

Consumption Access and the Spatial Concentration of Economic Activity: Evidence from Smartphone Data*

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Abstract

Using smartphone data for Japan, we show that non-commuting trips are frequent, more localized than commuting trips, strongly related to the availability of nontraded services, and occur along trip chains. Guided by these empirical findings, we develop a quantitative urban model that incorporates travel to work and travel to consume non-traded services. We use the gravity equation predictions of the model to estimate theoretically-consistent measures of travel access. We show that consumption access makes a substantial contribution to the observed variation in residents and land prices and the observed impact of the opening of a new subway line.

Keywords: Cities, Consumption Access, Economic Geography, Transportation
JEL Classification: O18, R12, R40

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1 Introduction

Understanding the spatial concentration of economic activity is one of the most central challenges in economics. Traditional theories of cities emphasize production decisions and the costs of workers commuting between their workplace and residence. However, much of the travel that occurs within urban areas is related not to commuting but rather to the consumption of nontraded services, such as trips to restaurants, coffee shops and bars, shopping centers, cultural venues, and other services. Although several scholars have emphasized the “consumer city,” two major challenges in this area are a limited ability to measure non-commuting trips and the absence of a widely-accepted theoretical model of travel for consumption. In this paper, we provide new theory and evidence on the role of consumption and workplace access in understanding the spatial distribution of economic activity. We combine smartphone data including high-frequency location information with spatially-disaggregated census data to measure commuting and non-commuting trips within the Greater Tokyo metropolitan area. Guided by our empirical findings, we develop a quantitative urban model that incorporates both workplace and consumption access. We use the model to evaluate the role of consumption access in explaining the observed spatial variation in economic activity. We show that incorporating consumption access is quantitatively relevant for evaluating the observed impact of a new subway line.

We first use our smartphone data to provide fine resolution evidence on travel within the Greater Tokyo metropolitan area. Our data come from a major smartphone mapping application in Japan (*Docomo Chizu NAVI*), which records the Geographical Positioning System (GPS) location of each device every 5 minutes. In July of 2019, the data covers about 545,000 users, with 1.4 billion data points. We measure each location visited by a user using a “stay,” which corresponds to no movement within 100 meters for 15 minutes. We designate each anonymized user’s home location as her most frequent location (defined by groups of geographically contiguous stays) and her work location as her second most frequent location. We allocate non-commuting trips to other locations into different types using spatially-disaggregated census data on employment by sector. We validate our smartphone commuting measures by showing that they are highly correlated with the measures from the official census data.

Having validated our smartphone data, we show that focusing solely on these commuting trips provides a misleading picture of travel patterns. First, we show that non-commuting trips are more frequent than commuting trips, so that concentrating solely on commuting trips substantially underestimates the amount of travel within urban areas. Second, we show that these non-commuting trips are closely related to the availability of nontraded services, which is consistent with our modelling of them as travel to consume non-traded services. Third, we find that non-commuting trips have destinations closer to home than commuting trips, with semi-

elasticities of travel flows to travel times that are larger in absolute value than those for commuting trips. Therefore, the spatial patterns of non-commuting trips are not well approximated by those for commuting trips. Fourth, we show that trip chains are a relevant feature of the data, in which non-commuting trips occur along the journey between home and work, highlighting the relevance of jointly modelling commuting and non-commuting trips.

We next develop quantitative theory of internal city structure that incorporates both commuting and consumption trips. We consider a city that consists of a discrete set of blocks that differ in productivity, amenities, supply of floor space and transport connections. Consumer preferences are defined over consumption of a traded good, a number of different types of nontraded services, and residential floor space. The traded good and nontraded services are produced using labor and commercial floor space. We assume that workers' location decisions are nested. First, workers observe idiosyncratic preferences for amenities in each location and choose where to live. Second, workers observe idiosyncratic productivities in each workplace and sector, and choose where to work. Third, workers observe idiosyncratic qualities for the non-traded services supplied by each location, and choose where to consume these non-traded services. Fourth, workers observe idiosyncratic taste shocks for each route to consume these non-traded services, and choose which of these routes to take (e.g. home-work-consume-home versus home-consume-home). When making each of these choices, workers take into account their expected access to surrounding locations. Population mobility implies that workers must obtain the same expected utility from all populated locations.

We show that the model implies extended gravity equations for commuting and non-commuting trips, which provide good approximations to the observed data. We use these extended gravity equations to estimate a theoretically-consistent measure of travel access. Intuitively, we use the observed trips in the data and the structure of the model to reveal the relative attractiveness of locations for employment and consumption. From the model's population mobility condition, we derive a sufficient statistic for the relative attractiveness of locations, which incorporates both the residential population share and the price of floor space. We show that this sufficient statistic for the relative attractiveness of locations can be decomposed into our measure of travel access and a residual for residential amenities. Comparing our model incorporating both consumption and workplace access to a special case capturing only workplace access, we find a substantially larger contribution of travel access once we take into account consumption access (56 percent compared to 37 percent), and a correspondingly smaller contribution from the residual of residential amenities (44 percent compared to 63 percent). Taken together, this pattern of results is consistent with the idea that much economic activity in urban areas is concentrated in the service sector, and that access to surrounding locations to consume these services is an important determinant of workers' choice of residence and workplace.

We show how the model can be used to undertake a counterfactual for a transport infrastructure improvement, such as the construction of a new subway line. In addition to the initial shares of commuting trips, the predictions of these counterfactuals now also depend on the initial shares of non-commuting trips. As a result, frameworks that focus solely on commuting trips generally underestimate the welfare gains from transport infrastructure improvements, because they undercount the number of passenger journeys that benefit from the reduction in travel costs. Furthermore, these frameworks generate different predictions for the impact of the new transport infrastructure on the spatial distribution of economic activity, because of the different bilateral patterns of commuting and non-commuting trips. We compare the model’s counterfactual predictions for the opening of a new subway line to the estimated impact in the observed data. We show that the model has predictive power for the observed data. We show that undercounting of travel from focusing on commuting trips leads to a substantial underestimate of the welfare gains from the new subway line.

Our paper is related to a number of different strands of research. First, our findings relate to recent research on endogenous amenities and social and spatial frictions within urban areas. Evidence of endogenous amenities has been provided in the context of spatial sorting ([Diamond 2016](#), [Almagro and Domínguez-Iino 2019](#) and [Samuels, Hausman, Cohen, and Sasson 2016](#)), gentrification and neighborhood change within cities ([Glaeser, Kolko, and Saiz 2001](#), [Couture, Dingel, Green, and Handbury 2019](#), [Hoelzlein 2020](#) and [Allen, Fuchs, Ganapati, Graziano, Madera, and Montoriol-Garriga 2020](#)), and industry clustering ([Leonardi and Moretti 2019](#)). Evidence that both spatial and social frictions matter for agents’ location decisions has been provided using restaurant choice data ([Couture 2016](#), [Davis, Dingel, Monras, and Morales 2019](#)), credit card data ([Agarwal, Jensen, and Monte 2020](#) and [Dolfen, Einav, Klenow, Klopck, Levin, Levin, and Best 2019](#)), travel surveys and ride sharing data ([Gorback 2020](#) and [Zárate 2020](#)) and cellphone data ([Couture, Dingel, Green, and Handbury 2019](#), [Athey, Ferguson, Gentzkow, and Schmidt 2018](#), [Kreindler and Miyauchi 2019](#), [Gupta, Kontokosta, and Van Nieuwerburgh 2020](#), [Büchel, Ehrlich, Puga, and Viladecans 2020](#) and [Atkin, Chen, and Popov 2021](#)). Relative to these existing studies, we provide high-frequency and spatially-disaggregated data on non-commuting trips, and develop a quantitative urban model for estimating workplace and consumption access.

Second, our work contributes to research on transport infrastructure and the location of economic activity. One strand of empirical research has used quasi-experimental variation on the impact of transport infrastructure improvements, including [Baum-Snow \(2007\)](#), [Michaels \(2008\)](#), [Duranton and Turner \(2012\)](#), [Faber \(2014\)](#), and [Storeygard \(2016\)](#). A second line of work has used quantitative spatial models to evaluate general equilibrium impacts of transport infrastructure investments, including [Anas and Liu \(2007\)](#), [Donaldson \(2018\)](#), [Donaldson and](#)

Hornbeck (2016), Heblich, Redding, and Sturm (2020), Tsivanidis (2018), Severen (2019), Balboni (2019), and Zárate (2020). While existing research emphasizes the costs of transporting goods and commuting costs, a key feature of our work is to highlight the role of the transport network in providing access to consume nontraded services.

Third, our research is related to recent research on the internal structure of cities, including including Ahlfeldt, Redding, Sturm, and Wolf (2015), Allen, Arkolakis, and Li (2017), Monte, Redding, and Rossi-Hansberg (2018), Tsivanidis (2018), and Dingel and Tintelnot (2020). All of these studies emphasize commuting and the separation of workplace and residence. In contrast, one of our main contributions is to highlight the importance of travel to consume nontraded services in shaping agents’ location decisions.

The remainder of the paper is structured as follows. Section 2 introduces our data. Section 3 presents reduced-form evidence on travel patterns. Section 4 introduces our theoretical framework that we use to rationalize these findings. Section 5 uses the model to quantify the relative importance of consumption and workplace access for explaining the spatial concentration of economic activity. Section 6 shows that incorporating consumption access is quantitatively relevant for evaluating the counterfactual impact of transport infrastructure improvements, such as the construction of a new subway line. Section 7 concludes.

2 Data Description

In this section, we introduce our smartphone data and the other data used in the quantitative analysis of the model. In Subsection 2.1, we explain how we use our smartphone data to identify home location, work location, commuting trips and non-commuting trips. In Subsection 2.2, we discuss the spatially-disaggregated economic census data by sector and location that we use to distinguish between different types of non-commuting trips, and discuss our data on land values and other location characteristics. In Subsection 2.3, we report validation checks of the commuting measures from our smartphone data using official census data on employment by residence, employment by workplace and bilateral commuting flows.

2.1 Smartphone GPS Data

Our main data source is one of the leading smartphone mapping applications in Japan: *Docomo Chizu NAVI*. Upon installing this application, individuals are asked to give permission to share location information in an anonymized form. Conditional on this permission being given, the application collects the Geographical Positioning System (GPS) coordinates of each smartphone device every 5 minutes whenever the device is turned on (regardless of whether the application is being used). These “big data” provide an immense volume of high-frequency and

spatially-disaggregated information on the geographical movements of users throughout each day. For example for the month of July 2019 alone, the data include 1.4 billion data points on 545,000 users (about 0.5 percent of the Japanese population).¹

The raw unstructured geo-coordinates are pre-processed by the cell phone operator: NTT Docomo Inc. to construct measures of “stays,” which correspond to distinct geographical locations visited by a user during a day. In particular, a stay corresponds to the set of geo-coordinates of a given user that are contiguous in time, whose first and last data points are more than 15 minutes apart, and whose geo-coordinates are all within 100 meters from the centroid of these points.² We have data on the sequence of stays of anonymized users with the necessary level of spatial aggregation to deidentify individuals. Our data comprise a randomly selected sample of 80 percent of users in Japan, where the randomization is again to deidentify individuals.

This pre-processing also categorizes all stays in each month into three categories of home, work and other locations for each anonymized user. “Home” location and “work” locations are defined as the centroid of the first and second most frequent locations of geographically contiguous stays, respectively. To ensure that these two locations do not correspond to different parts of a single property, we also require that the “work” location is more than 600 meters away from the “home” location. In particular, if the second most frequent location is within 600 meters of the “home” locations, we define the “work” location as the third most frequent location. To abstract from noise in geo-coordinate assignment, all stays within 500 meters of the home location are aggregated with the home location. Similarly, all stays within 500 meters of the work location are aggregated with the work location. We assign “Work” location as missing if the user appears in that location for less than 5 days per month, which applies for about 30 percent of users in our baseline sample during April 2019. These users primarily include those with limited number of data observations due to infrequent smartphone use, and also include irregular workers with unstable job locations and those who work at home.³ In Subsection 2.3 below, we report validation checks on our classification of home and work locations using commuting data from the population census. Stays which are neither assigned as home or work are classified as “other.” We distinguish between different types of these “other” stays, such as visits to restaurants and stores, using spatially-disaggregated data on economic activity by sector and location from the economic census, as discussed further in Section 2.2 below.

¹The mapping application does not send location data points if the smartphone does not sense movement, in which case it is likely that the user has not moved from the last reported location. For this reason, the data points are less frequent than 5 minutes intervals in practice.

²See Patent Number “JP 2013-89173 A” and “JP 2013-210969 A 2013.10.10” for the detailed proprietary algorithm. This algorithm involves processes to offset the potential noise in measuring GPS coordinates.

³In Section A.4 of our online appendix, we show that the devices with missing “work” locations have significantly fewer number of active days (even at home locations), and that the probability of assigning missing “work” locations is uncorrelated with the observable characteristics of the municipality of residence.

For most of our subsequent analysis, we focus on the sample of users in the month of April 2019 who have home and work locations in the Tokyo Metropolitan Area (which includes the four prefectures of Tokyo, Chiba, Kanagawa, and Saitama). To abstract from overnight trips, we focus on the sample of user-day observations for which the first and last stay of the day is the user’s home location.

2.2 Other Data Sources

We combine our smartphone data with a number of complementary data sources.

Spatial units: Data are available for the Tokyo metropolitan area at three main levels of spatial aggregation: (i) The four prefectures of Tokyo, Chiba, Kanagawa and Saitama; (ii) The 242 municipalities (excluding islands); (iii) The 9,956 *Oaza*. Each *Oaza* has an area of around 1.30 squared kilometers and an average 2011 population of around 3,600.

Population Census: We measure residential population, employment by workplace and bilateral commuting flows using the 2015 population census, which is conducted by the Statistics Bureau, Ministry of Internal Affairs and Communications every five years. Residential population and total employment are available at the finest level of spatial disaggregation of 250-meter grid cells. Bilateral commuting flows are reported between pairs of municipalities.

Economic Census: We use data from the 2016 Economic Census on total employment and the number of establishments by one-digit industry for each 500-meter grid cell in the Tokyo metropolitan area, the finest level of disaggregation from publicly available data. We also use data on total revenue and factor inputs that are available at the municipality level.

Building Data: We measure floor space in each city block using the Zmap-TOWN II Digital Building Map Data for 2008. This data set contains polygons for all buildings in Japan, with their precise geo-coordinates and information on building use and characteristics. We measure floor space using the number of stories and land area for each building.

Land Price Data: We measure the residential land price for each city block using the evaluated land price that is used for the calculation of property tax. We take a simple average of these values to construct the average land prices per unit of land at the *Oaza* or Municipality level.

Travel Time Data: We measure travel time by public transportation using the web-based route choice service, *Eki-spert* API.⁴ *Eki-spert* API provides the minimum travel times between any pairs of coordinates using public transport, including suburban rail, subway, and bus, and walking. We use the extracted travel time data from October 2, 2020 (weekday timetable). We also construct car travel time using the Open Source Routing Machine (OSRM).

Municipality Income Tax Base Data: We measure the average income of the residents in each

⁴See <https://roote.ekispert.net/en> for details.

municipality using official data on the tax base for that municipality.

2.3 Validation of Smartphone Data Using Census Commuting Data

We now report an external validation exercise, in which we compare our measures of “home” location, “work location” and “commuting trips” from the smartphone data to official census data that are available at the municipality level. In the left panel of Figure 1, we display the log density of residents in each municipality in our smartphone data against log population density in the census data. As our smartphone data cover only a fraction of the total population, the levels of the two variables necessarily differ from one another. Nevertheless, we find a tight and approximately log linear relationship between them, with a slope coefficient of 0.923 (standard error 0.011) and a R-squared of 0.968. The coefficient is slightly less than one, indicating that the smartphone data has higher coverage in less dense areas. In the right panel of Figure 1, we show the log density of workers in each Tokyo municipality in our smartphone data against log employment density by workplace in the census data. Again, we find a close and approximately log linear relationship between them, with a slope coefficient of 0.996 (standard error 0.008) and a R-squared of 0.985.

In Section A.1 of the online appendix, we provide further evidence on the representativeness of our smartphone data by comparing the coverage by residence characteristics (income, age and distance to city center) and workplace characteristics (employment by industry and distance to city center). In Section A.2, we show that we find the same pattern of decline of bilateral commuting with distance in smartphone data and official census commuting data. In Section A.3, we show that home stays tend to occur during nighttime (outside 6am-9pm) and both work and other stays rise during the daytime (from 6am-9pm), providing additional internal validation of our home and work classification from smartphone data.

3 Reduced-Form Evidence

In this section, we provide reduced-form evidence on commuting and non-commuting trips that guides our theoretical model below. First, we show that non-commuting trips are more frequent than commuting trips, so that concentrating solely on commuting trips underestimates the amount of travel within urban areas. Second, we demonstrate that non-commuting trips are closely-related to the availability of non-traded services, which is consistent with these trips playing an important role in determining consumption access. Third, we show that non-commuting trips exhibit different spatial patterns from commuting trips, so that abstracting from non-commuting trips yields a misleading picture of bilateral travel patterns. Fourth, we provide

Figure 1: Representativeness of Smartphone Users



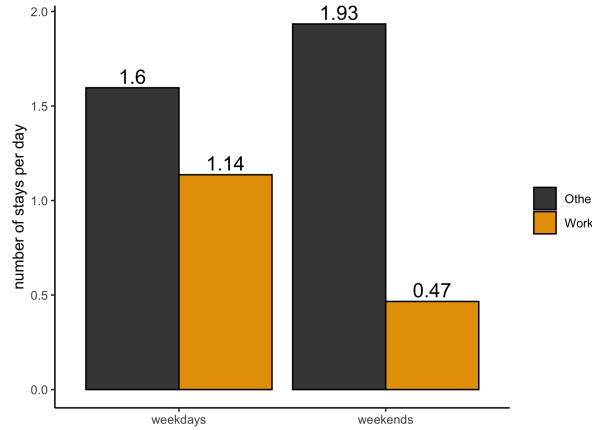
Note: Each dot is a municipality in the Tokyo metropolitan area. In the left panel, the vertical axis is the log of the number of smartphone users with a home location in the municipality divided by its geographic area, and the horizontal axis is the log of the number of residents in that municipality from the Population Census in 2011 divided by its geographic area. In the right panel, the vertical axis is the log of the number of smartphone users with a work location in the municipality divided by its geographic area, and the horizontal axis is the log of employment by workplace in that municipality from the Population Census in 2011 divided by its geographic area. The definitions of home and work in the smartphone data are discussed in the text of Subsection 2.1 above.

evidence of trip chains, in which non-commuting trips occur along the journey between home and work, highlighting the relevance of jointly modelling commuting and non-commuting trips.

Fact 1. Non-commuting trips are pervasive. In Figure 2, we display the average number of stays per day for work and non-work locations (excluding home locations) for our baseline sample of users with home and work locations in the Tokyo Metropolitan Area during April 2019. Note that the average number of work stays can be greater than one during weekdays, because workers can leave their workplace during the day and return there later the same day (e.g. after attending a lunch meeting outside their workplace). Similarly, the average number of work stays can be greater than zero at the weekend, because some workers can be employed during the weekend (e.g. in restaurants and stores). As apparent from the figure, even during weekdays, we find that non-commuting trips are more frequent than commuting trips, with an average of 1.6 non-work stays per day compared to 1.14 work stays per day. This pattern is magnified at weekends, with an average of 1.93 non-work stays per day compared to 0.47 work stays per day. These results are consistent with evidence from travel surveys, in which

commuting is only one of many reasons for travel.⁵ A key advantage of our smartphone data is that they reveal bilateral patterns of travel at a fine level of spatial disaggregation within the urban area, and capture the sequence in which users travel between their home, work and consumption locations, as used to measure trip chains in our quantitative analysis of the model.

Figure 2: Frequency of Stays at Work and Other Locations (Excluding Home Locations)



Note: Average number of work and other stays per day for weekdays and weekends (excluding home stays) for our baseline sample users in the metropolitan area of Tokyo in April 2019. See Section 2 above for the definitions of home, work and other stays.

Fact 2. Non-commuting trips are closely related to consumption. We now show that non-commuting trips are closely related to consumption by combining our GPS smartphone data with spatially-disaggregated census data on employment by sector. In particular, we stochastically assign other stays (stays at neither home nor work locations) to different types based on the local economic activity undertaken at each geographical location, as captured by the share of service sectors in employment. For each 500×500 meter grid cell in the Tokyo metropolitan area, we compute the employment share of each service sector in total service sector employment. We disaggregate service-sector employment into the following five categories: “Finance, Real Estate, Communication, and Professional”, “Wholesale and Retail”, “Accommodations, Eating, Drinking”, “Medical and Health Care”, and “Other Services”.⁶ For each other stay in a given grid cell, we allocate that stay to these five categories probabilistically using their shares of service-sector employment. If no service-sector employment is observed in the grid cell, we allocate that other stay to the category “Z Others.”

⁵In Section A.5 of the online appendix, we show that this pattern of more frequent non-commuting stays than commuting stays holds in separate Japanese travel survey data, which are available for weekdays only.

⁶These sectors correspond to the one-digit classification of the Japan Standard Industrial Classification (JSIC), for which we have data available by 500×500 meter grid cells. “Finance, Real Estate, Communication, and Professional” corresponds to sectors of G, J, K, L; “Wholesale and Retail” corresponds to I, “Accommodations, Eating, Drinking” corresponds to M, “Medical and Health Care” corresponds to P, and “Other Services” corresponds to Q.

Table 1: Frequency of Non-Commuting Trips and Service-Sector Employment Shares

Industry	Weekdays		Weekends		Employment Share in Service (%)	
	Stays / Day	Share (%)	Stays / Day	Share (%)	Total	Average (500m Grids)
GJKL finance realestate communication professional	0.23	14.3	0.21	10.7	11.9	23.2
I wholesale retail	0.69	43.4	0.91	46.1	32.0	28.7
M accomodations eating drinking	0.15	9.4	0.21	10.8	13.2	13.2
P medical welfare healthcare	0.23	14.2	0.27	13.7	18.7	15.2
Q other services	0.25	15.8	0.29	14.8	24.3	19.8
Z others	0.05	2.9	0.08	3.9		

Note: Average number of each type of other stay per day for weekdays and weekends (excluding home stays) for our baseline sample for the metropolitan area of Tokyo in April 2019. Other stays are allocated probabilistically to each category using the shares of these service sectors in total service-sector employment. The table also reports the share of each type of stay in the total number of other stays, the share of each service sector in total service-sector employment for the Tokyo metropolitan area, and the average share of each service sector in total service-sector employment across the 500×500 meter grid cells. See Section 2 for the definitions of home, work and other stays.

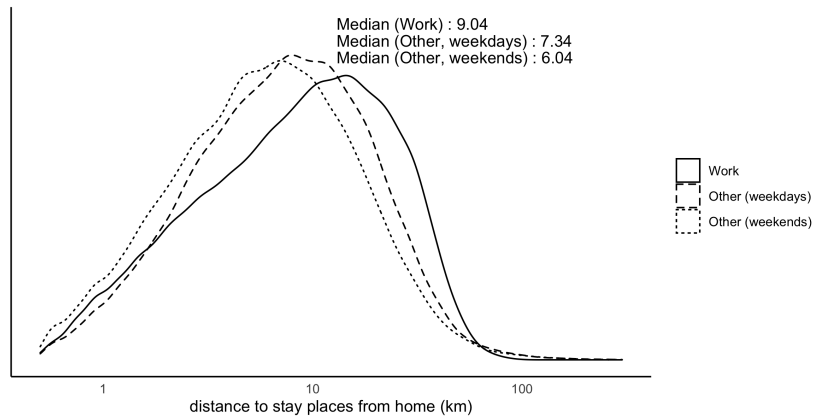
In Table 1, we report the average number of these different types of other stays per day during the working week and at weekends. We find that “Wholesale and Retail” stays are by far the most frequent, with an average of 0.69 per day on weekdays and 0.91 per day on weekends. To provide a point of comparison, we also report the share of each individual service sector in overall service-sector employment for the Tokyo metropolitan area as a whole (penultimate column) and the average share of each individual service sector in overall service-sector employment across the 500×500 meter grid cells (final column). We find that “Wholesale and Retail” stays are substantially more frequent than would be implied by their shares of overall service-sector employment, accounting for 43.4 percent of weekday stays and 46.1 percent of weekend stays, compared to an aggregate employment share of 32.0 percent and an average employment share of 28.7 percent. This pattern of results implies that other stays are targeted towards locations with relatively high shares of the “Wholesale and Retail” sector in employment, which is consistent with these other stays capturing access to consumption opportunities. Although “Wholesale and Retail” stays are the most frequent, there is considerable variation in the composition of service-sector employment across the locations visited by users, with most sectors accounting for 10 percent or more of the total number of stays.⁷

As a check on our probabilistic assignment of other stays, Figure A.6.1 in Section A.6 of the online appendix displays the density of each type of other stay by hour and day, as a share of all stays for our baseline sample for the Tokyo metropolitan area in April 2019. We find that our probabilistic assignment captures the expected pattern of these different service-sector activities over the course of the week. First, we typically find a higher density of other stays during the middle of the day at weekends than during weekdays, which is in line with the fact that many of these services are consumed more intensively during leisure time. Second, we find that the peak

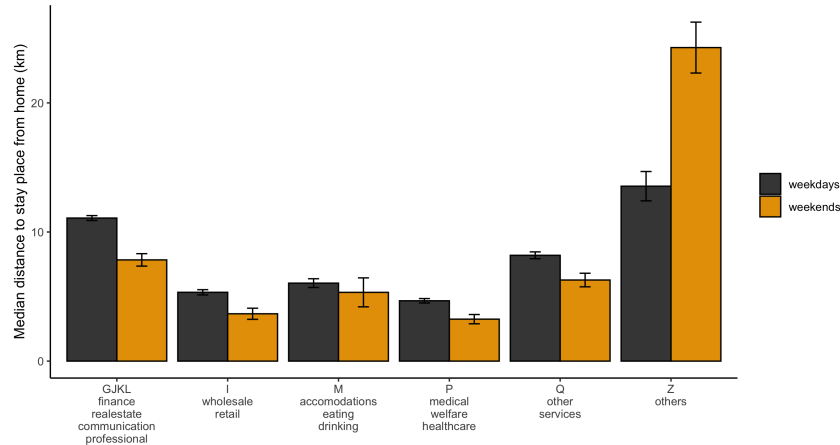
⁷Some non-commuting trips could be business-related (e.g., meetings). In Figure A.5.2 of the online appendix, we show that business-related trips are a minor fraction (20 percent) of all non-commuting weekday trips using separate travel survey data, where some of these business trips could involve consumption (e.g. lunches).

Figure 3: Distances of Commuting and Non-Commuting Trips

(A) Distribution of Distances of Work and Other Stays from Home Locations



(B) Average Distances of Different Types of Other Stays from Home Locations



(0.75) (Note: Panel (A): Distributions of distance in kilometers of work locations from home location and of other stays from home locations during weekdays and weekends. Panel (B): Distributions of distance in kilometers for each type of other stay from home locations during weekdays and weekends. Results for our baseline sample of users in the Tokyo metropolitan area in April 2019.

densities of stays for “Wholesale and Retail” and “Accommodations, Eating, Drinking” occur at around 6pm on weekdays, corroborating the fact that these activities are typically concentrated after work during the week. Additionally, for “Accommodations, Eating, Drinking,” we find a smaller peak around noon on weekdays, capturing lunch time.

Fact 3. Non-commuting trips are closer to home. We now show that non-commuting trips exhibit different spatial patterns from commuting trips, such that observed bilateral commuting flows provide an incomplete picture of patterns of travel within urban areas. In Panel (A) of Figure 3, we display the distribution of distances from home locations to work locations and from home locations to other stays for our baseline sample of users in the Tokyo metropolitan area in the month of April 2019. We find that other stays are concentrated closer to home than

work stays, with average distances travelled of 7.34 and 9.04 kilometers respectively during weekdays, with an even larger difference in distances travelled at the weekend. In Panel (B) of Figure 3, we display the distribution of distances travelled for each type of other stay separately. We find that “Wholesale and Retail” and “Accommodations, Eating, Drinking” stays are concentrated closer to home than “Finance, Real Estate, Communication, and Professional” and “Other Services stays.” This clustering of other stays closer to home highlights the relevance of these non-commuting trips for residential location decisions. More generally, these differences in the geographical pattern of stays suggests that focusing on commuting trips yields an incomplete picture of bilateral patterns of travel.

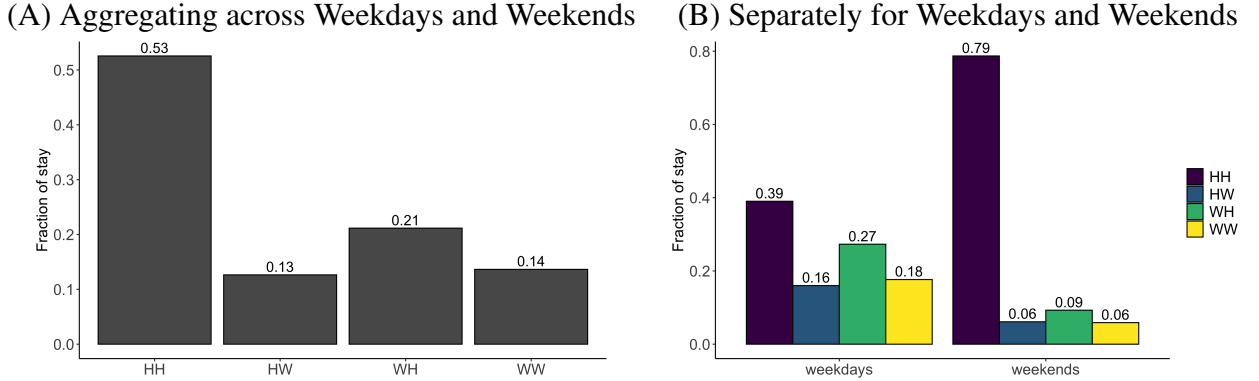
Fact 4. Trip chains. We now provide evidence of trip chains, in which non-commuting trips occur on the way from home and work. In Figure 4, we use the fact that in the smartphone data we observe the sequence of stays originating from a user’s home location and ending at a user’s home location (without going back home in between each stay), which we term “round trips.” Using this information, we divide all other stays that occur along such round trips into four mutually-exclusive categories: (i) HH stays, in which the other stay is part of a round trip that does not include the work location; (ii) HW stays, in which the other stay happens on the way from the home location to the work location; (iii) WH stays, in which the other stay happens on the way back from the work location to the home location; (iv) WW stays, in which the other stay happens in between two stays at the work location (e.g. a visit to a restaurant in the middle of the working day). Panel A shows the frequency of these four different types of other stays aggregating across weekdays and weekends, while Panel B shows their frequency for weekdays and weekends separately. We find that the majority of non-commuting trips occur separately from commuting trips (53 percent), which is driven primarily by weekends (79 percent) when users are significantly less likely to visit workplaces (Figure 2). Nevertheless, a substantial fraction of non-commuting trips (47 percent) occur as part of commuting trips (47 percent), highlighting the relevance of jointly modelling these two types of trips.

Taking the findings of this section as a whole, we have shown that non-commuting trips are frequent, are closely related to consumption, exhibit different spatial patterns from commuting trips, and can occur as part of trip chains. Each of these four features of our smartphone data guides our theoretical modelling of commuting and non-commuting trips in the next section.

4 Theoretical Framework

In this section, we develop our quantitative urban model of internal city structure that incorporates both commuting and non-commuting trips, where the derivations for all theoretical results in this section are reported in Section B of the online appendix.

Figure 4: Fractions of Different Types of Other Stays on Round Trips from Home



Note: Fractions of different types of other stays that occur as part of a round trip originating from a user’s home location and ending at a user’s home location (without going back home in between each stay); (i) on a round trip that does not include the work location (HH); (ii) on the way from home to work (HW); (iii) on the way back from work to home (WH); (iv) in between two stays at the work location (WW), such as a visit to restaurant in the middle of the working day; Panel A shows frequencies aggregating weekdays and weekends; Panel B shows frequencies separately for weekdays and weekends.

We consider a city (Tokyo) that is embedded in a larger economy (Japan). We consider both a closed-city specification (in which total city population is exogenous) and an open-city specification (in which total city population is endogenously determined by population mobility with the wider economy that offers a reservation level of utility \bar{U}). The city consists of a discrete set of locations $i, j, n \in N$ that differ in productivity, amenities, supply of floor space and transport connections. Utility is defined over consumption of a single traded good, a number of different types of non-traded services (e.g. restaurants, coffee shops, stores), and residential floor space use. Both the traded good and the non-traded services are produced with labor and commercial floor space according to constant returns to scale under conditions of perfect competition. Floor space is supplied by a competitive construction sector using land and capital according to a constant returns to scale construction technology.

A continuous measure of workers (\bar{L}) choose a residence, a workplace and a set of locations to consume non-traded services in the city.⁸ We assume the following timing or nesting structure for workers’ location decisions. First, each worker observes her idiosyncratic preferences or amenities (b) for each location within the city, and chooses her residence n . Second, given a choice of residence, each worker observes her idiosyncratic productivities (a) for each workplace i and sector g , and chooses her sector and location of employment. Third, given a choice of residence and workplace, she observes idiosyncratic qualities (q) for each type of non-traded service k available in each location j , and chooses her consumption loca-

⁸In the model, we assume a continuous measure of workers, which ensures that the expected values of variables equal their realized values. In our empirical analysis, we allow for granularity and a finite number of workers in our estimation (using the PPML estimator) and counterfactuals (using predicted shares from this estimation).

tion for each type of non-traded service. Fourth, given a choice of residence, workplace, and the set of consumption locations, she observes idiosyncratic shocks (ν) over different possible travel routes: home-consume-home, work-consume-work, home-consume-work-home, or home-work-consume-home. We choose this nesting structure because it permits a transparent decomposition of residents and land prices into the contribution of travel access and the residual of amenities, but the importance of consumption access is robust across other nesting structures. We also compare the predictions of our model with the special case abstracting from consumption trips, which corresponds to a conventional urban model, in which workers choose workplace and residence and consume only traded goods.

4.1 Preferences

The indirect utility for worker ω who chooses residence n , works in location i and sector $g \in K$, and consumes non-traded service $k \in K^S$ (where $K^S \subset K$) in location $j(k)$ using route $r(k)$ is assumed to take the following Cobb-Douglas form:

$$\begin{aligned}
 U_{ni g\{j(k)r(k)\}}(\omega) &= \left\{ B_n b_n(\omega) (P_n^T)^{-\alpha^T} Q_n^{-\alpha^H} \right\} \{ a_{i,g}(\omega) w_{i,g} \} \\
 &\times \left\{ \prod_{k \in K^S} [P_{j(k)}^S / (q_{j(k)}(\omega))]^{-\alpha_k^S} \right\} \left\{ d_{ni\{j(k)r(k)\}} \prod_{k \in K^S} \nu_{r(k)}(\omega) \right\} \\
 0 &< \alpha^T, \alpha^H, \alpha_k^S < 1, \quad \alpha^T + \alpha^H + \sum_{k \in K^S} \alpha_k^S = 1,
 \end{aligned} \tag{1}$$

where we use the notation $j(k)$ to indicate that that non-traded service k is consumed in a single location j that is an implicit function of the type of non-traded service k ; $r(k) \in \mathbb{R} \equiv \{HH, WW, HW, WH\}$ indicates the “route” choice of whether to visit consumption locations from home (HH), from work (WW), on the way from home to work (HW), or on the way from work to home (WH) for each non-traded service k ; $K^S \subset K$ is the subset of sectors that are non-traded; the first term in brackets captures a residence component of utility; the second term in brackets corresponds to a workplace component; the third term in brackets reflects a non-traded services component; the fourth term in brackets reflects a travel cost component.

The first, residence component includes amenities (B_n) that are common for all workers in residence n ; the idiosyncratic amenity draw for residence n for worker ω ($b_n(\omega)$); the price of the traded good (P_n^T); and the price of residential floor space (Q_n). We allow the common amenities (B_n) to be either exogenous or endogenous to the surrounding concentration of economic activity in the presence of agglomeration forces, as discussed further below. The second, workplace component comprises the wage per efficiency unit in sector g in workplace i ($w_{i,g}$) and the idiosyncratic draw for productivity or efficiency units of labor for worker ω in sector

g in workplace i ($a_{i,g}(\omega)$).⁹ The third, non-traded services component depends on the price of the non-traded service k in the location $j(k)$ where it is supplied ($P_{j(k)}^S$ for $k \in K^S$) and the idiosyncratic draw for quality for that service in that location ($q_{j(k)}(\omega)$ for $k \in K^S$). The fourth component captures the iceberg travel cost for each combination of residence, workplace, consumption locations and routes ($d_{ni\{j(k)r(k)\}}$) and the idiosyncratic draw for route preference for each non-traded sector ($\nu_{r(k)}(\omega)$ for $k \in K^S$).

To capture trip chains, we model the iceberg travel cost for each combination of residence n , workplace i , consumption location $j(k)$ and route $r(k)$ ($d_{ni\{j(k)r(k)\}}$) as follows:

$$d_{ni\{j(k)r(k)\}} = \exp(-\kappa^W \tau_{ni}^W) \prod_{k \in K^S} \exp(-\kappa_k^S \tau_{nij(k)r(k)}^S). \quad (2)$$

The first term before the product sign captures the cost of commuting from residence n to workplace i without any detour to consume non-traded services, which depends on travel time (τ_{ni}^W) and the commuting cost parameter (κ^W), where overall commuting travel time is the sum of that in each direction:

$$\tau_{ni}^W = \tau_{ni} + \tau_{in}. \quad (3)$$

The second term in equation (2) captures the additional travel costs involved in consuming each type of non-traded service k in location $j(k)$ by the route $r(k)$, which depends on the additional travel time involved ($\tau_{nij(k)r(k)}^S$) and the consumption travel cost parameter (κ_k^S). This additional travel time depends on the route taken: whether the worker visits consumption location $j(k)$ from home ($r(k) = HH$), from work (WW), on the way from home to work (HW), or on the way from work to home (WH):

$$\begin{aligned} \tau_{nij(k)HH}^S &= \tau_{nj} + \tau_{jn}, & \tau_{nij(k)WW}^S &= \tau_{ij} + \tau_{ji}, \\ \tau_{nij(k)HW}^S &= \tau_{nj} + \tau_{ji} - \tau_{ni}, & \tau_{nij(k)WH}^S &= \tau_{ij} + \tau_{jn} - \tau_{in}, \end{aligned} \quad (4)$$

where the negative terms on the second line above reflects the fact that the worker travels indirectly between residence n and workplace i via consumption location j on one leg of her journey between home and work, and hence does not incur the direct travel time between residence n and workplace i for that leg.¹⁰

We make the conventional assumption in the location choice literature following [McFadden \(1974\)](#) that the idiosyncratic shocks are drawn from an extreme value distribution. In particular,

⁹Although we model the workplace idiosyncratic draw as a productivity draw, there is a closely-related formulation in which it is instead modelled as an amenity draw.

