsilon(R,\theta)}\right)^{-1} \tag{32}$$

In Table A12, we show that composite residential amenities are highly correlated with external data on amenities — specifically schools, community clubs, and parks. Both high- and low-income residents care about community clubs, schools, and parks.

5.5 Calibrated Parameters

Calibrated values are reported in Table A13 in the Online Appendix. The consumption shares, (α,γ), for low- and high-income groups (below and above the 20th percentile) are calibrated to match line-itemized expenditures data from the 2018 Singapore Household Expenditure Survey.[54] These expenditures data are available by income bracket. The overall labor share by sector, β^j, is matched to estimates from the 2013 Economic Survey of Singapore. Labor shares by type, $\beta^j(\theta)$, are calibrated to the average share of the wage bill paid to low- and high-income workers in Singapore by sector using the 2018 Singapore Labor Force Survey. We assume a share of land in construction costs of $\varphi = 0.25$ following Epple, Gordon, and Sieg (2010), Combes, Duranton, and Gobillon (2019) and Ahlfeldt et al. (2015). We consider production agglomeration parameters consistent with Rosenthal and Strange (2004), Melo et al. (2009), and Ahlfeldt et al. (2015).

[54] See Table A3 for a detailed breakdown of expenditures on non-tradable goods and services by worker group. We only include expenditures on goods and services tied closely to urban public transit trips. For goods, we restrict to expenditures on retail products, using data from a 2017 PricewaterhouseCoopers survey of consumer preferences for in-store shopping by product. Our non-tradable goods are those preferred by over 50% of respondents to be purchased in person.

6 Counterfactuals

In this section, we evaluate the impact of the Downtown Line on inequality and welfare.[55] First, we outline our exact-hat approach. Second, we present our main results. Finally, we assess robustness via a model decomposition.

6.1 Exact-Hat Algebra

We undertake counterfactuals with an exact-hat approach (Dekle, Eaton, and Kortum 2008). Rather than estimating our model in terms of levels, we specify the model in terms of changes from the current equilibrium, thereby finessing having to assemble proxies for various unobservables in our model.[56] We let $\hat{x} = x'/x$ denote the relative change in the equilibrium endogenous variable x, where x' is the value of x in the new equilibrium. We consider an exogenous change in travel times $\Delta\tau_{ni} = \tau'_{ni} - \tau_{ni}$. Given model parameters $\{\alpha, \beta, \gamma, \kappa(\theta), \varepsilon(R,\theta), \varepsilon(L,\theta), \varepsilon(C,\theta), \varphi, \mu(A), \mu(U,\theta)\}$, assumed bilateral changes in travel times, $\{\exp(\Delta\tau_{ni})\}$, and endogenous variables in the initial equilibrium $\{\lambda_{nl}(C,\theta), \lambda^j_{ni}(L,\theta), \lambda_n(R,\theta), H^j_i, H_n(R), \mathbb{W}\}$, we solve the system of "hat equations"[57] starting with an initial guess in each endogenous variable such that $\hat{x} = 1$, updating our guess till the algorithm has converged to an equilibrium. With the counterfactual changes in endogenous variables $\{\hat{B}_n(\theta), \hat{\mathbb{C}}_n(\theta), \hat{\mathbb{W}}_n(\theta), \hat{Q}_n\}$, the change in expected utility by type is:

$$\hat{U}(\theta) = \left(\sum_{n\in\mathbb{N}} \lambda_n(R,\theta) \hat{B}_n(\theta) \left(\hat{Q}_n^{-\gamma(\theta)} \hat{\mathbb{W}}_n(\theta) \hat{\mathbb{C}}_n(\theta) \right)^{\varepsilon(R,\theta)} \right)^{1/\varepsilon(R,\theta)} \tag{33}$$

We estimate the initial equilibrium using data from 2015, then use changes in travel times as observed in the fare card data from before the opening of DTL2 in 2015 to after the opening of

[55] For data availability reasons, we focus on Phase 2 and 3 of the line. These two phases comprise 80% of the line and connect the outer neighborhoods of the city to downtown.

[56] These unobservables include the prices of non-tradable goods, neighborhood-sector wages per efficiency unit by type, mean idiosyncratic draws, and so on.

