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CONSUMPTION ACCESS AND AGGLOMERATION:
EVIDENCE FROM SMARTPHONE DATA

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ABSTRACT

We provide new theory and evidence on the role of consumption access in understanding the agglomeration of economic activity. We combine smartphone data that records user location every 5 minutes of the day with economic census data on the location of service-sector establishments to measure commuting and non-commuting trips within the Greater Tokyo metropolitan area. 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. Using the structure of the model, we estimate theoretically-consistent measures of travel access, and show that consumption access makes a sizable contribution relative to workplace access in explaining the observed variation in residents and land prices across locations. Undertaking counterfactuals for changes in travel costs, we show that abstracting from consumption trips leads to a substantial underestimate of the welfare gains from a transport improvement (because of the undercounting of trips) and leads to a distorted picture of changes in travel patterns within the city (because of the different geography of commuting and non-commuting trips).

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1 Introduction

Understanding the agglomeration of economic activity is one of the most central challenges in economics. Traditional theories of agglomeration emphasize increasing returns in production 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 expeditions, excursions to cinemas, theaters, music venues and museums, and visits to professional service providers. Although a growing number of writers have emphasized the idea of the "consumer city" and the role of consumption in agglomeration, two major challenges faced by research in this area are a limited ability to measure consumption trips within cities and the absence of a widely-accepted theoretical model of agglomeration in consumption.[1] In this paper, we provide new theory and evidence on the role of consumption and workplace access in understanding agglomeration. We combine smartphone data including high-frequency location information with spatially-disaggregated economic 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 as a source of agglomeration and for explaining the observed variation in land prices. We show that incorporating consumption access is quantitatively relevant for evaluating transport infrastructure improvements.

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. Based on this definition, we measure 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 comparing them with official census data. We show that our measures of the shares of residents and workers in each municipality are strongly correlated with those from census data. We also demonstrate similar bilateral commuting patterns between municipalities as in census data.

Having validated our smartphone data using census commuting data, we show that focusing solely on these commuting trips provides a misleading picture of travel within the Tokyo metropolitan area. 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. This finding is consistent with other evidence from travel surveys, but a key advantage of our smartphone data is that they provide a much finer spatial and temporal resolution, and they reveal the sequence in which users travel between home, work and consumption locations, as used in our quantitative analysis. Second, using our spatially-disaggregated data on employment by sector, 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 des-

[1] Early research on the "consumer city" is Glaeser, Kolko, and Saiz (2001) and an influential popular discussion is Florida (2009). A growing number of empirical studies provide empirical evidence of endogenous amenities, including Ahlfeldt, Redding, Sturm, and Wolf (2015) and Diamond (2016), for which we show consumption access provides microfoundations.

tinations 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. 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. Therefore, focusing solely on commuting trips also yields a misleading picture of bilateral patterns of travel within cities.

We next develop quantitative theory of internal city structure that incorporates both consumption and workplace access. 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). At each stage of this decision process, workers take into account their expected access to surrounding locations in subsequent stages. Population mobility implies that workers must obtain the same expected utility from all locations with positive population.

We show that the model implies extended gravity equations for commuting and non-commuting trips, which provide good approximations to the observed data, and can be used to estimate theoretically-consistent measures of access to surrounding locations. We use the model's population mobility condition to 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 a 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, using either the observed initial travel shares as in the conventional exact-hat algebra approach, or the initial travel shares predicted by the estimated model. 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. Undertaking counterfactuals for the construction of a new subway line, we show that taking consumption access into account is quantitatively relevant for the impact of this new transport infrastructure on travel patterns, the spatial organization of economic activity within the city, and welfare.

Our paper is related to a number of different strands of research. First, our paper connects with the broad theoretical and empirical literature on agglomeration, including Henderson (1974), Fujita, Krugman, and Venables (1999), Fujita and Thisse (2002), Davis and Weinstein (2002) and Kline and Moretti (2014), as reviewed in Rosenthal and Strange (2004), Duranton and Puga (2004), Moretti (2011) and Combes and Gobillon (2015). Although the vast majority of this existing research emphasizes agglomeration economies of production, a key focus of our analysis is the way in which access to nontraded services provides an agglomeration force in consumption.