¹⁰While we capture the relative importance of the consumption of non-traded services using the Cobb-Douglas expenditure shares (α_k^S), the frequency of trips can also differ across non-traded sectors, as shown in [Figure 1](#). In [Section C.1](#) of the online appendix, we explicitly incorporate this additional type of heterogeneity and show that the model is isomorphic up to a reinterpretation of the parameters κ_k^S . Therefore, all of our counterfactual results are unaffected by this extension of the model except for the interpretation of the estimated κ_k^S .

amenities (b), productivity (a), quality (q), route preferences (ν) for worker ω , residence n , workplace i , consumption location $j(k)$ and route $r(k)$ for non-traded service k are drawn from independent Fréchet distributions:

$$\begin{aligned}
G_n^B(b) &= \exp\left(-T_n^B b^{-\theta^B}\right), & T_n^B > 0, \theta^B > 1, \\
G_{i,g}^W(a) &= \exp\left(-T_{i,g}^W a^{-\theta^W}\right), & T_{i,g}^W > 0, \theta^W > 1, \\
G_{j(k)}^S(q) &= \exp\left(-T_{j(k)}^S q^{-\theta_k^S}\right), & T_{j(k)}^S > 0, \theta_k^S > 1, k \in K^S, \\
G_{r(k)}^R(\nu) &= \exp\left(-T_{r(k)}^R \nu^{-\theta_k^R}\right), & T_{r(k)}^R > 0, \theta_k^R > 1, k \in K^S.
\end{aligned} \tag{5}$$

where the scale parameters $\{T_n^B, T_{i,g}^W, T_{j(k)}^S, T_{r(k)}^R\}$ control the average draws and the shape parameters $\{\theta^B, \theta^W, \theta_k^S, \theta_k^R\}$ regulate the dispersions of amenities, productivity, quality and route preferences, respectively. The smaller these dispersion parameters, the greater the heterogeneity in idiosyncratic draws, and the less responsive worker decisions to economic variables.¹¹

Using our assumption about the timing or nesting structure, the worker location choice problem is recursive and can be solved backwards. First, for given a choice of residence, workplace and sector, and consumption location for each non-traded service, we characterize the probability that a worker chooses each route for each non-traded sector (whether to visit consumption locations from home, from work, or in-between). Second, for given a choice of residence, workplace and sector, we characterize the probability that a worker chooses each consumption location in each non-traded sector, taking into account the expected travel cost for consumption trips. Third, for given a choice of residence, we characterize the probability that a worker chooses each workplace and sector, taking into account expected consumption access for that workplace and sector. Fourth, we characterize the probability that a worker chooses each residence, taking into account its expected travel access for both commuting and consumption.

4.2 Route Choices

We begin with the worker's choice of route for each non-traded service sector k . Conditional on her residence n , workplace i , and consumption location $j(k)$, she chooses whether to visit consumption location $j(k)$ from home ($r(k) = HH$), from work (WW), on the way from home to work (HW), or on the way from work to home (WH). Given the indirect utility (1) and the specification of the travel cost (2), the component of the utility that depends on the route $r(k)$

¹¹ Although we assume independent Fréchet distributions for amenities, productivity and quality, some locations can have high expected values for all these idiosyncratic shocks if they have high values for T_n^B , $T_{i,g}^W$, $T_{j(k)}^S$ and $T_{r(k)}^R$. Additionally, correlations between the shocks can be introduced using a multivariate Fréchet distribution, as in Hsieh, Hurst, Jones, and Klenow (2019).

for non-traded service k is given by:

$$\delta_{nij(k)r(k)}(\omega) = \exp(-\kappa_k^S T_{nij(k)r(k)}^S) \nu_{r(k)}(\omega). \quad (6)$$

where the first component is the route-specific travel cost and the second component is the idiosyncratic route preference. Under our assumption of independent route draws $\nu_{r(k)}(\omega)$ across each non-traded sector k , each worker chooses the route $r(k)$ that maximizes $\delta_{nij(k)r(k)}(\omega)$ independently for each sector k .

Using our independent extreme value assumption, the route choice probability is characterized by a logit form. In particular, the probability that a worker living in residence n and employed in workplace i consuming non-traded service k in location $j(k)$ chooses the route $r(k)$ ($\lambda_{r(k)|nij(k)}^R$) is:

$$\lambda_{r(k)|nij(k)}^R = \frac{T_{r(k)}^R \exp(-\theta_k^R \kappa_k^S T_{nij(k)r(k)}^S)}{\sum_{r' \in \mathbb{R}} T_{r'(k)}^R \exp(-\theta_k^R \kappa_k^S T_{nij(k)r'(k)}^S)}. \quad (7)$$

Using the properties of the extreme value distribution, we can also compute the expected contribution to utility from the travel cost from consumption trips

$$d_{nij(k)}^S = \mathbb{E}_{nij(k)} [\delta_{nij(k)r(k)}(\omega)] = \vartheta_k^R \left[\sum_{r' \in \mathbb{R}} T_{r'(k)}^R \exp(-\theta_k^R \kappa_k^S T_{nij(k)r'(k)}^S) \right]^{\frac{1}{\theta_k^R}} \quad (8)$$

where $\vartheta_k^R \equiv \Gamma\left(\frac{\theta_k^R - 1}{\theta_k^R}\right)$ and $\Gamma(\cdot)$ is the Gamma function.

4.3 Consumption Choices

We next describe the worker's decision of where to consume each type of non-traded service, given these expected travel costs. Conditional on living in residence n and being employed in workplace i , each worker chooses a consumption location $j(k)$ for each non-traded service k , after observing her idiosyncratic draws for the quality of non-traded services (d), but before observing her idiosyncratic route preferences (ν). Therefore, each worker chooses the consumption location $j(k)$ that maximizes the contribution to indirect utility (1) from consuming that non-traded service k , taking into account the expected travel costs across alternative routes:

$$\gamma_{nij(k)}(\omega) = [P_{j(k)}^S / (q_{j(k)}(\omega))]^{-\alpha_k^S} d_{nij(k)}^S, \quad k \in K^S. \quad (9)$$

where $d_{nij(k)}^S$ is the expected travel cost across these alternative routes from equation (8) above.¹²

¹²Although for simplicity we assume that workers choose a single consumption location for each non-traded service, it is straightforward to extend the model to incorporate multiple consumption locations, by allowing workers to make multiple discrete choices for each non-traded service.

Using our extreme value assumption, the probability that a worker living in residence n and employed in workplace i consumes non-traded service k in location $j(k)$ ($\lambda_{j(k)|ni}^S$) is:

$$\lambda_{j(k)|ni}^S = \frac{T_{j(k)}^S \left(P_{j(k)}^S\right)^{-\theta_k^S} \left(d_{nij(k)}^S\right)^{\frac{\theta_k^S}{\alpha_k^S}}}{\sum_{\ell \in N} T_{\ell(k)}^S \left(P_{\ell(k)}^S\right)^{-\theta_k^S} \left(d_{ni\ell(k)}^S\right)^{\frac{\theta_k^S}{\alpha_k^S}}}, \quad k \in K^S, \quad (10)$$

which we term the conditional consumption probability, since it is computed conditional on residence n and workplace i . This probability depends on destination characteristics (the price of non-traded services $P_{j(k)}^S$ and their average quality $T_{j(k)}^S$ in the numerator); expected travel costs (as determined by $d_{nij(k)}^S$ in the numerator); and origin (residence and workplace) characteristics (as captured by the expected-travel-cost weighted average of destination characteristics in the denominator). Importantly, the frequency of consumption trips for each destination $j(k)$ and non-traded service k depends on both the worker's residence n and her workplace i , because she can travel to consume non-traded services from either of these locations.

Using the properties of the extreme value distribution, we can also compute the expected contribution to utility from consuming non-traded service k , conditional on living in residence n and being employed in workplace i . This expectation for residence n and workplace i corresponds to a measure of consumption access for non-traded service k , and depends on the travel-time weighed average of destination characteristics:

$$\mathbb{S}_{nik} \equiv \mathbb{E}_{nik} [\gamma_{nij(k)}] = \vartheta_k^S \left[\sum_{\ell \in N} T_{\ell(k)}^S \left(P_{\ell(k)}^S\right)^{-\theta_k^S} \left(d_{ni\ell(k)}^S\right)^{\frac{\theta_k^S}{\alpha_k^S}} \right]^{\frac{\alpha_k^S}{\theta_k^S}}, \quad k \in K^S. \quad (11)$$

where $\vartheta_k^S \equiv \Gamma\left(\frac{(\theta_k^S/\alpha_k^S)-1}{(\theta_k^S/\alpha_k^S)}\right)$ and $\Gamma(\cdot)$ is the Gamma function.

Noting that idiosyncratic quality is independently distributed across non-traded sectors, we can also compute the expected overall contribution to utility from non-traded services:

$$\mathbb{S}_{ni} \equiv \prod_{k \in K^S} \mathbb{S}_{nik} = \prod_{k \in K^S} \vartheta_k^S \left[\sum_{\ell \in N} T_{\ell(k)}^S \left(P_{\ell(k)}^S\right)^{-\theta_k^S} \left(d_{ni\ell(k)}^S\right)^{\frac{\theta_k^S}{\alpha_k^S}} \right]^{\frac{\alpha_k^S}{\theta_k^S}}. \quad (12)$$

4.4 Workplace Choice

We next turn to the worker's choice of workplace, given consumption access. In particular, conditional on living in residence n , each worker chooses the workplace i and sector $g \in K$ that offers the highest utility, taking into account the wage per efficiency unit ($w_{i,g}$), the idiosyncratic draw for productivity ($a_{i,g}(\omega)$), commuting costs (d_{ni}^W), and expected consumption access (\mathbb{S}_{ni}):

$$v_{ni,g}(\omega) = w_{i,g} a_{i,g}(\omega) d_{ni}^W \mathbb{S}_{ni}. \quad (13)$$

where $d_{ni}^W \equiv \exp(-\kappa^W \tau_{ni}^W)$ is commuting travel cost from equation (2).

Using our independent extreme value assumption for idiosyncratic productivity, the model also implies a gravity equation for bilateral commuting, such that the probability that a worker in residence n commutes to workplace i in sector g ($\lambda_{ig|n}^W$) is as follows:

$$\lambda_{ig|n}^W = \frac{T_{i,g}^W w_{i,g}^{\theta^W} (d_{ni}^W)^{\theta^W} (\mathbb{S}_{ni})^{\theta^W}}{\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} (d_{n\ell}^W)^{\theta^W} (\mathbb{S}_{n\ell})^{\theta^W}}, \quad (14)$$

which we term the conditional commuting probability, since it is computed conditional on living in residence n . Bilateral commuting flows also depend on destination characteristics (the wage $w_{i,g}$, average efficiency units $T_{i,g}^W$ and consumption access \mathbb{S}_{ni} in the numerator); bilateral travel costs (as captured by d_{ni}^W in the numerator); and origin characteristics (as captured by the travel-cost weighted average of destination characteristics across sectors in the denominator). Aggregating across the different sectors $k \in K$, we also obtain the overall commuting probability between residence n and workplace i :

$$\lambda_{i|n}^W = \sum_{g \in K} \lambda_{ig|n}^W. \quad (15)$$

Using the properties of the extreme value distribution, we can also compute an overall measure of travel access for residence n (\mathbb{A}_n), which is a weighted average of the characteristics of each workplace i , including consumption access (\mathbb{S}_{ni}):

$$\mathbb{A}_n = \mathbb{E}_n [v_{ni,g}] = \vartheta^W \left[\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} (d_{n\ell}^W)^{\theta^W} (\mathbb{S}_{n\ell})^{\theta^W} \right]^{\frac{1}{\theta^W}}, \quad (16)$$

where $\vartheta^W \equiv \Gamma\left(\frac{\theta^W-1}{\theta^W}\right)$ and $\Gamma(\cdot)$ is the Gamma function.

4.5 Residence Choice

Having characterized a worker's consumption and workplace choices conditional on her residence, we now turn to her residence choice. Each worker chooses her residence after observing her idiosyncratic draws for amenities (b), but before observing her idiosyncratic draws for productivity (a), the quality of non-traded services (q), and route preferences (ν). Therefore, each worker ω chooses the residence n that offers her the highest utility given her idiosyncratic amenity draws ($b_n(\omega)$), expected travel access (\mathbb{A}_n), and other residence characteristics (the price of floor space (Q_n), the price of the traded good (P_n^T) and common amenities (B_n)):

$$U_n(\omega) = B_n b_n(\omega) (P_n^T)^{-\alpha^T} Q_n^{-\alpha^H} \mathbb{A}_n,$$

Using our extreme value assumption for idiosyncratic amenities, the probability that each worker chooses residence n (λ_n^B) depends on its relative attractiveness in terms of travel access (\mathbb{A}_n), and residential characteristics (B_n , $P_{T,n}$ and Q_n):

$$\lambda_n^B = \frac{T_n^B B_n^{\theta^B} \mathbb{A}_n^{\theta^B} (P_n^T)^{-\alpha^T \theta^B} Q_n^{-\alpha^H \theta^B}}{\sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} (P_\ell^T)^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B}}. \quad (17)$$

Taking expectations over idiosyncratic amenities, expected utility from living in the city depends on the travel access and other residential characteristics of all locations within the city:

$$\mathbb{E}[u] = \vartheta^B \left[\sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} (P_\ell^T)^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B} \right]^{\frac{1}{\theta^B}}. \quad (18)$$

where $\vartheta^B \equiv \Gamma\left(\frac{\theta^B-1}{\theta^B}\right)$ and $\Gamma(\cdot)$ is the Gamma function.

In Section 5.2, we use these residential choice probabilities to decompose the observed variation in economic activity into the contributions of travel access and a residual for amenities, without taking a stand on production technology and market structure in the traded and non-traded sectors. As a result, this quantitative analysis holds in an entire class of quantitative urban models, with different specifications for production technology and market structure.

Expected income in residence n (E_n) in turn depends on the overall commuting probabilities ($\lambda_{i|n}^W$) and expected income conditional on commuting from residence n to workplace i (E_{ni}):

$$E_n = \sum_{i \in N} \lambda_{i|n}^W E_{ni}, \quad (19)$$

where E_{ni} depends on both wages and expected worker idiosyncratic productivity.

4.6 Production

When we undertake counterfactuals in Section 6, we do need to take a stand on a specific production technology and market structure. In particular, we assume that both the traded good and non-traded services are produced using labor and commercial floor space according a constant returns to scale technology. We assume for simplicity that this production technology is Cobb-Douglas and that production occurs under conditions of perfect competition.¹³ Together these assumptions imply that profits are zero in each location with positive production:

$$\begin{aligned} P_i^T &= \frac{1}{A_{i,k}} w_{i,k}^{\beta^T} Q_i^{1-\beta^T}, & 0 < \beta^T < 1, & \quad k \in K/K^S, \\ P_{i(k)}^S &= \frac{1}{A_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S}, & 0 < \beta^S < 1, & \quad k \in K^S, \end{aligned} \quad (20)$$

¹³In Section C.2 of the online appendix, we show that our specification is isomorphic to a model of monopolistic competition under free entry, once we allow for agglomeration forces (equation (25) below).

where $A_{i,k}$ is productivity in location i in sector k .

We allow productivity ($A_{i,k}$) to be either exogenous or endogenous to the surrounding concentration of economic activity because of agglomeration forces, as discussed further below. We assume no-arbitrage between residential and commercial floor space, and across the different sectors in which commercial floor space is used, such that there is a single price for floor space within each location (Q_i). In general, the wage per efficiency unit ($w_{i,k}$) differs across both sectors and locations, because workers draw efficiency units for each sector and location pair, and hence each sector and location pair faces an upward-sloping supply function for effective units of labor. Finally, we assume that the traded good is costlessly traded within the city and wider economy and choose it as our numeraire, such that:

$$P_i^T = 1 \quad \forall i \in N. \quad (21)$$

4.7 Market Clearing

The price for non-traded service k in each location j ($P_{j(k)}^S$ for $k \in K^S$) is determined by market clearing, which equates revenue and expenditure for that sector k and location j :

$$P_{j(k)}^S A_{j,k} \left(\frac{\tilde{L}_{j,k}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{j,k}}{1 - \beta^S} \right)^{1 - \beta^S} = \alpha_k^S \sum_{n \in N} R_n \sum_{i \in N} \lambda_{j(k)|ni}^S \lambda_{i|n}^W E_{ni}, \quad k \in K^S, \quad (22)$$

where expenditure on the right-hand side equals the sum across locations of workers travelling to consume non-traded service k in location j ; $\tilde{L}_{j,k}$ is the labor input adjusted for expected idiosyncratic worker productivity in sector k in location j ; R_n is the measure of residents in location n ; and recall that $\lambda_{j(k)|ni}^S$ is the conditional consumption probability and E_{ni} is expected worker income for residence n and workplace i .

Labor market clearing equates the measure of workers employed in workplace j in sector k to the measure of workers commuting from all residences n to that workplace j in sector k :

$$L_{j,k} = \sum_{n \in N} \lambda_{jk|n}^W R_n, \quad k \in K, \quad (23)$$

where we use $L_{j,k}$ without a tilde to denote the measure of workers without adjusting for effective units of labor; and recall that $\lambda_{jk|n}^W$ is the conditional commuting probability.

Land market clearing equates the demand for residential floor space ($H_{i,U}$) plus commercial floor space in each sector ($H_{i,k}$) to the total supply of floor space (H_i):

$$H_i = H_{i,U} + \sum_{k \in K} H_{i,k}. \quad (24)$$

4.8 General Equilibrium

We begin by considering the case in which productivity ($A_{i,k}$), amenities (B_i) and the supply of floor space (H_i) are exogenously determined. The general equilibrium of the model is referenced by the price for floor space in each location (Q_i), the wage in each sector and location ($w_{i,k}$), the price of the non-traded good in each service sector and location ($P_{i(k)}^S$), the route choice probabilities ($\lambda_{r(k)|nij(k)}^R$), the conditional consumption probabilities ($\lambda_{j(k)|ni}^S$), the conditional commuting probabilities ($\lambda_{ik|n}^W$), the residence probabilities (λ_n^B), and the total measure of workers living in the city (\bar{L}), where we focus on the open-city specification, in which the total measure of workers is endogenously determined by population mobility with the wider economy. These eight equilibrium variables are determined by the system of eight equations given by the land market clearing condition for each location (24), the labor market clearing condition for each location (23), the non-traded goods market clearing condition for each location and service sector (22), the route choice probabilities (7), the conditional consumption probabilities (10), the conditional commuting probabilities (14), the residence probabilities (17), and the population mobility condition that equates expected utility (18) to the reservation utility in the wider economy (\bar{U}).

4.9 Agglomeration Forces and Endogenous Floor Space

We next extend the analysis to allow productivity and amenities to be endogenous to the surrounding concentration of economic activity through agglomeration forces and to allow for an endogenous supply of floor space. In both the traded and non-traded sector, we allow productivity ($A_{i,k}$) to depend on production fundamentals and production externalities. Production fundamentals ($a_{i,k}$) capture features of physical geography that make a location more or less productive independently of neighboring economic activity (e.g. access to natural water). Production externalities capture productivity benefits from the density of employment across all sectors (L_i/K_i), where employment density is measured per unit of geographical land area:¹⁴

$$A_{i,k} = a_{i,k} \left(\frac{L_i}{K_i} \right)^{\eta^W} \quad (25)$$

where $L_i = \sum_{k \in K} L_{i,k}$ is the total employment in location i , and η^W parameters the strength of production externalities, which we assume to be the same across all sectors.

In addition to the pecuniary externalities from consumption access, we allow residential amenities (B_n) to depend on residential fundamentals and residential externalities. Residential fundamentals (b_n) capture features of physical geography that make a location a more or less

¹⁴We assume for simplicity that production externalities depend solely on a location's own employment density, but we can also allow for the case in which there are spillovers of these production externalities across locations.

attractive place to live independently of neighboring economic activity (e.g. green areas). Residential externalities capture the effects of the surrounding density of residents (L_i/K_i) and are modeled symmetrically to production externalities:¹⁵

$$B_n = b_n \left(\frac{R_n}{K_n} \right)^{\eta^B} \quad (26)$$

where η^B parameters the strength of residential externalities.

We follow the standard approach in the urban literature of assuming that floor space is supplied by a competitive construction sector that uses land K and capital M as inputs. In particular, we assume that floor space (H_i) is produced using geographical land (K_i) and building capital (M_i) according to the following constant return scale technology:

$$H_i = M_i^\mu K_i^{1-\mu}, \quad 0 < \mu < 1. \quad (27)$$

Using cost minimization and zero profits, this construction technology implies a constant elasticity supply function for floor space as in [Saiz \(2010\)](#):

$$Q_i = \psi_i H_i^{\frac{1-\mu}{\mu}} \quad (28)$$

where ψ_i depends solely on geographical land area (K_i) and parameters.

Given these agglomeration forces and endogenous floor space, the determination of general equilibrium remains the same as above, except that productivity (A_n), amenities (B_n) and the supply of floor space (H_n) are now endogenously determined by equations (25), (26) and (28).

5 Quantitative Analysis

In this section, we use our theoretical model to quantify the contributions of workplace access and consumption access to location choices. The key insight underlying our approach is that the observed consumption and commuting probabilities in our smartphone data can be used to reveal the relative valuation placed by users on different locations as consumption and workplace locations, and hence can be used to estimate travel access in a theory-consistent way. In [Section 5.1](#), we develop a sequential procedure to estimate the model's parameters. In [Section 5.2](#), we use these estimated parameters and model's residential choice probabilities to quantify the relative importance of workplace access, consumption access and residential amenities in explaining the observed spatial concentration of economic activity.

¹⁵As for production externalities above, we assume that residential externalities depend solely on a location's own residents density, but we can allow spillovers of these residential externalities across locations.

5.1 Estimation Procedure

We begin by discussing the estimation and calibration of the model’s parameters. We proceed in a number of steps, where each step uses additional model structure. First, we calibrate the Fréchet dispersion parameters for commuting, consumption, and residence choices (θ^W , θ_k^S , θ^B , respectively), and the shares of consumer expenditure on housing (α^H), traded goods (α^T), and each type of non-traded service (α_k^S) using central values from the existing empirical literature and the observed data. Second, we estimate the worker’s route choice problem for each non-traded service and obtain an estimate of the expected travel cost for consumption trips ($d_{nij(k)}^S$). Third, we estimate her consumption choice problem conditional on her residence and workplace, and obtain an estimate of the travel time parameter for consumption trips ($\phi_k^S = \theta_k^S \kappa_k^S / \alpha_k^S$) and consumption access (\mathbb{S}_{ni}). Fourth, we estimate her commuting choice problem, and obtain an estimate of the travel time parameter for commuting trips ($\phi^W = \theta^W \kappa^W$) and travel access (\mathbb{A}_n). Fifth, we calibrate the remaining parameters using the observed data and central values from the existing empirical literature.

5.1.1 Preference Parameters (θ^W , θ^B , θ_k^S , α^H , α^T and α_k^S) (Step 1)

In our first step, we calibrate the preference dispersion parameters (θ^W , θ_k^S and θ^B) and expenditure shares (α^H , α^T , α_k^S). We set the preference dispersion parameters for commuting, consumption and residence choices equal to $\theta^W = \theta_k^S = \theta^B = 6$, which consistent with the range of estimated values for these parameters. In the existing literature on commuting, [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#) estimates a preference dispersion parameter for workplace-residence choices of 6.83 using the division of Berlin by the Berlin Wall; [Heblich, Redding, and Sturm \(2020\)](#) estimates a value for the same parameter of 5.25 using the construction of London’s 19th-century railway network; and [Kreindler and Miyauchi \(2019\)](#) estimates the same parameter of 8.3 using information on the spatial dispersion of income in Dhaka, Bangladesh. In Section [D.2.1](#) of the online appendix, we provide an over-identification check on our model’s predictions, using the property that its predictions for residential income depend importantly on these parameter values. In particular, we compare the model’s predictions for residential income in each Tokyo municipality to separate data on residential income not used in its calibration. Although our model is necessarily an abstraction, we find a strong positive relationship between the model’s predictions and the observed data.

Fewer empirical estimates are available for the preference dispersion parameter for consumption trips (θ_k^S), which determines the elasticity of consumption trips and consumption expenditure with respect to changes in the cost of sourcing non-traded services. Our calibrated value for this parameter of $\theta_k^S = 6$ is in line with the existing empirical literature that has esti-

mated elasticities of substitution across retail stores. In particular, [Atkin, Faber, and Gonzalez-Navarro \(2018\)](#) estimates an elasticity of substitution of 3.9 using Mexican data, while [Couture, Gaubert, Handbury, and Hurst \(2019\)](#) estimates an elasticity of substitution of 6.5 using US data. In Section [D.2.2](#) of the online appendix, we provide another overidentification check on our model’s predictions, using the property that its predictions for non-traded service prices in each location are sensitive to this parameter value. Again we show that there is a strong positive relationship between the model’s predictions and the observed data.

Finally, we calibrate the Cobb-Douglas expenditure share parameters using aggregate data on observed expenditure shares in Japan. We set the share of expenditure on residential floor space equal to $\alpha^H = 0.25$, which also corresponds to the values in [Davis and Ortalo-Magné \(2011\)](#) and [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#). We set the expenditure share parameter for each type of non-traded service (α_k^S) equal to the observed expenditure share on that sector for the Tokyo metropolitan area. Lastly, we solve for the implied traded goods expenditure share: $\alpha^T = 1 - \alpha^H - \sum_{k \in K^S} \alpha_k^S$.

5.1.2 Estimating the Route-Choice Probabilities (Step 2)

In our second step, we estimate expected consumption travel costs ($d_{nij(k)}^S$), using the model’s predictions for route choice (HH, WW, HW, WH) and our smartphone data. From the route choice probability (7), the probability of choosing route $r(k)$ for non-traded service k conditional on residence n , workplace i , and consumption location $j(k)$ can be written as:

$$\lambda_{r(k)|nij(k)}^R = \frac{\exp(-\phi_k^R \tau_{nij(k)r(k)}^S) \xi_{r(k)}^R \exp(u_{nij(k)r(k)}^R)}{\zeta_{nij(k)}^R}, \quad (29)$$

where $u_{nij(k)r(k)}^R$ is a stochastic error that captures idiosyncratic determinants of route choice, given residence, workplace, and consumption location.

We estimate this route choice probability using the Poisson Pseudo Maximum Likelihood (PPML) estimator of [Santos Silva and Tenreyro \(2006\)](#).¹⁶ The estimated semi-elasticity of travel time (ϕ_k^R) in equation (29) is a composite of the response of consumption trips to travel costs (θ_k^R) and the response of travel costs to travel times (κ_k^S), such that $\phi_k^R = \theta_k^R \kappa_k^S$. The estimated route fixed effect $\xi_{r(k)}^R$ corresponds to the tendency that each route is chosen conditional on travel time, such that $\xi_{r(k)}^R = T_{r(k)}^R$. The estimated residence-workplace-consumption-location fixed effect $\zeta_{nij(k)}^R$ captures the average tendency that routes are chosen for each residence, workplace, consumption location, such that $\zeta_{nij(k)}^R = \sum_{\ell \in \mathbb{R}} T_{\ell(k)}^R \exp(-\theta_k^R \kappa_k^S \tau_{nij(k)\ell(k)}^S)$.

Table 2 presents the estimation results for each of the different types of non-traded services: “Finance, Real Estate, Communication, and Professional”; “Wholesale and Retail”; “Accom-

¹⁶We find a similar pattern of results if we estimate this choice probability using the multinomial logit model.

modation, Eating and Drinking”; “Medical, Welfare and Health Care”; “Other Services”. In the first row, we report the coefficient on the travel time (ϕ_k^R). In the second to fourth row report, we report the coefficient on the dummy variables for each route choice, where $r(k) = HH$ is the excluded category. Two features of Table 2 are noteworthy. First, we estimate a negative and statistically significant composite coefficient on travel time ($-\phi_k^R = -\theta_k^R \kappa_k^S$), highlighting its relevance for route choice. Second, we estimate negative and statistically significant coefficients on the indicator variables for the included route choices ($r(k) \in \{HW, WH, WW\}$) relative to the excluded category of $r(k) = HH$. These results imply a high average preference for consuming non-traded services from home, consistent with Figure 4 in Section 3.

Using these estimates of ϕ_k^R and $\xi_{r(k)}^R$, we construct adjusted expected travel costs for consumption trips conditional on residence n and workplace i from equation (8) above as:

$$\tilde{d}_{nij(k)}^S \equiv (d_{nij(k)}^S)^{1/\kappa_k^S} = \vartheta_k^R \left[\sum_{r' \in \mathbb{R}} \xi_{r'(k)}^R \exp(-\phi_k^R \tau_{nij(k)r'(k)}^S) \right]^{\frac{1}{\phi_k^R}}, \quad (30)$$

where ϑ_k^R is again $\vartheta_k^R \equiv \Gamma\left(\frac{\theta_k^R - 1}{\theta_k^R}\right)$ and recall $\mathbb{R} = \{HH, HW, WH, WW\}$.

In this second step of our estimation, the composite semi-elasticity of travel time ($\phi_k^R = \theta_k^R \kappa_k^S / \alpha_k^S$) is a sufficient statistic for the impact of travel time on route choices, as estimated from the route choice probabilities (29). We do not need to separate out the contributions of θ_k^R and κ_k^S to the overall value of this parameter. Similarly, our adjusted measure of expected travel costs ($\tilde{d}_{nij(k)}^S \equiv (d_{nij(k)}^S)^{1/\kappa_k^S}$) from equation (30) is a sufficient statistic for the impact of expected travel costs on workers choice of consumption locations, workplace and residence in the subsequent steps of our estimation below. We do not need to separate out the contributions of $1/\kappa_k^S$ and $d_{nij(k)}^S$ to the overall value of adjusted expected travel costs ($\tilde{d}_{nij(k)}^S$).

5.1.3 Estimating Consumption Access (\mathbb{S}_{ni}) (Step 3)

In our third step, we estimate the consumption choice probability and consumption access (\mathbb{S}_{ni}), using the observed frequencies of consumption trips to reveal the relative attractiveness of each location for each type of non-traded service. From the conditional consumption probabilities (10), the probability that a worker travels to consume non-traded service k in location $j(k)$, conditional on residence n and workplace i is:

$$\lambda_{j(k)|ni}^S = \frac{\xi_{j(k)}^S \left(\tilde{d}_{nij(k)}^S \right)^{-\phi_k^S} \exp\left(u_{nij(k)}^S\right)}{\zeta_{ni,k}^S}, \quad (31)$$

where $\tilde{d}_{nij(k)}^S$ is our estimated adjusted expected travel costs from equation (30); and $u_{nij(k)}^S$ is a stochastic error that captures idiosyncratic determinants of consumption travel costs.

Table 2: Estimation Results for Route Choice

Dependent Variable:	Route Choice Probability				
	Finance realestate communication professional (1)	Wholesale retail (2)	Accomoda- tions eating drinking (3)	Medical welfare healthcare (4)	Other services (5)
<i>Variables</i>					
Travel Time (Hours)	-0.312 (0.004)	-0.269 (0.004)	-0.264 (0.004)	-0.297 (0.004)	-0.271 (0.004)
Dummy (HW)	-1.58 (0.010)	-1.66 (0.010)	-1.75 (0.009)	-1.67 (0.011)	-1.61 (0.012)
Dummy (WH)	-1.04 (0.009)	-1.16 (0.010)	-1.10 (0.009)	-1.23 (0.011)	-1.12 (0.010)
Dummy (WW)	-1.03 (0.009)	-1.13 (0.009)	-1.30 (0.008)	-1.09 (0.010)	-1.09 (0.011)
<i>Fixed-effects</i>					
Home-Work-Consumption Location	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
AIC	3,753,940.7	7,015,231.9	3,461,408.3	3,674,206.4	4,511,086.5
BIC	6,348,159.7	9,717,411.9	6,081,904.7	6,174,892.1	7,210,376.1
Observations	887,212	921,176	895,488	857,704	920,268

Note: Results of estimating the route choice probability (29) using the Poisson Pseudo Maximum Likelihood (PPML) estimator. Observations are triplets of municipalities in the Tokyo metropolitan area (residence n , workplace i , and consumption location $j(k)$) for each type of non-traded service k . We construct the empirical frequencies of route choice ($\lambda_{r(k)|nij(k)}^R$) using our smartphone data (aggregated across weekdays and weekends), as discussed in Figure 4 in Section 3 above. The dependent variable is these empirical frequencies ($\lambda_{r(k)|nij(k)}^R$), where $r \in \mathbb{R} \equiv \{HH, WW, HW, WH\}$ corresponds to the different route choices: consuming non-traded services from home (HH), from work (WW), on the way from home to work (HW), and on the way from work to home (WH). The independent variables are travel time and the dummy variables for the different route choices, where $r(k) = HH$ is the excluded category. Regressions are weighted by the frequency of observations for each residence, workplace, consumption-location, and sector, where we stochastically assign each trip to each sector following the procedure described in Figure 4 in Section 3. Standard errors in parentheses are clustered at the level of the combination of residence, workplace, and consumption location.

In a conventional gravity equation, travel flows are determined for a bilateral pair of locations. In contrast, in our extended gravity equation (31), consumption trips are determined at the level of triplets of residence, workplace and consumption locations. Since workers can travel to consume non-traded services from either their residence or their workplace, the adjusted expected consumption travel cost ($\tilde{d}_{nij(k)}^S$) from equation (30) to consume non-traded service k in location $j(k)$ depends on both residence n and workplace i .

We estimate this extended gravity equation (31) separately for each type of non-traded service using the Poisson Pseudo Maximum Likelihood (PPML) estimator. This estimator yields theoretically-consistent estimates of the fixed effects (as shown in Fally 2015) and allows for granularity and zeros in travel flows (as discussed further in Dingel and Tintelnot 2020). We obtain three key sets of estimates from this extended gravity equation. First, the estimated elasticity of consumption trips with respect to travel costs (ϕ_k^S) is a composite of the elasticity of

consumption trips with respect to travel costs (θ_k^S/α_k^S) and the elasticity of travel costs with respect to travel times (κ_k^S) in equation (10), such that $\phi_k^S = \theta_k^S \kappa_k^S / \alpha_k^S$. Second, the estimated consumption destination fixed effect ($\xi_{j(k)}^S$) in equation (31) captures the average attractiveness of consumption destination $j(k)$ for service k in terms of its price for that non-traded service ($P_{j(k)}^S$) and quality draws ($T_{j(k)}^S$) in equation (10), such that:

$$\xi_{j(k)}^S = T_{j(k)}^S (P_{j(k)}^S)^{-\theta_k^S}. \quad (32)$$

Third, the estimated residence fixed effect in equation (31) corresponds to the denominator in the conditional consumption probability in equation (10) and captures the overall attractiveness of residence n in terms of its access to all consumption locations $\ell(k)$ for service k :

$$\zeta_{ni,k}^S = \sum_{\ell \in N} T_{\ell(k)}^S (P_{\ell(k)}^S)^{-\theta_k^S} \left(\tilde{d}_{ni\ell(k)}^S \right)^{-\phi_k^S}. \quad (33)$$

From these estimated fixed effects, we recover a theoretically-consistent estimate of consumption access for each type of non-traded service ($\mathbb{S}_{ni,k}$). Indeed, consumption access can be recovered from either the consumption destination fixed effects or the residence fixed effects. First, summing the estimated consumption destination fixed effects ($\xi_{j(k)}^S$) weighted by the estimated bilateral travel cost ($(\tilde{d}_{ni\ell(k)}^S)^{-\phi_k^S}$) across locations, and using our calibrated values of θ_k^S and α_k^S , we obtain our baseline estimate of consumption access:

$$\mathbb{S}_{ni} = \prod_{k \in K^S} \Gamma \left(\frac{\theta_k^S / \alpha_k^S - 1}{\theta_k^S / \alpha_k^S} \right) \left[\sum_{\ell \in N} \xi_{\ell(k)}^S \left(\tilde{d}_{ni\ell(k)}^S \right)^{-\phi_k^S} \right]^{\frac{\alpha_k^S}{\theta_k^S}}. \quad (34)$$

Second, using the estimated residence fixed effects ($\zeta_{ni,k}^S$), and our calibrated values of θ_k^S and α_k^S , we obtain another estimate of consumption access: $\mathbb{S}_{ni} = \prod_{k \in K^S} \left[\Gamma \left(\frac{\theta_k^S / \alpha_k^S - 1}{\theta_k^S / \alpha_k^S} \right) \right] (\zeta_{ni,k}^S)^{\frac{\alpha_k^S}{\theta_k^S}}$. As sample size becomes sufficiently large, these two sets of estimates of consumption access converge asymptotically towards one another if the model is a correct specification of the true data generating process, as shown in an international trade context in Fally (2015). In practice, even in our finite sample, we find that these two estimates are extremely highly correlated with one another, as shown in Section D.4 of the online appendix.

In Table 3, we report the results of estimating the consumption extended gravity equation (31) for each type of non-traded service separately. In all cases, we estimate negative and statistically significant semi-elasticities of consumption trips with respect to travel costs ($-\phi_k^S$). We find that these estimated semi-elasticities are relatively constant across the different types of consumption trips, ranging from -1.08 to -1.19, with the most localized consumption trips observed for “Finance, Real Estate, Communication, and Professional” and “Medical, Welfare

and Health Care”. In Section D.3 of the online appendix, we report a specification check in which model the relationship between consumption trips and travel costs non-parametrically and demonstrate a similar pattern of results.¹⁷

Table 3: Estimation Results for Consumption Location Choice

Dependent Variable:	Consumption Location Choice Probability				
	Finance realestate communication professional (1)	Wholesale retail (2)	Accommodations eating drinking (3)	Medical welfare healthcare (4)	Other services (5)
<i>Variables</i>					
$\log \tilde{d}_{nij(k)}^S$	-1.15 (0.040)	-1.12 (0.036)	-1.09 (0.035)	-1.19 (0.038)	-1.08 (0.036)
<i>Fixed-effects</i>					
Home and Work Location Pairs	Yes	Yes	Yes	Yes	Yes
Consumption Location	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
AIC	129,480.5	130,876.3	131,837.4	128,831.5	132,020.7
BIC	291,657.6	293,164.9	294,084.1	290,841.4	294,295.3
Observations	2,981,924	2,983,860	2,983,134	2,979,020	2,983,618

Note: Results of estimating the consumption trip probability (31) using the Poisson Pseudo Maximum Likelihood (PPML) estimator. Observations are triplets of municipalities in the Tokyo metropolitan area (residence n , workplace i , and consumption location $j(k)$). Each column regresses the consumption trip probability for each type of non-traded service on the adjusted expected travel cost ($\tilde{d}_{nij(k)}^S$) from the previous step, consumption location fixed effects, and residence-workplace pair fixed effects. Standard errors in parentheses are clustered two-way on consumption location and residence-workplace pair.

5.1.4 Estimating the Workplace Choice and Travel Access (\mathbb{A}_n) (Step 4)

In our fourth step, we estimate the workplace choice probability and overall travel access (\mathbb{A}_n), by using the observed frequencies of commuting trips to reveal the relative attractiveness of residences and workplaces. From our parameterization of commuting costs and equations (14) and (15), the probability that a worker commutes from residence n to workplace i can be written as the following extended gravity equation:

$$\lambda_{i|n}^W = \frac{\xi_i^W \exp(-\phi^W \tau_{ni}^W) (\mathbb{S}_{ni})^{\theta^W} \exp(u_{ni}^W)}{\zeta_n^W}, \quad (35)$$

where u_{ni}^W is a stochastic error that reflects idiosyncratic determinants of bilateral commuting costs not captured in bilateral travel times (τ_{ni}).

¹⁷As a specification check, we re-estimated the consumption gravity equation under the false assumption that all consumption trips originate from home. As shown in Table D.5.1 in Section D.5 of the online appendix, we find substantially smaller semi-elasticities in this robustness check (ranging from -0.8 to -0.6), highlighting the importance of endogenous route choice. Furthermore, we find a better model fit incorporating route choice than this alternative specification, as evident from the smaller Akaike Information Criteria (AIC) or Bayesian Information Criteria (BIC) than in Panel (B) of Table D.5.1.