[57] Equations are available in Online Appendix E.

Phase 3 in 2018. Figure A6 presents the distribution of the changes in travel time.[58]

6.2 Welfare and Inequality

6.2.1 Main Results

In the top panel of Table 2, column 1 presents the effect of the Downtown line on welfare. This effect is broken down by access to employment and consumption by high- and low-income types respectively. We find that the DTL improves welfare, $\bar{U}(\theta)$, for high income workers, but not for low-income workers. Welfare increases by 1.8% for high-income workers, while welfare for low-income workers remains stagnant at a 0.1% increase. Although consumption access increases for both groups, non-tradable production and low-income jobs move to less attractive locations. Access to consumption, $\mathbb{C}$, improves for both workers, with high income workers benefiting by 1.4%, higher than low-income workers at 1.0%. However, while access to employment (expected wages net of commuting costs), $\mathbb{W}$, increases for high-income workers by 1.11%, low-income workers experience a 1.13% decline. Overall, high income workers experience a 1.7 p.p. larger increase in welfare compared to low income workers.[59]

There are two main mechanisms driving our results. First, the DTL disproportionately improves access to residents of many high-income areas. Figure 1a shows that the Downtown Line directly serves the many high income areas in a cluster just west of the city center. This partially explains the larger improvements in both access to consumption and employment experienced by high-income workers relative to low-income workers. Second, in response to the DTL, a greater number of consumers travel to consume non-tradables near the center of the city. These consumers benefit from improved access to downtown via the new line. Figure 1b plots the model predictions

[58]In Online Appendix F.1, we show our model predicts well post-DTL changes in 2018.

[59]Our results are qualitatively similar if housing supply were assumed perfectly price inelastic; see Table A15. The main results are also robust to the absence of spillovers (see Table 2) and the "covariates-based approach" of Dingel and Tintelnot (2020). Our results are also similar (see Table A17) if we (1) incorporate roundabout production (Caliendo and Parro 2015); or if (2) the DTL only reduces consumption travel time but not commute times. See Online Appendix F for details.

for changes in consumption trips across neighborhoods. We see a large increase in consumption trips made to the center of the city. As a result, non-tradable jobs, disproportionately low-income, move to the center of the city; meanwhile, low-income workers live far away from the center, as seen in Figure 1a. Indeed, average commute times increased 0.9% for low-income workers, while high income workers saw a 0.5% reduction.[60]

6.2.2 Results with Only Work Travel

We see much larger inequality effects by including travel to consume non-tradables. To see how our results change when consumption travel is not accounted for, we set the shares of non-tradable consumption for both worker groups to zero, $\alpha(\theta)=0$, $\alpha^{(1)}(\theta)=1-\gamma(\theta)$,[61] and assume that all workers are employed in the tradable sector, $\lambda_{nl}(C,\theta)=0$.[62]

Column 2 of the top panel of Table 2 presents the results from the re-estimated model. We find that the DTL improves welfare, $\bar{U}(\theta)$, for both worker groups. Welfare increases by 1.44% for high-income workers, while welfare increases by 0.84% for low-income workers. Expected income net of commuting, or access to employment, increases by 1.43% for high-income workers and by 0.43% for low-income workers. We do not capture improvements in consumption access. High income workers experience a 0.6 p.p. larger increase in welfare compared to low income workers, a three-fold underestimation relative to our baseline results.

When estimated without consumption trips, the model understates the welfare effects of the DTL because it ignores the fact that workers value access to consumption.[63] Furthermore, the

[60] Consistent with this finding, we estimate an increase in segregation as measured by the dissimilarity index. Our measure of dissimilarity is $\frac{1}{2}\sum_n |R(+)/R(-)-R(+)\lambda_n(R,+)/[R(-)\lambda_n(R,-)]|$.

[61] In this scenario, workers make no consumption trips; no consumption travel data are used.

[62] Workers are employed in the same location as in the baseline. Our setup mirrors most standard quantitative spatial models (e.g., Ahlfeldt et al. 2015; Heblich, S. Redding, and D. Sturm 2020); all consumption is "tradable", no consumption requires travel, and goods can be produced anywhere.