Second, a key part of this agglomeration literature is concerned with the internal structure of cities. Early contributions assumed monocentric organizations of economic activity, including Alonso (1964), Mills (1967) and Muth (1969). Subsequent research explored the conditions under which non-monocentric organizations of economic activity emerge in stylized settings such as a linear city or a symmetric circular city, including Fujita and Ogawa (1982), Fujita and Krugman (1995) and Lucas and Rossi-Hansberg (2002). More recent research has developed quantitative models of internal city structure that allow for asymmetries across locations and yet remain amenable to quantitative analysis, including Ahlfeldt, Redding, Sturm, and Wolf (2015), Allen, Arkolakis, and Li (2017), Monte, Redding, and Rossi-Hansberg (2018), Tsivanidis (2018), Dingel and Tintelnot (2020), and Owens, Rossi-Hansberg, and Sarte (2020), as reviewed in Redding and Rossi-Hansberg (2017).[2] 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.

Third, our findings relate to recent research within the agglomeration literature on endogenous amenities and social and spatial frictions. Evidence of endogenous amenities has been provided in the context of spatial sorting (Diamond 2016 and Almagro and Domínguez-Iino 2019), gentrification and neighborhood change within cities (Couture and Handbury 2019, 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 (Davis, Dingel, Monras, and Morales 2019), credit card data (Agarwal, Jensen, and Monte 2020 and Dolfen, Einav, Klenow, Klopack, 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 and Büchel, Ehrlich, Puga, and Viladecans 2020). Relative to these existing studies, we incorporate consumption trips into a quantitative urban model of internal city structure, and use high-frequency and spatially-disaggregated data on these consumption trips to evaluate their implications for the strength of agglomeration forces and the impact of transport infrastructure improvements.

Fourth, our work contributes to research on transport infrastructure and the spatial distribution of economic activity. One strand of empirical research has used quasi-experimental variation to provide evidence on the causal impact of transport infrastructure improvements, including Chandra and Thompson (2000), Baum-Snow (2007), Michaels (2008), Duranton and Turner (2011, 2012), Faber (2014), Storeygard (2016), Baum-Snow, Brandt, Henderson, Turner, and Zhang (2017), and Couture, Duranton, and Turner (2018). A second line of work has used quantitative spatial models to evaluate general equilibrium impacts of transport infrastructure investments, including Anas and Liu (2007),

[2]The broader literature on quantitative spatial models across cities or regions includes Allen and Arkolakis (2014), Caliendo, Parro, Rossi-Hansberg, and Sarte (2018), Fajgelbaum and Gaubert (2020), Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016), and Redding (2016).

Donaldson (2018), Donaldson and Hornbeck (2016), Heblich, Redding, and Sturm (2020), Tsivanidis (2018), Severen (2019), Balboni (2019), and Zárate (2020). A third group of papers has compared actual and optimal transport networks, including Allen and Arkolakis (2017) and Fajgelbaum and Schaal (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.

The remainder of the paper is structured as follows. Section 2 introduces our data. Section 3 presents reduced-form evidence on travel patterns that motivates the theoretical model that we develop below. Section 4 introduces our quantitative urban model that incorporates a role for both consumption access and workplace access in influencing location choices. Section 5 uses the model to the 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 main smartphone data and the other data used in the quantitative analysis of the model. In Subsection 2.1, we discuss our smartphone data and explain how we use it 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. An important advantage of these data over other sources of smartphone data is that location information is collected regardless of what application the user has open, as long as the device is turned on. 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).[3]

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

[3]The 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.

centroid of these points.[4] We have access to the 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.[5] 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.