In a conventional gravity equation for commuting, the key bilateral determinant of commuting flows is bilateral travel time τ_{ni}^W . In contrast, in our extended gravity equation for commuting (35), a worker's choice of workplace depends on the extent to which it enhances the worker's access to consumption opportunities, which in turn depends on the worker's residence. Therefore, consumption access (\mathbb{S}_{ni}) varies bilaterally with both workplace and residence, and enters as an additional determinant of bilateral commuting flows alongside bilateral travel time

We estimate this extended commuting gravity equation (35) using the Poisson Pseudo Maximum Likelihood (PPML) estimator, our measures of commuting travel times (τ_{ni}^W), and our estimates of bilateral consumption access (\mathbb{S}_{ni}) from the previous step. We again obtain three key sets of estimates from this extended gravity equation. First, the estimated semi-elasticity of commuting flows with respect to travel times (ϕ^W) in equation (35) is again a composite of the response of commuting flows to commuting costs (θ^W) and the response of commuting costs to travel times (κ^W) in equation (14), such that $\phi^W = \theta^W \kappa^W$. Second, the estimated workplace fixed effect (ξ_i^W) in equation (35) captures the average attractiveness of workplace i across sectors in terms of its wage ($w_{i,g}$) and productivity draws ($T_{i,g}^W$):

$$\xi_i^W = \sum_{m \in K} T_{i,m}^W w_{i,m}^{\theta^W}. \quad (36)$$

Third, the estimated residence fixed effect (ζ_n^W) in equation (35) corresponds to the denominator in the conditional commuting probability in equation (14) and captures the overall attractiveness of residence n in terms of its travel-time weighted access to all workplaces:

$$\zeta_n^W = \sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} \exp(-\phi^W \tau_{n\ell}^W) (\mathbb{S}_{n\ell})^{\theta^W}. \quad (37)$$

From these estimated fixed effects, we recover a theoretically-consistent measure of overall travel access. Indeed, as for consumption access in the previous step, we can recover travel access in two different ways. First, summing the estimated workplace fixed effects (ξ_i^W) weighted using the estimated bilateral travel costs ($\exp(-\phi^W \tau_{ni}^W)$) across locations, and using θ^W , we obtain our baseline estimate of travel access:

$$\mathbb{A}_n = \Gamma\left(\frac{\theta^W - 1}{\theta^W}\right) \left[\sum_{\ell \in N} \xi_\ell^W \exp(-\phi^W \tau_{n\ell}^W) (\mathbb{S}_{n\ell})^{\theta^W} \right]^{\frac{1}{\theta^W}}. \quad (38)$$

Second, using the estimated residence fixed effects (ζ_n^W) and θ^W , we obtain another estimate of workplace access: $\mathbb{A}_n = \Gamma\left(\frac{\theta^W - 1}{\theta^W}\right) (\zeta_n^W)^{\frac{1}{\theta^W}}$. As sample size becomes sufficiently large, these two sets of estimates of travel access again converge asymptotically towards one another if the model is a correct specification of the true data generating process. In practice, even in our finite sample, we find that these two estimates are extremely highly correlated with one another, as shown in Section D.4 of the online appendix.

In Table 4, we present the results of estimating our commuting extended gravity equation (31). We include the commuting travel time, consumption access ($\mathbb{S}_{n\ell}$) with a known exponent of θ^W , workplace fixed effects and residence fixed effects. We estimate a negative and statistically significant semi-elasticity of commuting flows with respect to commuting time of $-\phi^W = -0.617$. This estimated value of ϕ^W is significantly smaller than our estimates of ϕ_k^S above, suggesting that consumption choices are more responsive to travel time than workplace choices. In Section D.3 of the online appendix, we report a specification check in which we model the relationship between commuting trips and travel time non-parametrically, and show that our semi-log specification provides a good approximation to the data.¹⁸

Table 4: Estimation Results for Workplace Choice

Dependent Variable: Model:	Commuting Choice Probability (1)
<i>Variables</i>	
Commuting Time (Hours)	-0.617 (0.037)
<i>Fixed-effects</i>	
Home Location	Yes
Work Location	Yes
<i>Fit statistics</i>	
AIC	1,212.0
BIC	5,557.3
Observations	58,564

Note: Results of estimating the commuting probability (35) using the Poisson Pseudo Maximum Likelihood (PPML) estimator. Observations are all pairs of municipalities in the Tokyo metropolitan area (residence n and workplace i). Each column regresses the commuting probability on commuting time, workplace fixed effects, residence fixed effects, and consumption access ($\mathbb{S}_{n\ell}$) with a coefficient restricted to equal θ^W . Standard errors in parentheses are clustered two-way on residence and workplaces.

5.1.5 Other Model Parameters (Step 5)

Together Steps 1-4 are sufficient to undertake our decomposition of the observed spatial variation in economic activity into the contributions of travel access and a residual for amenities, within an entire class of quantitative urban models with different specifications of production technology and market structure. However, when we undertake counterfactuals, such as for example for transport infrastructure improvements, we need to determine additional structural parameters related to the supply-side of the economy (land supply, tradable and non-tradable

¹⁸As a further specification check, we re-estimated the commuting gravity equation excluding consumption access ($\log(\mathbb{S}_{n\ell})^{\theta^W}$). As shown in Table D.5.2 in Section D.5 of the online appendix, we find a larger travel time semi-elasticity when omitting consumption access (-0.649 instead of -0.617), highlighting the relevance of controlling for this term. Furthermore, we find a better model fit for our specification incorporating consumption access, as measured by the Akaike Information Criteria (AIC) or Bayesian Information Criteria (BIC).

production, and production and amenity spillovers). In our fifth step, we calibrate these parameters directly from the data or using central values from the existing empirical literature.

We calibrate the Cobb-Douglas cost shares for labor in each sector (β^S, β^T) as 0.8, which are broadly consistent with the labor share on production costs for Tokyo metropolitan area. We assume a standard share of land in construction costs of $\mu = 0.75$. We explore a range of values for the production and residential agglomeration parameters ranging from zero to the values estimated in [Ahlfeldt, Redding, Sturm, and Wolf \(2015\)](#): $\eta^W \in [0, 0.08]$ and $\eta^B \in [0, 0.15]$, which spans most of the existing empirical estimates in the meta-analyses of [Melo, Graham, and Noland \(2009\)](#) and [Ahlfeldt and Pietrostefani \(2019\)](#).

5.2 Quantifying the Role of Workplace and Consumption Access

We now use our estimates from Steps 1-4 above to quantify the contributions of travel access and the residual of residential amenities to explaining the observed spatial concentration of economic activity and to examine the relative importance of workplace access and consumption access for overall travel access. Re-writing the residential choice probabilities (17), we have:

$$(\lambda_n^B)^{1/\theta^B} Q_n^{\alpha^H} = \mathbb{B}_n \mathbb{A}_n. \quad (39)$$

The left-hand side of this relationship corresponds to a summary measure of the relative attractiveness of locations. A larger share of residents (λ_n^B) and/or a higher price of floor space (Q_n) both imply that a location is a more attractive place to live. On the right-hand side, \mathbb{B}_n is a composite amenities parameter that includes common amenities (B_n), the parameter determining average idiosyncratic amenities (T_n^B), the common price of the traded good ($P_n^T = P^T = 1$), and the common reservation level of utility (\bar{U}):

$$\mathbb{B}_n \equiv B_n (T_n^B)^{1/\theta^B} (P_n^T)^{-\alpha^T} (\bar{U}/\vartheta^B)^{-1} \quad (40)$$

In these residential choice probabilities (39), we observe the share of residents (λ_n^B) and the price of floor space (Q_n), and we estimated travel access (\mathbb{A}_n) in equation (38). Therefore, we can use these residential choice probabilities (39) to recover the unobserved composite amenities (\mathbb{B}_n) as a structural residual that exactly rationalizes the observed data as an equilibrium of the model. This residential choice decomposition has an intuitive interpretation. If a location has a high share of residents (λ_n^B) and high price of floor space (Q_n) on the left-hand side, despite having relatively low values of composite access (\mathbb{A}_n) on the right-hand side, this is rationalized in the model by that location having relatively high residential amenities (\mathbb{B}_n).

We now decompose the variance of our summary measure of the relative attractiveness of locations into the contributions of travel access (\mathbb{A}_n) and residential amenities (\mathbb{B}_n). In particular, we use a regression-based variance decomposition from the international trade literature.

We estimate an ordinary least squares (OLS) regression of each of the components on the right-hand side of the residential choice probabilities (39) on our summary measure of the relative attractiveness of locations from the left-hand side:

$$\begin{aligned}\ln \mathbb{A}_n &= c_0^A + c_1^A \ln \left((\lambda_n^B)^{1/\theta^B} Q_n^{\alpha^H} \right) + u_{nt}^A, \\ \ln \mathbb{B}_n &= c_0^B + c_1^B \ln \left((\lambda_n^B)^{1/\theta^B} Q_n^{\alpha^H} \right) + u_{nt}^B,\end{aligned}\quad (41)$$

Noting that OLS is a linear estimator with mean zero residuals, and using the residential choice probabilities (39), we have $c_0^A + c_0^B = 0$ and $c_1^A + c_1^B = 1$. Implicitly, this variance decomposition allocates the covariance terms equally across each of the two components. The relative values of the slope coefficients $\{c_1^B, c_1^A\}$ provide measures of the relative importance of travel access (\mathbb{A}_n) and residential amenities (\mathbb{B}_n) in explaining the observed variation in our summary measure of the relative attractiveness of locations.

We next examine the relative importance of workplace access and consumption access for overall travel access, by considering a special case of our quantitative urban model without consumption trips ($\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $\mathbb{S}_{ni} = 1$). In this special case, we ignore the data on consumption trips, and estimate a standard quantitative urban model of workplace-residence choice using only the data on commuting trips. As a result, travel accessibility ($\mathbb{A}_n^{\text{nocons}}$) depends on workplace access alone, and can be constructed using the estimates from our extended gravity equation estimation of equation (35), but omitting the consumption access term ($\log(\mathbb{S}_{nl})^{\theta^W}$):

$$\mathbb{A}_n^{\text{nocons}} = \Gamma \left(\frac{\theta^W - 1}{\theta^W} \right) \left[\sum_{\ell \in N} \xi_\ell^W \exp(-\phi^W \tau_{nl}^W) \right]^{\frac{1}{\theta^W}}, \quad (42)$$

where ϕ^W and ξ_ℓ^W are the estimated travel time coefficient and workplace fixed effects from the extended commuting gravity equation (35). Using this measure of travel access without consumption trips ($\mathbb{A}_n^{\text{nocons}}$) in equation (39), we can recover a measure of amenities without consumption trips ($\mathbb{B}_n^{\text{nocons}}$), and implement our variance decomposition in equation (41) above.¹⁹

Table 5 reports the results of these variance decompositions for our model including consumption trips (Panel A) and the special case excluding consumption trips (Panel B). Observations correspond to municipalities in the Tokyo metropolitan area for which we have land price data. We measure the price of floor space (Q_n) using the observed land price data (\tilde{Q}_n)

¹⁹As a robustness check, Panel (B) of online appendix Table D.5.3 construct travel access without consumption trips ($\mathbb{A}_n^{\text{nocons}}$) using the estimates of ϕ^W and ξ_ℓ^W from a conventional commuting gravity equation excluding consumption access. Although the estimated travel time coefficients differ between these two gravity equation specifications, we find a similar pattern of results for the relative importance of consumption access and residential amenities in this robustness test as in our baseline specification.

Table 5: Decomposition of our Summary Statistic for Relative Attractiveness ($\log \left[(\lambda_n^B)^{1/\theta^B} Q_n^{\alpha^H} \right]$) into Travel Access (\mathbb{A}_n) and Residential Amenities (\mathbb{B}_n)

	$\log \mathbb{A}_n$	$\log \mathbb{B}_n$
	(1)	(2)
Panel A: Baseline Model		
$\log Q_n^{\alpha^H} (\lambda_n^B)^{1/\theta^B}$	0.566 (0.049)	0.434 (0.049)
Observations	201	201
R ²	0.403	0.284
Panel B: No Consumption Trips		
$\log Q_n^{\alpha^H} (\lambda_n^B)^{1/\theta^B}$	0.373 (0.036)	0.627 (0.036)
Observations	201	201
R ²	0.352	0.606

Note: Ordinary least squares (OLS) estimates of the regression-based variance decomposition in equation (41). Panel (A) corresponds to our baseline model, in which we compute travel access (\mathbb{A}_n) incorporating consumption trips; Panel (B) corresponds to the special case of our model in which we abstract from consumption trips ($\mathbb{A}_n^{\text{nocons}}$), such that $\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $\mathbb{S}_{ni} = 1$. Observations are municipalities in the Tokyo metropolitan area. Heteroskedasticity robust standard errors in parentheses.

and our assumption of competitive construction sector (such that $Q_n \propto \tilde{Q}_n^{1-\mu}$). In our model including consumption trips, we find that travel access (\mathbb{A}_n) is about as important as the residual of residential amenities (\mathbb{B}_n) in explaining variation in the relative attractiveness of locations ($Q_n^{\alpha^H} (\lambda_n^B)^{1/\theta^B}$), with a contribution of 56 percent compared to 44 percent. In contrast, when we consider a conventional quantitative urban model excluding consumption trips, we find a substantially reduced contribution from travel access ($\mathbb{A}_n^{\text{nocons}}$) of only 37 percent, with the residual of residential amenities making up the remaining 63 percent. These results suggest that a substantial component of the variation in conventional measures of residential amenities that do not control for consumption trips may reflect unobserved differences in consumption access. They also suggest that workplace access ($\mathbb{A}_n^{\text{nocons}}$) is far from perfectly correlated with overall travel access incorporating consumption trips (\mathbb{A}_n), because we find a much smaller contribution from travel access when we restrict attention to commuting information alone.

6 Counterfactuals

We next use our theoretical framework to undertake counterfactuals for changes in travel costs to provide further evidence on the role of consumption access in understanding the spatial concentration of economic activity. In particular, we examine the role of consumption trips in shaping

the welfare effects of transport infrastructure improvements. We undertake a counterfactual for the construction of a new subway (underground) line in the city of *Sendai* and compare the model’s predictions to the observed impact in the data.²⁰

Before the opening of its new subway (underground) line, the city of *Sendai* had only one *Nanboku* (North-South) subway line, which had been in operation since 1987. In December 2015, the new *Tozai* (East-West) subway line opened, thereby providing a substantial expansion in the overall subway network. In Section 6.1, we report reduced-form evidence on the impact of the Tozai Subway line on floor space prices, residential population and travel access. We compare the results of differences-in-differences specifications estimated using the actual data and the counterfactual predictions of our model. In Section 6.2, we present the model’s counterfactual predictions for the welfare gains from the opening of the Tozai Subway Line and evaluate the contribution from consumption access towards these welfare gains.

To undertake the counterfactual simulation, we solve the system of equations for a general equilibrium of the model using an exact-hat algebra approach, in which we rewrite the counterfactual equilibrium conditions of the model in terms of the initial travel shares and endogenous variables of the model and the counterfactual changes in these endogenous variables, as shown in Section E of the online appendix. In our baseline specification, we use the fitted values for the initial travel shares from our gravity equation estimation to address potential concerns about granularity. In Section G.5 of the online appendix, we report a robustness test using the observed initial travel shares, and demonstrate similar results using both approaches. In our baseline specification, we consider the closed-city specification of the model, in which total population for the city as a whole (\bar{L}) is exogenous, and hence the change in travel costs affects worker welfare.²¹

6.1 Difference-in-Difference Effects of Tozai Subway Line

We start by analyzing in the impact of the Tozai Subway Line in our observed smartphone and land price data. Our analysis is based on the following difference-in-difference regression:

$$\Delta \log Y_n = c_0 + c_1 T_n + u_n, \quad (43)$$

where n indexes Oaza; T_n is a dummy variable that equals one if the Oaza includes the new stations of the Tozai Subway Line (except for Sendai station which is also a station for the existing Nanboku Subway Line) and zero otherwise; $\Delta \log Y_n$ is the log difference of an outcome

²⁰In Section F of the online appendix, we provide further evidence on the relative importance of consumption and workplace access for location decisions by comparing the results of separate counterfactuals for changes in travel costs for commuting and consumption trips for the Tokyo metropolitan area.

²¹It is straightforward to instead consider the open-city specification, in which case total population is endogenous, and the welfare effects of the change in travel costs accrue only to landlords, as in the public finance literature following [George \(1879\)](#).

of interest before and after the opening of the Tozai Line; any fixed effect in the level of the outcome of interest is differenced out; the constant c_0 captures any common change in the outcome of interest across all locations; and the coefficient c_1 is an estimate of the treatment effect from the opening of a station on the new Tozai Subway Line. We consider the following outcomes: (i) the price of floor space (Q_n); (ii) the residential probability or share of the city’s residential population in each Oaza (λ_n^B); (iii) travel access (\mathbb{A}_n); and (iv) residential amenities (\mathbb{B}_n).

We first estimate this regression using the observed data for the pre- and post-periods. We measure the price of floor space (Q_n) using the observed land price data (\tilde{Q}_n) and our assumption of competitive construction sector (such that $Q_n \propto \tilde{Q}_n^{1-\mu}$). For the land price data, we use 2009 as the pre-period (the earliest available year to mitigate anticipation effects) and 2018 as the post-period. We construct the residential probability (λ_n^B) using our smartphone data. We estimate travel access \mathbb{A}_n and residential amenities \mathbb{B}_n using our smartphone data for the pre- and post-period separately. For these variables constructed from our smartphone data, we use June 2015 as the pre-period (shortly before the opening of the new subway line), and we use June 2017 as our post-period (the same month two years after the pre-period). To better proxy the changes in travel time from the opening of the new subway line in this context where residents use different travel modes, we extend our baseline model to incorporate a mode choice between public transportation and cars, as discussed in Appendix G.1.²²

In Panel (A) of Table 6, we present the results of estimating equation (43) using the observed data. As shown in Columns (1) and (2), we find larger increases in floor space prices and residential population in Oaza containing new stations than in other Oaza following the opening of the new subway line, which is consistent with these locations becoming relatively more attractive. As reported in Column (3), we also observe a larger increase in our estimate of travel access in locations with new stations, which is consistent with the idea that the increase in floor space prices and residential population in these location is driven by the model’s mechanism of an improvement in travel access. In contrast, as shown in Column (4), there is no evidence of a larger increase in the structural residual of residential amenities in these locations. Therefore, we find that the model is quantitatively able to explain the observed increase in floor space prices and residential population through its mechanism of an improvement in travel access, without requiring increases in the residual of residential amenities in these locations. Notably, if we consider the special case of our model excluding consumption trips, we find a smaller increase in travel access (0.042 instead of 0.054) and a larger increase in the residual of residential amenities (0.017 instead of 0.004), as shown in Table G.3.1 in Section G.3 of the online appendix. Hence, we also find that incorporating consumption trips is important for

²²We use the same parameters as above, except for ϕ^W and ϕ_k^S , which we re-estimate using our smartphone data for the city of Sendai, as discussed in Section G.2 of the online appendix.

the quantitative success of the model’s mechanism in explaining the observed data.

Table 6: Difference-in-Difference Estimates for the Opening of the Tozai Subway Line Using the Observed Data and our Model’s Counterfactual Predictions

	$\Delta \log Q_n$	$\Delta \log \lambda_n^B$	$\Delta \log \mathbb{A}_n$	$\Delta \log \mathbb{B}_n$
	(1)	(2)	(3)	(4)
Panel A: Data				
Dummy (Tozai Line Stations)	0.046 (0.014)	0.311 (0.210)	0.054 (0.008)	0.004 (0.036)
Observations	368	305	305	305
R ²	0.030	0.007	0.123	0.0001
Panel B: Model Prediction ($\eta^B = 0; \eta^W = 0.08$)				
Dummy (Tozai Line Stations)	0.091 (0.010)	0.300 (0.032)	0.073 (0.008)	0.000 (0.000)
Observations	370	370	370	370
R ²	0.197	0.191	0.199	

Note: Results of estimating the difference-in-difference regression (43) using the observed outcome variables (Panel A) and the counterfactual model predictions (Panel B). The treatment dummy is an indicator that takes the value one when the Oaza includes stations of the new Tozai Subway Line (except for Sendai station which is also a station for the existing Nanboku Subway Line) and zero otherwise. Observations are the 370 Oaza in the City of Sendai. In Panel (A), 2 observations are missing in Column (1) because land price data is not available, and 65 observations are missing in Columns (2)-(4), because we observe no residents in either the pre- or post-period in our smartphone data. Standard errors are clustered by Oaza.

To provide further evidence on the predictive power of our model, we next undertake counterfactuals for the impact of the reduction in travel time from the opening of the new subway line using only information from the pre-period, and estimate the same reduced-form regressions using the model’s counterfactual predictions. In our baseline specification, we assume the standard value for production agglomeration forces from the existing empirical literature ($\eta^W = 0.08$), and assume that our mechanism of consumption access captures all agglomeration forces in residential decisions ($\eta^B = 0$). In Panel (B) of Table 6, we present the results from estimating equation (43) using these counterfactual predictions for the change in each economic outcome of interest. We find that the model’s counterfactual predictions align closely with the observed patterns in the data. In Column (1), we estimate a positive and statistically significant treatment effect for the price of floor space, which is somewhat larger than that in the observed data, perhaps in part because the model may not fully capture the expansion in the supply of floor space following the opening of the new subway line. In Columns (2) and (3), we also estimate positive and statistically significant treatment effects for the residential probability and travel access, which lie within the 95 percent confidence intervals around the estimated treatments in the observed data. Finally, in Column (4), the model necessarily implies

zero treatment effect for residential amenities in the absence of residential agglomeration forces ($\eta^B = 0$), which is consistent with our finding above using the observed data that the estimated treatment effect for residential amenities is close to zero and statistically insignificant.²³

As an additional specification check, we estimate the same reduced-form regressions, but use a dummy variable that takes the value one for Oazas that contain stations on the existing Nanboku (North-South) Subway Line (which opened in 1987) rather than stations on the new Tozai (East-West) Subway Line (which opened in 2015). If there are positive or negative network effects from the new Tozai Subway Line on locations with stations on the existing Nanboku Subway Line, we would expect to again detect statistically significant treatment effects. In Section G.4 of the online appendix, we show that we find no evidence of statistically significant treatments effects on the price of floor space, residential population, travel access, and residential amenities for this existing Nanboku Subway Line. These results are consistent with a limited net impact of network effects on the existing subway line and suggest that our earlier estimates for the Tozai Subway Line are indeed capturing effects specific to this new subway line. Consistent with these findings using the observed data, we also find no evidence of statistically significant treatment effects for the existing Nanboku Subway Line using our counterfactual predictions of the model.

6.2 Welfare Gains from the Tozai Subway Line

We now use our baseline closed-city version of the model to evaluate the welfare impact of the opening of this new subway line. In Table 7, we present the results for the different model specifications shown in the left-most column. In the second column, we report the percentage point increase in expected utility for the residents of the city of Sendai. In our baseline specification in the first row, we again assume the standard value for production agglomeration forces from the existing empirical literature ($\eta^W = 0.08$), and assume that our mechanism of consumption access captures all agglomeration forces in residential decisions ($\eta^B = 0$). In the robustness checks in the subsequent rows, we report results for a number of alternative specifications. In the third column, we report the change in expected utility in each of these alternative specifications as a percentage of that in our baseline specification in the first row.

As reported in Row (1), we find an increase in the flow of expected utility from the opening of the new Tozai Subway Line of 2.74 percentage points in our baseline specification. Therefore, even though we take into account the existence of other modes of transport prior to the opening

²³In a robustness test in Section G.3 of the online appendix, we estimate η^B using the identifying assumption that the log change in residential fundamentals (b_n in equation (26)) is uncorrelated with proximity to new subway stations. We find a small estimate of $\eta^B = 0.01$. In the special case of the model that abstracts from consumption trips, we obtain a somewhat larger estimate of $\eta^B = 0.05$, again highlighting the importance of incorporating consumption trips for the model's mechanism of travel access to explain the observed data.

of the new line (such as buses), we find substantial welfare gains from the reduction in bilateral travel times achieved by the opening of the new subway line. To provide a point of comparison, Row (2) reports results for the special case of our model excluding consumption trips ($\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $\mathbb{S}_{nt} = 1$). In this specification, we find a welfare gain from the new subway line of 1.44 percentage points, or 53 percent of that in our baseline specification. Therefore, we find that the undercounting of travel journeys from focusing solely on commuting trips is quantitatively important for the evaluation of the welfare effects of observed transport infrastructure improvements.

In Row (3), we consider another special case of the model, in which we falsely assume that all consumption trips originate from home locations, thereby ruling out travel to consume non-traded services from work or on the way between home and work.²⁴ In this special case, we find somewhat larger welfare gains from the new subway line of 2.99 percentage points, or 9 percent larger than our baseline specification. This pattern of results is intuitive, because excluding consumption travel from work or on the way between home and work increases average travel distances for consumption trips, and hence increases the magnitude of the welfare gain from the reduction in travel times achieved by the opening of the new subway line.

Table 7: Counterfactual Increase in Expected Utility in Sendai from the new Tozai Subway Line

	Percentage Point Increase in Residential Utility	Relative to Baseline (%)
(1) Baseline ($\eta^B = 0; \eta^W = 0.08$)	2.74	1.00
(2) No consumption trips	1.44	0.53
(3) No trip chains for consumption trips	2.99	1.09
(4) Include residential spillover ($\eta^B = 0.15$)	3.24	1.18
(5) Eliminate production spillover ($\eta^W = 0$)	2.61	0.95

Note: The second column reports model counterfactuals for the percentage point increase in expected utility as a result of the reduction in travel time from the opening of the new Tozai (East-West) subway line in the city of Sendai. The first row presents results for our baseline specification (residential agglomeration forces of $\eta^B = 0$, workplace agglomeration forces of $\eta^W = 0.08$) and the subsequent rows present results for a number of alternative specifications. The third column reports the change in expected utility in each of these alternative specifications as a percentage of the change in our baseline specification in the first row.

In the remaining two rows, we examine the sensitivity of our results to alternative assumptions about the strength of residential and production agglomeration forces. In Row (4), we introduce residential agglomeration forces by assuming $\eta^B = 0.15$ instead of $\eta^B = 0$. In this specification, we find welfare gains from the new subway line that are around 18 percent larger than those in our baseline specification. In Row (5), we exclude productivity spillovers by assuming $\eta^W = 0$ instead of $\eta^W = 0.08$. In this case, we find welfare gains from the new subway line that are around 5 percent smaller than those in our baseline specification. Therefore, we find that agglomeration forces magnify the welfare gains from transport infrastructure improvements, consistent with the findings of existing studies, such as [Tsivanidis \(2018\)](#) and [Heblich,](#)

²⁴More specifically, we consider the limiting case in which $T_{r(k)}^R \rightarrow 0$ for $r(k) \in \{WW, HW, WH\}$ and $T_{HH}^R > 0$, which ensures that workers always travel to consume non-traded services from home.

Redding, and Sturm (2020). Nevertheless, the impact of these agglomeration forces on the welfare gains from transport infrastructure improvements (comparing Rows (4) and (5) to Row (1)) is smaller than the impact of excluding consumption trips (comparing Row (2) to Row (1)), again highlighting the relevance of consumption access for the evaluation of the welfare effects of transport infrastructure improvements.

7 Conclusions

We provide new theory and evidence on the role of consumption access in understanding the spatial concentration of economic activity. We use smartphone data that records the global positioning system (GPS) location of users every 5 minutes to provide high-resolution evidence on patterns of travel by hour and day within the Tokyo metropolitan area. Guided by our empirical findings, we develop a quantitative model of internal city structure that captures the fact that much of the travel that occurs within urban areas is related not to commuting but rather to the consumption of non-traded services, such as trips to restaurants, coffee shops and bars, shopping expeditions, excursions to cinemas, theaters, music venues and museums, and visits to professional service providers.

We begin by establishing four key empirical properties of these non-commuting trips. First, we show that they are more frequent than commuting trips, so that concentrating solely on commuting substantially underestimates travel within urban areas. Second, we find that they are concentrated closer to home and are more responsive to travel time than commuting trips, which implies that focusing solely on commuting yields a misleading picture of bilateral patterns of travel within cities. Third, combining our smartphone data with highly spatially-disaggregated data on employment by sector, we show that these non-commuting trips are closely related to the availability of nontraded sectors, consistent with our modelling of them as travel to consume non-traded services. Fourth, we find evidence of trip chains, in which these consumption trips can occur along the journey between home and work, highlighting the relevance of jointly modelling both commuting and consumption trips.

We next develop our quantitative theoretical model of internal city structure that incorporates these consumption trips. Workers choose their preferred residence, workplace and consumption locations, taking into account the bilateral costs of travel and idiosyncratic draws for amenities for each residence, productivity for each workplace, service quality for each consumption location, and preferences for each route. We show that the observed travel data and model's gravity equations for commuting and consumption trips can be used to estimate theoretically-consistent measures of travel access. We use the model's residential choice probabilities to derive a summary measure of the relative attractiveness of locations based on the

observed share of residents and the price of floor space. We show that travel access is more important than the residual of residential amenities in explaining variation in this summary measure of relative attractiveness, with a contribution of 56 percent compared to 44 percent. In a special case of our model excluding consumption trips, we find a substantially smaller contribution from travel access of 37 percent, suggesting that conventional measures of amenities may in part capture consumption access, and highlighting the usefulness of smartphone data in measuring consumption trips that are otherwise hard to observe.

Finally, we show how the model can be used to undertake counterfactuals for changes in transport infrastructure. We compare the model's counterfactual predictions for the opening of a new subway line in the city of Sendai to the observed impact in the data. We show that our model incorporating consumption access generates a similar pattern of estimated treatment effects as in the observed data. We show that focusing solely on commuting trips leads to an underestimate of the welfare gains from the transport improvement by around one half, because of the substantial undercounting of trips that results from abstracting from the many other reasons besides commuting why individuals travel within urban areas.

Taken together, our findings suggest that access to consumption opportunities as well as access to employment opportunities plays a central role in understanding the spatial concentration of economic activity.

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Online Appendix for “Consumption Access and the Spatial Concentration of Economic Activity: Evidence from Smartphone Data” (Not for Publication)

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A Data Appendix

This section of the appendix provides additional information about our smartphone data. In Section A.1 we provide further evidence on the representativeness of our smartphone data by comparing coverage by residence characteristics (income, age and distance to city center) and workplace characteristics (employment by industry and distance to city center). In Section A.2, we report further evidence validating our smartphone commuting data using census commuting data, supplementing the results reported in Section 2.3 of the paper. In Section A.3, we provide further internal validation of smartphone data by reporting the average number of work and non-work stays by day and hour of the week.

In Section A.4, we present descriptive statistics on users with missing work locations, showing that they have more infrequent smartphone use, and demonstrating that the probability of assigning missing work locations is uncorrelated with the observable characteristics of users' municipality of residence. In Section A.5, we show that our findings from our smartphone data that non-commuting trips are more frequent than commuting trips are consistent with evidence from separate Japanese travel survey data that reports travel behavior during the working week.

In Section A.6, we provide further evidence on different types of non-commuting trips, supplementing the evidence for Fact 2 in Section 3 of the paper.

A.1 Coverage of Smartphone Data

In this subsection of the appendix, we provide further evidence about the coverage of the samples of our smartphone GPS data. In Figure A.1.1, we plot the coverage rates of our smartphone data by the users' home municipality (defined by the number of users whose home location is in the municipality divided by the number of residents in the municipality in population census) against various characteristics of the municipalities, such as the population density, the share of university graduates, average income, average age and the distance to the central business district (Chiyoda Ward). The dots in each figure represents the average coverage rate for each decile of the characteristics described in the horizontal axis, and the line segments indicate the 95 percent confidence interval. We find no systematic patterns between the the coverage rates and municipality characteristics. The coverage rates have some inverse U-shaped pattern for the share of university graduates and the average income. However, these variations are not quantitatively large.

Similarly, in Figure A.1.2, we plot the coverage rates of our smartphone data by the users' work municipality (defined by the number of users whose work location is in the municipality divided by the number of employment in the municipality in population census) against various characteristics of the municipalities, such as the employment density, employment share of manufacturing, employment share of service, and the distance to the central business district (Chiyoda Ward). Similarly as the coverage rates by the residential locations, we find no systematic association between the coverage rates and these municipality characteristics.

Figure A.1.1: Representativeness of Smartphone GPS Data by Residential Location

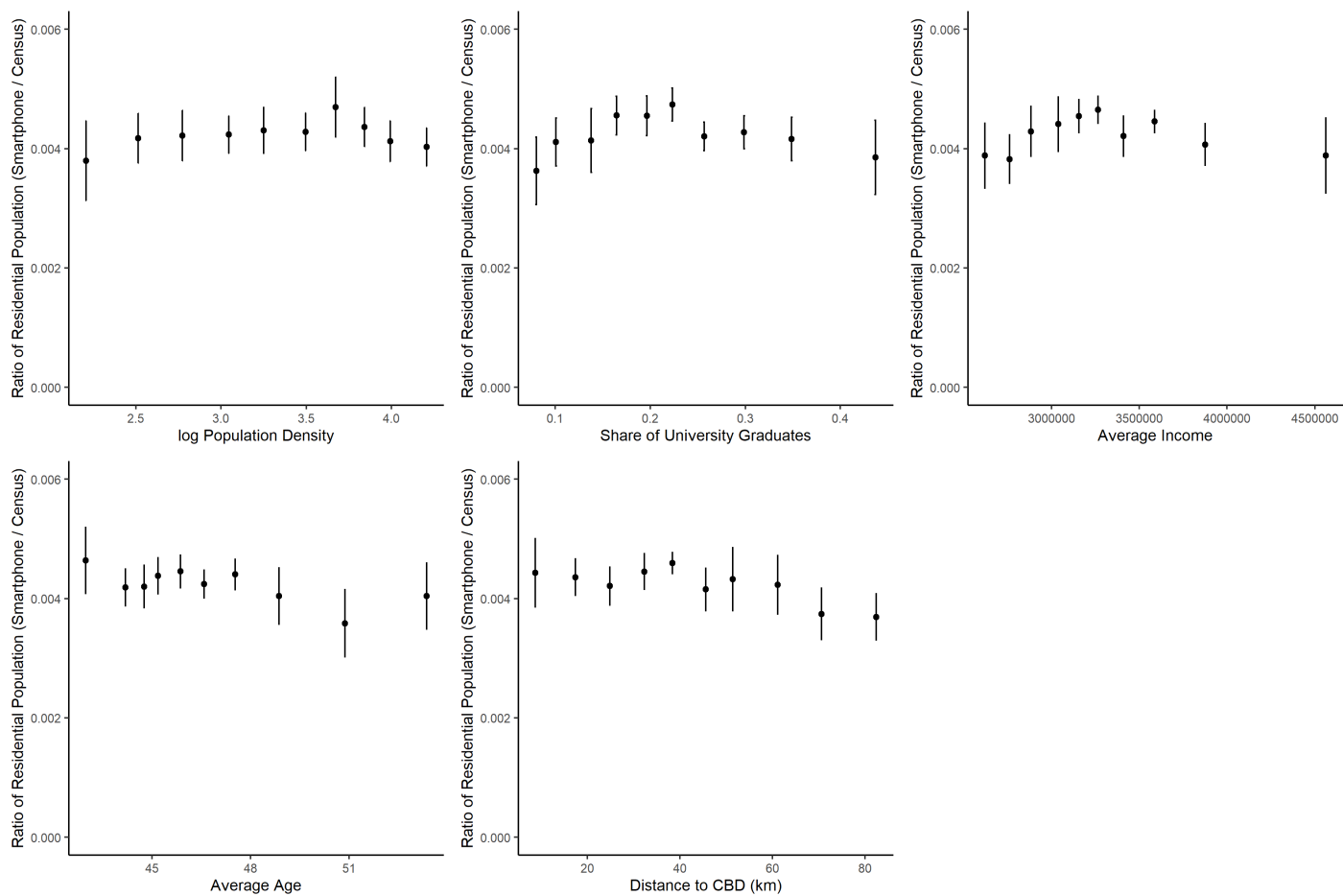
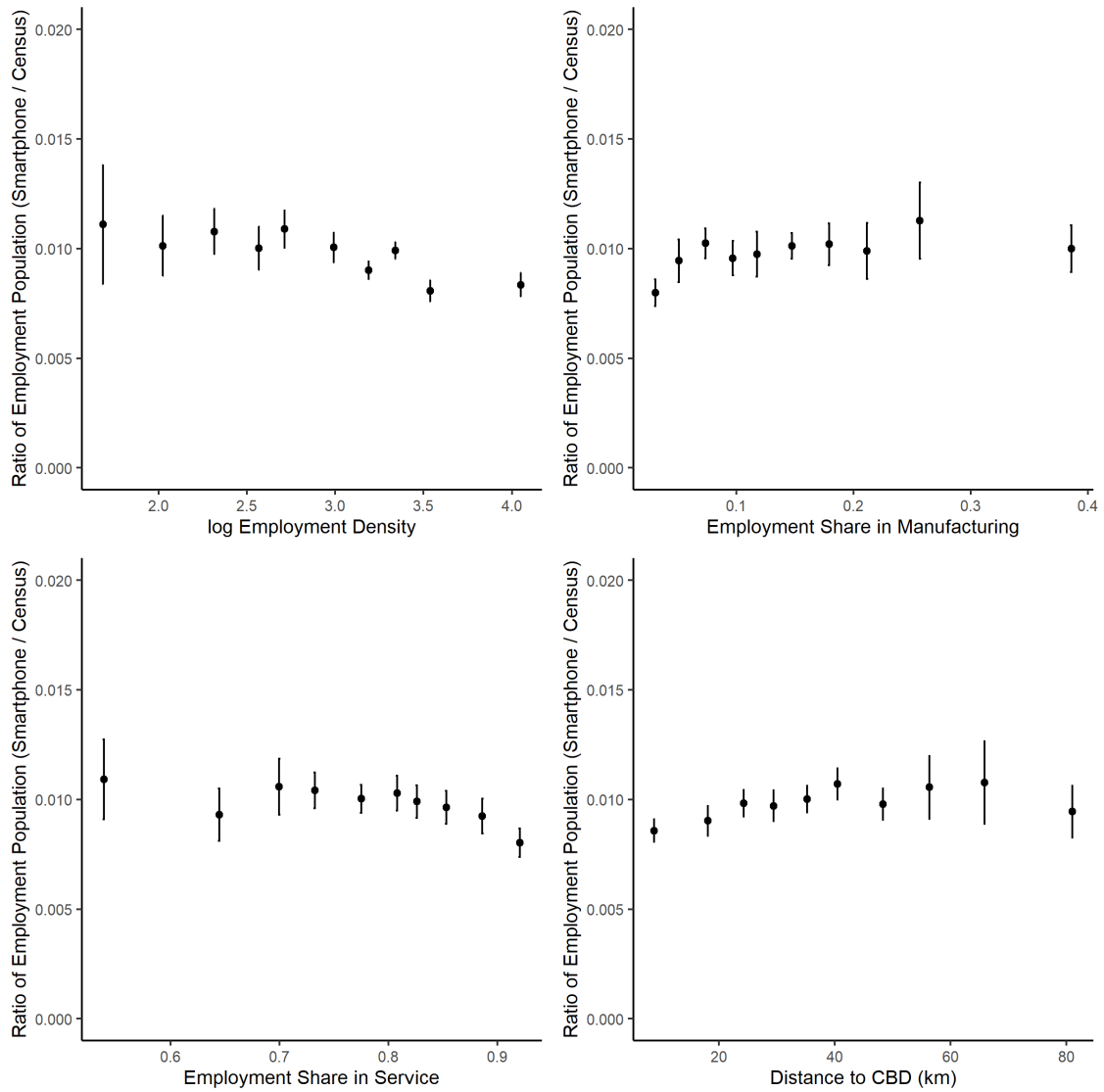


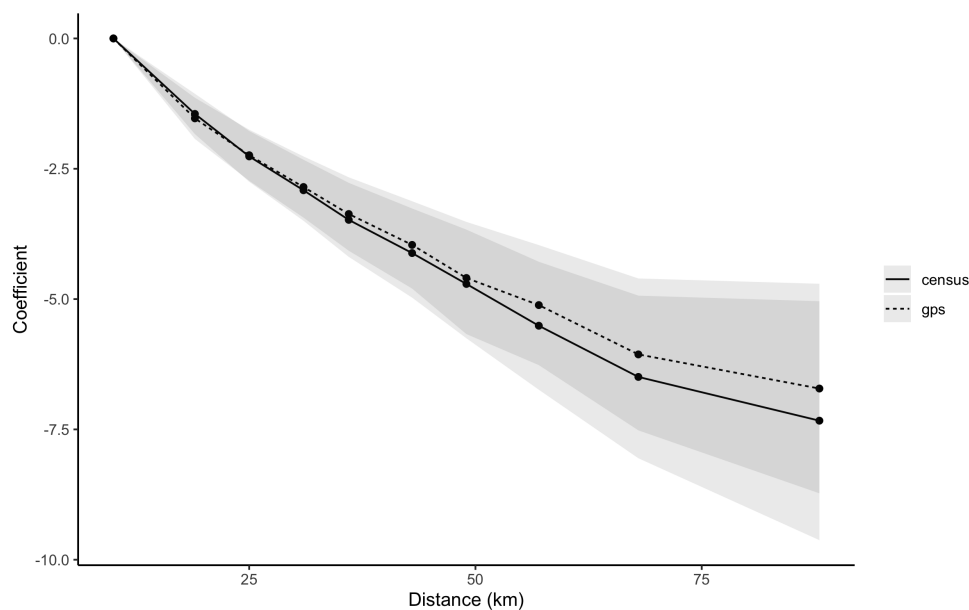
Figure A.1.2: Representativeness of Smartphone GPS Data by Employment Location



A.2 Additional Validations for Commuting Flows from Smartphone Data

In this subsection of the online appendix, we show that we find the same pattern of spatial decay of bilateral commuting flows with geographical distance in the smartphone data as in the official census data. In each case, we regress the log of bilateral commuting flows between Tokyo municipalities on residence fixed effects, workplace fixed effects and a set of indicator variables for deciles of log bilateral distance using the Poisson Pseudo Maximum Likelihood (PPML) estimator, which allows for zero flows. In Figure A.2.1, we display the estimated coefficients on the indicator variables for both the smartphone and official census data and the 95 percent confidence intervals. As sample size is smaller in our smartphone data than in the official census data, we find marginally larger confidence intervals using the smartphone data, particularly for bilateral distances of more than 50 kilometers for which there are relatively few commuters. Nonetheless, for distances of less than 50 kilometers, which account for the vast majority of all commuters in both datasets, we find that the estimates in the smartphone and census data are lie extremely close to one another.