[63] We find similar results for an alternative benchmark: assume all consumption is local to the neighborhood of residence. See Table A17 and Online Appendix F for details.

model also severely underestimates the inequality effects of the line in two key ways. First, the model fails to capture the disproportionate gains in access to consumption for high-income workers. Second, this version of the model misses the re-organization of non-tradable production across the city in response to changes in consumption travel, worsening access to employment for low-income workers.[64]

6.3 Model Decomposition

We conduct a decomposition exercise to assess how robust our inequality findings are to different model assumptions, summarized in Table 3.[65] Relative to the version of our model with no spillovers (Column 1 of the bottom panel of Table 2), the disparate impacts of the DTL remain similar, even if, for low-income workers, their consumption shares (Row 2), travel costs (Row 3), dispersion of idiosyncratic consumption amenities and productivities (Row 4), or idiosyncratic residential amenities (Row 5) are assumed equal to those of high-income workers.

7 Conclusion

This paper demonstrates that consumption trips have important implications for the inequality effects of public transit expansions. We develop an urban spatial model with heterogeneous worker groups, low- and high-income, which incorporates both commuting and travel to consume non-tradable goods and services. We use the model to study the impact of the Downtown Line (DTL) in Singapore. We find that the DTL improves welfare for high income workers by 1.8%. Abstracting away from travel to consume non-tradables results in a three-fold underestimation of the disparate impact of the DTL across worker groups. That is, absent consumption travel, we find that

[64] Additionally, we consider how line placement drives our results. In Online Appendix Section F.2, we simulate removing the North-South Line (NSL), a trunk line primarily serving more diverse neighborhoods. When the NSL is removed, welfare falls for both low and high types, by 4.2% and 2.0% respectively. Low income workers experience a 2.2 p.p. greater loss in welfare compared to high income workers. Both types experience worse consumption and employment access. Thus, line placement matters for how transit expansion affects welfare and equity.

[65] For a longer version of this discussion, see Online Appendix Section F.8.

both worker groups benefit, but a slightly larger share of the gains goes to high-income workers. This underestimation follows because low-income non-tradable sector jobs reorganize in space. Aggregate welfare gains are also underestimated, ignoring gains in access to consumption opportunities for both groups. Our results sound a note of caution to a transit planner: line placement matters. Policymakers should consider the welfare and distributional implications of changes in consumption patterns, in addition to commuting, as they plan their mass transit systems.

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Figures and Tables

Table 1: Gravity Estimation

	Travel Share Conditional on Residence			
	Commuting (High Income)	Commuting (Low Income)	Consumption (High Income)	Consumption (Low Income)
	(1)	(2)	(3)	(4)
Travel Time (Minutes)	-0.051^{***}	-0.070^{***}	-0.053^{***}	-0.094^{***}
	(0.001)	(0.002)	(0.001)	(0.004)
Dest. FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
IV (geog. dist)	Yes	Yes	Yes	Yes
R^2	0.854	0.660	0.792	0.576
Adjusted R^2	0.846	0.643	0.781	0.554

*p<0.1; **p<0.05; ***p<0.01

Notes: This table displays results from estimating Equation (27) *in Columns 1 and 2, and Equation* (26) *in in Columns 3 and 4, for high- and low-income workers respectively. Destination and origin fixed effects are included, as well as an instrument, for mean travel time, of straight-line distance between neighborhood centroids. Each observation is a bilateral share of travel to a destination, conditional on residence, from 2015 fare card data. Mean travel times are computed, averaging across subzone pairs, before DTL2 opened.*

Table 2: Impact of the Downtown Line

Main Estimates	**(1) Full Model**		**(2) Only Commuting**	
% Change in	Low Type	High Type	Low Type	High Type
Welfare, $\bar{U}$	0.12	1.82	0.84	1.44
Access to Consumption, $\mathbb{C}$	1.01	1.39	0	0
Access to Employment, $\mathbb{W}$	-0.86	0.53	0.43	1.43
Gap in Welfare Impact	1.70		0.60	
Segregation	0.98		1.79	