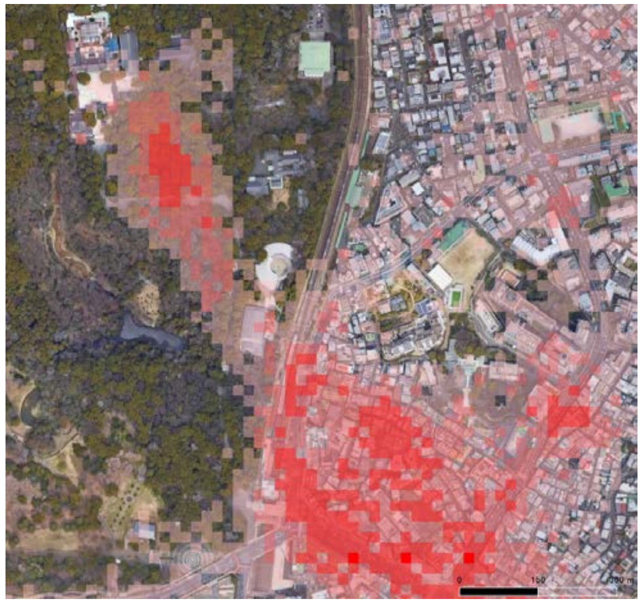
As an illustration of our data, Figure 1 displays the “stays” recorded in our data for the example of a *Meiji Shrine* in the Shibuya municipality of Tokyo over the period from December 2017 to February 2018. Each red-shaded rectangle corresponds a 25 meter by 25 meter grid cell. The darker the red shading of the grid cell, the larger the number of stays in that grid cell. We have overlaid these grid cells on a satellite photograph of the neighborhood. In this photograph, the building towards the top-left of the image surrounded by trees corresponds to the main building of the Meiji shrine. Several features of our data are apparent from this image. First, we observe movement within the city at an extremely fine level of spatial resolution. Second, we find a sharp discountinuity in the density of stays at the road that separates the wooded area surrounding the shrine to the left from the developed area to the right, suggesting that the stays accurately capture the density of movement. Third, in the middle of this wooded area, the stays are concentrated tightly along the path that runs from the road to the main building of the shrine, again confirming the ability of our data to capture the main pathways of movement through the city.

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). Additionally, in Section 6.3, we use our quantative model to examine the impact of the opening of a new subway line in the City of Sendai. 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. In Figure 2, we show the spatial pattern of “stays" in the entire Tokyo Metropolitan Area for this sample. For each user and on each hour of the clock for each

[4] See 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.

[5] In Section A.3 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.

Figure 1: Example of Stays Around a Meiji Shrine in the Shibuya Municipality of Tokyo



Note: The map shows the geographic location of "stays" around a Meiji Shrine. Each red-shaded rectangle corresponds a 25×25 meter grid cell. The darkness of the color represents the number of stays in each grid cell between December 2017 and February 2018. The building towards the top-left surrounded by trees is the main building of the shrine. The stays are concentrated tightly along the path that runs from the road to the main building of the shrine, consistent with them accurately capturing patterns of movement within the city.

day (e.g. at 11am on Monday), we first assign a user's location based on their most recent stay. Using this assignment, we next compute the density function of users, as the share of users in each location. Finally, we take averages by hour across days, separately for weekdays and weekends.

Panel (A) of Figure 2 plots the geographic density of smartphone users at 11am on weekdays, where we use brighter yellow colors to indicate higher densities of users. Consistent with an approximately monocentric structure of economic activity, we find that the density has a clear peak at the city center of the Tokyo metropolitan area. Panel (B) plots the log difference of the density of users at 11am and 11pm. On both weekdays and weekends, the center of the city gains population and the suburbs lose population during the day-time relative to the night-time. But these differences between day- and night-time populations are larger on weekdays than weekends, consistent with people staying closer to their residential locations during the weeekend. Both panels confirm that our assignment of home and work locations captures an intuitive spatial distribution of users within the metropolitan area.