Figure A.2.1: Gravity Equation Estimates for Bilateral Commuting Flows Using Smartphone GPS and Official Census Data

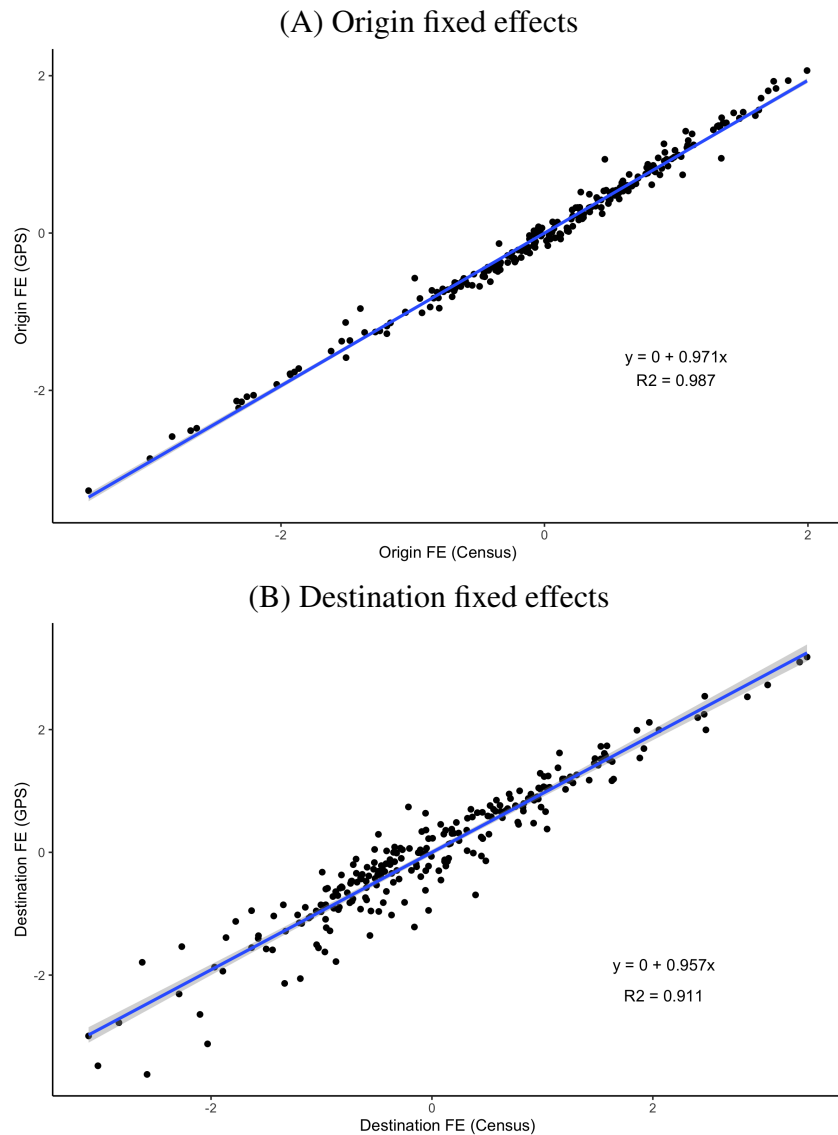


Note: Gravity equation estimation including workplace fixed effects, residence fixed effects and indicator variables for deciles of bilateral distance between workplace and residence using the Poisson Pseudo Maximum Likelihood (PPML) estimator; solid black line and dark gray shading show point estimates and 95 percent confidence intervals respectively for the distance decile indicators using the official census data; dashed black line and light gray shading show point estimates and 95 percent confidence intervals respectively for the distance decile indicators using our smartphone GPS data. Online appendix Section A.2 shows that the fixed effects and residuals from the gravity equations estimated separately using smartphone data and census data are also strongly correlated with one another.

In Figure A.2.2, we compare the origin (residence) fixed effects (Panel A) and the destination (workplace) fixed effects (Panel B) from the gravity equations estimated using our smartphone data and the official census data. In each panel, vertical axis corresponds to the estimates from the smartphone GPS data and horizontal

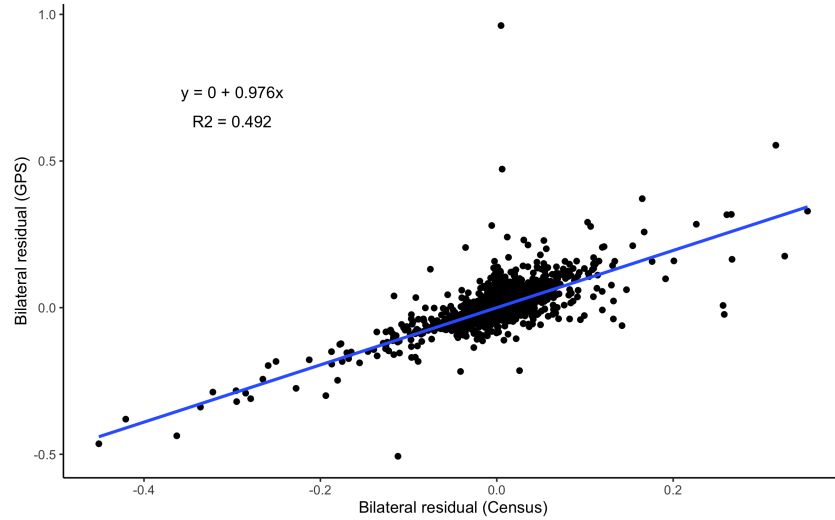
axis corresponds to the estimates from the census data. Both fixed effects have approximately log-linear relationships with coefficients close to one and R-squared of above 0.9. Therefore, these results provide further supportive evidence that the attractiveness of residential locations taking out the effects of proximity to workplaces (origin fixed effects; Panel A), and the attractiveness of employment locations taking out the effects of proximity to residences (destination fixed effects; Panel B), are closely aligned between our smartphone data and official census data.

Figure A.2.2: Correlation of fixed effects in commuting gravity estimation



As another validation for our commuting flow data, in Figure A.2.3, we compare the residuals of the same gravity equations using the two data sets. The vertical axis represents the residuals of the gravity equations using smartphone data, and the horizontal axis takes the analogous objects using official census data. If these two residuals are closely aligned, it implies that the idiosyncratic shocks to commuting flows at the bilateral pair level that are not captured by the bilateral distances shows up in both data sets. We indeed find the regression coefficient of 0.976 that is close to one and R-squared of 0.482.

Figure A.2.3: Correlation of bilateral residuals in commuting gravity estimation

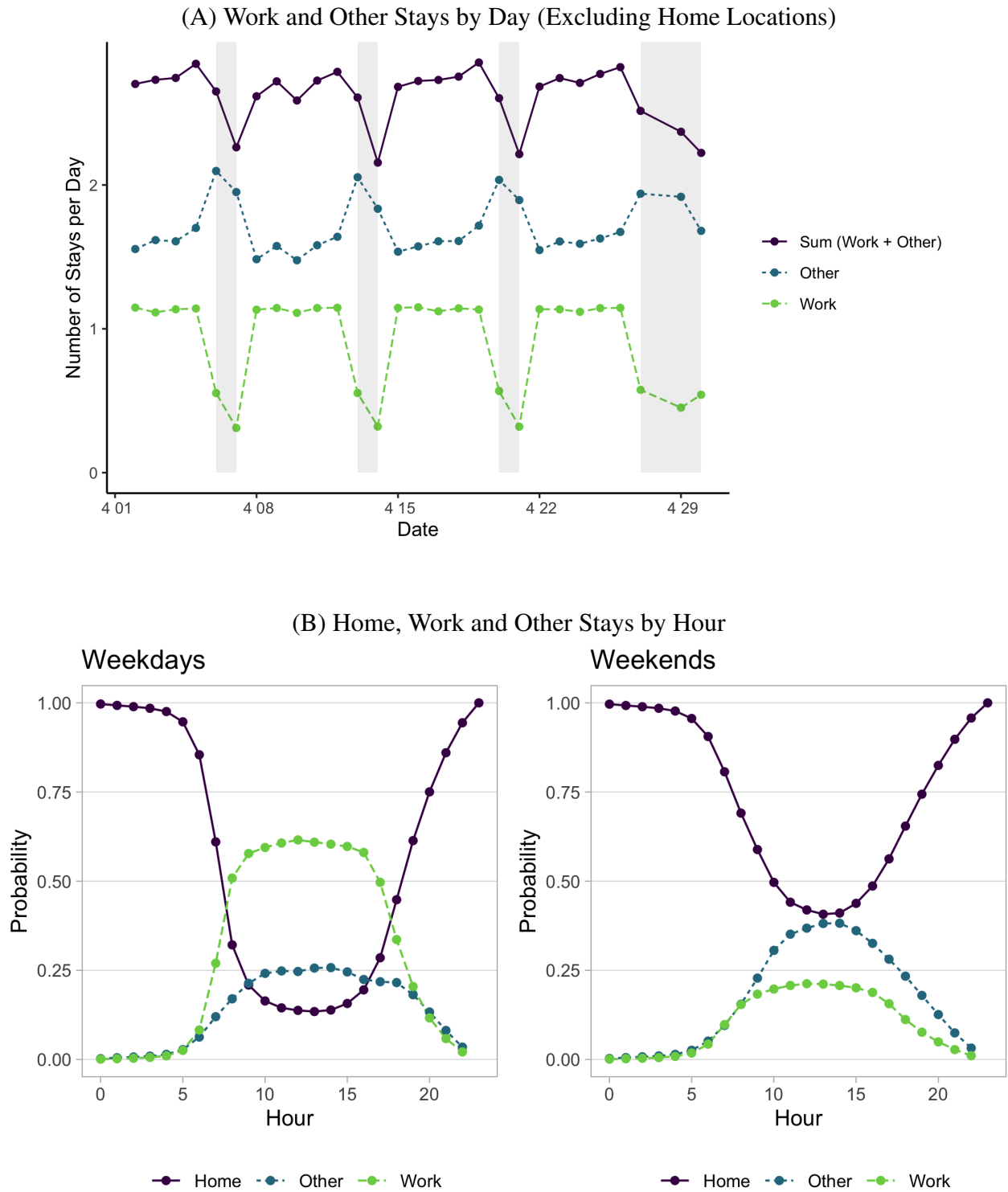


Together, these pieces of evidence support that our commuting flows constructed from smartphone data closely replicates the rate of spatial decay (gravity coefficients on distances), the attractiveness of employment and residences (residence and workplace fixed effects), and the residuals from gravity equations.

A.3 Work and Non-Work Stays by Day and Hour

In this section of the online appendix, we provide further evidence on travel patterns by reporting the average number of work and non-work stays by day and hour of the week from 1-30 April 2019. Consistent with the patterns discussed in Section 3 of the paper, we find that non-commuting trips are more frequent than commuting trips for each day of the week, with non-commuting and commuting trips increasing and decreasing respectively at weekends. In Panel (B) of Figure A.3.1, we show the average probability that a user stays at home, work or other locations by hour, based on their most recent stays. A key difference from Panel (A) is that stays in Panel (B) are implicitly weighted by the length of time that a user spends at each stay. This weighting explains why work stays have a higher probability than other stays in the middle of day during weekdays in Panel (B), even though there is a larger average number of other stays than of work stays in Panel (A). The three probabilities in Panel (B) sum to one, since home, work, and other stays are mutually exclusive and sum to the total number of stays. Even after weighting by time, other stays are quantitatively relevant compared to work stays during both weekdays and weekends. Comparing across hours of the day, we find the expected pattern that home stays fall and both work and other stays rise during the daytime (from around 6am-9pm). During weekdays, the probability of a stay rises more rapidly during the waking hours for work stays than for other stays. During weekends, we find the opposite pattern, with the probability of a stay rising more rapidly during the waking hours for other stays than for work stays.

Figure A.3.1: Work and Other Stays by Day and Hour



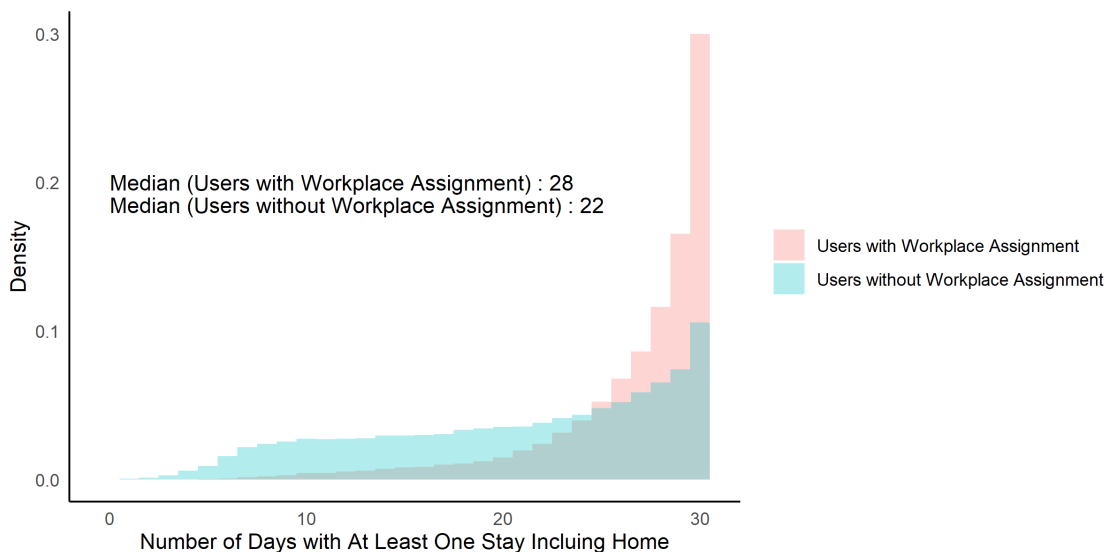
Note: Panel (A): Average number of work and other stays per day (excluding stays at home locations) for our baseline sample of users in the Tokyo metropolitan area in April 2019. Gray shaded areas indicate weekends and holidays in Japan. Panel (B): shows the probability that each user stays at home, work or other locations by each hour of the day, where these three probabilities sum to one. To construct Panel (B), for each user and for each hour of the clock for each day (e.g. at 11am), we measure the user's location as the stay location that has started most recently. We then compute the probability of each type of stay by averaging across days, separately for weekdays and weekends, and for each hour. See Section 2 above for the definitions of home, work and other stays.

A.4 Patterns of Users without Workplace Assignment

As discussed in Section 2.1 of our main paper, “home” location and “work” locations are defined as the centroid of the first and second most frequent locations of geographically contiguous stays, respectively. To ensure that these two locations do not correspond to different parts of a single property, we also require that the “work” location is more than 600 meters away from “home” location. In particular, if the second most frequent location is within 600 meters of the “home” locations, we define the “work” location as the third most frequent location. To abstract from noise in geo-coordinate assignment, all stays within 500 meters of the home location are aggregated with the home location. Similarly, all stays within 500 meters of the work location are aggregated with the work location. We assign “work” location as missing if the user appears in that location for less than 5 days per month, which applies for about 30 percent of users in our baseline sample during April 2019. In this section of the online appendix, we characterize the pattern of users whose workplace is not assigned in this procedure.

We first provide suggestive evidence that a large fraction of cases with missing “work” locations is likely to be due to the inactive usage of smartphone devices themselves. Figure A.4.1 shows the distribution of the number of days that we observe any stays in April 2019, including stays at home. As discussed in Section 2.1, location information is collected regardless of what application the user has open, as long as the device is turned on (upon users’ consent). Therefore, the number of days with any stays is a proxy for how active the device is used (i.e., whether it is regularly turned on, or whether the user bring the device with them when they move out). We find that the median active days is 22 for users without workplace assignment, which is significantly smaller than 28 days for users with workplace assignment. Therefore, many devices we have “missing” workplaces are not actively used in April 2019.

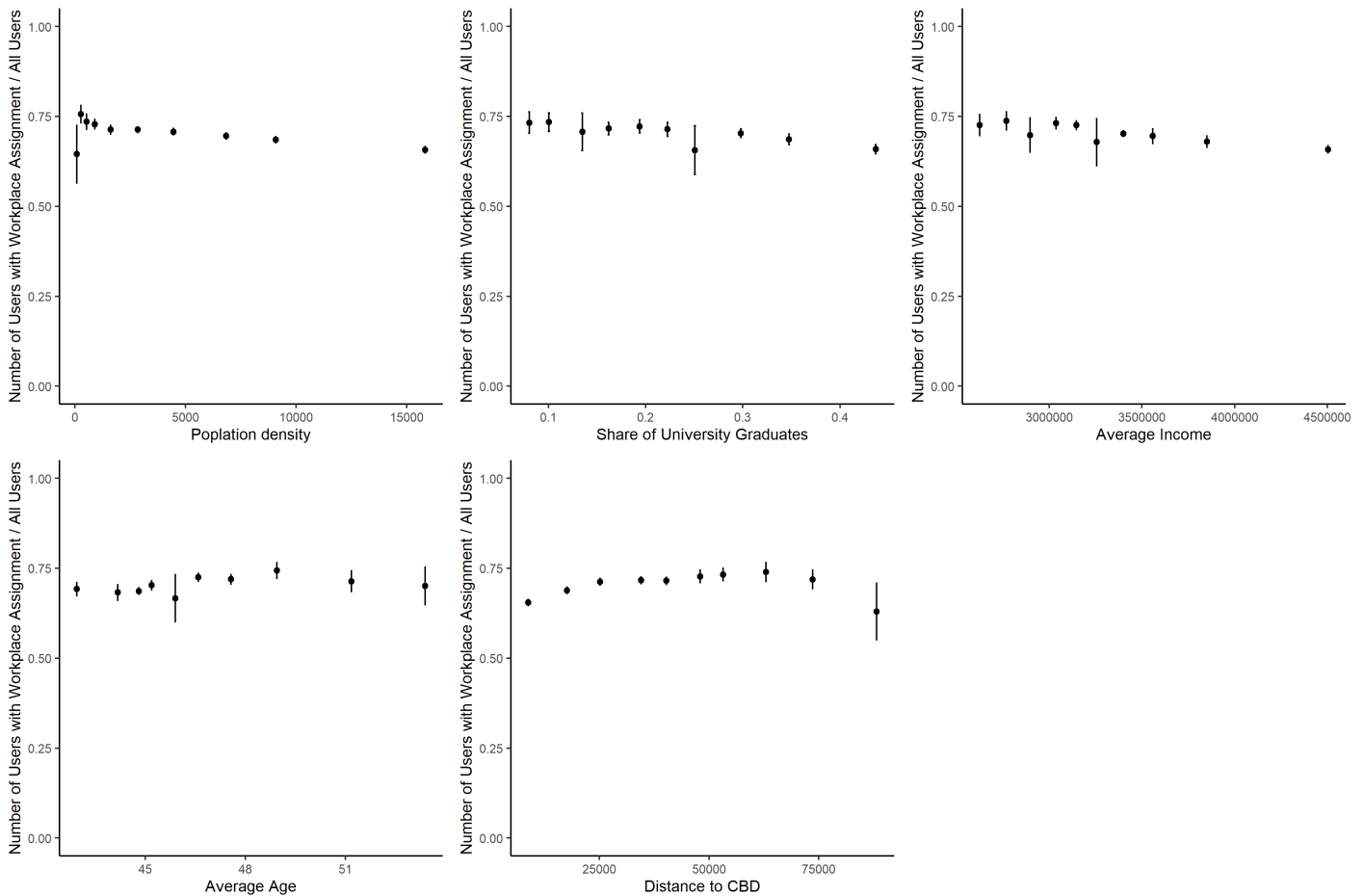
Figure A.4.1: Number of Stays by Users with and without Workplace Assignment



If these devices are not actively used, one may worry about the potential bias due to this attrition. To check this point, in Figure A.4.2, we display how the probability of missing “work” location is correlated with the residential characteristics. In each of the panel, we plot the fraction of users whose workplace is assigned (on

the vertical axis) against the characteristics of their residential municipality, such as the population density, the share of university graduates, average income, average age and the distance to the central business district (Chiyoda Ward). The dots in each figure represents the average fraction of non-missing “work” for each decile of the characteristics described in the horizontal axis at the users’ “home” location, and the line segments indicate the 95 percent confidence interval. We find no strong associations between non-missing “work” with these municipality characteristics. There is a mild decreasing pattern in the share of university graduates and the average income, but the magnitudes are not quantitatively large. Therefore, along the dimensions of observable residential characteristics, we find limited evidence of the bias in the probability of missing “work” locations.

Figure A.4.2: Pattern of the Ratio of Users with Workplace Assignment



A.5 Comparison with Travel Survey

In this section of the online appendix, we validate our smartphone GPS data using a separate travel survey (person trip survey). We show that similar patterns of urban trips documented in our paper using our smartphone data also hold with the travel survey data.

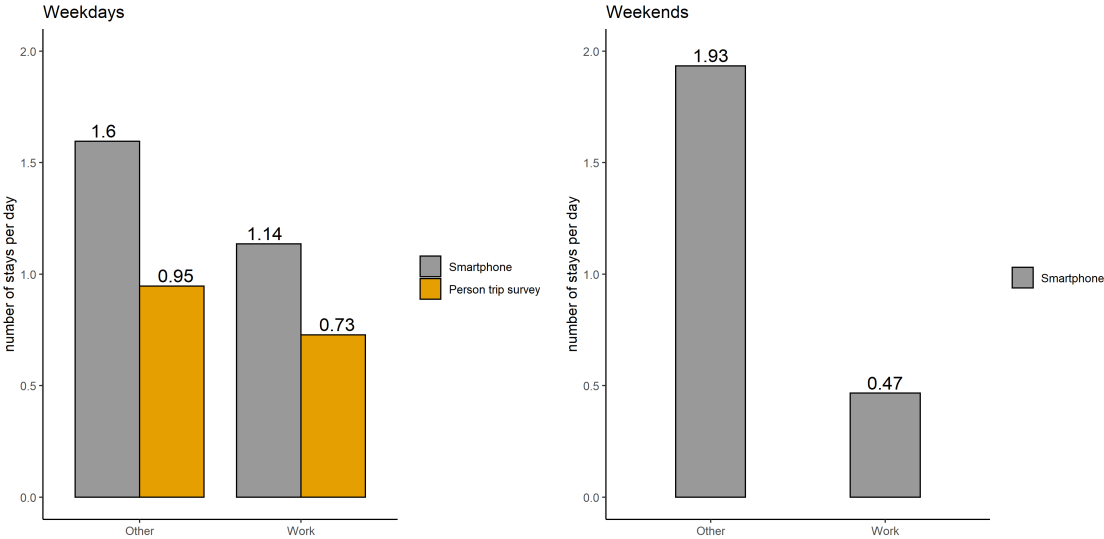
In greater Tokyo Metropolitan Area, travel surveys (person trip surveys) are conducted at a decennial frequency. For this validation, we use the information from person trip survey data conducted in 2008. The respondents of this survey are members of households residing in Tokyo, Saitama, Chiba, and Kanagawa and a

part of Ibaraki prefectures, which is mostly consistent with our definition of Greater Tokyo Metropolitan Area. The respondents are asked about their travel behavior on a specific weekday. The survey asks about a sequence of travel she made during the day (a sequence of segments of movements from one place to another). For each trip segment, the survey asks where and when the trip starts and ends, the purpose of the trip, and what transportation mode is used. This survey also asks basic demographic information, work status, and home address. We use all non-student samples for the following validation exercises.

Figure A.5.1 compares the number of stays per day per person in our smartphone data and in this person trip survey. The left panel depicts the number of stays at workplaces and the number of stays at other (non-work) stays separately for the two data sets. The right panel depicts the same information. Given that the travel survey only asks about the pattern on a specific weekday, the number of stays from the travel survey is missing in the right panel, showing frequency of stays on weekends.

Focusing on the pattern on weekdays (left panel), we find that the number of stays is greater for smartphone data than for the person trip survey. One possible reason for this difference is under-reporting of trips in the person trip survey. Recall that we define “stays” if a user is static for more than 15 minutes. In the person trip survey, if the actual stay length is as short as 15 minutes, one may not report the stay in the survey. Despite this difference, the relative number of work stays and other (non-work) stays is similar between the two types of data sets. In smartphone data, 58 percent ($= 1.6 / (1.6 + 1.14)$) of all stays are related to other purposes. In person trip data, this number is 56 percent ($= 0.95 / (0.95 + 0.73)$), which is approximately the same as the same number from smartphone data.

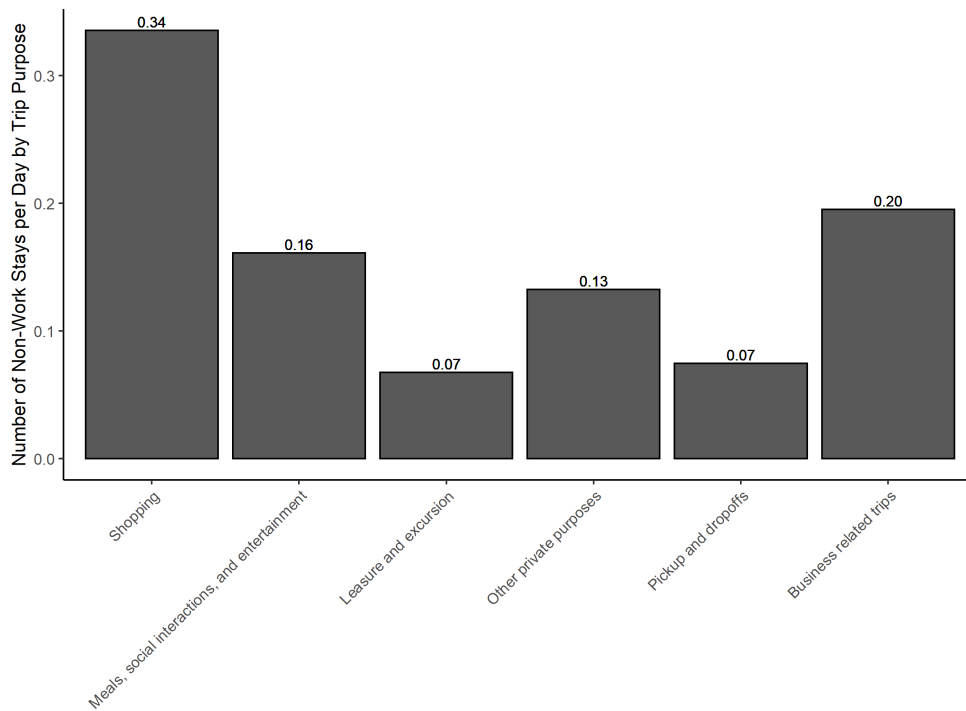
Figure A.5.1: Frequency of Stays at Work and Other Locations



We next compare the types of non-commuting stays between our smartphone data and the person trip survey. In our main paper, we assign sectors of “Other” stays from our smartphone data using separate economic census data, and presented the decomposition of these non-commuting stays into different sector (Figure 1). As a comparison with Figure 1, Figure A.5.2 displays the average number of stays per day for other locations in Person Trip Survey data by the stated purpose of the trip. While the precise comparison with our assign-

ment of trip sectors from smartphone data is difficult due to different classifications, we find a similar overall pattern. In particular, we find that “Shopping” is the most frequent category (34 percent), consistent with our finding from our smartphone data that “Retail and Wholesales” sectors are the most frequent category of non-commuting stays with the share of 43 percent on weekdays (Figure 1). We also find a substantially smaller fraction of business-related trips (e.g., business meetings, procurement; 20 percent) compared to trips related to consumption.

Figure A.5.2: Frequency of Stays at Other Locations by purpose using trip survey data



As a final comparison between our smartphone data and the travel survey, Table A.5.1 displays the average distances to work and other stays in kilometers; from home location for smartphone GPS data (Column 1) and the person trip survey data (Column 2). In Column 1, we find that the destinations of other stays are more concentrated around home location than commuting trips from smartphone data (as documented by Fact 3 of Section 3 of our main paper). Consistent with this finding, we find a similar pattern using our travel survey data in Column 2. Moreover, the average distance to work locations from home locations are closely aligned between smartphone GPS data and the survey data (12.68 and 12.78 kilometers, respectively). For other (non-work) stays, the average distances are slightly more distant from home locations in our smartphone data (10.95 kilometer) than our travel survey data (7.39 kilometer). These differences potentially come from a noisier measure of distances in our travel survey data due to a coarser geographic aggregation, or due to underreporting of stays in the survey in far distances from home in travel survey data (for example, people may not report small errands along the commuting paths, or the lunch or coffee during the office hours).

Table A.5.1: Average Distances of Work Stays from Home Locations

	Smartphone	Person trip survey
Work	12.68	12.78
Other	10.95	7.39

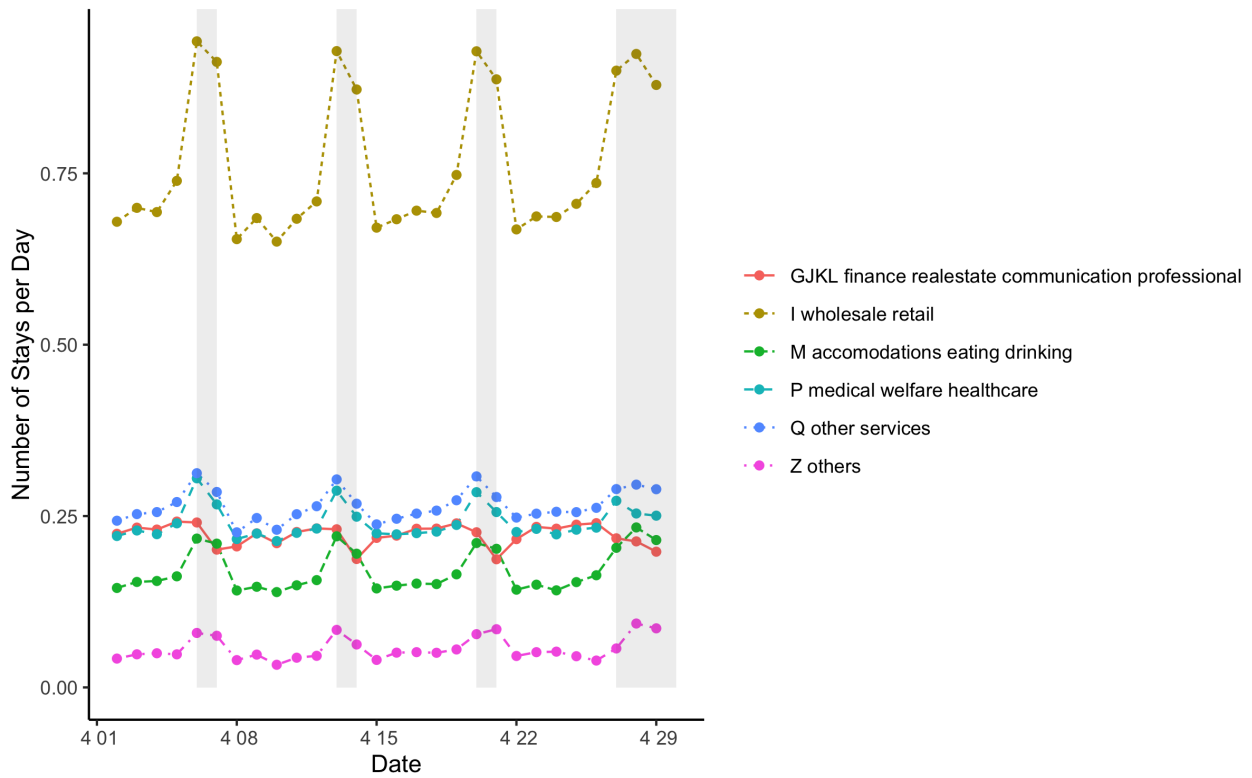
Note: Average distances of work stays and other (non-work) stays from home location (in kilometers); from smartphone data (first column) and from travel survey data (second column).

A.6 Additional Validation of Sector Assignment of Non-Commuting Stays

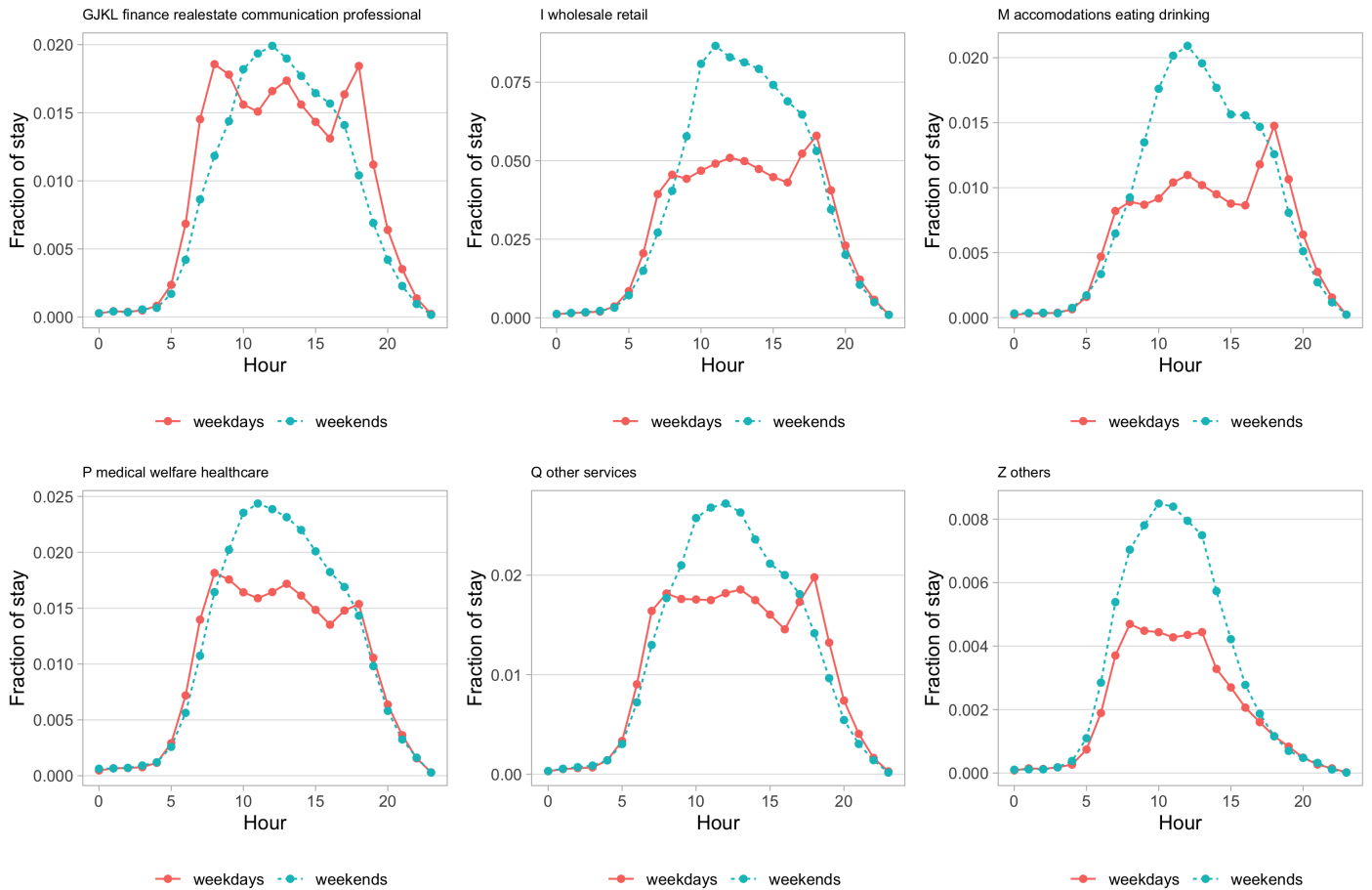
In this subsection of the appendix, we provide additional validation of our assignment of “other” stays (stays at neither home nor work locations) to sectors using separate economic census as defined in Figure 1 in the paper. Figure A.6.1 displays the density of each type of other stay by starting hour and day, as a share of all stays for our baseline sample for the Tokyo metropolitan area in April 2019. We find that our probabilistic assignment captures the expected pattern of these different service-sector activities over the course of the week. First, we typically find a higher density of other stays during the middle of the day at weekends than during weekdays, which is in line with the fact that many of these services are consumed more intensively during leisure time. The one exception is “Finance, Real Estate, Communication, and Professional,” which displays the opposite pattern, consistent with the fact that establishments providing these services are often closed at the weekends in Japan. Second, we find that the peak densities of stays for “Wholesale and Retail” and “Accommodations, Eating, Drinking” occur at around 6pm on weekdays, corroborating the fact that these activities are typically concentrated after work during the week. For “Accommodations, Eating, Drinking,” we find a smaller peak around noon on weekdays, as expected from the typical timing of lunch in Japan. Third, and finally, both of these activities are more concentrated in the middle of the day on weekends than during the week, which again is in line with workers having greater leisure time in the middle of day at weekends.

Figure A.6.1: Other Stays by Type, Day, and Hour

(A) Number of other stays by day



(B) Number of other stays by starting hour



B Theoretical Framework Appendix

In this section of the online appendix, we report the detailed derivations of the results in Section 4 of the paper. We consider a city (Tokyo) that is embedded in a larger economy (Japan). We consider both a closed-city specification (in which total city population is exogenous) and an open-city specification (in which total city population is endogenously determined by population mobility with the wider economy that offers a reservation level of utility \bar{U}). The city consists of a discrete set of locations $i, j, n \in N$ that differ in productivity, amenities, supply of floor space and transport connections. Utility is defined over consumption of a single traded good, a number of different types of non-traded services (e.g. restaurants, coffee shops, stores), and residential floor space use. Both the traded good and the non-traded services are produced with labor and commercial floor space according to constant returns to scale under conditions of perfect competition. Floor space is supplied by a competitive construction sector using land and capital according to a constant returns to scale construction technology.