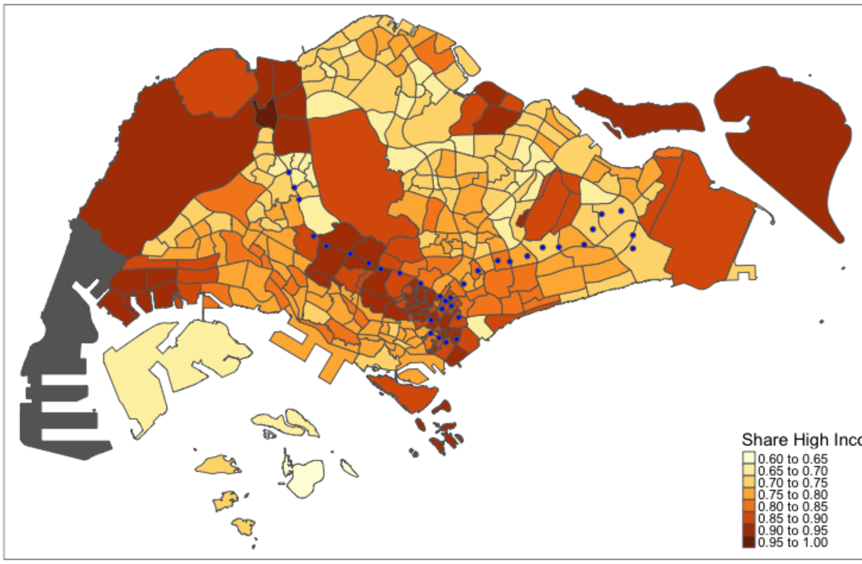
No Spillovers	**(1) Full Model**		**(2) Only Commuting**	
% Change in	Low Type	High Type	Low Type	High Type
Welfare, $\bar{U}$	-0.17	1.69	0.55	1.32
Access to Consumption, $\mathbb{C}$	0.92	1.25	0	0
Access to Employment, $\mathbb{W}$	-1.08	0.51	0.59	1.37
Gap in Welfare Impact	1.86		0.77	
Segregation	0.86		0.59	

Notes: This table displays results from the counterfactual estimation in Section 6. The top panel displays the main estimates while the bottom panel sets agglomeration and residential spillover parameters to zero. Column 1 displays results from the full model. Column 2 shows results abstracting away from consumption trips. Welfare, access to consumption and access to employment are defined by the model in Section 4. Gap in Welfare Impact is the difference in percentage changes in welfare across high- and low-income workers. Segregation is measured by the dissimilarity index.

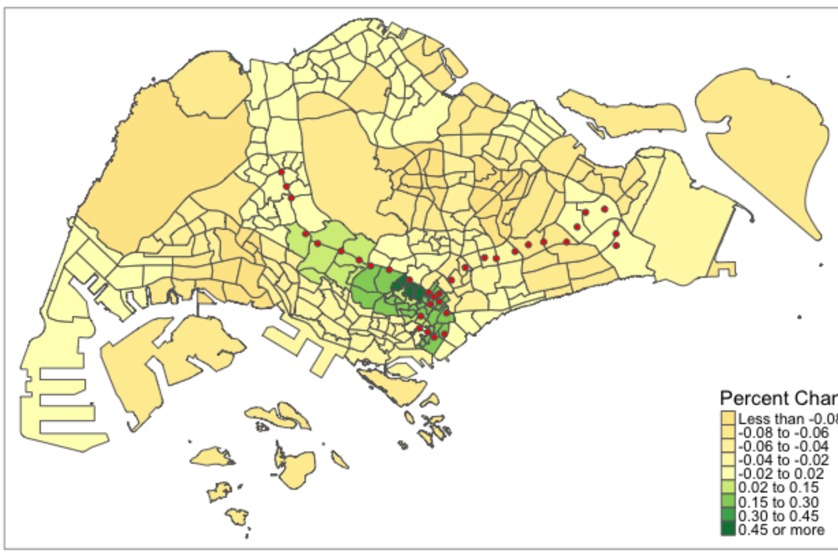
Table 3: Impact of the Downtown Line: Decomposition of Parameters