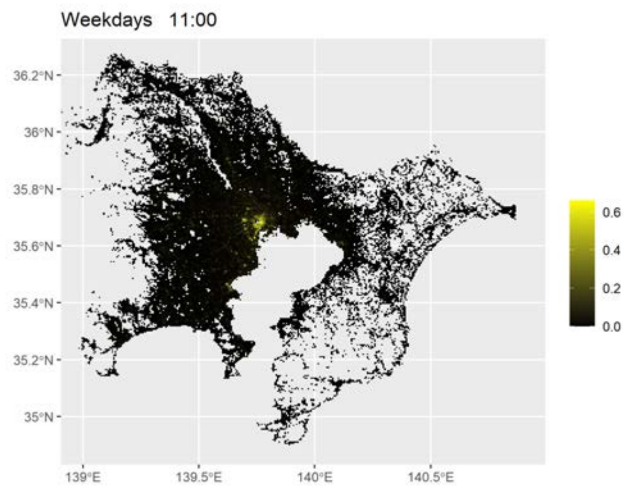
2.2 Other Data Sources

We combine our smartphone data with a number of complementary spatially-disaggregated data sources. We use these additional data sources for the validation of our smartphone data in the next subsection as well as for the quantification of the model in later sections of the paper.

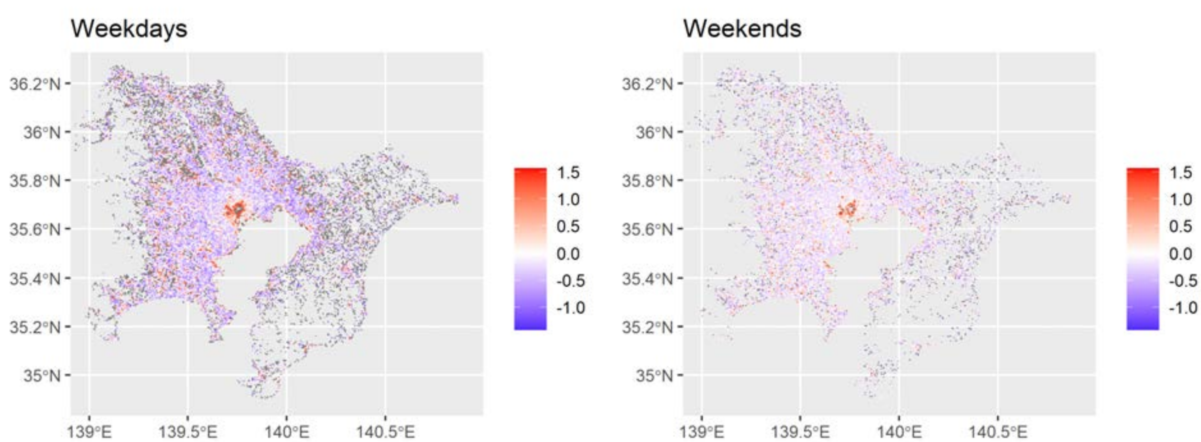
Spatial units: Data are available for the Tokyo metropolitan area at three main levels of spatial aggregation. At the highest level, the metropolitan area includes the four prefectures of Tokyo, Chiba, Kanagawa and Saitama. Each prefecture can be disaggregated into municipalities, of which there are 242 in the Tokyo metropolitan area as a whole (excluding island municipalities). Each municipality can be further disaggregated into *Oaza*, of which there are 9,956 in

Figure 2: Stays in the Tokyo Metropolitan Area

(A) Day-time Population



(B) Log Difference of Day- and Night-time Population



Notes: Panel (A): Density of smartphone users at 11am on weekdays by 500×500 meter grid cell for our baseline sample for the Tokyo metropolitan area in April 2019. Panel (B): Difference in the density of smartphone users between 11am and 11pm by 500×500 meter grid cell. Density equals number of users in a 500×500 meter grid cell divided by the total number of users in our baseline sample.

the Tokyo metropolitan area. 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 population census, which is conducted by the Statistics Bureau, Ministry of Internal Affairs and Communications every five years. We use the publicly-available data from the 2015 population census that are reported on their website. We use these population census data in validation checks on our smartphone data. Residential population and total employment are available at the finest level of spatial disaggregation of 250-meter grid cells. Demographic information used in some of our specification is available at a slightly more aggregated level. Bilateral commuting flows are reported between pairs of municipalities.

Economic Census: We use the Economic Census to distinguish between different types of non-commuting trips, as well as to capture industry-specific employment for the quantification of the model. Economic Censuses are conducted every 2 to 3 years by the Statistics Bureau, Ministry of Internal Affairs and Communications, and the Ministry of Economy, Trade and Industry. We use the publicly-available 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. 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, which is accessible through the Center for Spatial Information Science at the University of Tokyo. 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. Local governments, typically at the municipality level, calculate these land prices for each road segment throughout the city. We take a simple average of these values to construct the average land prices per unit of land at the Oaza or Municipality level. We obtain the consolidated data on these land values from the Research Center for Property Assessment System.