A continuous measure of workers (\bar{L}) choose a residence, a workplace and a set of locations to consume non-traded services in the city.¹ We assume the following timing or nesting structure for workers' location decisions. First, each worker observes her idiosyncratic preferences or amenities (b) for each location within the city, and chooses her residence n . Second, given a choice of residence, each worker observes her idiosyncratic productivities (a) for each workplace i and sector g , and chooses her sector and location of employment. Third, given a choice of residence and workplace, she observes idiosyncratic qualities (q) for each type of non-traded service k available in each location j , and chooses her consumption location for each type of non-traded service. Fourth, given a choice of residence, workplace, and the set of consumption locations, she observes idiosyncratic shocks (ν) of whether to visit the consumption location from their residence, returning to their residence after the visiting the consumption location, from their workplace, again a round trip, or on the way to work from home (which we call a "route"), and chooses the route for each consumption location r . We choose this nesting structure because it permits a transparent decomposition of residents and land prices into the contribution of travel accessibility and the residual of amenities. We also compare the predictions of our model with the special case abstracting from consumption trips, which corresponds to a conventional urban model, in which workers choose workplace and residence and consume only traded goods. In the open-city specification, population mobility ensures that the expected utility from living in the city equals the reservation utility in the wider economy.

B.1 Preferences

The indirect utility for worker ω who chooses residence n , works in location i and sector g , and consumes non-traded service k in location $j(k)$ with the route $r(k)$ (the choice of whether to visit consumption locations

¹In our theoretical analysis, we assume for simplicity a continuous measure of workers, which ensures that the expected values of variables equal their realized values. In our empirical analysis, we allow for granularity and a finite number of workers in both our estimation (using the PPML estimator) and our counterfactuals (using predicted shares from this estimation).

from home, from work, or in-between) is assumed to take the following Cobb-Douglas form:

$$\begin{aligned}
U_{nig\{j(k)r(k)\}}(\omega) &= \left\{ B_n b_n(\omega) (P_n^T)^{-\alpha^T} Q_n^{-\alpha^H} \right\} \{ a_{i,g}(\omega) w_{i,g} \}, \\
&\times \left\{ \prod_{k \in K^S} [P_{j(k)}^S / (q_{j(k)}(\omega))]^{-\alpha_k^S} \right\} \left\{ d_{ni\{j(k)r(k)\}} \prod_{k \in K^S} \nu_{r(k)}(\omega) \right\} \\
0 &< \alpha^T, \alpha^H, \alpha_k^S < 1, \quad \alpha^T + \alpha^H + \sum_{k \in K^S} \alpha_k^S = 1,
\end{aligned} \tag{B.1}$$

where we use the notation $j(k)$ to indicate that that non-traded service k is consumed in a single location j that is an implicit function of the type of non-traded service k ; $r(k) \in \mathbb{R} \equiv \{HH, WW, HW, WH\}$ indicates the “route” choice of whether to visit consumption locations from home (HH), from work (WW), on the way from home to work (HW), or on the way from work to home (WH) for each non-traded service k ; $K^S \subset K$ is the subset of sectors that are non-traded; the first term in brackets captures a residence component of utility; the second term in brackets corresponds to a workplace component of utility; the third term in brackets reflects a non-traded services component of utility; the fourth term in brackets reflects a travel cost component of utility.

The first, residence component, includes amenities (B_n) that are common for all workers in residence n ; the idiosyncratic amenity draw for residence n for worker ω ($b_n(\omega)$); the price of the traded good (P_n^T); and the price of residential floor space (Q_n). We allow the common amenities (B_n) to be either exogenous or endogenous to the surrounding concentration of economic activity in the presence of agglomeration forces, as discussed further below. The second, workplace component, comprises the wage per efficiency unit in sector g in workplace i ($w_{i,g}$); the idiosyncratic draw for productivity or efficiency units of labor for worker ω in sector g in workplace i ($a_{i,g}(\omega)$).² The third, non-traded services component, depends on the price of the non-traded service k in the location $j(k)$ where it is supplied ($P_{j(k)}^S$ for $k \in K^S$); the idiosyncratic draw for quality for that service in that location ($q_{j(k)}(\omega)$ for $k \in K^S$). The fourth, travel cost component, includes iceberg form of travel cost for each combination of residence, workplace, the consumption locations and their routes ($d_{ni\{j(k)r(k)\}}$); and the idiosyncratic draw for route preference for each non-traded sector ($\nu_{r(k)}(\omega)$ for $k \in K^S$).

To make a precise mapping between the travel cost ($d_{ni\{j(k)r(k)\}}$) and the travel time between any bilateral locations, we parametrize $d_{ni\{j(k)r(k)\}}$ as follows:

$$d_{ni\{j(k)r(k)\}} = \exp(-\kappa^W \tau_{ni}^W) \prod_{k \in K^S} \exp(-\kappa^S \tau_{ni\{j(k)r(k)\}}^S) \tag{B.2}$$

In this expression, the first term before the product sign captures the cost of commuting from residence n to workplace i without any detour to consume non-traded services, which depends on travel time (τ_{ni}^W) and the commuting cost parameter (κ^W), where overall commuting travel time is the sum of the travel time incurred in each direction:

$$\tau_{ni}^W = \tau_{ni} + \tau_{in}. \tag{B.3}$$

The second term in equation (2) captures the additional travel costs involved in consuming each type of non-traded service k in location $j(k)$ by the route $r(k)$, which depends on the additional travel time involved

²Although we model the workplace idiosyncratic draw as a productivity draw, there is a closely-related formulation in which it is instead modelled as an amenity draw.

$(\tau_{nij(k)r(k)}^S)$ and the consumption travel cost parameter (κ_k^S) . This additional travel time depends on the route taken: whether the worker visits consumption location $j(k)$ from home ($r(k) = HH$), from work (WW), on the way from home to work (HW), or on the way from work to home (WH):

$$\begin{aligned}\tau_{nij(k)HH}^S &= \tau_{nj} + \tau_{jn}, \\ \tau_{nij(k)WW}^S &= \tau_{ij} + \tau_{ji}, \\ \tau_{nij(k)HW}^S &= \tau_{nj} + \tau_{ji} - \tau_{ni}, \\ \tau_{nij(k)WH}^S &= \tau_{ij} + \tau_{jn} - \tau_{in},\end{aligned}\tag{B.4}$$

where the negative term at the end of the third and fourth lines above reflects the fact that the worker travels indirectly between residence n and workplace i via consumption location j on one leg of her journey between home and work, and hence does not incur the direct travel time between residence n and workplace i for that leg of the journey.

We make the conventional assumption in the location choice literature following [McFadden \(1974\)](#) that the idiosyncratic shocks are drawn from an extreme value distribution. In particular, idiosyncratic amenities (b), productivity (a), quality (q), route preferences (ν) for worker ω , residence n , workplace i and consumption location $j(k)$ for non-traded service k are drawn from the following independent Fréchet distributions:

$$\begin{aligned}G_n^B(b) &= \exp\left(-T_n^B b^{-\theta^B}\right), & T_n^B > 0, \theta^B > 1, \\ G_{i,g}^W(a) &= \exp\left(-T_{i,g}^W a^{-\theta^W}\right), & T_{i,g}^W > 0, \theta^W > 1, \\ G_{j(k)}^S(q) &= \exp\left(-T_{j(k)}^S q^{-\theta_k^S}\right), & T_{j(k)}^S > 0, \theta_k^S > 1, k \in K^S, \\ G_{r(k)}^R(\nu) &= \exp\left(-T_{r(k)}^R \nu^{-\theta_k^R}\right), & T_{r(k)}^R > 0, \theta_k^R > 1, k \in K^S\end{aligned}\tag{B.5}$$

where the scale parameters $\{T_n^B, T_{i,g}^W, T_{j(k)}^S, T_{r(k)}^R\}$ control the average draws and the shape parameters $\{\theta^B, \theta^W, \theta_k^S, \theta_k^R\}$ regulate the dispersion of amenities, productivity and quality respectively. The smaller these dispersion parameters, the greater the heterogeneity in idiosyncratic draws, and the less responsive worker decisions to economic variables.³

Using our assumption about the timing or nesting structure, the worker location choice problem is recursive and can be solved backwards. First, for given a choice of residence, workplace and sector, and the set of consumption locations, we characterize the probability that a worker chooses each route for each non-traded sector (whether to visit consumption locations from home, from work, or in-between). Second, for given a choice of residence, workplace and sector, we characterize the probability that a worker chooses each consumption location in each non-traded sector, taking into account the expected travel cost for consumption trips. Third, for given a choice of residence, we characterize the probability that a worker chooses each workplace and sector, taking into account the expected consumption access of that workplace and sector. Fourth, we characterize the probability that a worker chooses each residence, taking into account its expected travel accessibility for both commuting and consumption.

³Although we assume independent Fréchet distributions for amenities, productivity and quality, some locations can have high expected values for all three shocks if they have high values for T_n^B , $T_{i,g}^W$ and $T_{j(k)}^S$. Additionally, correlations between the shocks can be introduced using a multivariate Fréchet distribution, as in [Hsieh, Hurst, Jones, and Klenow \(2019\)](#).

B.2 Route Choices

We begin with the worker's decision of the route choice for each non-traded service sector k . More specifically, conditional on residence, workplace, and consumption location, the worker chooses whether to visit consumption location $j(k)$ from home ($r(k) = HH$), from work (WW), on the way from home to work (HW), or on the way from work to home (WH). Given the indirect utility (B.1) and the specification of the travel cost (B.2), the indirect utility is rewritten as:

$$U_{nig\{j(k)r(k)\}}(\omega) = \left\{ B_n b_n(\omega) (P_n^T)^{-\alpha^T} Q_n^{-\alpha^H} \right\} \{a_{i,g}(\omega) w_{i,g}\}, \\ \times \left\{ \prod_{k \in K^S} [P_{j(k)}^S / (q_{j(k)}(\omega))]^{-\alpha_k^S} \right\} \left\{ \exp(-\kappa^W \tau_{ni}^W) \prod_{k \in K^S} \exp(-\kappa^S \tau_{nij(k)r(k)}^S) \nu_{r(k)}(\omega) \right\}$$

The component of the utility that depends on the route $r(k)$ for non-traded service k is given by:

$$\delta_{nij(k)r(k)}(\omega) = \exp(-\kappa^S \tau_{nij(k)r(k)}^S) \nu_{r(k)}(\omega). \quad (\text{B.6})$$

where the first component is the route-specific travel cost and the second component is the idiosyncratic route preference. Under our assumption of independent route-preference draws $\nu_{r(k)}(\omega)$ across each non-traded sector k , each worker chooses the route $r(k)$ that maximizes $\delta_{nij(k)r(k)}(\omega)$ independently for each sector k .

Using our independent extreme value assumption for idiosyncratic preference shocks for the route choice, the route choice probability is characterized by a logit form. In particular, the probability that a worker living in residence n and employed in workplace i consuming non-traded service k in location $j(k)$ chooses the route $r(k)$ ($\lambda_{r(k)|nij(k)}^R$) is derived as follows:

$$\lambda_{r(k)|nij(k)}^R = \Pr \left[\delta_{nij(k)r(k)}(\omega) > \max \{ \delta_{nij(k)\ell(k)}(\omega) : \ell \neq r \} \right], \\ = \int_0^\infty \prod_{\ell \neq r} G_{\ell(k)}^R(\delta) g_{nr(k)}^R(\delta) d\delta, \\ = \int_0^\infty \prod_{\ell \neq r} \exp\left(-\Phi_{nij(k)\ell(k)}^R \delta^{-\theta_k^R}\right) \theta_k^R \Phi_{nij(k)r(k)}^R \delta^{-(\theta_k^R+1)} \exp\left(-\Phi_{nij(k)r(k)}^R \delta^{-\theta_k^R}\right) d\delta, \\ = \int_0^\infty \exp\left(-\Phi_{nij(k)}^R \delta^{-\theta_k^R}\right) \theta_k^R \Phi_{nij(k)r(k)}^R \delta^{-(\theta_k^R+1)} d\delta,$$

where

$$\Phi_{nij(k)}^R \equiv \sum_{r'(k) \in \mathbb{R}} \Phi_{nij(k)r'(k)}^R = \sum_{r'(k) \in \mathbb{R}} T_{r'(k)}^R \exp\left(-\theta_k^R \kappa^S \tau_{nij(k)r'(k)}^S\right).$$

Note that

$$\frac{d}{d\gamma} \left[\frac{1}{\Phi_{nij(k)}^R} \exp\left(-\Phi_{nij(k)}^R \delta^{-\theta_k^R}\right) \right] = \exp\left(-\Phi_{nij(k)}^R \delta^{-\theta_k^R}\right) \theta_k^R \delta^{-(\theta_k^R+1)}.$$

Using this result to evaluate the integral above, we have:

$$\lambda_{r(k)|nij(k)}^R = \Phi_{nij(k)}^R \left[\frac{1}{\Phi_{nij(k)}^R} \exp\left(-\Phi_{nij(k)}^R \delta^{-\theta_k^R}\right) \right]_0^\infty,$$

which becomes:

$$\lambda_{r(k)|nij(k)}^R = \frac{T_{r(k)}^R \exp(-\theta_k^R \kappa_k^S \tau_{nij(k)r(k)}^S)}{\sum_{r' \in \mathbb{R}} T_{r'(k)}^R \exp(-\theta_k^R \kappa_k^S \tau_{nij(k)r'(k)}^S)}. \quad (\text{B.7})$$

Using our independent extreme value assumption for idiosyncratic preference shocks for route choice, we can also compute the expected contribution to utility from the travel cost from consumption trips as follows. Using the property that the maximum of a sequence of Fréchet distributions is itself Fréchet distributed, the contribution to utility from the preferred route choice also has a Fréchet distribution:

$$G_{nij(k)}^R(\delta) = \prod_{r'(k) \in \mathbb{R}} G_{nij(k)r'(k)}^R(\delta) = \prod_{r' \in \mathbb{R}} \exp\left(-\Phi_{nij(k)r'(k)}^R \delta^{-\theta_k^R}\right),$$

$$G_{nij(k)}^R(\delta) = \exp\left(-\Phi_{nij(k)}^R \delta^{-\theta_k^R}\right), \quad \Phi_{nij(k)}^R \equiv \sum_{r'(k) \in \mathbb{R}} \Phi_{nij(k)r'(k)}^R.$$

Given this Fréchet distribution for the contribution to utility from the preferred location, the expected contribution to utility from the preferred route choice is:

$$\begin{aligned} \mathbb{E}_{nij(k)}[\delta] &= \int_0^\infty \delta g_{nij(k)}^R(\delta) d\delta \\ &= \int_0^\infty \theta_k^R \Phi_{nij(k)}^R \delta^{-\theta_k^R} \exp\left(-\Phi_{nij(k)}^R \delta^{-\theta_k^R}\right) d\delta \end{aligned}$$

Now define the following change of variables:

$$y = \Phi_{nij(k)}^R \delta^{-\theta_k^R}, \quad dy = (\theta_k^R) \Phi_{nij(k)}^R \delta^{-(\theta_k^R+1)} d\delta.$$

$$\delta = \left(\frac{y}{\Phi_{nij(k)}^R}\right)^{-\frac{1}{\theta_k^R}}, \quad d\delta = \frac{dy}{(\theta_k^R) \Phi_{nij(k)}^R \delta^{-(\theta_k^R+1)}}.$$

Using this change of variables, we can write the expected contribution to utility as:

$$\begin{aligned} \mathbb{E}_{nij(k)}[\delta] &= \int_0^\infty (\theta_k^R) \Phi_{nij(k)}^R \frac{y}{\Phi_{nij(k)}^R} \exp(-y) \frac{dy}{(\theta_k^R) \Phi_{nij(k)}^R \left(\frac{y}{\Phi_{nij(k)}^R}\right)^{\frac{\theta_k^R+1}{\theta_k^R}}}, \\ &= \int_0^\infty y \exp(-y) \frac{dy}{\Phi_{nij(k)}^R \left(\frac{y}{\Phi_{nij(k)}^R}\right)^{\frac{\theta_k^R+1}{\theta_k^R}}}, \\ &= \int_0^\infty y^{-\frac{1}{\theta_k^R}} \exp(-y) \frac{dy}{\Phi_{nij(k)}^R \left(\Phi_{nij(k)}^R\right)^{-\frac{\theta_k^R+1}{\theta_k^R}}}, \\ &= (\Phi_{nij(k)}^R)^{\frac{1}{\theta_k^R}} \int_0^\infty y^{-\frac{1}{\theta_k^R}} \exp(-y) dy. \\ &= \vartheta_k^R (\Phi_{nij(k)}^R)^{\frac{1}{\theta_k^R}}, \end{aligned}$$

where

$$\vartheta_k^R \equiv \Gamma\left(\frac{\theta_k^R - 1}{\theta_k^R}\right) = \int_0^\infty y^{-\frac{1}{\theta_k^R}} \exp(-y) dy,$$

and $\Gamma(\cdot)$ is the Gamma function. To summarize,

$$d_{nij(k)}^S = \mathbb{E}_{nij(k)} [\delta_{nij(k)r(k)}(\omega)] = \vartheta_k^R \left[\sum_{r' \in \mathbb{R}} T_{r'(k)}^R \exp(-\theta_k^R \kappa_k^S T_{nij(k)r'(k)}^S) \right]^{\frac{1}{\theta_k^R}} \quad (\text{B.8})$$

which corresponds to equation (8) in the paper.

B.3 Consumption Choices

We begin with the worker's decision of where to consume each type of non-traded service. Conditional on living in residence n , each worker chooses consumption location $j(k)$ for non-traded service k to maximize the contribution to indirect utility (B.1) from consuming that non-traded service:

$$\gamma_{nij(k)}(\omega) = [P_{j(k)}^S / (q_{j(k)}(\omega))]^{-\alpha_k^S} d_{nij(k)}^S, \quad k \in K^S. \quad (\text{B.9})$$

We thus have the following monotonic relationship between the contribution to utility from consuming non-tradable services and quality:

$$q_{j(k)}(\omega) = (\gamma_{nij(k)}(\omega) / d_{nij(k)}^S)^{1/\alpha_k^S} (P_{j(k)}^S)$$

Therefore, using this relationship and the Fréchet distribution for idiosyncratic quality, we have:

$$\begin{aligned} \Pr [\gamma_{nij(k)} < \gamma] &= G_{nij(k)}^S \left(\gamma^{1/\alpha_k^S} P_{j(k)}^S (d_{nij(k)}^S)^{-1/\alpha_k^S} \right), \\ G_{nij(k)}^S(\gamma) &= e^{-\Phi_{nij(k)}^S \gamma^{-\theta_k^S/\alpha_k^S}}, \quad \Phi_{nij(k)}^S \equiv T_{j(k)}^S (P_{j(k)}^S)^{-\theta_k^S} (d_{nij(k)}^S)^{\theta_k^S/\alpha_k^S}. \end{aligned}$$

Using this distribution for the contribution of nontradable services to utility, the probability that a worker in residence n consumes nontradable service k in location $j(k)$ is:

$$\begin{aligned} \lambda_{j(k)|ni}^S &= \Pr [\gamma_{nj(k),k} > \max \{ \gamma_{n\ell(k),k} : \ell \neq j \}], \\ &= \int_0^\infty \prod_{\ell \neq j} G_{n\ell(k)}^S(\gamma) g_{nij(k)}^S(\gamma) d\gamma, \\ &= \int_0^\infty \prod_{\ell \neq j} \exp\left(-\Phi_{n\ell(k)}^S \gamma^{-\theta_k^S/\alpha_k^S}\right) (\theta_k^S/\alpha_k^S) \Phi_{nij(k)}^S \gamma^{-((\theta_k^S/\alpha_k^S)+1)} \exp\left(-\Phi_{nij(k)}^S \gamma^{-\theta_k^S/\alpha_k^S}\right) d\gamma, \\ &= \int_0^\infty \exp\left(-\Phi_{ni,k}^S \gamma^{-\theta_k^S/\alpha_k^S}\right) (\theta_k^S/\alpha_k^S) \Phi_{nij(k)}^S \gamma^{-((\theta_k^S/\alpha_k^S)+1)} d\gamma, \end{aligned}$$

where

$$\Phi_{ni,k}^S \equiv \sum_{\ell \in N} \Phi_{n\ell(k)}^S = \sum_{\ell \in N} T_{\ell(k)}^S (P_{\ell(k)}^S)^{-\theta_k^S} (d_{nij(k)}^S)^{\theta_k^S/\alpha_k^S}.$$

Note that

$$\frac{d}{d\gamma} \left[\frac{1}{\Phi_{ni,k}^S} \exp\left(-\Phi_{ni,k}^S \gamma^{-\theta_k^S/\alpha_k^S}\right) \right] = \exp\left(-\Phi_{ni,k}^S \gamma^{-\theta_k^S/\alpha_k^S}\right) (\theta_k^S/\alpha_k^S) \gamma^{-((\theta_k^S/\alpha_k^S)+1)}.$$

Using this result to evaluate the integral above, we have:

$$\lambda_{j(k)|ni}^S = \Phi_{nij(k)}^S \left[\frac{1}{\Phi_{ni,k}^S} e^{-\Phi_{ni,k}^S \gamma^{-\theta_k^S/\alpha_k^S}} \right]_0^\infty,$$

which becomes:

$$\lambda_{j(k)|ni}^S = \frac{\Phi_{nil(k)}^S}{\Phi_{ni,k}^S} = \frac{T_{j(k)}^S \left(P_{j(k)}^S \right)^{-\theta_k^S} \left(d_{nij(k)}^S \right)^{\frac{\theta_k^S}{\alpha_k^S}}}{\sum_{\ell \in N} T_{\ell(k)}^S \left(P_{\ell(k)}^S \right)^{-\theta_k^S} \left(d_{nil(k)}^S \right)^{\frac{\theta_k^S}{\alpha_k^S}}}. \quad (\text{B.10})$$

and corresponds to equation (10) in the paper. We refer to this probability as the conditional consumption probability, since it is computed conditional on living in residence n .

Using the property that the maximum of a sequence of Fréchet distributions is itself Fréchet distributed, the contribution to utility from the preferred location for consuming nontradable services of type k from residence n also has a Fréchet distribution:

$$G_{ni,k}^S(\gamma) = \prod_{\ell \in N} G_{ni\ell(k)}^S(\gamma) = \prod_{\ell \in N} \exp\left(-\Phi_{ni\ell(k)}^S \gamma^{-\left(\theta_k^S/\alpha_k^S\right)}\right),$$

$$G_{ni,k}^S(\gamma) = \exp\left(-\Phi_{ni,k}^S \gamma^{-\left(\theta_k^S/\alpha_k^S\right)}\right), \quad \Phi_{ni,k}^S \equiv \sum_{\ell \in N} \Phi_{ni\ell(k)}^S.$$

Given this Fréchet distribution for the contribution to utility from the preferred location, the expected contribution to utility from consuming nontradable services of type k from residence n is:

Now define the following change of variables:

$$y = \Phi_{ni,k}^S \gamma^{-\theta_k^S/\alpha_k^S}, \quad dy = \left(\theta_k^S/\alpha_k^S\right) \Phi_{ni,k}^S \gamma^{-\left(\left(\theta_k^S/\alpha_k^S\right)+1\right)} d\gamma.$$

$$\gamma = \left(\frac{y}{\Phi_{ni,k}^S}\right)^{-\frac{1}{\theta_k^S/\alpha_k^S}}, \quad d\gamma = \frac{dy}{\left(\theta_k^S/\alpha_k^S\right) \Phi_{ni,k}^S \gamma^{-\left(\left(\theta_k^S/\alpha_k^S\right)+1\right)}}.$$

Using this change of variables, we can write the expected contribution to utility as:

$$\begin{aligned} \mathbb{E}_{nik}[\gamma] &= \int_0^\infty \left(\theta_k^S/\alpha_k^S\right) \Phi_{ni,k}^S \frac{y}{\Phi_{ni,k}^S} \exp(-y) \frac{dy}{\left(\theta_k^S/\alpha_k^S\right) \Phi_{ni,k}^S \left(\frac{y}{\Phi_{ni,k}^S}\right)^{\frac{\left(\theta_k^S/\alpha_k^S\right)+1}{\left(\theta_k^S/\alpha_k^S\right)}}}, \\ &= \int_0^\infty y \exp(-y) \frac{dy}{\Phi_{ni,k}^S \left(\frac{y}{\Phi_{ni,k}^S}\right)^{\frac{\left(\theta_k^S/\alpha_k^S\right)+1}{\left(\theta_k^S/\alpha_k^S\right)}}}, \\ &= \int_0^\infty y^{-\frac{1}{\theta_k^S/\alpha_k^S}} \exp(-y) \frac{dy}{\Phi_{ni,k}^S \left(\Phi_{ni,k}^S\right)^{-\frac{\left(\theta_k^S/\alpha_k^S\right)+1}{\left(\theta_k^S/\alpha_k^S\right)}}}, \\ &= \left(\Phi_{ni,k}^S\right)^{\frac{1}{\theta_k^S/\alpha_k^S}} \int_0^\infty y^{-\frac{1}{\left(\theta_k^S/\alpha_k^S\right)}} \exp(-y) dy. \\ &= \vartheta_k^S \left(\Phi_{ni,k}^S\right)^{\frac{1}{\left(\theta_k^S/\alpha_k^S\right)}}, \end{aligned}$$

where

$$\vartheta_k^S \equiv \Gamma \left(\frac{(\theta_k^S / \alpha_k^S) - 1}{(\theta_k^S / \alpha_k^S)} \right) = \int_0^\infty y^{-\frac{1}{(\theta_k^S / \alpha_k^S)}} \exp(-y) dy,$$

and $\Gamma(\cdot)$ is the Gamma function. We thus obtain the following measure of residence n 's consumption access for non-traded service k :

$$\mathbb{S}_{nik} \equiv \mathbb{E}_{nik} [\gamma_{nij(k)}] = \vartheta_k^S (\Phi_{ni,k}^S)^{\frac{\alpha_k^S}{\theta_k^S}} = \vartheta_k^S \left[\sum_{\ell \in N} T_{\ell(k),k}^S (P_{\ell(k)}^S)^{-\theta_k^S} (d_{ni\ell(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}} \right]^{\frac{\alpha_k^S}{\theta_k^S}}, \quad (\text{B.11})$$

which corresponds to equation (11) in the paper.

Aggregating across sectors using the Cobb-Douglas function form for consumption of non-tradeable services, we arrive at the following expression for consumption access:

$$\mathbb{S}_{ni} = \prod_{k \in K^S} \mathbb{S}_{nik} = \prod_{k \in K^S} \vartheta_k^S \left[\sum_{\ell \in N} T_{\ell(k)}^S (P_{\ell(k)})^{-\theta_k^S} (d_{ni\ell(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}} \right]^{\frac{\alpha_k^S}{\theta_k^S}},$$

which corresponds to equation (12) in the paper.

B.4 Workplace Choice

We next turn to the worker's choice of workplace. In making this choice, each worker takes into account access to surrounding consumption possibilities. In particular, conditional on living in residence n , each worker chooses the workplace i and sector g that offers the highest utility, taking into account the wage per efficiency unit ($w_{i,g}$), the idiosyncratic draw for productivity ($a_{i,g}(\omega)$), commuting costs (d_{ni}^W), and expected consumption access (\mathbb{S}_{ni}):

$$v_{ni,g}(\omega) = w_{i,g} a_{i,g}(\omega) \exp(-\kappa^W \tau_{ni}^W) \mathbb{S}_{ni}. \quad (\text{B.12})$$

We thus have the following monotonic relationship between the contribution to utility from income and productivity:

$$a_{i,g}(\omega) = \frac{v_{ni,g}(\omega)}{w_{i,g} \exp(-\kappa^W \tau_{ni}^W) \mathbb{S}_{ni}}.$$

Therefore, using this relationship and the Fréchet distribution for idiosyncratic productivity, we have:

$$\Pr[v_{ni,g} < v] = G_{ni,g}^W \left(\frac{v}{w_{i,g} \exp(-\kappa^W \tau_{ni}^W) \mathbb{S}_{ni}} \right),$$

$$G_{ni}^W(v) = \exp(-\Phi_{ni,g}^W v^{-\theta^W}), \quad \Phi_{ni,g}^W \equiv T_{i,g}^W w_{i,g}^{\theta^W} \exp(-\theta^W \kappa^W \tau_{ni}^W) (\mathbb{S}_{ni})^{\theta^W}.$$

Using this distribution for the contribution to utility from income, the probability that a worker in residence n commute to workplace i in sector g is:

$$\begin{aligned}
\lambda_{ig|n}^W &= \Pr [v_{ni,g} \geq \max \{v_{n\ell,m}\}; \forall \ell, m], \\
&= \int_0^\infty \prod_{\ell \neq i} G_{n\ell,g}^W(v) \left[\prod_{\ell \in N} \prod_{m \neq g} G_{n\ell,m}(v) \right] g_{ni,g}^W(v) dv, \\
&= \int_0^\infty \prod_{\ell \neq i} \exp\left(-\Phi_{n\ell,g}^W v^{-\theta^W}\right) \left[\prod_{\ell \in N} \prod_{m \neq g} \exp\left(-\Phi_{n\ell,m}^W v^{-\theta^W}\right) \right] \theta^W \Phi_{ni,g}^W v^{-(\theta^W+1)} \exp\left(-\Phi_{ni,g}^W v^{-\theta^W}\right) dv, \\
&= \int_0^\infty \exp\left(-\Phi_n^W v^{-\theta^W}\right) \theta^W \Phi_{ni,g}^W v^{-(\theta^W+1)} dv,
\end{aligned}$$

where

$$\Phi_n^W \equiv \sum_{\ell \in N} \sum_{m \in G} \Phi_{n\ell,m}^W = \sum_{\ell \in N} \sum_{m \in G} T_{\ell,m}^W w_{\ell,m}^{\theta^W} \exp\left(-\theta^W \kappa^W \tau_{n\ell}^W\right).$$

Note that

$$\frac{d}{dv} \left[\frac{1}{\Phi_n^W} \exp\left(-\Phi_n^W v^{-\theta^W}\right) \right] = \exp\left(-\Phi_n^W v^{-\theta^W}\right) (\mathcal{S}_{ni})^{\theta^W} \theta^W v^{-(\theta^W+1)}.$$

Using this result to evaluate the integral above, we have:

$$\lambda_{ig|n}^W = \Phi_{ni,g}^W \left[\frac{1}{\Phi_n^W} \exp\left(-\Phi_n^W v^{-\theta^W}\right) \right]_0^\infty,$$

which becomes:

$$\lambda_{ig|n}^W = \frac{T_{i,g}^W w_{i,g}^{\theta^W} \exp\left(-\theta^W \kappa^W \tau_{ni}^W\right) (\mathcal{S}_{ni})^{\theta^W}}{\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} \exp\left(-\theta^W \kappa^W \tau_{n\ell}^W\right) (\mathcal{S}_{n\ell})^{\theta^W}}, \quad (\text{B.13})$$

and corresponds to equation (14) in the paper. We refer to this expression as the conditional commuting probability, since again it is computed conditional on living in residence n . Aggregating across sectors, we also obtain the overall commuting probability between residence n and workplace i :

$$\lambda_{i|n}^W = \sum_{g \in K} \lambda_{ig|n}^W. \quad (\text{B.14})$$

Using the property that the maximum of a sequence of Fréchet distributions is itself Fréchet distributed, the distribution of income for residence n across all workplaces ℓ and sectors m also has a Fréchet distribution:

$$\begin{aligned}
G_n^W(v) &= \prod_{\ell \in N} \prod_{m \in G} G_{n\ell,m}^W(v) = \prod_{\ell \in N} \prod_{m \in G} e^{-\Phi_{n\ell,m}^W v^{-\theta^W}}, \\
G_n^W(v) &= e^{-\Phi_n^W v^{-\theta^W}}, \quad \Phi_n^W \equiv \sum_{\ell \in N} \sum_{m \in G} \Phi_{n\ell,m}^W.
\end{aligned}$$

Given this Fréchet distribution for the contribution to utility from income from the chosen workplace, the expected contribution to utility from income is:

$$\begin{aligned}
\mathbb{E}_n^W[v] &= \int_0^\infty v g_n^W(v) dv, \\
&= \int_0^\infty \theta^W \Phi_n^W v^{-\theta^W} \exp\left(-\Phi_n^W v^{-\theta^W}\right) dv.
\end{aligned}$$

Now define the following change of variables:

$$y = \Phi_n^W v^{-\theta^W}, \quad dy = \theta^W \Phi_n^W v^{-(\theta^W+1)} dv. \quad (\text{B.15})$$

$$v = \left(\frac{y}{\Phi_n^W} \right)^{-\frac{1}{\theta^W}}, \quad dv = \frac{dy}{\theta^W \Phi_n^W v^{-(\theta^W+1)}}.$$

Using this change of variables, we can write the expected contribution to utility as:

$$\begin{aligned} \mathbb{E}_n [v] &= \int_0^\infty \theta^W \Phi_n^W \frac{y}{\Phi_n^W} \exp(-y) \frac{dy}{\theta^W \Phi_n^W \left(\frac{y}{\Phi_n^W} \right)^{\frac{\theta^W+1}{\theta^W}}}, \\ &= \int_0^\infty y \exp(-y) \frac{dy}{\Phi_n^W \left(\frac{y}{\Phi_n^W} \right)^{\frac{\theta^W+1}{\theta^W}}}, \\ &= \int_0^\infty y^{-\frac{1}{\theta^W}} \exp(-y) \frac{dy}{\Phi_n^W (\Phi_n^W)^{-\frac{\theta^W+1}{\theta^W}}}, \\ &= (\Phi_n^W)^{\frac{1}{\theta^W}} \int_0^\infty y^{-\frac{1}{\theta^W}} \exp(-y) dy. \\ &= \vartheta^W (\Phi_n^W)^{\frac{1}{\theta^W}}, \end{aligned}$$

where

$$\vartheta^W \equiv \Gamma \left(\frac{\theta^W - 1}{\theta^W} \right) = \int_0^\infty y^{-\frac{1}{\theta^W}} \exp(-y) dy,$$

and $\Gamma(\cdot)$ is the Gamma function. We thus have the following expression for expected income conditional on living in residence n :

$$\mathbb{A}_n = \mathbb{E}_n [v_{ni,g}] = \vartheta^W \left[\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} \exp(-\theta^W \kappa^W \tau_{n\ell}^W) (\mathbb{S}_{n\ell})^{\theta^W} \right]^{\frac{1}{\theta^W}}, \quad (\text{B.16})$$

which corresponds to equation (16) in the paper.

While expected utility is equalized across all workplaces conditional on residence, expected income is different because of the heterogeneity of consumption access \mathbb{S}_{ni} for bilateral commuting pairs. Therefore, expected income for workers in residence n and workplace i is given by:

$$E_{ni} = \frac{\mathbb{A}_i}{\mathbb{S}_{ni}}, \quad (\text{B.17})$$

and expected income by residents in n is given by:

$$E_n = \sum_{i \in N} E_{ni} \lambda_{i|n}^W. \quad (\text{B.18})$$

B.5 Residence Choice

Having characterized a worker's consumption and workplace choices conditional on her residence, we now turn to her residence choice. Each worker chooses her residence after observing her idiosyncratic draws for

amenities (b), but before observing her idiosyncratic draws for productivity (a) and the quality of non-traded services (q). Therefore, each worker ω chooses the residence n that offers her the highest utility given her idiosyncratic amenity draws ($b_n(\omega)$), expected travel accessibility (\mathbb{A}_n), and other residence characteristics (the price of floor space (Q_n), the price of the traded good (P_n^T) and common amenities (B_n):

$$U_n(\omega) = B_n b_n(\omega) (P_n^T)^{-\alpha^T} Q_n^{-\alpha^H} \mathbb{A}_n,$$

We thus have the following monotonic relationship between idiosyncratic amenities and utility:

$$b_n(\omega) = U_n(\omega) B_n^{-1} \mathbb{A}_n^{-1} (P_n^T)^{\alpha^T} Q_n^{\alpha^H}$$

Therefore, using this relationship and the Fréchet distribution for idiosyncratic amenities, we have:

$$\begin{aligned} \Pr[U_n(\omega) < u] &= G_n^B \left(u B_n^{-1} \mathbb{A}_n^{-1} (P_n^T)^{\alpha^T} Q_n^{\alpha^H} \right), \\ G_n^B(u) &= \exp \left(-\Phi_n^B u^{-\theta^B} \right), \quad \Phi_n^B \equiv T_n^B B_n^{\theta^B} \mathbb{A}_n^{\theta^B} (P_n^T)^{-\alpha^T \theta^B} Q_n^{-\alpha^H \theta^B}. \end{aligned}$$

Using this distribution for utility, the probability that a worker chooses residence n is:

$$\begin{aligned} \lambda_n^B &= \Pr[U_n > \max\{U_i : i \neq n\}], \\ &= \int_0^\infty \prod_{i \neq n} G_i^B(u) g_n^B(u) du, \\ &= \int_0^\infty \prod_{i \neq n} \exp \left(-\Phi_i^B u^{-\theta^B} \right) \theta^B \Phi_n^B u^{-(\theta^B+1)} \exp \left(-\Phi_n^B u^{-\theta^B} \right) du, \\ &= \int_0^\infty \exp \left(-\Phi^B u^{-\theta^B} \right) \theta^B \Phi_n^B u^{-(\theta^B+1)} du, \end{aligned}$$

where

$$\Phi^B \equiv \sum_{i \in N} \Phi_i^B = \sum_{i \in N} T_i^B B_i^{\theta^B} \mathbb{A}_i^{\theta^B} (P_i^T)^{-\alpha^T \theta^B} Q_i^{-\alpha^H \theta^B}.$$

Note that

$$\frac{d}{du} \left[\frac{1}{\Phi^B} \exp \left(-\Phi^B u^{-\theta^B} \right) \right] = \exp \left(-\Phi^B u^{-\theta^B} \right) \theta^B u^{-(\theta^B+1)}.$$

Using this result to evaluate the integral above, we have:

$$\lambda_n^B = \Phi_n^B \left[\frac{1}{\Phi^B} \exp \left(-\Phi^B u^{-\theta^B} \right) \right]_0^\infty,$$

which implies that the probability that each worker chooses residence n (λ_n^B) is given by:

$$\lambda_n^B = \frac{T_n^B B_n^{\theta^B} \mathbb{A}_n^{\theta^B} (P_n^T)^{-\alpha^T \theta^B} Q_n^{-\alpha^H \theta^B}}{\sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} (P_\ell^T)^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B}}, \quad (\text{B.19})$$

which corresponds to equation (17) in the paper.

Using the property that the maximum of a sequence of Fréchet distributions is itself Fréchet distributed, the distribution of utility across all locations is also Fréchet:

$$G^B(u) = \prod_{i \in N} G_i^B(u) = \prod_{i \in N} \exp \left(-\Phi_i^B u^{-\theta^B} \right),$$

$$G^B(u) = \exp\left(-\Phi^B u^{-\theta^B}\right), \quad \Phi^B \equiv \sum_{i \in N} \Phi_i^B.$$

Given this Fréchet distribution for utility, expected utility is:

$$\begin{aligned} \mathbb{E}^B[u] &= \int_0^\infty u g^B(u) du, \\ &= \int_0^\infty \theta^B \Phi^B u^{-\theta^B} \exp\left(-\Phi^B u^{-\theta^B}\right) du. \end{aligned}$$

Now define the following change of variables:

$$\begin{aligned} y &= \Phi^B u^{-\theta^B}, & dy &= \theta^B \Phi^B u^{-(\theta^B+1)} du, \\ u &= \left(\frac{y}{\Phi^B}\right)^{-\frac{1}{\theta^B}}, & du &= \frac{dy}{\theta^B \Phi^B u^{-(\theta^B+1)}}. \end{aligned}$$

Using this change of variables, we can write expected utility as:

$$\begin{aligned} \mathbb{E}^B[u] &= \int_0^\infty \theta^B \Phi^B \frac{y}{\Phi^B} \exp(-y) \frac{dy}{(\theta^B) \Phi^B \left(\frac{y}{\Phi^B}\right)^{\frac{\theta^B+1}{\theta^B}}}, \\ &= \int_0^\infty y \exp(-y) \frac{dy}{\Phi^B \left(\frac{y}{\Phi^B}\right)^{\frac{\theta^B+1}{\theta^B}}}, \\ &= \int_0^\infty y^{-\frac{1}{\theta^B}} \exp(-y) \frac{dy}{\Phi^B (\Phi^B)^{-\frac{\theta^B+1}{\theta^B}}}, \\ &= (\Phi^B)^{\frac{1}{\theta^B}} \int_0^\infty y^{-\frac{1}{\theta^B}} \exp(-y) dy, \\ &= \vartheta_B (\Phi^B)^{\frac{1}{\theta^B}}, \end{aligned}$$

where

$$\vartheta_B \equiv \Gamma\left(\frac{\theta^B - 1}{\theta^B}\right) = \int_0^\infty y^{-\frac{1}{\theta^B}} \exp(-y) dy,$$

and $\Gamma(\cdot)$ is the Gamma function. We thus have the following expression for the expected utility from living in the city:

$$\mathbb{E}[u] = \vartheta^B \left[\sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} P_{\ell,T}^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B} \right]^{\frac{1}{\theta^B}}, \quad (\text{B.20})$$

which corresponds to equation (18) in the paper.