% Change in	**Gap in Welfare Impact**	**Gap in Consumption Access Impact**	**Gap in Workplace Access Impact**
Baseline	1.86	0.33	1.60
$\alpha(-) = \alpha(+)$ $\gamma(-) = \gamma(+)$	1.90	0.21	1.71
$\kappa(-) = \kappa(+)$	1.57	0.26	1.38
$\varepsilon(L,-) = \varepsilon(L,+)$ $\varepsilon(C,-) = \varepsilon(C,+)$	1.60	0.30	1.32
$\varepsilon(R,-) = \varepsilon(R,+)$	1.74	0.33	1.48

Notes: This table displays model decomposition results from the counterfactual estimation in Section 6, with agglomeration and residential spillovers switched off. In this exercise, various parameters across high- and low-income workers are set to be equal. Row 1 presents the baseline results as in Column 1 of Table 2. Row 2 sets low-income consumption shares to equal high-income consumption shares. Row 3 sets low-income travel costs to equal high-income travel costs. Row 4 sets low-income travel elasticities to equal high-income travel elasticities. Row 5 sets low-income residential elasticities to equal high-income residential elasticities. Welfare, access to consumption and access to employment are defined by the model in Section 4. Gaps in impact are the differences in percentage changes in each quantity (welfare, consumption access, or workplace access) across high- and low-income workers.



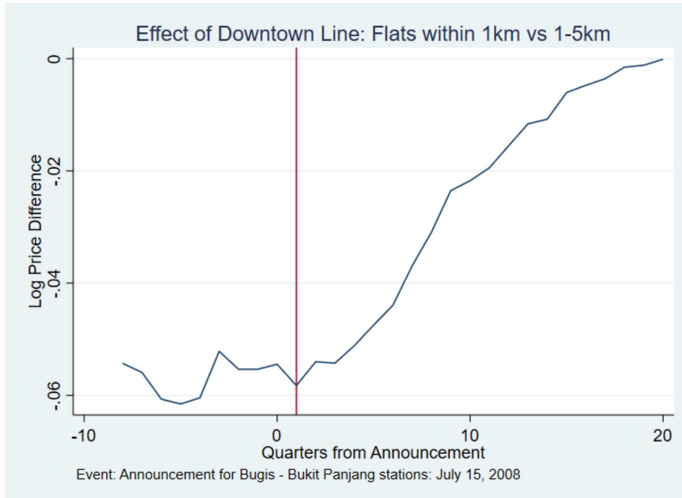
(a) High-Income Residence Shares and the Downtown Line (DTL)



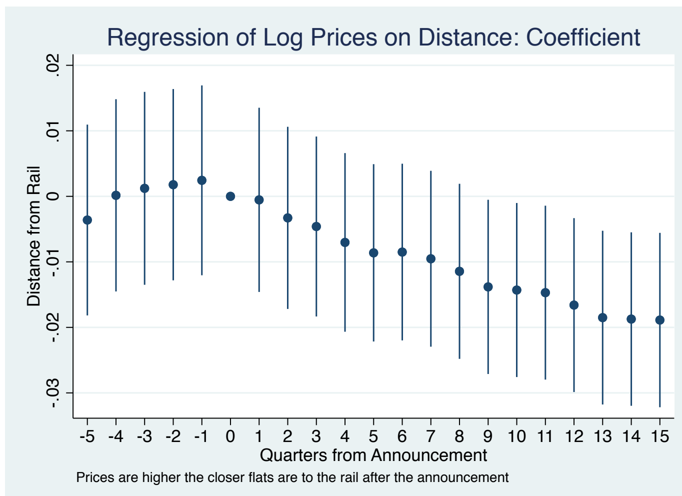
(b) Model Prediction: Change in Consumption Trips

Figure 1: High-Income Residential Population and Changes in Consumption Travel

Notes: The top map plots the relative shares of high-income residents by neighborhood (subzone) in 2015; the bottom shows predicted changes in total consumption trips post-DTL Stage 2 (Section 6). Residences are imputed from modal morning origins and modal evening destinations for each Adult (high-income) and Workfare (low-income) farecard from the Land Transport Authority. Dots represent DTL stations. Tuas (far west-southwest) has a population share below 0.1%.