Travel time: We measure travel time by public transportation using the web-based route choice service, *Eki-spert* API.[6] Eki-spert API provides the minimum travel times between any pairs of coordinates using public transport, including suburban rail, subway, and bus. The travel time between any two coordinates is calculated as the sum of public transportation time and the travel time by walking to/from the station or bus stop from origin/destination. 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), a routing service based on OpenStreetMap, which we use to examine the choice between alternative modes of transport.

Municipality Income Tax Base Data: We measure the average income of the residents in each municipality using official data on the tax base for that municipality.

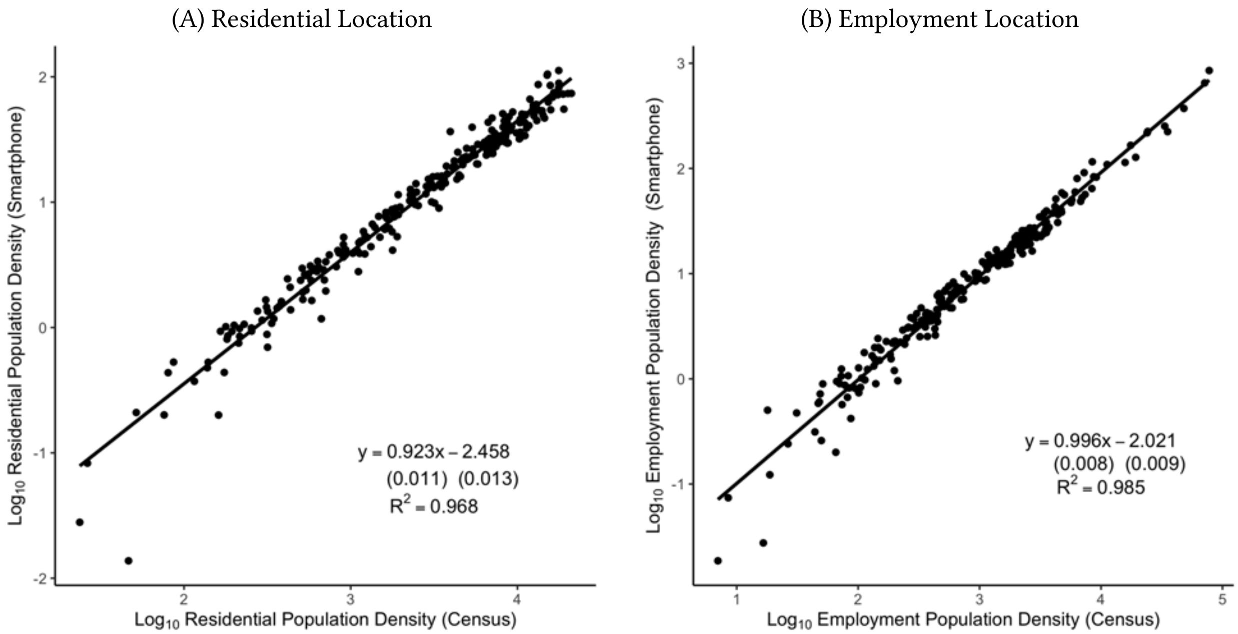
2.3 Validation of Smartphone Commuting Data Using Census Commuting Data

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 the corresponding measures available from official census data. As the most disaggregated spatial units for which these official census data are available are municipalities, we aggregate our smartphone data to the municipality level in order to undertake this comparison. In the left panel of Figure 3, 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

[6] See https://roote.ekispert.net/en for details.

than one, indicating that the smartphone data has higher coverage in less dense areas. In the right panel of Figure 3, 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, the levels of the two variables necessarily differ from one another, but 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. Taken together, these findings provide strong evidence in support of our measures of home and work location from the smartphone data. Furthermore, the fact that these relationships are so tight across municipalities with very different levels of economic activity suggests that the probability of inclusion in our sample is not strongly correlated with the population or employment of the municipality.[7]