Having characterized workplace and residence choices, we can also recover the demand for residential floor space in each location, using the implication of Cobb-Douglas utility that expenditure on residential floor space is a constant share of income:

$$H_{n,U} = \frac{\alpha^H E_n R_n}{Q_n}, \quad (\text{B.21})$$

where $R_n = \lambda_n^B \bar{L}$ is the measure of residents in location n ; recall that \bar{L} is total city population; and E_n is expected income in residence n .

B.6 Production

When we undertake counterfactuals in our quantitative analysis below, we do need to take a stand on production technology and market structure, in which case consider a version of the canonical urban model. In particular, we assume that both the traded good and non-traded services are produced using labor and commercial floor space according a constant returns to scale technology. We assume for simplicity that this production technology is Cobb-Douglas and that production occurs under conditions of perfect competition. Together these assumptions imply that profits are zero in each location in which a tradable good and non-tradable service is produced:

$$\begin{aligned} P_i^T &= \frac{1}{A_{i,k}} w_{i,k}^{\beta^T} Q_i^{1-\beta^T}, & 0 < \beta^T < 1, & \quad k \in K/K^S, \\ P_{i(k)}^S &= \frac{1}{A_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S}, & 0 < \beta^S < 1, & \quad k \in K^S, \end{aligned} \quad (\text{B.22})$$

where $A_{i,k}$ is productivity in location i in sector k . Using the first-order condition for profit maximization, we can obtain demand for commercial floor space in each sector and location ($H_{i,k}$) as a function of the goods or service price ($P_{i(k)}^S$), productivity ($A_{i,k}$), the price of floor space (Q_i) and labor input adjusted for effective units of labor ($\tilde{L}_{i,k}$):

$$H_{i,k} = \begin{cases} \frac{1-\beta^T}{\beta^T} \left(\frac{P_i^T A_{i,k}}{Q_i} \right)^{\frac{1}{\beta^T}} \tilde{L}_{i,k}, & k \in K/K^S \\ \frac{1-\beta^S}{\beta^S} \left(\frac{P_{i(k)}^S A_{i,k}}{Q_i} \right)^{\frac{1}{\beta^S}} \tilde{L}_{i,k}, & k \in K^S, \end{cases} \quad (\text{B.23})$$

where $\tilde{L}_{i,g}$ denotes labor input adjusted for expected idiosyncratic worker productivity, i.e.,

$$\tilde{L}_{i,g} = \frac{1}{w_{i,g}} \sum_{n \in N} E_{ni} \lambda_{ig|n}^W R_n.$$

where E_{ni} is the labor income earned by workers who reside in n and work in i .

We allow productivity in equations (B.22) and (B.23) to be either exogenous or endogenous to the surrounding concentration of economic activity in the presence of agglomeration forces, as discussed further below. We assume no-arbitrage between residential and commercial floor space, and across the different sectors in which commercial floor space is used, such that there is a single price for floor space within each location (Q_i) in equation (B.22). In general, the wage per efficiency unit ($w_{i,k}$) differs across both sectors and locations in equation (B.22), because workers draw efficiency units for each combination of sector and location pair, and hence each sector and location pair faces an upward-sloping supply function for effective units of labor. Finally, we assume that the traded good is costlessly traded within the city and wider economy and choose it as our numeraire such that:

$$P_i^T = 1 \quad \forall i \in N. \quad (\text{B.24})$$

B.7 Market Clearing

The price for each type of non-traded service k in each location j ($P_{j(k)}^S$ for $k \in K^S$) is endogenously determined by market clearing, which requires that revenue equals expenditure for that non-traded service k and

location j :

$$P_{j(k)}^S A_{j,k} \left(\frac{\tilde{L}_{j,k}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{j,k}}{1 - \beta^S} \right)^{1 - \beta^S} = \alpha_k^S \sum_{n \in N} R_n \sum_{i \in N} \lambda_{j(k)|ni}^S \lambda_{i|n}^W E_{ni}, \quad k \in K^S, \quad (\text{B.25})$$

where expenditure on the right-hand side equals the sum across locations of workers travelling to consume non-traded service k in location j ; R_n is the measure of residents in location n ; recall that $\lambda_{j(k)|n}^S$ is the conditional consumption probability and E_{ni} is expected income by workers with residence n and workplace i .

Labor market clearing implies that the measure of workers employed in workplace j in sector k equals the total measure of workers from all residences n who commute to that workplace j in sector k :

$$L_{j,k} = \sum_{n \in N} \lambda_{jk|n}^W R_n, \quad k \in K, \quad (\text{B.26})$$

where we use $L_{j,k}$ without a tilde to denote the measure of workers without adjusting for effective units of labor; and recall that $\lambda_{jk|n}^W$ is the conditional commuting probability.

Land market clearing requires that the demand for residential floor space ($H_{i,U}$) plus the sum across sectors of the demand for commercial floor space in each sector ($H_{i,k}$) equals the total supply of floor space (H_i):

$$H_i = H_{i,U} + \sum_{k \in K} H_{i,k}. \quad (\text{B.27})$$

B.8 General Equilibrium with Exogenous Location Characteristics

We begin by considering the case in which productivity ($A_{i,k}$), amenities (B_i) and the supply of floor space (H_i) are exogenously determined. The general equilibrium of the model is referenced by the price for floor space in each location (Q_i), the wage in each sector and location ($w_{i,k}$), the price of the non-traded good in each service sector and location ($P_{i(k)}^S$), the route choice probabilities ($\lambda_{r(k)|ni(j(k))}^R$), the conditional consumption probabilities ($\lambda_{j(k)|ni}^S$), the conditional commuting probabilities ($\lambda_{jk|n}^W$), the residence probabilities (λ_n^B), and the total measure of workers living in the city (\bar{L}), where we focus on the open-city specification, in which the total measure of workers is endogenously determined by population mobility with the wider economy. Given these seven equilibrium variables, we can solve for all other endogenous variables of the models. These equilibrium variables are determined by the system of seven equations given by the land market clearing condition for each location (B.27), the labor market clearing condition for each location (B.26), the non-traded goods market clearing condition for each location and service sector (B.25), the conditional consumption probabilities (B.10), the conditional commuting probabilities (B.13), the residence probabilities (B.19), and the population mobility condition that equates expected utility in the city (B.20) to the reservation level of utility in the wider economy (\bar{U}).

B.9 General Equilibrium with Agglomeration Forces and Endogenous Floor Space

We next extend the analysis to allow productivity and amenities to be endogenous to the surrounding concentration of economic activity through agglomeration forces and to allow for an endogenous supply of floor space.

Agglomeration in Production. In both the traded and non-traded sector, we allow productivity ($A_{i,k}$) to depend on production fundamentals and production externalities. Production fundamentals ($a_{i,k}$) capture features of physical geography that make a location more or less productive independently of neighboring economic activity (e.g. access to natural water). Production externalities capture productivity benefits from the density of employment across all sectors (L_i/K_i), where employment density is measured per unit of geographical land area.⁴

$$A_{i,k} = a_{i,k} \left(\frac{L_i}{K_i} \right)^{\eta^W} \quad (\text{B.28})$$

where $L_i = \sum_{k \in K} L_{i,k}$ is the total employment in location i , and η^W parameters the strength of production externalities, which we assume to be the same across all sectors.

Agglomeration in Residents. Similarly, we allow residential amenities (B_n) to depend on residential fundamentals and residential externalities. Residential fundamentals (b_n) capture features of physical geography that make a location a more or less attractive place to live independently of neighboring economic activity (e.g. green areas). Residential externalities capture the effects of the surrounding density of residents (L_i/K_i) and are modeled symmetrically to production externalities:⁵

$$B_n = b_n \left(\frac{R_n}{K_n} \right)^{\eta^B} \quad (\text{B.29})$$

where η^B parameters the strength of residential externalities.

Floor Space Supply We follow the standard approach in the urban literature of assuming that floor space is supplied by a competitive construction sector that uses land K and capital M as inputs. In particular, we assume that floor space (H_i) is produced using geographical land (K_i) and building capital (M_i) according to the following constant return scale technology:

$$H_i = M_i^\mu K_i^{1-\mu}, \quad 0 < \mu < 1. \quad (\text{B.30})$$

Using cost minimization and zero profits, this Cobb-Douglas construction technology implies that payments for building capital are a constant share of overall payments for the use of floor space:

$$\mu Q_i H_i = \mathbb{P} M_i, \quad (\text{B.31})$$

where \mathbb{P} is the common user cost of building capital. Using the construction technology (B.30) to substitute for building capital (M_i) in equation (B.31) linking payments for floor space and building capital, we obtain a constant elasticity supply function for floor space as in Saiz (2010), with the inverse supply function given by:

$$Q_i = \psi_i H_i^{\frac{1-\mu}{\mu}} \quad (\text{B.32})$$

⁴We assume for simplicity that production externalities depend solely on a location's own employment density, although it is straightforward to allow for spillovers of these production externalities across locations.

⁵As for production externalities above, we assume that residential externalities depend solely on a location's own residents density, but it is straightforward to allow for spillovers of these residential externalities across locations.

where $\psi_i = \mathbb{P}K_i^{\frac{\mu-1}{\mu}} / \mu$ depends solely on geographical land area (K_i) and parameters.

Furthermore, the cost minimization and zero profit condition also implies that:

$$Q_i = \left(\frac{\mathbb{P}}{\mu}\right)^\mu \left(\frac{\tilde{Q}_i}{1-\mu}\right)^{1-\mu} \quad (\text{B.33})$$

where \tilde{Q}_i is the price of land per unit area.

Given this specification of agglomeration forces and endogenous floor space, the determination of general equilibrium remains the same as above with exogenous location characteristics above, except that productivity (A_n), amenities (B_n) and the supply of floor space (H_n) are now endogenously determined by equations (B.28), (B.29) and (B.32).

C Model Extensions

In this section of the online appendix, we discuss a number of different extensions of our theoretical model. In Section C.1, we generalize the model to incorporate different frequencies of trips across the non-traded sectors, and show that the resulting model is isomorphic to our baseline specification up to the interpretation of the parameter κ_k^S that captures the response of commuting costs to travel times. In Section C.2, we show that our specification of the supply-side of the model with competitive markets and external economies of scale (through agglomeration forces in production) is isomorphic to a model of monopolistic competition under free entry.

C.1 Incorporating Frequency of Consumption Trips

In Section 4 of the paper, we capture the relative importance of each non-traded sector using its expenditure share, assuming for simplicity that users make one trip for each type of non-traded service. More generally, the frequency of trips can also differ across the non-traded sectors, as shown in Figure 1 in the paper. In this section of the online appendix, we explicitly incorporate this additional type of heterogeneity and show that the model is isomorphic up to a reinterpretation of the parameters κ_k^S . Therefore, all of our counterfactual results are unaffected by this extension of the model except for the interpretation of the estimated κ_k^S .

Similarly to equation (2) in our main paper, we assume that the iceberg travel cost for each combination of residence n , workplace i , consumption location $j(k)$, and route $r(k)$ ($d_{ni\{j(k)r(k)\}}$) as follows:

$$d_{ni\{j(k)r(k)\}} = \exp(-\kappa^W \tau_{ni}^W) \prod_{k \in K^S} \exp(-\kappa_k^S \tau_{ni\{j(k)r(k)\}}^S). \quad (\text{C.1})$$

In this expression, the first term before the product sign captures the cost of commuting from residence n to workplace i without any detour to consume non-traded services, which depends on travel time (τ_{ni}^W) and the commuting cost parameter (κ^W), where overall commuting travel time is the sum of the travel time incurred in each direction:

$$\tau_{ni}^W = \tau_{ni} + \tau_{in}.$$

The second term in equation (C.1) captures the additional travel costs involved in consuming each type of non-traded service k in location $j(k)$ by the route $r(k)$. Unlike in our main text, here we assume that workers have to visit the location of consumption δ_k times to meet their needs, where δ_k is an exogenous parameter depending on the model. δ_k can be less than one, in which case workers do not have to make a trip every day, while δ_k can be greater than one, in which case workers have to visit the location multiple times. δ_k intuitively captures the relative frequency of travel for different sectors as documented in Figure 1. For example, relatively frequent trips are required for grocery shopping, while less frequent trips are required for visiting banks. Accommodating the differences of the total travel time driven by these frequencies of trips, the additional travel

time for each route taken is given by:

$$\begin{aligned}\tau_{nij(k)HH}^S &= \delta_k (\tau_{nj} + \tau_{jn}), \\ \tau_{nij(k)WW}^S &= \delta_k (\tau_{ij} + \tau_{ji}), \\ \tau_{nij(k)HW}^S &= \delta_k (\tau_{nj} + \tau_{ji} - \tau_{ni}), \\ \tau_{nij(k)WH}^S &= \delta_k (\tau_{ij} + \tau_{jn} - \tau_{in}).\end{aligned}$$

Here, δ_k enters multiplicatively with consumption travel cost κ_k^S in equation (C.1). Therefore, this specification of the travel cost is isomorphic to our main specification by replacing κ_k^S in our main paper with $\kappa_k^S \delta_k$.

It is important to note that this specification does not affect any of our counterfactual simulation results. When undertaking counterfactual simulations, we only need the composite elasticity of travel time ($\phi_k^S (= \theta_k^S \kappa_k^S / \alpha_k^S)$), which we estimate following the procedure in Section 5.1. With this extension, we estimate the same values of ϕ_k^S , except that the interpretation of these parameters is different ($\phi_k^S = \theta_k^S \kappa_k^S \delta_k / \alpha_k^S$). Intuitively, given the observed spatial decay patterns ϕ_k^S , less frequency of making trips for nontradable sector k (a smaller δ_k) implies that travel cost for this sector k is higher (κ_k^S), but whether ϕ_k^S is driven by κ_k^S or δ_k do not matter for our counterfactual simulations. For this reason, our counterfactual simulation results are unaffected by this extension of our model.

C.2 Monopolistic Competition and Firm Entry

The model in our main paper assumes that firms are perfectly competitive in each location, and there are agglomeration spillovers for production. In this appendix, we instead assume that firms are monopolistically competitive, and firms enter in each location following the free-entry condition. We show that this alternative model leads to a similar expressions for the equilibrium conditions with a slight modification of the functional form of the agglomeration spillovers.

In this alternative model, we assume that there are potential entrepreneurs who consider setting up a store in each location in sector k . Below we discuss the case of nontradable sector $k \in K^S$, but the discussion is isomorphic to the tradable sector $k \in K/K^S$. Each entrepreneur has access to a distinct variety of goods and services. Entering in each location i requires a fixed cost payment $f_{i,k}^S$ in the unit of the Cobb-Douglas composite of labor and floor space with the labor share of β^S , such that an entry requires a lump-sum payment of $f_{i,k}^S w_{i,k}^{\beta^S} Q_i^{1-\beta^S}$. After the entry, she produces her good or service using the Cobb-Douglas production technology with labor and input. Therefore, the marginal cost is given by

$$c_{i(k)}^S = \frac{1}{a_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S}.$$

We assume that consumers have a constant elasticity of substitution (CES) utility over these differentiated varieties with elasticity of substitution σ . Firms are monopolistically competitive, and hence charge the prices with a constant markup:

$$p_{i(k)}^S = \frac{\sigma}{\sigma - 1} \frac{1}{a_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S}.$$

The measure of firms $M_{i(k)}^S$ is determined by the free entry condition. Under this condition, firm profit after entry is exactly offset by the fixed cost payment. Since firms earn $1/\sigma$ fraction of the revenue as profit, the free entry condition is given by

$$\begin{aligned} M_{i(k)}^S f_{i,k}^S w_{i,k}^{\beta^T} Q_i^{1-\beta^T} &= p_{i(k)}^S a_{i,k} \left(\frac{\tilde{L}_{i,k}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{i,k}}{1-\beta^S} \right)^{1-\beta^S} \\ &= \frac{\sigma}{\sigma-1} \left(\frac{w_{i,k} \tilde{L}_{i,k}}{\beta^S} \right)^{\beta^S} \left(\frac{Q_i H_{i,k}}{1-\beta^S} \right)^{1-\beta^S}. \end{aligned}$$

where $\tilde{L}_{i,k}$ and $H_{i,k}$ is the aggregate efficient unit of labor input and commercial floor space in location i and sector k . By reformulating this equation, we have

$$M_{i(k)}^S = \frac{1}{f_{i,k}^S} \frac{\sigma}{\sigma-1} \left(\frac{\tilde{L}_{i,k}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{i,k}}{1-\beta^S} \right)^{1-\beta^S}.$$

Using the standard property of the CES utility function, the price index of the composite of goods offered in location i in sector k is given by

$$\begin{aligned} P_{i(k)}^S &= p_{i(k)}^S (M_{i(k)}^S)^{\frac{1}{1-\sigma}} \\ &= \frac{\sigma}{\sigma-1} \frac{1}{a_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S} \left[\frac{1}{f_{i,k}^S} \frac{\sigma}{\sigma-1} \left(\frac{\tilde{L}_{i,k}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{i,k}}{1-\beta^S} \right)^{1-\beta^S} \right]^{\frac{1}{1-\sigma}} \\ &= \frac{1}{\tilde{A}_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S}, \end{aligned} \tag{C.2}$$

where $\tilde{A}_{i,k}$ is defined by

$$\tilde{A}_{i,k} = \tilde{a}_{i,k} \left(\tilde{L}_{i,k} \right)^{\frac{\beta^S}{\sigma-1}} \left(H_{i,k} \right)^{\frac{1-\beta^S}{\sigma-1}}, \tag{C.3}$$

where $\tilde{a}_{i,k} \equiv \frac{\sigma-1}{\sigma} \left[\frac{\sigma}{\sigma-1} \left(\frac{1}{\beta^S} \right)^{\beta^S} \left(\frac{1}{1-\beta^S} \right)^{1-\beta^S} \right]^{\frac{1}{\sigma-1}} \left(\frac{1}{f_{i,k}^S} \right)^{\frac{1}{\sigma-1}} a_{i,k}$. Note that $\tilde{a}_{i,k}$ is exogenously determined by the parameters of the model.

Therefore, we have shown that the price index is a function of the cost of composite inputs ($w_{i,k}^{\beta^S} Q_i^{1-\beta^S}$), location fundamentals ($\tilde{a}_{i,k}$), and additional terms corresponding to the benefit of the love of variety in consumption ($\left(\tilde{L}_{i,k} \right)^{\frac{\beta^S}{\sigma-1}} \left(H_{i,k} \right)^{\frac{1-\beta^S}{\sigma-1}}$). Note that this expression of the price index is isomorphic to the model with perfect competition (equation 20), as long as we assume that external agglomeration spillover takes the form of equation C.3 (unlike in equation 25 of our main paper, where we assume $A_{i,k} = a_{i,k} \left(\frac{L_i}{K_i} \right)^{\eta^W}$).

D Additional Estimation Results and Model Validation

This section of the appendix provides additional estimation results and model validation, supplementing the results reported in Section 5 of our main paper. In Section D.1, we summarize the calibrated and estimated parameters of the model. In Section D.2, we present a number of overidentification checks on the model's predictions using separate data not used its calibration, including data on residential income and prices. In Section D.3, we provide additional evidence on the fit of our extended gravity equations for consumption and commuting trips, supplementing the results reported in Section 5.1 of the paper.

In Section D.4, we demonstrate that we find a similar pattern of results whether we construct consumption access and travel access using destination or origin fixed effects, consistent with the predictions of our theoretical model. In Section D.5, we compare the estimates of our baseline theoretical model from the paper, which allows for endogenous route choice and trip chains, with those of an alternative specification in which all consumption trips are (falsely) assumed to originate from home.

D.1 Parameter Values

In Table D.1.1, we summarize the calibrated and estimated parameters of the model.

Table D.1.1: Calibrated and Estimated Structural Parameters

Parameter	Description	Value
θ^W	dispersion of Fréchet shocks for workplace	6
θ^B	dispersion of Fréchet shocks for residence	6
θ_k^S	dispersion of Fréchet shocks for consumption	6
α_k^S	expenditure share for nontradable sector	
	GJKL finance realestate communication professional	0.25
	I wholesale retail	0.31
	M accomodations eating drinking	0.01
	P medical welfare healthcare	0.03
	Q other services	0.05
α^H	expenditure share for residential floor space	0.25
α^T	expenditure share for tradable sector	0.09
$\phi^W (= \theta^W \kappa^W)$	elasticity of commuting cost with travel time	0.62
$\phi_k^S (= \theta_k^S \kappa_k^S / \alpha_k^S)$	elasticity of consumpcion travel cost with travel time	
	GJKL finance realestate communication professional	1.15
	I wholesale retail	1.12
	M accomodations eating drinking	1.09
	P medical welfare healthcare	1.19
	Q other services	1.08
β^S	labor share in production for nontradable sector	0.8
β^T	labor share in production for tradable sector	0.8
η^W	elasticity of production spillover	[0, 0.08]
η^B	elasticity of residential amenity spillover	[0, 0.15]
μ	share of capital for floor space production	0.75

Note: The table presents the set of calibrated and estimated parameters following the procedure discussed in the text of Section 5.1 in the paper.

D.2 Overidentification Test for Model Validation

In this subsection of the appendix, we provide additional model validation by comparing our model’s predictions with separate data. In particular, we validate our model’s prediction about residential income and the price index in each location, using separate data that we do not use for estimation (see Section 2.2 of our main paper for these other data sources.) Because we do not use these separate data in our model estimation procedure, these comparisons serve as an overidentification test for our model.

D.2.1 Residential Income

We first compare our model’s prediction of residential income. Our model predicts that the aggregate residential income for workers in home location n is given by equations (B.17) and (19):

$$E_n^{Model} = \sum_{i \in N} \lambda_{i|n}^W E_{ni} = \sum_{i \in N} \lambda_{i|n}^W \frac{\mathbb{A}_n}{\mathbb{S}_{ni}}. \quad (\text{D.1})$$

where \mathbb{A}_n is our estimate of travel access, and \mathbb{S}_{ni} is our estimate of consumption access under the parameter values of $\theta^W = 6$ and $\theta_k^S = 6$ for all nontradable sector k . We compare this model-predicted residential income with separate data of municipality income from tax-base information, E_n^{Data} .

Table D.2.1 presents the results of a linear regression of the log of income from the tax-base information on the log of model-predicted income. Our model is necessarily an abstraction and does not capture all of the idiosyncratic factors that can affect residential income in individual locations. For example, the tax base data includes non-labor income, whereas our model focuses on labor income. Nevertheless, we estimate a slope coefficient that is close to one and is not statistically significantly different from one: coefficient 0.987 (standard error 0.135). We find a regression R-squared of 0.213, which is in line with the values typically found in univariate regressions using cross-section micro data, and is consistent with the many idiosyncratic factors that affect residential income in individual locations.

This validation in particular supports our choice of the Fréchet dispersion parameter, particularly for θ^W . From equation (16), one can see that θ^W is directly related to the variation in travel access (\mathbb{A}_n), which affects residential income. Therefore, the choice of $\theta^W = 6$ is not only consistent with the estimates from previous literature (Ahlfeldt, Redding, Sturm, and Wolf 2015, Heblich, Redding, and Sturm 2020, Kreindler and Miyauchi 2019), but also consistent with external data on residential income for the Tokyo metropolitan area.

D.2.2 Price Index

In our last model validation exercise, we validate our model’s prediction of price indices in each location. We construct model-predicted price index from our estimated destination fixed effects of our consumption gravity equations. We compare this model-predicted price index with the analogous objects constructed from external data. Because we do not directly observe price indices of each municipality, we construct the price index consistent with the constant elasticity of substitution (CES) utility function in each location, following our extended model with monopolistic competition and firm entry (Section C.2). While these auxiliary assumptions can potentially add substantial measurement errors for our price indices, we find that our model prediction of price index is closely aligned with the price index that we observe in the data.

Table D.2.1: Model Validation of Price Index

	log income (data)
log income (model)	0.987*** (0.135)
Observations	198
R ²	0.213

Note: Results of the linear regression of the logarithm of the residential income from tax-base data on the logarithm of model-predicted residential income. Observations are weighted by the residential population. Heteroskedasticity robust standard errors in parentheses.

For the purpose of this validation, we construct our model-predicted proxy for the price index using the destination fixed effects of our consumption location choice estimation. More specifically, the destination fixed effects of consumption location choice is given by equation (32) in our main paper, reproduced here:

$$\xi_{j(k)}^S = T_{j(k)}^S (P_{j(k)}^S)^{-\theta_k^S}, \quad (\text{D.2})$$

where $P_{j(k)}^S$ is the price index, and $T_{j(k)}^S$ is the parameter that shifts the attractiveness of each consumption location other than from the factors related to price index $P_{j(k)}^S$. To recover the price index from equation (D.2), we impose an auxiliary assumption that $T_{j(k)}^S$ is uncorrelated with price index $P_{j(k)}^S$ such that $\text{Var}(T_{j(k)}^S, P_{j(k)}^S) = 0$. Under this assumption, we construct a mean-unbiased proxy for our model price index as

$$P_{j(k)}^{S, Model} \equiv \mathbb{E} [P_{j(k)}^S] = \mathbb{E} \left[T_{j(k)}^S (\xi_{j(k)}^S)^{\frac{1}{\theta_k^S}} \right] = (\xi_{j(k)}^S)^{\frac{1}{\theta_k^S}}, \quad (\text{D.3})$$

where the last transformation used our auxiliary assumption of $\text{Var}(T_{j(k)}^S, P_{j(k)}^S) = 0$ and the normalization that $\mathbb{E}[T_{j(k)}^S] = 1$. We assume $\theta_k^S = 6$ consistent with our main calibration (Table D.1.1).

We compare this model-predicted price index with the analogous object constructed from external data. Because the price index is not observed at the municipality level, we construct our proxy for price index under the constant elasticity of substitution (CES) demand system. More specifically, under CES demand system, the price index of location j in sector k is given by:

$$P_{j(k)}^{S, Data} = (M_{j(k)})^{\frac{1}{\sigma-1}} p_{j(k)}, \quad (\text{D.4})$$

where $M_{j(k)}$ is the number of varieties in location j in sector k ; $p_{j(k)}$ is the price of each variety in location j in sector k ; and σ is the elasticity of substitution. We proxy $M_{j(k)}$ by the number of establishments in each location j from economic census data. We proxy $p_{j(k)}$ from the separate retail survey data that provides the relative prices for broad categories of products at the level of prefecture level (4 prefectures covering 240 municipalities in Tokyo Metropolitan Area). Lastly, we set σ such that $\sigma = 5$ from the central estimates from the literature of this parameter in the context of retail products (Broda and Weinstein 2006).

Table D.2.2 presents the results of the OLS regression of the log of the price index constructed from the observed price data ($P_{j(k)}^{S,Data}$) on the log of our model-predicted price proxy ($P_{j(k)}^{S,Model}$). Again our model is necessarily an abstraction, but for all nontraded sectors, we find a strong and statistically significant correlation between our model's predictions and the price data. Furthermore, across the board, the slope coefficient ranges from 0.522-1.114, centered around one. As discussed above, the choice of θ_k^S crucially governs the dispersion of the model-predicted price index (equation (D.2)). Therefore, our choice of $\theta_k^S = 6$ is not only consistent with estimates from the existing empirical literature (Atkin, Faber, and Gonzalez-Navarro 2018, Couture, Gaubert, Handbury, and Hurst 2019), but also consistent with external data on price indices for the Tokyo metropolitan area.

Table D.2.2: Model Validation of Price Index

Dependent Variable: log(Price Index (data))					
	Finance realestate communication professional (1)	Wholesale retail (2)	Accom- dations eating drinking (3)	Medical welfare healthcare (4)	Other services (5)
log(Price Index (model))	1.114*** (0.103)	0.677*** (0.108)	0.718*** (0.108)	0.874*** (0.106)	0.522*** (0.103)
Observations	240	240	240	240	240
R ²	0.331	0.142	0.157	0.222	0.098

Note: Results of the linear regression of the logarithm of the price index constructed from external data on the logarithm of model-predicted price index. Heteroskedasticity robust standard errors in parentheses.

D.3 Fit of Gravity Equations

In this section of the appendix, we discuss the fit of our empirical models of consumption location choice probability and workplace choice probability (Table 3 and Table 4 of our main paper).

As a specification check, we estimate our workplace and consumption location choice probabilities by including the dummies of the bins of the travel time instead of the linear term. Namely, for the consumption location choice probabilities, we estimate:

$$\lambda_{j(k)|ni}^S = \frac{\xi_{j(k)}^S \exp\left(-\sum_b \tilde{\phi}_{k,b}^S 1\left[\log \tilde{d}_{nij(k)}^S = b\right]\right) \exp\left(u_{nij(k)}^S\right)}{\zeta_{ni,k}^S}, \quad (\text{D.5})$$

where b indicates the deciles of the consumption travel cost $\tilde{d}_{nij(k)}^S$, and the difference from equation (31) is that we replace $\phi_k^S \log \tilde{d}_{nij(k)}^S$ with $\sum_b \tilde{\phi}_{k,b}^S 1\left[\log \tilde{d}_{nij(k)}^S = b\right]$. Therefore, if our specification of exponential travel cost is correct, we expect that $\tilde{\phi}_{k,b}^S$ has a linear relationship with b .

For the workplace choice probabilities, we estimate:

$$\lambda_{i|n}^W = \frac{\xi_i^W \exp\left(-\sum_b \tilde{\phi}_b^W 1[\tau_{ni}^W = b]\right) (\mathbb{S}_{ni})^{\theta^W} \exp(u_{ni}^W)}{\zeta_n^W}, \quad (\text{D.6})$$

where b indicates the deciles of the commuting travel time τ_{ni}^W , and the difference from equation (35) is that we replace $\phi^W \tau_{ni}^W$ with $\sum_b \tilde{\phi}_b^W 1[\tau_{ni}^W = b]$. Therefore, if our specification of exponential travel cost is accurate, we expect that $\tilde{\phi}_b^W$ has a linear relationship with b .

Figure D.3.1 plots the estimated coefficients on these bins of travel time with their 95 percent confidence intervals. We plot the estimated coefficients $\tilde{\phi}_{k,b}^S$ and $\tilde{\phi}_b^W$ against the consumption travel cost and commuting travel time (b in the equations above). The coefficients exhibit an approximately linear relationship with travel time on the horizontal axis for the commuting choices. For consumption choices, there is some convex pattern, but the relationship is approximately linear for the first few deciles where most trips are concentrated. This pattern of results supports our specification of the workplace and consumption location choice, in which travel time enters exponentially in the iceberg travel cost.

D.4 Robustness of Access Measures by Using Origin Fixed Effects

In Section 5.1 of our main paper, we construct consumption access measure \mathbb{S}_{ni} and travel access measure \mathbb{A}_n as the distance-weighted sum of the destination effects of the consumption location choice and the commuting choice, respectively. As we discuss in our main paper, an alternative way of constructing these measures is to use the origin fixed effects. In this appendix, we show that our access measures are robust to these choices.

In Section 5.1.3 of our main paper, we estimate the consumption location choice probability using the following equation:

$$\lambda_{j(k)|ni}^S = \frac{\xi_{j(k)}^S \left(\tilde{d}_{nij(k)}^S\right)^{-\phi_k^S} \exp\left(u_{nij(k)}^S\right)}{\zeta_{ni,k}^S}, \quad (\text{D.7})$$

and the consumption access measures can be constructed by:

$$\mathbb{S}_{nik} = \Gamma\left(\frac{\theta_k^S/\alpha_k^S - 1}{\theta_k^S/\alpha_k^S}\right) \left[\sum_{\ell \in N} \xi_{\ell(k)}^S \left(\tilde{d}_{ni\ell(k)}^S\right)^{-\phi_k^S}\right]^{\frac{\alpha_k^S}{\theta_k^S}}. \quad (\text{D.8})$$

An alternative theory-consistent way of estimating the consumption access is to use residence-and-workplace fixed effects:

$$\mathbb{S}_{nik} = \left[\Gamma\left(\frac{\theta_k^S/\alpha_k^S - 1}{\theta_k^S/\alpha_k^S}\right)\right] (\zeta_{ni,k}^S)^{\frac{\alpha_k^S}{\theta_k^S}}. \quad (\text{D.9})$$

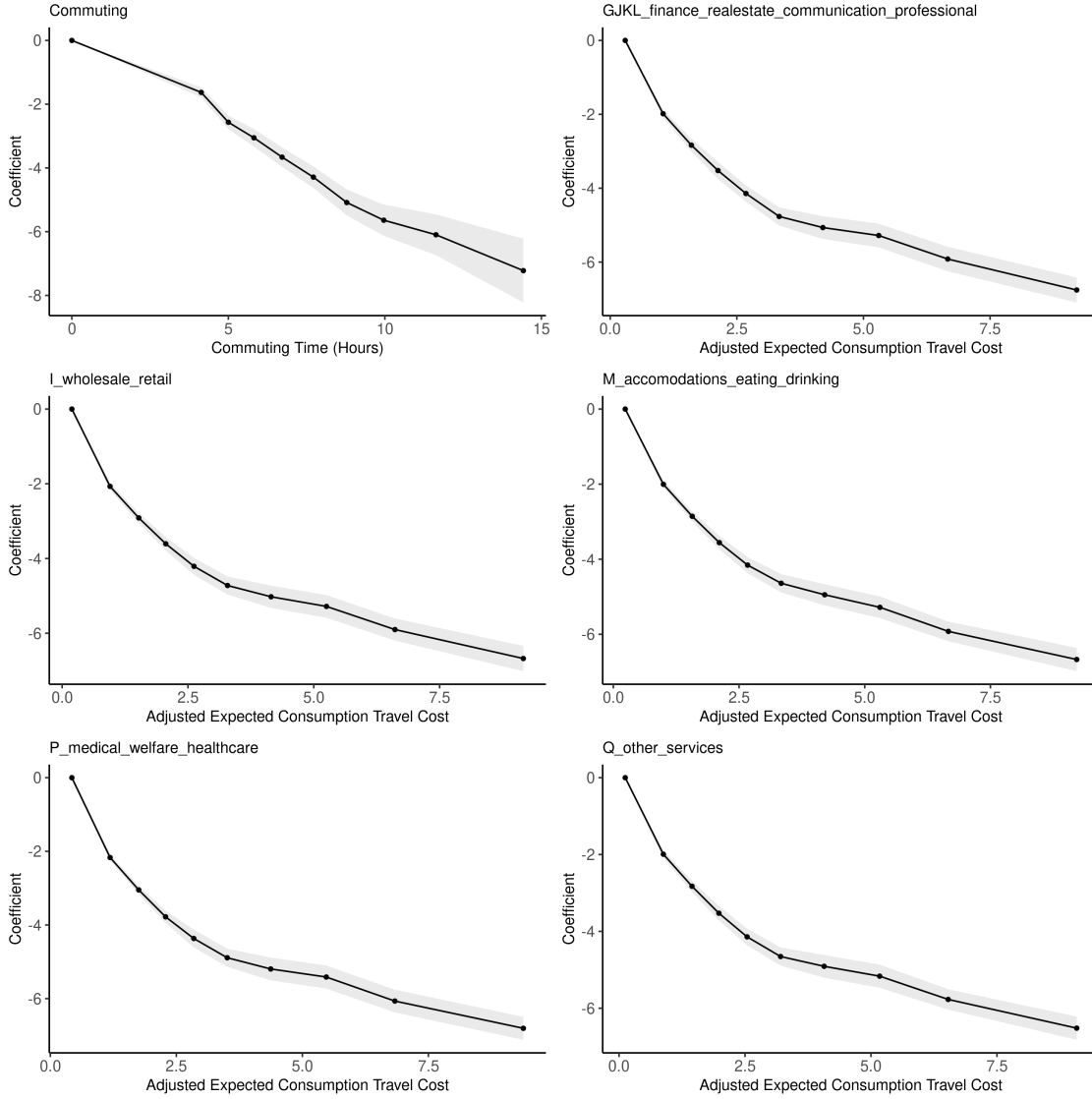
Similarly, in Section 5.1.4 of our main paper, we estimate the workplace choice probability using the following equation:

$$\lambda_{i|n}^W = \frac{\xi_i^W \exp\left(-\phi^W \tau_{ni}^W\right) (\mathbb{S}_{ni})^{\theta^W} \exp(u_{ni}^W)}{\zeta_n^W}, \quad (\text{D.10})$$

and the travel access measures can be constructed by:

$$\mathbb{A}_n = \Gamma\left(\frac{\theta^W - 1}{\theta^W}\right) \left[\sum_{\ell \in N} \xi_{\ell}^W \exp\left(-\phi^W \tau_{n\ell}^W\right) (\mathbb{S}_{n\ell})^{\theta^W}\right]^{\frac{1}{\theta^W}}. \quad (\text{D.11})$$

Figure D.3.1: Estimation Results of Nonparametric Gravity Equations



An alternative theory-consistent way of estimating the consumption access is to use residence fixed effects:

$$\mathbb{A}_n = \Gamma \left(\frac{\theta^W - 1}{\theta^W} \right) (\zeta_n^W)^{\frac{1}{\theta^W}}. \quad (\text{D.12})$$

In Table D.4.1, we present the results of the OLS regression of the origin fixed effects of commuting gravity equations (Column 1) and consumption gravity equations (Column 2-6) on the weighted sum of the destination fixed effects. We find that the regression slopes are essentially one, and the R-squared is also extremely close to one. Therefore, the two measures are essentially identical. In fact, Fally (2015) show that these two measures are asymptotically equivalent. Even within a finite sample, we find that this approximation performs closely as the asymptotic theory predicts.

Table D.4.1: Robustness to Alternative Definitions of Consumption and Travel Access

	Dependent Variable: Origin fixed effects					
	Commuting	Finance realestate communication professional	Wholesale retail	Accommodations eating drinking	Medical welfare healthcare	Other services
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted sum of destination fixed effects	0.985*** (0.004)	1.000*** (0.000)	1.000*** (0.000)	1.000*** (0.000)	1.000*** (0.000)	1.000*** (0.000)
Observations	242	12,322	12,330	12,327	12,310	12,329
R ²	0.997	1.000	1.000	1.000	1.000	1.000

Note: OLS regression of the origin fixed effects of commuting gravity equations (Column 1) and consumption gravity equations (Column 2-6) on the weighted sum of the destination fixed effects. Heteroskedasticity robust standard errors in parentheses.

D.5 Estimation of Commuting and Consumption Location Choice without Trip Chains

In Section 5.1 of our main paper, we estimate our baseline model assuming that visits to consumption location may happen not only from home but also workplaces or on the way between home to work. In this section, we show how our estimation results compare if we instead assume that visits to consumption locations originate solely from home locations.