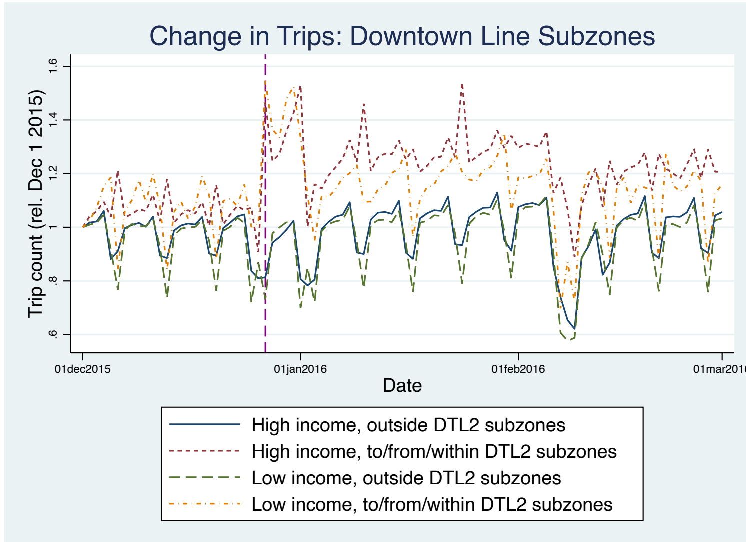
(a) Event Study: Flats Near DTL2 Appreciate More



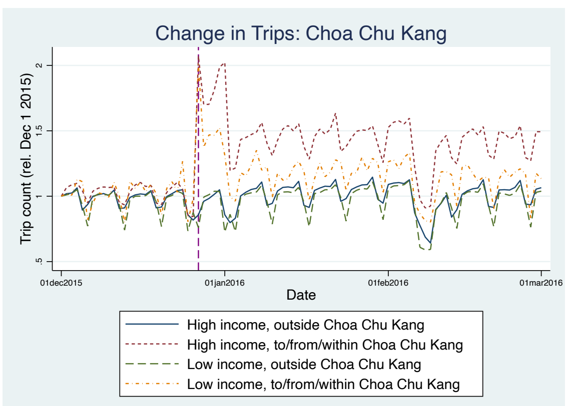
(b) Prices vs. Distance to DTL2, Over Time

Figure 2: Relationship between Prices and Distance to the Downtown Line Over Time

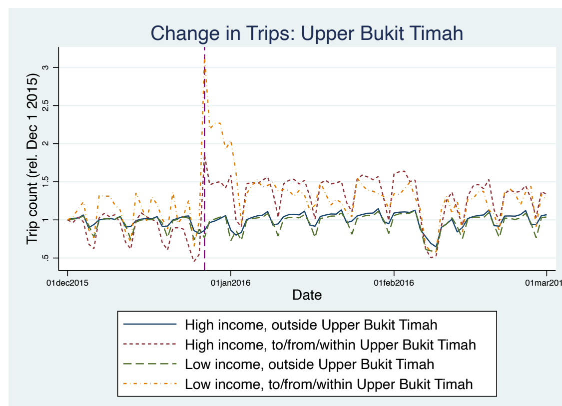
Notes: The top panel plots the quarterly log difference in mean prices, between Housing and Development Board (HDB) flats within 1 km and between 1 and 5 km of a DTL2 station, around the announcement of the alignment of DTL2 on 15 July 2008 (vertical line). The bottom panel plots the relationship, over time, between log apartment prices and the distance (in km) from DTL2. We estimate Equation (35) and plot the coefficients γ from that regression. Flat transactions are grouped by quarter, from 2007 to 2011, relative to the announcement of DTL2 alignment. Our sample comprises the universe of HDB resale transactions within 5km of a DTL2 station.



(a) Impact On Aggregate Travel



(b) Choa Chu Kang



(c) Upper Bukit Timah

Figure 3: Impact of the Downtown Line on Travel by High- and Low-Income Workers

Notes: This figure plots the daily volume of trips, over time, to and from: (a) subzones with and without a station on Stage 2 of the Downtown Line (DTL2); (b) Choa Chu Kang; and (c) Upper Bukit Timah, compared to all other stations, by high- and low-income workers (above and below the 25th percentile). Farecard data span December 2015 to February 2016 and are from the Land Transport Authority of Singapore. The number of trips is normalized with respect to that of December 1 2015.