Figure 3: Representativeness of Smartphone Users



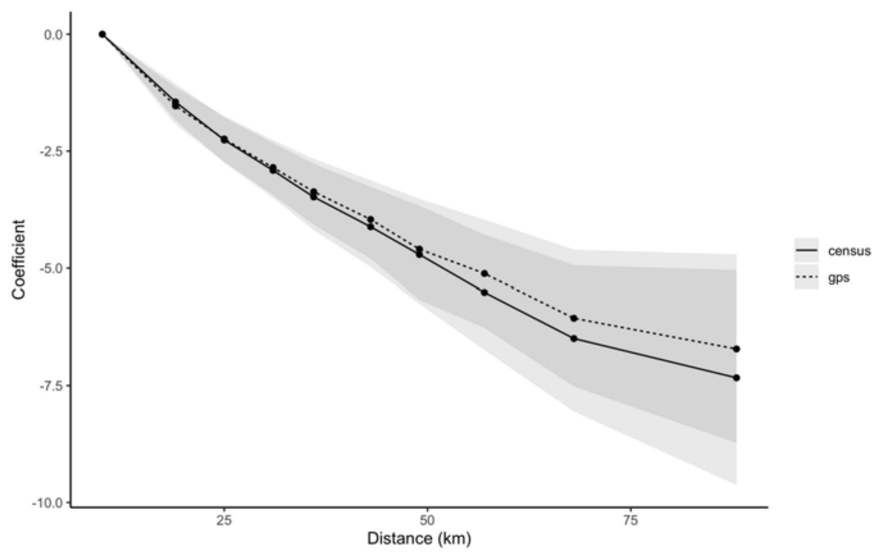
Note: Each dot represents a municipality in the Tokyo metropolitan area. In the left panel, the vertical axis is the log of the number of smartphone users with a home location in the municipality divided by its geographic area, and the horizontal axis is the log of the number of residents in that municipality 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 location in the smartphone data are discussed in the text of Subsection 2.1 above.

As a further check on the ability of our smartphone data to successfully capture commuting patterns, we now 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 4, 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

[7]In online appendix Figure A.1.1 and A.1.2, 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).

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 4: 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.

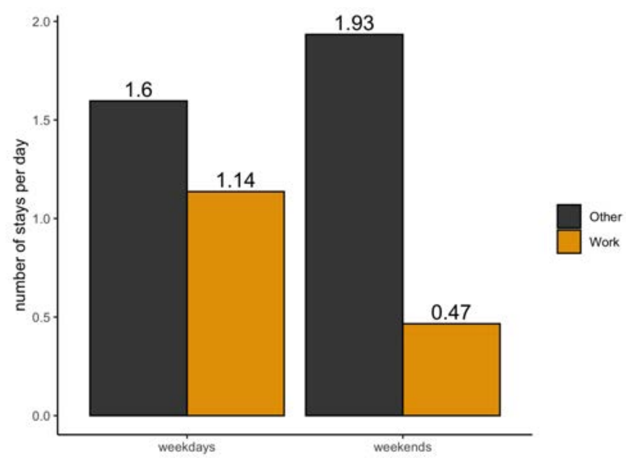
Taken together, the results of this section suggest that our smartphone data is relatively successful in identifying home locations, workplace locations and bilateral commuting patterns compared to official census data. However, a key advantage of our smartphone data relative to the official census data is that we can measure not only commuting trips but also the many non-commuting trips that individuals undertake and that are potentially consequential for our understanding of the spatial distribution of economic activity within cities.

3 Reduced-Form Evidence

In this section, we provide reduced-form evidence on patterns of commuting and non-commuting trips that guides the theoretical model that we develop 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 patterns of travel within urban areas. 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.