More specifically, we consider a special case of our model where workers receive an infinitely negative preference shocks for the consumption route of ($r(k) = WW$), such that $T_{r(k)}^R = -\infty$ for $r(k) = WW, HW, WH$. In this special case, the expected travel cost for consumption trips (equation 8 of our main paper) simplifies to

$$d_{nij(k)}^S = \mathbb{E}_{nij(k)} [\delta_{nij(k)r(k)}(\omega)] = \vartheta_k^R [T_{HH}^R]^{\frac{1}{\theta_k^R}} \exp(-\kappa_k^S \tau_{nij(k)HH}^S) \quad (\text{D.13})$$

where $\vartheta_k^R \equiv \Gamma\left(\frac{\theta_k^R - 1}{\theta_k^R}\right)$ and $\Gamma(\cdot)$ is the Gamma function, and $\tau_{nij(k)HH}^S = \tau_{nj} + \tau_{jn}$ is the travel time for visiting consumption location j from home location n . Therefore, our estimating equation for consumption location choice (equation 31 in our main paper) simplifies to:

$$\lambda_{j(k)|ni}^S = \frac{\xi_{j(k)}^S \exp\left(-\phi_k^S \tau_{nij(k)HH}^S\right) \exp\left(u_{nij(k)}^S\right)}{\zeta_{ni,k}^S}. \quad (\text{D.14})$$

Therefore, the relevant consumption travel cost is simply a function of the bilateral travel time from home to consumption location. Furthermore, because the travel time for consumption trips $\tau_{nij(k)HH}^S = \tau_{nj} + \tau_{jn}$ does not depend on workplace i , the consumption location choice $\lambda_{j(k)|ni}^S$ does not depend on workplace i . Therefore, we can estimate the consumption location choice at the bilateral pair of home and consumption locations.

Furthermore, because the consumption location choice is independent of work location, the consumption access \mathbb{S}_{ni} does not depend on workplace i . Therefore, this term is now irrelevant for the commuting choice, and the commuting choice (equation 35 of our main paper) comes down to

$$\lambda_{i|n}^W = \frac{\xi_i^W \exp\left(-\phi^W \tau_{ni}^W\right) \exp\left(u_{ni}^W\right)}{\zeta_n^W}, \quad (\text{D.15})$$

where the difference from equation (35) is again the omission of the consumption access term $(S_{ni})^{\theta^W}$.

Table D.5.1 presents our estimation results of consumption location choice when we assume that all consumption trips originate from home ($T_{r(k)}^R = -\infty$ for $r(k) = WW, HW, WH$). This table corresponds to Table 3 of our main paper where we allow for trip chains for consumption trips. Because we can now estimate these equations at the bilateral location pairs of home location and consumption location (because work location is irrelevant to this choice), we report the results of the estimation at the unit of the bilateral location pairs of home location and consumption location in Panel (A), and the results of the estimation where we define the unit of the observations at the triplets of home, work and consumption locations in Panel (B). (The estimated coefficients are similar between the two panels, despite the large differences in sample size). We find that the travel time coefficient for consumption trips somewhat smaller in magnitude when we restrict consumption trips are only generated from home (ranging from -0.8 to -0.6, instead of -1.2 to -1.0 in Table 3). This is suggestive of the measurement error of travel time by assuming all trips originate from home location. Furthermore, we find a better model fit with the consumption gravity equation with route choice than this alternative specification, as evident from the smaller Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC). This is the expected pattern of estimates if in reality consumption trips can originate from either work or home. Workers may frequently consume non-traded services that are close to work but far from home, precisely because they can easily access these non-traded services from work. In the model that falsely assumes that all consumption trips originate from home, the way the model tries to rationalize these consumption trips far from home is with artificially low semi-elasticities with respect to travel time.

Table D.5.2 presents our estimation results of commuting choices when we assume that all consumption trips originate from home ($T_{r(k)}^R = -\infty$ for $r(k) = WW, HW, WH$). This table corresponds to Table 4 of our main paper where we allow for trip chains for consumption trips. We find that the travel time coefficient for commuting trips somewhat larger when we restrict that all consumption trips are generated from home (-0.649 instead of -0.617 in Table 4). Furthermore, we find a better model fit with the consumption gravity equation with route choice than this alternative specification, as evident from the smaller Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC). This pattern of results is consistent with the idea that workers willingness to commute longer bilateral distance may reflect not only higher wages or other characteristics of their workplace itself but also the greater access to consumption possibilities that this workplace provides. As for other large metropolitan areas such as London and New York, the downtown area of Tokyo to which workers commute long distances on average provide dense access to bars, restaurants and other non-traded consumption services.

Lastly, we conduct the same decomposition exercise of the observed concentration of the attractiveness of the summary measure of the relative attractiveness of locations for residence. We follow the same procedure in Section 5.2 and present our regression-based decomposition with the following equations:

$$\begin{aligned}\ln \mathbb{A}_n &= c_0^A + c_1^A \ln \left((\lambda_n^A)^{1/\theta^B} Q_n^{\alpha^H} \right) + u_{nt}^A, \\ \ln \mathbb{B}_n &= c_0^B + c_1^B \ln \left((\lambda_n^B)^{1/\theta^B} Q_n^{\alpha^H} \right) + u_{nt}^B.\end{aligned}\tag{D.16}$$

Table D.5.3 presents our results. Panel (A) presents the results of the regressions (41) from our baseline model, and Panel (B) presents the same regression results from our special case of omitting consumption trips

Table D.5.1: Estimation of Consumption Location Choice without Trip Chains

(A) Estimate at the pair of home and consumption location

Dependent Variable:	Consumption Location Choice Probability				
	Finance realestate communication professional	Wholesale retail	Accomoda- tions eating drinking	Medical welfare healthcare	Other services
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Consumption Travel Time (Hours)	-0.758*** (0.040)	-0.697*** (0.038)	-0.693*** (0.039)	-0.780*** (0.041)	-0.656*** (0.037)
<i>Fixed-effects</i>					
Home Location	Yes	Yes	Yes	Yes	Yes
Consumption Location	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
AIC	1,374.5	1,805.7	1,409.3	1,412.7	1,527.3
BIC	5,719.8	6,151.0	5,754.6	5,758.0	5,872.6
Observations	58,564	58,564	58,564	58,564	58,564

(B) Estimate at the triplets of home, work and consumption location

Dependent Variable:	Consumption Location Choice Probability				
	Finance realestate communication professional	Wholesale retail	Accomoda- tions eating drinking	Medical welfare healthcare	Other services
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Consumption Travel Time (Hours)	-0.690*** (0.026)	-0.699*** (0.023)	-0.698*** (0.025)	-0.737*** (0.024)	-0.665*** (0.022)
<i>Fixed-effects</i>					
Home and Work Location	Yes	Yes	Yes	Yes	Yes
Consumption Location	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
AIC	140,263.4	141,209.4	141,197.0	139,977.4	142,431.2
BIC	302,440.5	303,498.0	303,443.7	301,987.4	304,705.8
Observations	2,981,924	2,983,860	2,983,134	2,979,020	2,983,618

Note: A version of Table 3 of our main paper where we assume that all consumption trips originate from home ($T_{r(k)}^R = -\infty$ for $r(k) = WW, HW, WH$). Results of the estimation of regression (D.14) by the Poisson Pseudo Maximum Likelihood (PPML) estimator. In Panel (A), we estimate the model with the observations at all bilateral pairs of municipalities in the Tokyo metropolitan area (residence n and consumption location $j(k)$). In Panel (B), we estimate the model with the triplets of municipalities in the Tokyo metropolitan area (residence n , workplace i , and consumption location $j(k)$). See the footnote of Table 3 for other comments.

($\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $S_{ni} = 1$). Compared to the results which incorporate the possibility of trip chains, we find a greater coefficients for both panels compared to the case which include trip chains (0.56 and 0.35, respectively; Table 5). This difference primarily arise from the difference of the estimate of the travel cost elasticity (ϕ^W). As discussed above, ϕ^W is overestimated by omitting trip chains (Table D.5.2). A greater ϕ^W tend to give a greater variation of travel access \mathbb{A}_n . Despite this difference, our main conclusion stays the same: As evident from the comparison between Panel (A) and (B), omitting the

Table D.5.2: Estimation of Commuting Choice on Residence without Trip Chains

Dependent Variable: Model:	Commuting Choice Probability (1)
<i>Variables</i>	
Commuting Time (Hours)	-0.649*** (0.034)
<i>Fixed-effects</i>	
Home Location	Yes
dest_cityid	Yes
<i>Fit statistics</i>	
AIC	3,097.1
BIC	7,442.4
Observations	58,564

Note: A version of Table D.15 of our main paper where we assume that all consumption trips originate from home ($T_{r(k)}^R = -\infty$ for $r(k) = WW, HW, WH$). Results of the estimation of regression (D.15) by the Poisson Pseudo Maximum Likelihood (PPML) estimator. Observations are all bilateral pairs of municipalities in the Tokyo metropolitan area (residence n and work location i). See the footnote of Table 4 for other comments.

consumption trips tend to underestimate the contribution of travel access (\mathbb{A}_n) and overestimate the contribution of \mathbb{B}_n for the revealed attractiveness of residential location.⁶

⁶Panel (B) of Table D.5.3 also corresponds to the exercise where we omit consumption trips and construct \mathbb{A}_n^{nocons} using the estimates the commuting gravity equations by omitting consumption access terms $\log(\mathbb{S}_{n\ell})^{\theta^W}$, as opposed to Panel (B) of Table 5 of our main paper where we construct \mathbb{A}_n^{nocons} using the estimates of gravity equations including the term of $\log(\mathbb{S}_{n\ell})^{\theta^W}$.

Table D.5.3: Variance Decomposition of the Relative Attractiveness of Locations without Trip Chains

	$\log \mathbb{A}_n$	$\log \mathbb{B}_n$
	(1)	(2)
Panel A: Baseline Model		
$\log Q_n^{\alpha^H} (\lambda_n^B)^{1/\theta^B}$	0.845*** (0.067)	0.155** (0.067)
Observations	201	201
R ²	0.441	0.026
Panel B: No Consumption Trips		
$\log Q_n^{\alpha^H} (\lambda_n^B)^{1/\theta^B}$	0.479*** (0.038)	0.521*** (0.038)
Observations	201	201
R ²	0.450	0.491

Note: A version of Table 5 of our main paper where we assume that all consumption trips originate from home ($T_{r(k)}^R = -\infty$ for $r(k) = WW, HW, WH$). Panel (A): Ordinary least squares (OLS) estimates of the regression-based variance decomposition in equation (41) when we commute travel access \mathbb{A}_n with consumption trips; Panel (B) presents the results when we omit consumption access to construct \mathbb{A}_n ($\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $\mathbb{S}_{ni} = 1$). Note that Panel (B) is equivalent to a version of Panel (B) of Table 5 using the estimates of ϕ^W and ξ_ℓ^W from a conventional commuting gravity equation excluding consumption access. Observations are municipalities in the Tokyo metropolitan area. Heteroskedasticity robust standard errors in parentheses.

E Details of Calibration and Simulation Procedure

This section of the online appendix explains further details of the counterfactual simulation procedure of Section 6 of the paper. In Section E.1, we report the derivation of the system of equations that we use to solve for a counterfactual equilibrium. In Section E.2, we provide further details on the calibration of the baseline variables in the initial equilibrium that are used in this system of equations to solve for a counterfactual equilibrium. In Section F, we present additional empirical results for our counterfactuals for changes in travel costs in the Tokyo Metropolitan Area. In Section G, we report further empirical results for our counterfactuals for the opening of the Tozai subway line in the city of Sendai, as discussed in Section 6 of the paper.

E.1 Mathematical Details for the System of Equations for Counterfactual Simulation

In this section of the online appendix, we derive the system of equations that we use to solve for a counterfactual equilibrium. In our baseline specification, we consider the closed-city specification of the model, in which total population for the city as a whole (\bar{L}) is exogenous, and hence the change in travel costs affects worker welfare. We denote the value of a variable in the initial equilibrium by x , the value of this variable in the counterfactual equilibrium by x' (with a prime), the relative change in this variable by $\hat{x} = x'/x$ (with a hat). Given values for the model parameters ($\alpha^H, \alpha^T, \{\alpha_k^S\}, \{\theta_k^S\}, \theta^W, \theta^B, \kappa^W, \kappa^S, \eta^B, \eta^W, \beta^S, \beta^T, \mu$), assumed bilateral changes in travel cost $\{\hat{d}_{ni}^W, \hat{d}_{nij(k)}^S\}$, and observed values for the endogenous variables in the initial equilibrium ($\{\lambda_{ig|n}^W, \lambda_{j(k)|ni}^S, \lambda_n^B\}, \{H_{j,k}, H_{n,U}\}, \{E_{ni}\}$), we solve for the counterfactual equilibrium by solving the following system of equations for the general equilibrium of the model.

(i) Changes in Commuting and consumption probabilities From equations (10) and (14), the counterfactual changes in conditional commuting probabilities ($\hat{\lambda}_{ig|n}^W$) and conditional consumption probabilities ($\hat{\lambda}_{j(k)|ni}^S$) satisfy:

$$\begin{aligned} \hat{\lambda}_{ig|n}^W &= \frac{T_{i,g}^W w_{i,g}'^{\theta^W} (d_{ni}^{W'})^{\theta^W} (\mathbb{S}'_{ni})^{\theta^W}}{T_{i,g}^W w_{i,g}^{\theta^W} (d_{ni}^W)^{\theta^W} (\mathbb{S}_{ni})^{\theta^W}} \frac{\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} (d_{n\ell}^W)^{\theta^W} (\mathbb{S}_{n\ell})^{\theta^W}}{\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^{W'} w_{\ell,m}'^{\theta^W} (d_{n\ell}^{W'})^{\theta^W} (\mathbb{S}'_{n\ell})^{\theta^W}} \\ &= \frac{\hat{w}_{i,g}^{\theta^W} (\hat{d}_{ni}^W)^{\theta^W} \hat{\mathbb{S}}_{ni}^{\theta^W}}{\sum_{\ell \in N} \sum_{m \in K} \hat{w}_{\ell,m}^{\theta^W} (\hat{d}_{n\ell}^W)^{\theta^W} \hat{\mathbb{S}}_{n\ell}^{\theta^W} \lambda_{\ell m|n}^W}, \end{aligned} \quad (\text{E.1})$$

$$\begin{aligned} \hat{\lambda}_{j(k)|ni}^S &= \frac{T_{j(k)}^S (P_{j(k)}^S)^{-\theta_k^S} (d_{nij(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}} \sum_{\ell \in N} T_{\ell(k)}^S (P_{\ell(k)}^S)^{-\theta_k^S} (d_{ni\ell(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}}}{T_{j(k)}^S (P_{j(k)}^{S'})^{-\theta_k^S} (d_{nij(k)}^{S'})^{\frac{\theta_k^S}{\alpha_k^S}} \sum_{\ell \in N} T_{\ell(k)}^{S'} (P_{\ell(k)}^{S'})^{-\theta_k^S} (d_{ni\ell(k)}^{S'})^{\frac{\theta_k^S}{\alpha_k^S}}} \\ &= \frac{(\hat{P}_{j(k)}^S)^{-\theta_k^S} (\hat{d}_{nij(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}}}{\sum_{\ell \in N} (\hat{P}_{\ell(k)}^S)^{-\theta_k^S} (\hat{d}_{ni\ell(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}} \lambda_{\ell(k)|ni}^S}. \end{aligned} \quad (\text{E.2})$$

Using equations (10), (12), (14) and (16), the corresponding changes in travel access ($\hat{\mathbb{A}}_n$) and consumption access ($\hat{\mathbb{S}}_n$) can be written in terms of own commuting shares ($\hat{\lambda}_{nT|n}^W$) and own consumption shares ($\hat{\lambda}_{n(k)|ni}^S$):

$$\begin{aligned}\hat{\mathbb{A}}_n &= \left[\frac{\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^{W'} w_{\ell,m}'^{\theta^W} (d_{n\ell}^{W'})^{\theta^W} (\mathbb{S}'_{n\ell})^{\theta^W}}{\sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} (d_{n\ell}^W)^{\theta^W} (\mathbb{S}_{n\ell})^{\theta^W}} \right]^{\frac{1}{\theta^W}} \\ &= \left[\hat{w}_{n,g}^{\theta^W} (\hat{d}_{nn}^W)^{\theta^W} \hat{\mathbb{S}}_{nn}^{\theta^W} / \hat{\lambda}_{ng|n}^W \right]^{\frac{1}{\theta^W}},\end{aligned}\quad (\text{E.3})$$

for some $g \in K$, and

$$\begin{aligned}\hat{\mathbb{S}}_{ni} &= \prod_k \left[\frac{\sum_{\ell \in N} T_{\ell(k)}^{S'} (P_{\ell(k)}^{S'})^{-\theta_k^S} (d_{ni\ell(k)}^{S'})^{\frac{\theta_k^S}{\alpha_k^S}}}{\sum_{\ell \in N} T_{\ell(k)}^S (P_{\ell(k)}^S)^{-\theta_k^S} (d_{ni\ell(k)}^S)^{\frac{\theta_k^S}{\alpha_k^S}}} \right]^{\frac{\alpha_k^S}{\theta_k^S}} \\ &= \prod_k \left[(\hat{P}_{n,k}^S)^{-\theta_k^S} (\hat{d}_{nin(k)}^S)^{\theta_k^S} / \hat{\lambda}_{n(k)|ni}^S \right]^{\frac{\alpha_k^S}{\theta_k^S}}.\end{aligned}\quad (\text{E.4})$$

(ii) Changes in residential location decision From equations (20) and (17), the counterfactual changes in residential probabilities ($\hat{\lambda}_n^B$) satisfy:

$$\begin{aligned}\hat{\lambda}_n^B &= \frac{T_n^B B_n'^{\theta^B} \mathbb{A}_n'^{\theta^B} (P_n^T)^{-\alpha^T \theta^B} Q_n'^{-\alpha^H \theta^B} \sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} (P_\ell^T)^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B}}{T_n^B B_n^{\theta^B} \mathbb{A}_n^{\theta^B} (P_n^T)^{-\alpha^T \theta^B} Q_n^{-\alpha^H \theta^B} \sum_{\ell \in N} T_\ell^{B'} B_\ell'^{\theta^B} \mathbb{A}_\ell'^{\theta^B} (P_\ell^T)^{-\alpha^T \theta^B} Q_\ell'^{-\alpha^H \theta^B}} \\ &= \frac{\hat{\mathbb{A}}_n^{\theta^B} \hat{Q}_n^{-\alpha^H \theta^B} \hat{B}_n^{\theta^B}}{\sum_{\ell \in N} \hat{\mathbb{A}}_\ell^{\theta^B} \hat{Q}_\ell^{-\alpha^H \theta^B} \hat{B}_\ell^{\theta^B} \lambda_\ell^B}.\end{aligned}\quad (\text{E.5})$$

(iii) Changes in commercial and residential floor space demand The changes in commercial floor space in each sector ($\hat{H}_{i,g}$) are given by:

$$\hat{H}_{i,g} = \frac{\hat{w}_{i,g} \hat{L}_{i,g}}{\hat{Q}_i}, \quad (\text{E.6})$$

where the change in labor input adjusted for effective units of labor ($\hat{L}_{i,g}$) can be derived from equation (B.6) as:

$$\hat{L}_{i,g} = \frac{1}{\hat{w}_{i,g}} \frac{\sum_{n \in N} E'_{ni} \lambda'_{ig|n} \lambda_n^{B'}}{\sum_{n \in N} E_{ni} \lambda_{ig|n} \lambda_n^B}. \quad (\text{E.7})$$

The changes in residential floor space ($\hat{H}_{i,U}$) satisfy:

$$\hat{H}_{i,U} = \frac{\hat{E}_i \hat{\lambda}_i^B}{\hat{Q}_i}, \quad (\text{E.8})$$

where the counterfactual residential income E'_n is given by equation (19):

$$E'_n = \sum_{i \in N} E'_{ni} \lambda'_{i|n}, \quad (\text{E.9})$$

and the changes of commuting-pair specific income \hat{E}_{ni} is derived from equation (B.17):

$$\hat{E}_{ni} = \frac{\hat{\mathbb{A}}_n}{\hat{\mathbb{S}}_{ni}}. \quad (\text{E.10})$$

(iv) Changes in the price of floor space From equation (28), the change in the price of floor space (\hat{Q}_i) and the overall quantity of floor space (\hat{H}_i) are related as follows:

$$\hat{Q}_i = \hat{H}_i^{\frac{1-\mu}{\mu}}, \quad (\text{E.11})$$

where the change in this overall quantity of floor space (\hat{H}_i) is a weighted average of the changes in the quantities of commercial floor space in each sector ($\hat{H}_{i,k}$) and the quantity of residential floor space ($\hat{H}_{i,U}$):

$$\hat{H}_i = \frac{H_{i,U} \hat{H}_{i,U} + \sum_{k \in K} H_{i,k} \hat{H}_{i,k}}{H_{i,U} + \sum_{k \in K} H_{i,k}}. \quad (\text{E.12})$$

(v) Changes in endogenous productivities and amenities From equations (25) and (26), the changes in endogenous productivities ($\hat{A}_{i,k}$) and amenities (\hat{B}_n) as a result of agglomeration forces satisfy:

$$\hat{A}_{i,k} = \hat{L}_i^{\eta^W}, \quad (\text{E.13})$$

$$\hat{B}_n = \hat{R}_n^{\eta^B}. \quad (\text{E.14})$$

(vi) Changes in nontraded goods prices From equation (22), the changes in non-traded goods prices ($\hat{P}_{j,k}^S$) satisfy:

$$\hat{P}_{j,k}^S = \frac{1}{\hat{A}_{j,k} \hat{L}_{j,k}^{\beta^S} \hat{H}_{j,k}^{1-\beta^S}} \frac{\sum_{n,i \in N} E_{ni}' \lambda_{j(k)|ni}^{\prime S} \lambda_{i|n}^{\prime W} \lambda_n^{\prime B}}{\sum_{n,i \in N} E_{ni} \lambda_{j(k)|ni}^S \lambda_{i|n}^W \lambda_n^B}. \quad (\text{E.15})$$

(viii) Changes in Wages From the zero-profit condition (20), the changes in wages in each sector and location with positive production ($\hat{w}_{i,k}$) are given by:

$$\hat{w}_{i,k} = \left(\frac{\hat{A}_{i,k} \hat{P}_{i(k)}^S}{\hat{Q}_i^{1-\beta^S}} \right)^{1/\beta^S}. \quad (\text{E.16})$$

We solve this system of equations, starting with an initial guess of the relative change in each endogenous variable ($\hat{x} = 1$), and updating this initial guess until the solution to this system converges to equilibrium. Using the resulting counterfactual changes in the endogenous variables of the model ($\hat{\lambda}_{ig|n}^W$, $\hat{\lambda}_{j(k)|ni}^S$, $\hat{\mathbb{A}}_n$, $\hat{\mathbb{S}}_n$, $\hat{\lambda}_n^B$, $\hat{H}_{i,g}$, $\hat{H}_{i,U}$, $\hat{L}_{i,g}$, \hat{Q}_i , $\hat{A}_{i,k}$, \hat{B}_n , $\hat{P}_{i(k)}^S$, $\hat{w}_{i,k}$), together with equation (18), we can compute the implied change in expected utility ($\widehat{\mathbb{E}[u]}$) induced by the change in travel costs as follows:

$$\begin{aligned} \widehat{\mathbb{E}[u]} &= \left[\frac{\sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} (P_\ell^{T'})^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B}}{\sum_{\ell \in N} T_\ell^B B_\ell^{\theta^B} \mathbb{A}_\ell^{\theta^B} (P_\ell^T)^{-\alpha^T \theta^B} Q_\ell^{-\alpha^H \theta^B}} \right]^{\frac{1}{\theta^B}} \\ &= \left[\sum_{\ell \in N} \lambda_\ell^B \hat{B}_\ell^{\theta^B} \hat{\mathbb{A}}_\ell^{\theta^B} \hat{Q}_\ell^{-\alpha^H \theta^B} \right]^{\frac{1}{\theta^B}}, \end{aligned} \quad (\text{E.17})$$

where we have used our choice of numeraire ($P_\ell^T = 1$ for all $\ell \in N$).

E.2 Calibration of Baseline Variables

In this section, we discuss the calibration of the initial equilibrium variables used in the system of equations from the previous section to solve for a counterfactual equilibrium. In general, the system of equations for a counterfactual equilibrium can be solved using either the observed initial travel shares or using the initial travel shares predicted by the estimated model. In our baseline specification, we use this covariate-based approach to address concerns about granularity. In later sections of this online appendix, we report robustness tests, in which we use the observed initial travel shares following the conventional exact-hat algebra approach. In our empirical application, we find a relatively similar pattern of results using both approaches.

In addition to the parameters as presented in Table D.1.1, we use a set of baseline variables ($\{\lambda_{ig|n}^W, \lambda_{j(k)|ni}^S, \lambda_n^B\}$, $\{\tilde{L}_{i,k}\}$, $\{H_{j,k}, H_{n,U}\}$, $\{E_{ni}\}$) and the changes of travel cost $\{\hat{d}_{ni}^W, \hat{d}_{nij(k)}^S\}$ for this counterfactual simulation. Below, we discuss how we construct these baseline variables using our smartphone data and separate data sources (see Section 2.2 of our main paper for these other data sources).

Spatial Units. We first need to take a stand on the spatial units at which we conduct counterfactual simulations. In the counterfactual of reducing travel cost in Tokyo Metropolitan Area (Section F), the spatial unit is specified as 242 municipalities, which together form the Tokyo Metropolitan Area. In the counterfactual of the subway opening in Sendai City (Section 6), the spatial unit is specified as 370 Oazas, which together form the municipality of Sendai City.

Calibration of commuting probability $\{\lambda_{ig|n}^W\}$. We construct $\lambda_{ig|n}^W$ using our smartphone data and separate economic census data. From our smartphone data and its assignment of “home” and “work” locations for each device, we define the bilateral commuting flows $\lambda_{i|n}^W$ at specified bilateral spatial units. Our model assumes that the probability that each worker works in a certain industry ($\lambda_{ig|n}^W / \sum_{k \in K} \lambda_{ik|n}^W$) is independent of the worker’s residential location n . Therefore, we use the separate economic census data to construct the employment share of each sector ($L_{i,g} / \sum_{k \in K} L_{i,k}$), and define the commuting probability for each bilateral location and sector by $\lambda_{ig|n}^W = \lambda_{i|n}^W \times L_{i,g} / \sum_{k \in K} L_{i,k}$.

In measuring the commuting shares in the initial equilibrium, one potential concern is granularity (the difference between realized and expected values because of a small integer number of commuters on some bilateral routes). In particular, [Dingel and Tintelnot \(2020\)](#) show that counterfactuals using the observed initial commuting shares can be potentially biased, because of the model overfitting from using the observed commuting flows to calibrate the model. Instead, they recommend “covariate-based approach,” in which one calibrates the commuting flows by the predicted flows using covariates such as travel time. Following their recommendations, we use the predicted commuting flows from our commuting choice probability estimation (equation (35)) to construct the initial commuting shares in the baseline specification for our counterfactuals. As a robustness test, we also report the results of counterfactuals based on the conventional exact-hat algebra approach using the observed initial commuting shares.

Calibration of consumption probability $\{\lambda_{j(k)|ni}^S\}$. We construct $\lambda_{j(k)|ni}^S$ using our smartphone data and separate economic census data. Using our smartphone data, we assign ‘‘Other’’ stays to each nontradable service sector as discussed in Section 3 of our main paper. Using this assignment, we define the travel for consumption trips for each location and sector given residential and work locations. In our baseline specification, we again follow the ‘covariate-based approach,’ in which we use the predicted consumption flows from our consumption choice probability estimation (equation (31)) to construct the initial travel shares in the baseline specification for our counterfactuals. As a robustness test, we also report the results of counterfactuals based on the conventional exact-hat algebra approach using the observed initial travel shares.

Calibration of residential share $\{\lambda_n^B\}$. We construct λ_n^B from our smartphone data using the devices’ ‘‘Home’’ locations.

Calibration of floor space $\{H_{j,k}, H_{n,U}\}$. We construct $\{H_{j,k}, H_{n,U}\}$ using our building use data and economic census data. From the building data, we construct the floor space in each location separately for residential purposes ($H_{n,U}$) and commercial purposes ($\sum_{k \in K} H_{j,k}$). We allocate commercial floor space into each sector k proportionally to the employment share of the sector in each locations using economic census data.

Calibration of income $\{E_{ni}\}$. We construct $\{E_{ni}\}$ using equation (B.17) such that $E_{ni} = \mathbb{A}_n / \mathbb{S}_{ni}$, where \mathbb{A}_n and \mathbb{S}_{ni} are estimated following the procedures in Section 5.1 of our main paper.

Calibration of changes in travel cost $\{\hat{d}_{ni}^W, \hat{d}_{nij(k)}^S\}$. We construct the travel cost change $\{\hat{d}_{ni}^W, \hat{d}_{nij(k)}^S\}$ from the specified parameter changes of κ^W and κ_k^S (for the counterfactual in Tokyo Metropolitan Area in Section F) and the travel time change (for the counterfactual in Sendai City in Section 6). We construct $\{\hat{d}_{ni}^W\}$ from equation (14) such that

$$\hat{d}_{ni}^W \equiv \exp(-\kappa^W \Delta \tau_{ni}^W) \quad (\text{E.18})$$

where Δ indicates the difference operation. We construct $\{\hat{d}_{nij(k)}^S\}$ from our definition of d_{ni}^W in equation (30) such that

$$\hat{d}_{nij(k)}^S = \vartheta_k^R \left[\sum_{r' \in \mathbb{R}} \xi_{r'(k)}^R \exp(-\phi_k^R \Delta \tau_{nij(k)r'(k)}^S) \right]^{\frac{\alpha_k^S}{\theta_k^R}}. \quad (\text{E.19})$$

F Counterfactual Simulations for Tokyo Metropolitan Area

In this section of the appendix, we report counterfactuals examining the role of travel costs within the Tokyo Metropolitan Area. We undertake counterfactuals for changes in travel costs for commuting and consumption, both separately and jointly, and examine their relative importance in shaping the spatial concentration of economic activity. In a first exercise, we halve travel costs for commuting trips ($\kappa^{W'} = 0.5 \cdot \kappa^{W'}$), maintain travel costs for consumption trips equal to their estimated value ($\kappa_k^S = \phi_k^S \alpha_k^S / \theta_k^S > 0$), and solve for the counterfactual equilibrium distribution of economic activity. In a second exercise, we halve travel costs for consumption trips ($\kappa_k^{S'} = 0.5 \cdot \kappa_k^S$), maintain travel costs for commuting trips equal to their estimated value ($\kappa^W = \phi^W / \theta^W > 0$), and solve for the counterfactual equilibrium. Finally, in a third exercise, we halve travel costs for both commuting and consumption trips ($\kappa^{W'} = 0.5 \cdot \kappa^{W'}$ and $\kappa_k^{S'} = 0.5 \cdot \kappa_k^S$), and solve for the counterfactual equilibrium. In our baseline specification, we use the parameter values from Table D.1.1 of this online appendix, with the agglomeration parameters given by $\eta^B = 0.08$ and $\eta^W = 0.15$. In robustness tests, we examine the sensitivity of the results to alternative values for these agglomeration parameters.

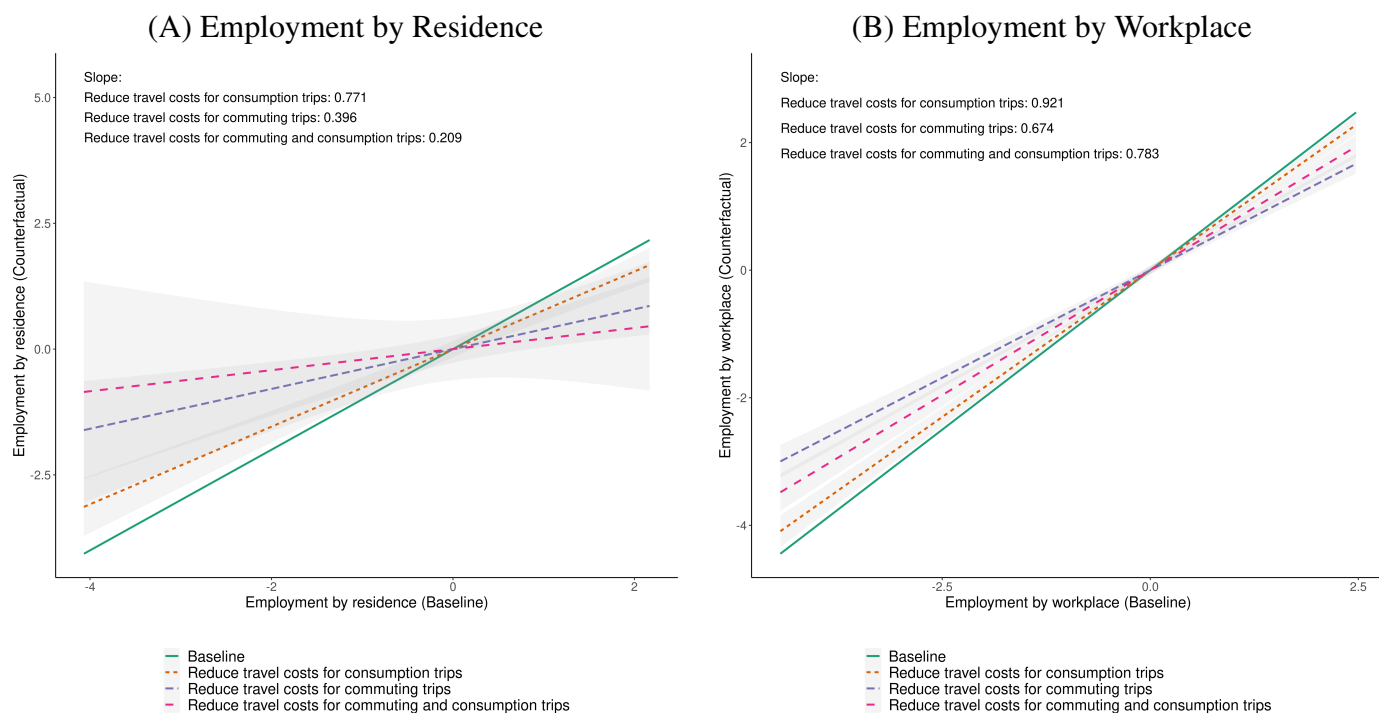
F.1 Counterfactual Results

In Figure F.1.1, we display the results of these three counterfactuals. In Panel (A), we show counterfactual employment by residence against observed employment by residence (both variables are normalized to have a mean of zero in logs). In Panel (B), we show the corresponding figure for employment by workplace. To provide a point of comparison, we begin by displaying the 45 degree line (labeled “Baseline”). On top of this, we overlay the linear fit and its confidence interval for the same outcomes under our three counterfactuals. If employment is unaffected by the change in travel costs, the counterfactual plot coincides with the 45-degree line. If the regression slope is flatter than 45 degree line, counterfactual employment is more decentralized than actual employment, because employment decreases in locations with higher actual employment, and increases in locations with lower actual employment.

We first discuss how the three counterfactuals change the spatial distribution of employment by residence (Panel A). We start with our first counterfactual of halving the travel cost for consumption trips. We find that the regression slope is shallower than 45 degree line (a coefficient is 0.77 instead of one), such that the spatial inequality of the residential population decreases by about 23 percent ($= 1 - 0.77$). This result is intuitive. In the initial equilibrium in the data, employment in non-traded services is spatially concentrated, and workers trade off the lower prices of floor space in outlying locations against the higher costs of travelling to consume non-traded services. When we halve the travel cost parameter for consumption trips in the counterfactual, we reduce this difference in consumption travel costs between central and outlying locations, which increases the relative attractiveness of outlying locations.

In our second counterfactual, we halve travel costs for commuting trips (labelled “reduce travel costs for commuting trips”). We again find that the regression slope is significantly flatter than 45 degree line (a coefficient of 0.39), such that the observed spatial inequality of the residential population decreases by about 61 percent ($= 1 - 0.39$). The intuition is similar to our first counterfactual. When we halve the travel costs for commuting trips in the counterfactual, we reduce the difference in commuting costs between central and

Figure F.1.1: Counterfactuals for Reducing Travel Costs for Commuting and Consumption Trips



Note: Panel (A) shows counterfactual employment by residence against observed employment by residence; right panel shows the analogous plot for employment by workplace; baseline corresponds to the observed distributions for our baseline sample for April 2019; the three counterfactuals halve travel costs for consumption trips, for commuting trips, and for both consumption and commuting trips, respectively. All counterfactuals use the parameter values from Table D.1.1, with the agglomeration parameters given by $\eta^B = 0.08$ and $\eta^W = 0.15$. In Table F.2.1 in Section F of the online appendix, we report robustness tests using alternative values for these agglomeration parameters.

outlying locations, which increases the relative attractiveness of outlying locations. Comparing the magnitude of these first and second counterfactuals, commuting costs are more important than consumption travel costs for the spatial concentration of residents, but the contribution from consumption travel costs is more than half that from commuting costs.

In our third counterfactual, we halve travel costs for both commuting and consumption trips (labelled “reduce travel costs for commuting and consumption trips”). Here the reductions in travel costs for the two types of trips reinforce one another, resulting in an even flatter regression slope (a coefficient of 0.20), such that the spatial inequality of the residential population decreases by about 80 percent ($= 1 - 0.20$).

We now turn to how the three counterfactuals would change the spatial distribution of employment by workplace (Panel B). In our first counterfactual of halving the travel cost for consumption trips, the regression slope of counterfactual employment by workplace is 0.92, such that the spatial inequality of employment by workplace decreases by 8 percent ($= 1 - 0.92$). Theoretically, there are two counteracting forces for how the reduction in consumption travel costs affects the spatial concentration of employment by workplaces. On the one hand, consumers can now travel more easily to locations that offer lower prices for nontradable services. This force tends to increase the concentration of employment by workplace. On the other hand, firms in the outskirts can now expect a higher volume of consumer travel, increasing the relative attractiveness of these

locations for firms. This force acts to decrease the concentration of employment by workplace. Quantitatively, we find that the latter force dominates, such that the reduction in consumption travel costs decreases the spatial concentration of employment by workplace.

In our second counterfactual of halving the travel cost for commuting trips, the regression slope of counterfactual employment by workplace is 0.67, such that the spatial inequality of employment by workplace decreases by 33 percent ($= 1 - 0.67$). As in our first counterfactual, there are two counteracting forces for how the reduction of commuting travel cost affects the spatial concentration of employment by workplace. On the one hand, workers can now more easily commute to central locations that offer higher wages. This force tends to increase the spatial concentration of employment by workplace. On the other hand, firms can now expect more commuters even if they locate in the outskirts. This force tends to decrease the spatial concentration of employment by workplace. Quantitatively, we find that the latter force dominates, such that the reduction in commuting travel costs also decreases the spatial concentration of employment by workplace.

In our third counterfactual of halving the travel costs for both commuting and consumption trips, we find that the regression slope of counterfactual employment by workplace is 0.78, such that the spatial inequality of employment by workplace decreases by 22 percent ($= 1 - 0.78$). Interestingly, this reduction is smaller than our second counterfactual of halving only the commuting cost, which reflects the interaction of the two counteracting forces from the reduction in consumption and commuting travel costs discussed above.

Overall, the results of these counterfactuals for changes in travel costs provide further evidence that consumption access is quantitatively important for the spatial concentration of economic activity in urban areas relative to the workplace access that has received much greater emphasis in previous research.

F.2 Robustness

We now examine the sensitivity of our results to alternative values for the residential spillover parameter η^B and the production spillover parameter η^W . Overall, regardless of the choice of η^B and η^W , we find that a robust pattern that consumption access is quantitatively important for the spatial concentration of economic activity in urban areas relative to workplace access.

In our first set of counterfactuals, we provide further evidence on the role of travel costs for commuting and consumption in shaping the spatial concentration of economic activity, by shutting down each of these sources of spatial frictions. In a first exercise, we halve travel costs for commuting trips ($\kappa^{W'} = 0.5 \cdot \kappa^{W'}$), maintain travel costs for consumption trips equal to their estimated value in the data ($\kappa_k^S > 0$), and solve for the counterfactual equilibrium distribution of economic activity. In a second exercise, we halve travel costs for consumption trips ($\kappa_k^{S'} = 0.5 \cdot \kappa_k^S$), maintain travel costs for commuting trips equal to their estimated value in the data ($\kappa^W > 0$), and solve for the counterfactual equilibrium. Finally, in a third exercise, we halve travel costs for both commuting and consumption trips ($\kappa^{W'} = 0.5 \cdot \kappa^{W'}$ and $\kappa_k^{S'} = 0.5 \cdot \kappa_k^S$), and solve for the counterfactual equilibrium.