Fact 1. Non-commuting trips are pervasive. In Figure 5, 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 may 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, as found for example in Couture, Duranton, and Turner (2018). A key advantage of our smartphone data relative to travel surveys is that our data reveal bilateral patterns of travel at a fine level of spatial disaggregation within the urban area, and the sequence in which users travel between between their home, work and consumption locations, as used in our quantitative analysis of the model.[8]

Figure 5: Frequency of Stays at Work and Other Locations (Excluding Home Locations)



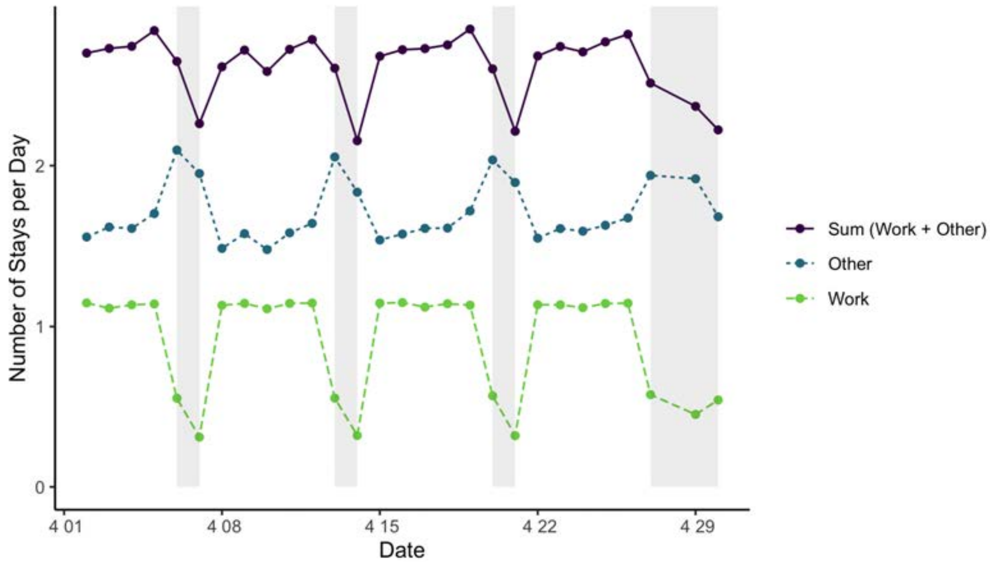
Note: Average number of work and other stays per day for weekdays and weekends (excluding stays at home locations) for our baseline sample users in the metropolitan area of Tokyo in April 2019. See Section 2 above for the definitions of home, work and other stays.

In Panel (A) of Figure 6, we provide further evidence on travel patterns by reporting the average number of work and non-work stays by day of the week from 1-30 April 2019. Consistent with the patterns discussed above, 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 6, 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

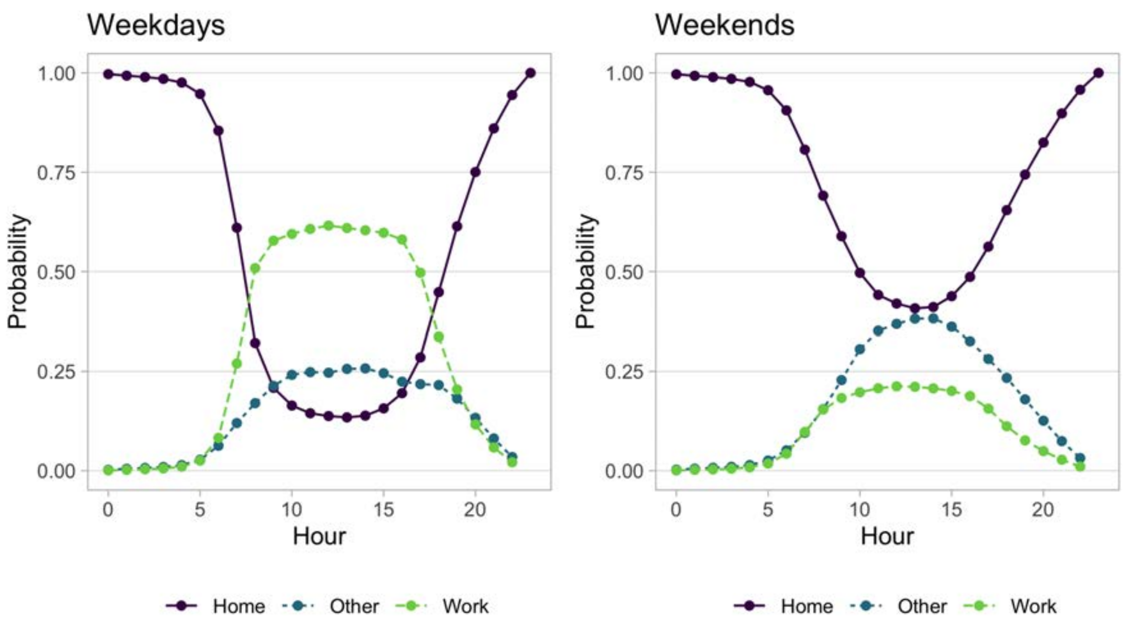
[8] In online appendix A.4, we show that this pattern of more frequent non-commuting stays than commuting stays holds in separate Japanese travel survey data for weekdays. These travel survey data do not include questions about respondents' travel behavior at weekends.