Table F.2.1 presents the results of our three counterfactuals (reduce consumption travel cost, reduce commuting travel cost, and reduce both consumption and commuting travel cost). Each entry in the table corresponds to the regression slope of the counterfactual prediction of the employment by residence (Table (i)) and employment by workplace (Table (ii)) on those variables from actual data. Within each table, Panel A-C cor-

responds to the counterfactual simulations under different values of η^B and η^W , and each of the three columns indicates our three counterfactuals. If employment is unaffected by the change in travel costs, counterfactual employment is more decentralized than actual employment, because employment decreases in locations with higher actual employment, and increases in locations with lower actual employment.

By comparing the panels in Table (i) and (ii), we find that the counterfactual predictions are affected by the choice of η^B and η^W . In particular, when we increase η^B from 0 to 0.15, the counterfactual changes of regression slopes become larger (from Panel A to Panel B). Furthermore, we decrease the value of η^W from 0.08 to 0, the counterfactual changes become smaller (from Panel B to Panel C). Therefore, we find that both η^B and η^W amplify the changes in counterfactuals. Nonetheless, our main conclusions continue to hold under different choices of η^B and η^W : consumption access is quantitatively important for the spatial concentration of economic activity in urban areas relative to the workplace access (comparing Column 1 to 2).

Table F.2.1: Counterfactuals for Reducing Travel Costs for Commuting and Consumption Trips

(i) Employment by Residence			
Dependent variable: log(R)			
	Reduce travel costs for consumption trips	Reduce travel costs for commuting trips	Reduce travel costs for commuting and consumption trips
	(1)	(2)	(3)
Panel A: $\eta^B = 0, \eta^W = 0.08$			
log(R) (baseline)	0.943*** (0.013)	0.807*** (0.018)	0.778*** (0.030)
Panel B: $\eta^B = 0.15, \eta^W = 0.08$			
log(R) (baseline)	0.771*** (0.069)	0.396*** (0.117)	0.209 (0.263)
Panel C: $\eta^B = 0.15, \eta^W = 0$			
log(R) (baseline)	0.795*** (0.053)	0.481*** (0.145)	0.235 (0.289)
Observations	242	242	242
(ii) Employment by Workplace			
Dependent variable: log(L)			
	Reduce travel costs for consumption trips	Reduce travel costs for commuting trips	Reduce travel costs for commuting and consumption trips
	(1)	(2)	(3)
Panel A: $\eta^B = 0, \eta^W = 0.08$			
log(L) (baseline)	0.976*** (0.017)	0.939*** (0.021)	0.919*** (0.034)
Panel B: $\eta^B = 0.15, \eta^W = 0.08$			
log(L) (baseline)	0.921*** (0.027)	0.674*** (0.029)	0.783*** (0.032)
Panel C: $\eta^B = 0.15, \eta^W = 0$			
log(L) (baseline)	0.948*** (0.016)	0.794*** (0.017)	0.855*** (0.021)
Observations	242	242	242

Note: Each entry in the table corresponds to the regression slope of the counterfactual prediction of the employment by residence (Table (i)) and employment by workplace (Table (ii)) on those variables from actual data. Within each table, Panel A-C corresponds to the counterfactual simulations under different values of η^B and η^W , and each of the three columns indicates our three counterfactuals. Figure F.1.1 of our main paper displays the graphical version of the relationships in Panel B ($\eta^B = 0.15; \eta^W = 0.08$).

G Additional Results on Sendai Subway Analysis

In this section of the appendix, we present additional results for our analysis of the opening of the new Tozai (East-West) Subway Line in the city of Sendai as discussed in Section 6 of the paper. In Subsection G.1, we discuss the extension of our baseline theoretical model to incorporate an endogenous transport mode choice between the railway and road transportation. In Subsection G.2, we discuss our estimation of travel access in the city of Sendai, following the same approach as developed in Section 5.1 of the paper.

In Subsection G.3, we report additional difference-in-differences estimates for the impact of the opening of the new Tozai (East-West) Subway Line in the city of Sendai, as discussed in Section 6 of the paper. In Subsection G.4, we present the results of our Placebo specification, in which we repeat our empirical analysis for the already-existing Nanbuko (North-South) Subway Line.

In Subsection G.5, we compare our baseline counterfactual results for the new Tozai (East-West) Subway Line using the predicted values of the initial equilibrium travel shares from our estimation with the alternative approach of using the observed initial travel shares. In our empirical application, we find a relatively similar pattern of results using both approaches.

G.1 Incorporating Transportation Mode Choice

In this subsection, we extend our baseline model (Section 4) to incorporate the mode choice between the railway and the road transportation. This extension is important for the correct assessment of subway opening, because the welfare estimates are greatly influenced by the intensity at which residents use railways as opposed to road traffic. In Section G.1.1, we set up our extended model and show that the extended model remains isomorphic to our main model by replacing the travel time with mode-adjusted travel time. In Section G.1.2, we estimate the mode choice and mode-adjusted travel time.

G.1.1 Model Extension to Incorporate Transportation Mode Choice

We introduce the mode choice as an additional choice of transportation made by each worker for each leg of travel (for each movement from one place to another). These decisions are made after workers decide their residence, workplace, the set of consumption locations, and the routes (as in our baseline model). After the worker chooses the set of routes for each consumption location (whether to visit her consumption location from home, from work, or in between), she observes an idiosyncratic preference shock for each transportation mode for each leg of her travel, and decides her optimal transportation mode for each leg of travel.

Utility. The indirect utility of the worker is given as follows:

$$\begin{aligned}
 U_{ni g\{j(k)r(k)\}}(\omega) &= \left\{ B_n b_n(\omega) (P_n^T)^{-\alpha^T} Q_n^{-\alpha^H} \right\} \{ a_{i,g}(\omega) w_{i,g} \}, \\
 &\times \left\{ \prod_{k \in K^S} [P_{j(k)}^S / (q_{j(k)}(\omega))]^{-\alpha_k^S} \right\} \left\{ d_{ni\{j(k)r(k)\}}(\omega) \prod_{k \in K^S} \nu_{r(k)}(\omega) \right\} \\
 0 &< \alpha^T, \alpha^H, \alpha_k^S < 1, \quad \alpha^T + \alpha^H + \sum_{k \in K^S} \alpha_k^S = 1,
 \end{aligned} \tag{G.1}$$

The only difference from our main specification (equation 1 in the main paper) is that the travel cost $d_{ni\{j(k)r(k)\}}(\omega)$ now depends on worker ω , which reflects the optimal mode choice specific to each individual. Similarly as in our baseline model, we specify that $d_{ni\{j(k)r(k)\}}(\omega)$ is decomposed into the component related to commuting and consumption trips. More specifically, we assume:

$$d_{ni\{j(k)r(k)\}}(\omega) = \exp(-\kappa^W \tau_{ni}^W(\omega)) \prod_{k \in K^S} \exp(-\kappa_k^S \tau_{nij(k)r(k)}^S(\omega)), \quad (\text{G.2})$$

where $\tau_{ni}^W(\omega)$ is the travel cost required for commuting from residence n to workplace i without making any detour, and $\tau_{nij(k)r(k)}^S$ is the travel cost additionally required to visit consumption location $j(k)$ by the route $r(k)$ by deviating from the commuting path. Again, the only difference from the definition of travel cost from our baseline model (equation 2) is that $\tau_{ni}^W(\omega)$ and $\tau_{nij(k)r(k)}^S(\omega)$ now depend on worker ω through the optimal choice of transportation mode.

We proceed by specifying $\tau_{ni}^W(\omega)$. Noting that workers decide the transportation mode for each leg of travel (separately for traveling from home to work and from work to home), we have:⁷

$$\tau_{ni}^W(\omega) = \tau_{ni}(\omega, m_{ni}) + \tau_{in}(\omega, m_{in}),$$

where $\tau_{ni}(\omega, m_{ni})$ is the expected travel cost from n to i using mode $m_{ni} \in \mathbb{M}$ inclusive of the preference shock for each mode. Denoting these mode-specific preference shock by $\nu_{ni,m}^M$, we can express $\tau_{ni}(\omega, m)$ as:

$$\tau_{ni}(\omega, m) = \delta_{ni,m} + \log \nu_{ni,m}^M(\omega)$$

where $\delta_{ni,m}$ is the travel time from n to i using mode m , and $\nu_{ni,m}^M(\omega)$ is again the stochastic preference shock for mode m for the leg of travel from n to i .

Similarly, the consumption trip component of travel time ($\tau_{nij(k)r(k)}^S(\omega)$) in equation (G.2) is given by:

$$\begin{aligned} \tau_{nij(k)HH}^S(\omega) &= \tau_{nj}(\omega, m_{nj}) + \tau_{jn}(\omega, m_{jn}), \\ \tau_{nij(k)WW}^S(\omega) &= \tau_{ij}(\omega, m_{ij}) + \tau_{ji}(\omega, m_{ji}), \\ \tau_{nij(k)HW}^S(\omega) &= \tau_{nj}(\omega, m_{nj}) + \tau_{ji}(\omega, m_{ji}) - \tau_{ni}(\omega, m_{ni}), \\ \tau_{nij(k)WH}^S(\omega) &= \tau_{ij}(\omega, m_{ij}) + \tau_{jn}(\omega, m_{ni}) - \tau_{in}(\omega, m_{ni}), \end{aligned}$$

where each component is the the sum of the mode-specific travel time and the preference shock given by equation (G.1.1).

Similarly as the idiosyncratic shocks for residence choice, workplace choice, consumption location choice and the route choice, we assume that $\nu_{ni,m}^M(\omega)$ is drawn from the following independent Fréchet distributions:

$$G_m^M(\nu) = \exp\left(-T_m^M \nu^{-\theta^M}\right), \quad T_m^M > 0, \quad \theta^M > 1,$$

where the scale parameter $\{T_m^M\}$ control the average draws and the shape parameter θ^M regulates the dispersion of the shock.

⁷While we assume that workers can use different transportation modes for each direction of travel, it is straightforward to assume that the same transportation mode is used for both directions.

Mode choice. After making decisions about the residence, workplace, set of consumption locations, and the routes (as discussed in the main paper), and after observing the idiosyncratic shocks $\nu_{ni,m}^M(\omega)$, each worker chooses the optimal mode for each leg of travel (e.g., travel from home to work, work to consumption locations). The optimal choice of the mode for the leg of travel from n to i is given by:

$$m_{ni}(\omega) = \arg \max_{m \in \mathbb{M}} \{ \delta_{ni,m} + \log \nu_{ni,m}^M(\omega) \}.$$

where $\delta_{ni,m}$ is again the travel time from n to i using mode m . Using the same property of the Fréchet distributions as used in the main paper (see, for example, Section 4.2 for the route choice), the probability that workers use mode m for moving from n to i ($\lambda_{m|ni}^M$) is given by:

$$\lambda_{m|ni}^M = \frac{T_m^B \exp(-\theta^M \delta_{ni,m})}{\sum_{m' \in \mathbb{M}} T_{m'}^R \exp(-\theta^M \delta_{ni,m'})}. \quad (\text{G.3})$$

As we assumed above, workers decide their residence, workplace, the set of consumption locations, and the routes (as discussed in the main paper) before observing the realizations of the idiosyncratic shock for each mode and travel leg ($\nu_{ni,m}^M(\omega)$). Therefore, workers make these decisions based on the expected travel cost for each leg of travel.

The expected commuting cost in the indirect utility function (equation G.2) is given by

$$\begin{aligned} \mathbb{E} [\exp(-\kappa^W \tau_{ni}^W(\omega))] &= \mathbb{E} [\exp(-\kappa^W \tau_{ni}(\omega, m_{ni})) \exp(-\kappa^W \tau_{in}(\omega, m_{in}))] \\ &= \mathbb{E} [\exp(-\kappa^W \tau_{ni}(\omega, m_{ni}))] \mathbb{E} [\exp(-\kappa^W \tau_{in}(\omega, m_{in}))], \end{aligned} \quad (\text{G.4})$$

where the expectations are with respect to $\nu_{ni,m}^M(\omega)$, and the second transformation used the property that $\nu_{ni,m}^M(\omega)$ are independent for each segment of travel (for each movement of one location to another). The first term is transformed as:

$$\begin{aligned} \mathbb{E} [\exp(-\kappa^W \tau_{ni}(\omega, m_{ni}))] &= \mathbb{E} \left[\max_m \exp(-\kappa^W (\delta_{ni,m} + \log \nu_{ni,m}^M(\omega))) \right] \\ &= \vartheta^M \left(\sum_{m' \in \mathbb{M}} T_{m'}^R \exp(-\theta^M \delta_{ni,m'}) \right)^{\frac{\kappa^W}{\theta^M}}, \end{aligned}$$

where $\vartheta^M \equiv \Gamma \left(\frac{\theta^M / \kappa^M - 1}{\theta^M / \kappa^M} \right)$, and we use the same property of the Fréchet distribution (see, for example, Section 4.2 for the route choice).

Mode-adjusted travel cost. For notational convenience, we define “mode-adjusted travel time” $\tilde{\tau}_{ni}$ such that:

$$\tilde{\tau}_{ni} \equiv \log \vartheta^M \left(\sum_{m' \in \mathbb{M}} T_{m'}^R \exp(-\theta^M \delta_{ni,m'}) \right)^{\frac{1}{\theta^M}}, \quad (\text{G.5})$$

where $\tilde{\tau}_{ni}$ is a summary statistic for the travel cost relevant for moving from n to i by anticipating the mode choice. The reason why we call this object by $\tilde{\tau}_{ni}$ will be immediately clear below. By combining this definition of $\tilde{\tau}_{ni}$ with equation (G.4), the expected commuting cost is given by:

$$\begin{aligned} \mathbb{E} [\exp(-\kappa^W \tau_{ni}^W(\omega))] &= \mathbb{E} [\exp(-\kappa^W \tau_{ni}(\omega, m_{ni}))] \mathbb{E} [\exp(-\kappa^W \tau_{in}(\omega, m_{in}))] \\ &= \exp(-\kappa^W \tilde{\tau}_{ni}) \exp(-\kappa^W \tilde{\tau}_{in}). \end{aligned}$$

Furthermore, we can derive the expected consumption travel cost similarly as in the derivation for the expected commuting cost.

Together, the expected travel cost over the mode choice (conditional on the choice of residence, workplace, consumption locations and the routes) is given by:

$$\begin{aligned}\mathbb{E} [d_{ni\{j(k)r(k)\}}(\omega)] &= \mathbb{E} [\exp(-\kappa^W \tau_{ni}^W(\omega))] \prod_{k \in K^S} \mathbb{E} [\exp(-\kappa^S \tau_{nij(k)r(k)}^S(\omega))] \\ &= \exp(-\kappa^W \tilde{\tau}_{ni}^W) \prod_{k \in K^S} \exp(-\kappa_k^S \tilde{\tau}_{nij(k)r(k)}^S)\end{aligned}$$

where

$$\tilde{\tau}_{ni}^W = \tilde{\tau}_{ni} + \tilde{\tau}_{in}$$

and

$$\begin{aligned}\tilde{\tau}_{nij(k)HH}^S &= \tilde{\tau}_{nj} + \tilde{\tau}_{jn}, \\ \tilde{\tau}_{nij(k)WW}^S &= \tilde{\tau}_{ij} + \tilde{\tau}_{ji}, \\ \tilde{\tau}_{nij(k)HW}^S &= \tilde{\tau}_{nj} + \tilde{\tau}_{ji} - \tilde{\tau}_{ni}, \\ \tilde{\tau}_{nij(k)WH}^S &= \tilde{\tau}_{ij} + \tilde{\tau}_{jn} - \tilde{\tau}_{in}.\end{aligned}$$

Note that this expression of the travel cost is isomorphic to the baseline model without the mode choice (equation 2) except that the travel time τ_{ni} is replaced by the “mode-adjusted travel time” $\tilde{\tau}_{ni}$. Therefore, the choices of residence, workplace, consumption locations, and the route choice are as discussed in the baseline model except that travel time τ_{ni} is replaced by mode-adjusted travel time $\tilde{\tau}_{ni}$.

G.1.2 Estimation of Mode Choice Probability and Estimation of Mode-Adjusted Travel Time $\tilde{\tau}_{ni}$

Now we discuss the data that we use for estimating the mode choice probability and the mode-adjusted travel time $\tilde{\tau}_{ni}$. To construct $\tilde{\tau}_{ni}$ from expression (G.5), we need (1) the mode-specific travel time $\delta_{ni,m}$ for each bilateral pair of locations, and (2) the parameter θ^M and T_m^R . (Note that ϑ^M is a constant term common to all bilateral pair of locations and hence the value of ϑ^M does not affect any of our results.)

We construct the mode-specific travel time $\delta_{ni,m}$ for each bilateral pair of locations as follows. First, we assume that workers face two possible transportation modes: public transportation and cars. We extract the travel time after Tozai Subway Line has opened using public transportation by the web-based route choice service, Eki-spert API, as discussed in Section 2.2. Since Eki-spert API does not allow us to extract the travel time before Tozai Subway Line has opened, we construct the travel time with public transportation in the following procedure. We first compute the approximate travel time with and without the Tozai subway line for all pairs of Oazas in Sendai City using ArcGIS and the geocoded data of subways and bus lines under certain assumptions of the travel speed for each mode.⁸ We then compute the ratio of the travel times without Tozai Subway Line relative to that with Tozai Subway Line. Finally, we multiply this ratio by the travel time from

⁸We assume that 80 meter per minute for walk, 600 meter per minute for rail, and 150 meter per minute for buses. We obtain the geocoded railway and bus networks from the website of the Ministry of Land, Infrastructure, Transport and Tourism.

Eki-spert API to obtain our final estimates for the travel time with public transportation in the absence of Tozai Subway Line.

We construct car travel time by Open Source Routing Machine (OSRM), a routing service based on OpenStreetMap.⁹ OSRM finds the shortest routes on public roads by car, bicycle and on foot between a pair of coordinates. We collected data on all the pairs of the centroids of Oazas in Sendai City in October 2020.

We estimate the mode choice probability (G.4) to obtain parameters θ^M and T_m^R . To do so, we use the travel survey data from Sendai City conducted in 2017. From a representative households, the survey collects information of the origin location, destination location and what travel mode is used. From this data, we construct the probability that railway (including other public transportation) or road transportation mode is used for each movement of the respondent.

Table G.1.1 presents our results of the mode choice estimation in equation (G.4) by Poisson Pseudo-Maximum Likelihood (PPML) with origin-destination fixed effects. Column (1) starts with the specification with the dummy of public transportation. The negative significant coefficient for this dummy indicates that people have a strong preference to use cars instead of using public transportation. In Column (2), we show our estimation results where we additionally control for travel time. The coefficient on travel time is negative and statistically significant, indicating that people have strong tendency to choose the transportation mode that provides shorter travel time. However, the dummy for public transportation is still negative and significant, indicating that people have strong preference to travel by cars even after controlling for the fact that travelling cars provides shorter travel time.

Table G.1.1: Mode Choice Estimation

Dependent Variable:	Mode Choice Probability	
Model:	(1)	(2)
<i>Variables</i>		
Dummy (Public Transportation Including Railways)	-1.50*** (0.020)	-0.953*** (0.042)
Travel Time (Hours)		-0.318*** (0.023)
<i>Fixed-effects</i>		
Origin and Destination Locations	Yes	Yes
<i>Fit statistics</i>		
Pseudo R ²	0.12210	0.12512
Log-Likelihood	-42,367.3	-42,221.4
AIC	121,474.7	121,184.8
BIC	290,555.3	290,274.6
Observations	73,436	73,436

Note: The results of the mode choice estimation in equation (G.4) by Poisson Pseudo-Maximum Likelihood (PPML). The unit of observations are all bilateral pairs of Oazas where there are positive flows. Heteroskedasticity robust standard errors in parentheses.

Using the estimates of these parameters and the mode-specific travel time, we construct the changes of the mode-adjusted travel time $\tilde{\tau}_{ni}$ using the expression (G.5). As discussed above, the counterfactual simulation procedure is unaffected from our baseline model except that we replace travel time τ_{ni} by the mode-adjusted

⁹See <http://project-osrm.org/> for more detail.

travel time $\tilde{\tau}_{ni}$.

G.2 Estimation of Travel Access \mathbb{A}_n in Sendai City

In Section 6, we study the impacts of Tozai Subway Line on the travel access \mathbb{A}_n . In this appendix, we discuss how we construct \mathbb{A}_n in pre-period (before the subway opening) and post-period (after the subway opening) in more detail.

We construct travel access \mathbb{A}_n in the pre-period following the same procedure in Section 5.1, except that we use the mode-adjusted travel time as discussed in Appendix G.1. In this procedure, we also recover travel time elasticity (ϕ^W and ϕ_k^S). We then estimate the post-period consumption location choice and commuting choices given estimated parameters ϕ^W and ϕ_k^S . Using these estimates, we construct the post-period travel access \mathbb{A}_n following the same expression.

Below, we present our estimation results of the route choice probability (Table G.2.1), consumption location choice probability (Table G.2.2), and commuting choice probability (Table G.2.3). Each of these tables corresponds to Table 2, Table 3, and Table 4 of the main paper estimated using data in Tokyo Metropolitan Area. The qualitative findings are broadly the same as in our estimates from Tokyo Metropolitan Area, except that the coefficients on travel time for route choice, consumption location choice and commuting choice are greater.

Table G.2.1: Estimation of Route Choice in Sendai City

Dependent Variable:	Route Choice Probability				
	Finance realestate communication professional	Wholesale retail	Accomoda- tions eating drinking	Medical welfare healthcare	Other services
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
Travel Time (Hours)	-0.394*** (0.032)	-0.387*** (0.027)	-0.332*** (0.026)	-0.376*** (0.044)	-0.355*** (0.028)
Dummy (HW)	-1.37*** (0.050)	-1.49*** (0.047)	-1.57*** (0.043)	-1.44*** (0.053)	-1.44*** (0.051)
Dummy (WH)	-0.784*** (0.039)	-0.911*** (0.034)	-0.809*** (0.034)	-0.964*** (0.045)	-0.816*** (0.036)
Dummy (WW)	-0.917*** (0.056)	-1.01*** (0.055)	-1.16*** (0.057)	-1.03*** (0.065)	-1.00*** (0.056)
<i>Fixed-effects</i>					
Home-Work-Consumption Location	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
AIC	74,821.5	185,222.9	69,038.2	83,774.2	97,380.3
BIC	96,834.8	207,420.2	90,941.0	105,604.8	119,501.4
Observations	98,385	102,227	96,137	94,331	100,975

Note: A version of Table 2 where we use pre-period data from Sendai City. See the footnote of Table 2 for other comments.

Table G.2.2: Estimation of Consumption Location Choice in Sendai City

Dependent Variable:	Finance realestate communication professional	Consumption Wholesale retail	Location Choice Accomodations eating drinking	Probability Medical welfare healthcare	Other services
Model:	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
$\log \tilde{d}_{nij(k)}^S$	-3.48*** (0.117)	-3.43*** (0.100)	-3.26*** (0.104)	-3.48*** (0.099)	-3.34*** (0.110)
<i>Fixed-effects</i>					
Home and Work Location Pairs	Yes	Yes	Yes	Yes	Yes
Consumption Location	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
AIC	26,702.4	27,301.8	26,449.9	27,684.4	26,821.4
BIC	54,680.9	55,630.4	54,185.5	55,567.7	55,125.2
Observations	565,455	594,395	538,876	561,708	593,865

Note: A version of Table 3 where we use pre-period data from Sendai City. See the footnote of Table 3 for other comments.

Table G.2.3: Estimation of Commuting Choice in Sendai City

Dependent Variable:	Commuting Choice Probability
Model:	(1)
<i>Variables</i>	
Commuting Time (Hours)	-2.29*** (0.105)
<i>Fixed-effects</i>	
Home Location	Yes
Work Location	Yes
<i>Fit statistics</i>	
AIC	1,289.9
BIC	7,334.8
Observations	100,650

Note: A version of Table 4 where we use pre-period data from Sendai City. See the footnote of Table 4 for other comments.

G.3 Additional Results of the Difference-in-Difference Estimates of Tozai Subway Line

In this appendix, we provide additional results of our difference-in-difference effects of Tozai Subway Line (Table 6 of our main paper). In Section G.3.1, we show how our results are biased when we omit the consumption trips to construct travel access \mathbb{A}_n . In Section G.3.2, we show the sensitivity of our results under different values of the residential spillover elasticity η^B and productivity spillover elasticity η^W . In Section G.3.3, we provide a procedure to estimate η^B using the difference-in-difference estimates and present our estimation results.

G.3.1 Bias of Omitting Consumption Trips

In this subsection, we show how we obtain biased conclusions about the reduced-form effects of Tozai Subway Line when we omit the consumption trips to construct travel access \mathbb{A}_n . In Table G.3.1, we compare our results by including and omitting consumption trips when constructing travel access \mathbb{A}_n , following the same difference-in-difference specification as in Panel (A) of Table 6 of our main paper. Panel (A) uses outcome variables constructed directly from observed data, and it is identical to Panel (A) of Table 6. In Panel (B), we construct travel access \mathbb{A}_n and residential amenity \mathbb{B}_n by omitting consumption trips ($\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $\mathbb{S}_{nt} = 1$). Columns (1) and (2) are identical between the two panels because they are directly obtained from data and unaffected by the construction of travel access \mathbb{A}_n . In Column (3), we find an underestimation of the effects of Tozai Subway Line on travel access \mathbb{A}_n (0.042 instead of 0.054), and an overestimation on residential amenity (0.017 instead of 0.004). Therefore, by omitting consumption trips, one would mis-attribute the changes of residential values from subways due to unobserved changes in residential amenity. Hence, we find that incorporating consumption trips is important for the quantitative success of the model's mechanism in explaining the observed data.

Table G.3.1: Bias of Difference-in-Difference Effects of Tozai Subway Line by Omitting Consumption Trips

	$\Delta \log Q_n$	$\Delta \log \lambda_n^B$	$\Delta \log \mathbb{A}_n$	$\Delta \log \mathbb{B}_n$
	(1)	(2)	(3)	(4)
Panel A: Data				
Dummy (Tozai Line Stations)	0.046*** (0.014)	0.311 (0.210)	0.054*** (0.008)	0.004 (0.036)
Observations	368	305	305	305
R ²	0.030	0.007	0.123	0.0001
Panel B: Data (Travel Access Constructed by Omitting Consumption Trips)				
Dummy (Tozai Line Stations)	0.046*** (0.014)	0.311 (0.210)	0.042*** (0.010)	0.017 (0.036)
Observations	368	305	305	305
R ²	0.030	0.007	0.057	0.001

Note: In Panel (A), we construct travel access \mathbb{A}_n and residual amenity \mathbb{B}_n by including consumption trips, and it is identical to Panel (A) of Table 6 of our main paper. In Panel (B), we construct travel access \mathbb{A}_n and residential amenity \mathbb{B}_n by omitting consumption trips ($\alpha_k^S = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda_{j(k)|ni}^S = 0$ and $\mathbb{S}_{nt} = 1$). By construction, columns (1) and (2) are identical between the two panels.

G.3.2 Robustness to Different Elasticities of Agglomeration Spillovers

In this section of the appendix, we show the sensitivity of our results of the difference-in-difference regression of Tozai Subway Line under different values of the elasticities of agglomeration spillovers.

Table G.3.2 presents the results. Panel (A) uses outcome variables constructed directly from observed data, and Panel (B) is those from model prediction under $\eta^B = 0$ and $\eta^W = 0.08$, and the two panels are identical to those of Table 6. As discussed in the main paper, the results between Panel (A) and Panel (B) closely align with each other, validating our model and our choice of the parameter values for η^B and η^W .

In Panel (C), we report the results of the difference-in-difference regression with outcome variables constructed from model prediction when we increase residential amenity spillover η^B from 0 to 0.15. The model substantially over-predicts the impacts on floor space price (Column 1) and the residential probability (Column 2). This overestimation primarily comes from the predicted increase of residential amenity (Column 4), which we do not find from our observed data (Panel A). Therefore, we find that the model is quantitatively able to explain the observed increase in floor space prices and residential population through its mechanism of an improvement in travel access, without requiring increases in the residual of residential amenities in these locations.

In Panel (D), we report the results of the difference-in-difference with outcome variables constructed from model prediction when we decrease the productivity spillover η^W from 0.08 to 0. By comparing with Panel (B), we find somewhat smaller changes of floor space price and residential population, while this difference is modest.

Table G.3.2: Robustness of Difference-in-Difference Effects of Tozai Subway Line under Different Elasticities of Agglomeration Spillovers

	$\Delta \log Q_n$	$\Delta \log \lambda_n^B$	$\Delta \log A_n$	$\Delta \log B_n$
	(1)	(2)	(3)	(4)
Panel A: Data				
Dummy (Tozai Line Stations)	0.046*** (0.014)	0.311 (0.210)	0.054*** (0.008)	0.004 (0.036)
Observations	368	305	305	305
R ²	0.030	0.007	0.123	0.0001
Panel B: Model Prediction ($\eta^B = 0; \eta^W = 0.08$)				
Dummy (Tozai Line Stations)	0.091*** (0.010)	0.300*** (0.032)	0.073*** (0.008)	0.000 (0.000)
Observations	370	370	370	370
R ²	0.197	0.191	0.199	
Panel C: Model Prediction ($\eta^B = 0.15; \eta^W = 0.08$)				
Dummy (Tozai Line Stations)	0.206*** (0.022)	1.182*** (0.127)	0.074*** (0.008)	0.175*** (0.019)
Observations	370	370	370	370
R ²	0.198	0.189	0.196	0.190
Panel D: Model Prediction ($\eta^B = 0; \eta^W = 0$)				
Dummy (Tozai Line Stations)	0.077*** (0.008)	0.295*** (0.031)	0.068*** (0.007)	0.000 (0.000)
Observations	370	370	370	370
R ²	0.203	0.197	0.203	

Note: The results of the difference-in-difference regression of Tozai Subway Line using the observed outcome variables (Panel A) and the model prediction (Panel B-D). Panels A and B are identical to Table 6 of our main paper. Panel C and D use our model prediction under different values of agglomeration spillovers (η^B and η^W) Standard errors are clustered at Oaza level. See the footnote of Table 6 for other comments.

G.3.3 Estimation of Residential Amenity Spillover Elasticity η^B

In this section of the appendix, we show how we can estimate the residential spillover elasticity η^B using the opening of Tozai Subway Line. To do so, we introduce an identification assumption that the changes unobserved residential amenity is uncorrelated with the proximity to the stations of Tozai Subway Line. More

specifically, from equations (26) and (40), we have:

$$\begin{aligned}\mathbb{B}_n &= B_n (T_n^B)^{1/\theta^B} (P_n^T)^{-\alpha^T} (\bar{U}/\vartheta^B)^{-1} \\ &= b_n \left(\frac{L\lambda_n^B}{K_n} \right)^{\eta^B} (T_n^B)^{1/\theta^B} (P_n^T)^{-\alpha^T} (\bar{U}/\vartheta^B)^{-1}.\end{aligned}$$

By assuming the geographic area K_n and the shifter for idiosyncratic preference shocks T_n^B are time-invariant and tradable prices are equalized across locations as numeraire, we obtain our estimating equation for η^B by log-differencing the above equation:

$$\Delta \log \mathbb{B}_n = c_0 + \eta^B \Delta \log \lambda_n^B + u_n \quad (\text{G.6})$$

where $c_0 = \Delta \log (L\eta^B \bar{U}^{-1}) + \mathbb{E} \Delta \log b_n$ and u_n is the mean-zero error term capturing the idiosyncratic shift of the exogenous component of the residential amenity ($u_n = \Delta \log b_n - \mathbb{E} \Delta \log b_n$). We assume that u_n is uncorrelated with whether Oaza n has a Tozai Subway Line station (T_n). Under this assumption, we obtain a consistent estimate of residential spillover elasticity η^B by the instrumental variable (IV) regression using T_n as an instrument for $\Delta \log \lambda_n^B$.

Table G.3.3 presents our estimates of η^B . In Column (1), we present our results when we include consumption trips for constructing $\Delta \log \mathbb{B}_n$. We find a small point estimate of $\eta^B = 0.015$. In Column (2), we present our results when we omit consumption trips for constructing $\Delta \log \mathbb{B}_n$ (use $\Delta \log \mathbb{A}_n^{\text{nocons}}$ instead of $\Delta \log \mathbb{A}_n$ as discussed in Section 5.2). Interestingly, when we omit the consumption trips to estimate η^B , we obtain a larger point estimate of $\eta^B = 0.054$. Therefore, by omitting consumption trips, one would overestimate the residential spillover elasticity.

Table G.3.3: Estimation of Residential Amenity Spillover Elasticity in Sendai City

	$\Delta \log \mathbb{B}_n$	
	(1)	(2)
$\Delta \log \lambda_n^B$	0.014 (0.105)	0.054 (0.080)
First Stage F-Statistics	1.1	1.1
Specification	Include Consumption Trips	Omit Consumption Trips
Observations	305	305
Adjusted R ²	0.155	0.509

Note: This table presents our estimation results of η^B . We estimate these parameters using the IV regression (G.6) where we instrument $\Delta \log \lambda_n^B$ by whether Oaza n has a Tozai Subway Line station (T_n).

G.4 Network Effects on Nanboku (North-South) Subway Line

As an additional specification check, we repeat the same difference-in-difference regression with Tozai Subway Line (Table 6), but use a dummy variable that takes the value one for Oazas that contain stations on the existing

Nanboku (North-South) Subway Line (which opened in 1987) rather than stations on the new Tozai (East-West) Subway Line (which opened in 2015). If there are positive or negative network effects from the new Tozai Subway Line on locations with stations on the existing Nanboku Subway Line, we would expect to again detect statistically significant treatment effects.

In Panel (A) of Table G.4.1, we show that we find no evidence of statistically significant treatments effects on the price of floor space, residential population, travel access, and residential amenities for this existing Nanboku Subway Line. These results are consistent with a limited net impact of network effects on the existing subway line and suggest that our earlier estimates for the Tozai Subway Line are capturing effects specific to this new subway line. Consistent with these findings using the observed data, in Panel (B), we find no evidence of statistically significant treatment effects for existing Nanboku Subway Line using our counterfactual predictions of the model.

Table G.4.1: Network Effects of Nanboku Subway Line

	$\Delta \log Q_n$	$\Delta \log \lambda_n^B$	$\Delta \log A_n$	$\Delta \log B_n$
	(1)	(2)	(3)	(4)
Panel A: Data				
Dummy (Tozai Line Stations)	-0.002 (0.011)	0.086 (0.160)	0.004 (0.006)	0.009 (0.027)
Observations	357	296	296	296
R ²	0.0001	0.001	0.002	0.0004
Panel B: Model Prediction ($\eta^B = 0; \eta^W = 0.08$)				
Dummy (Tozai Line Stations)	-0.003 (0.008)	-0.010 (0.027)	-0.003 (0.006)	0.000 (0.000)
Observations	359	359	359	359
R ²	0.0005	0.0004	0.0005	

Note: The results of the difference-in-difference regression by defining treatment by the stations around Nanboku (North-South) Subway Line (which already opened in 1987) instead of Tozai (East-West) Subway Line (which actually opened in 2015) for the same time interval. We exclude the observations of Oazas containing Tozai Subway Line from this analysis. We use observed outcome variables in Panel A and the model prediction in Panel B. See the footnote of Table 6 for additional comments.

G.5 Implications of Granularity

As discussed in Section 6 of the paper, one important issue of the counterfactual simulation of this type of model is the granularity of observed travel flows ($\{\lambda_{ig|n}^W, \lambda_{j(k)|ni}^S, \lambda_n^B\}$). In our main paper, we presented results using the predicted initial values of travel shares from our consumption location choice and workplace choice estimation. In this section, we compare these baseline results with the alternative specification of using the observed initial values of travel shares in the data.

Table G.5.1 shows how our results of the difference-in-difference regression of Tozai Subway Line is affected by this choice of the calibration strategy. Identically to Table 6 of our main paper, Panel (A) corresponds to the estimates using the observed data. Panel (B) estimates the same reduced-form regressions using the model's counterfactual predictions when we calibrate the model using predicted travel flows (as in Panel (B) of Table 6 of our main paper). In Panel (C), we present the estimates based on the model prediction when we instead calibrate the model with actual travel flows. Comparing Panel (B) and (C), we find somewhat smaller impacts on the model prediction of floor space price, residential probability, and the travel access. This difference is intuitive. We observe zero travel flows in many pairs of locations in our data due to granularity. Some of these routes are directly affected by the new subway line. Therefore, if we use actual travel flows to calibrate the model, we implicitly assume no direct gains from the travel time reduction of these routes with zero travel flows in baseline. Therefore, the model predicts smaller effects from subway line. Lastly, we cannot conclude which of the two assumptions perform better (by comparing Panel B and C with Panel A) because of the relatively large standard errors in these estimates.

In Table G.5.2, we compare our estimates of the welfare gains from Tozai Subway Line under these two calibration strategies. Consistent with the observation above, we find a smaller welfare gain using the model calibrated with actual travel flows (2.74 percentage points as opposed to 2.55 percentage points). While this difference is non-negligible, it is significantly less than the difference in the results arising from the omission of consumption trips (Table 7). Therefore, the main message of the paper about the importance of consumption trips remains robust across these two different calibration strategies.

Table G.5.1: Impacts of Tozai Subway Line: Granularity

	$\Delta \log Q_n$	$\Delta \log \lambda_n^B$	$\Delta \log A_n$	$\Delta \log B_n$
	(1)	(2)	(3)	(4)
Panel A: Data				
Dummy (Tozai Line Stations)	0.046*** (0.014)	0.311 (0.210)	0.054*** (0.008)	0.004 (0.036)
Observations	368	305	305	305
R ²	0.030	0.007	0.123	0.0001
Panel B: Model Prediction with Smoothed Flows ($\eta^B = 0; \eta^W = 0.08$)				
Dummy (Tozai Line Stations)	0.091*** (0.010)	0.300*** (0.032)	0.073*** (0.008)	0.000 (0.000)
Observations	370	370	370	370
R ²	0.197	0.191	0.199	
Panel C: Model Prediction with Actual Flows ($\eta^B = 0; \eta^W = 0.08$)				
Dummy (Tozai Line Stations)	0.062*** (0.010)	0.205*** (0.037)	0.050*** (0.009)	0.000 (0.000)
Observations	370	370	370	370
R ²	0.092	0.079	0.083	

Note: The results of the difference-in-difference regression of Tozai Subway Line using the observed outcome variables (Panel A) and the model prediction (Panel B-C). Panels A and B are identical to Table 6 of our main paper. In Panel C, we calibrate the model using actual consumption travel flows and commuting flows ($\{\lambda_{ig|n}^W, \lambda_{j(k)|ni}^S, \lambda_n^B\}$) instead of the predicted flows as reported in Panel (B). See the footnote of Table 6 for other comments.

Table G.5.2: Counterfactual Increase in Expected Utility in Sendai from the new Tozai Subway Line: Granularity

	Percentage Point Increase in Residential Utility	Relative to Baseline (%)
(1) Use Smoothed Travel Flows in Baseline	2.74	1.00
(2) Use Actual Travel Flows in Baseline	2.55	0.93

Note: The second column reports model counterfactuals for the percentage point increase in expected utility as a result of the reduction in travel time from the opening of the new Tozai (East-West) subway line in the City of Sendai. The first row presents results for our baseline specification ($\eta^B = 0, \eta^W = 0.08$), and this corresponds to Table 7 of our main paper. The second row presents the same results by calibrating the model using actual consumption travel flows and commuting flows ($\{\lambda_{ig|n}^W, \lambda_{j(k)|ni}^S, \lambda_n^B\}$).