Figure 6: Work and Other Stays by Day and Hour

(A) Work and Other Stays by Day (Excluding Home Locations)



(B) Home, Work and Other Stays by 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 shared 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). 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.

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".[9] 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." Therefore, if non-commuting trips are unrelated to the availability of nontradable services, our algorithm assigns these stays to "Z Others."

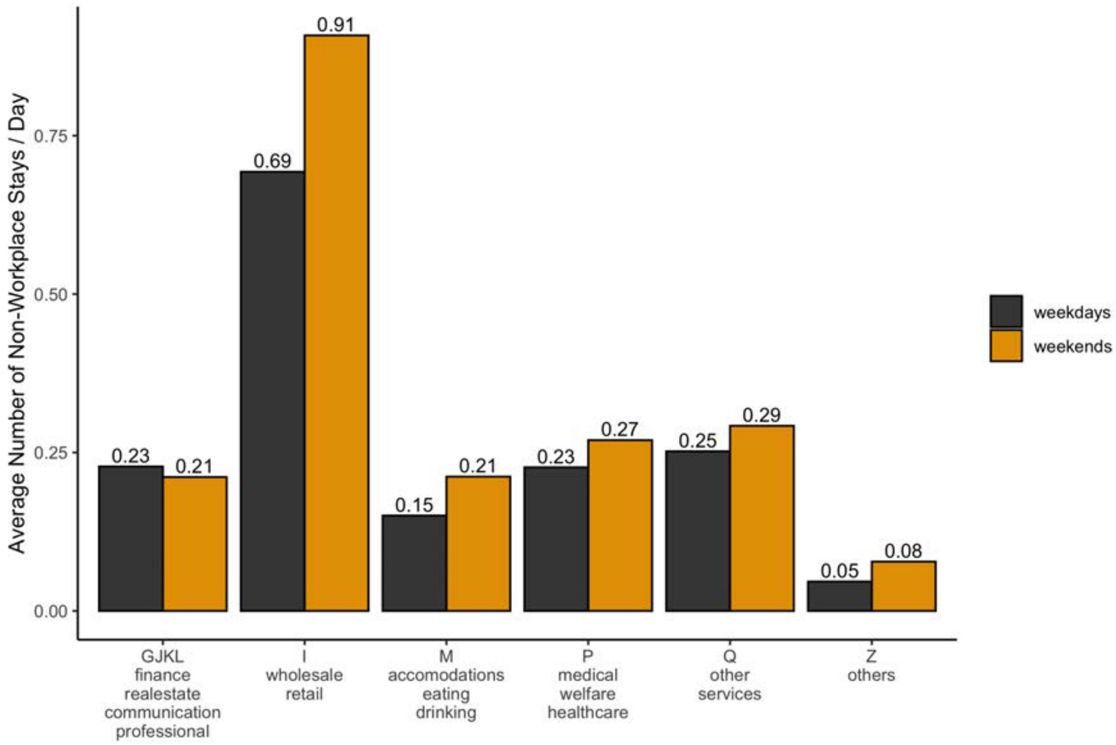
As a check on this probabilistic assignment of other stays, Figure A.5.1 in the online appendix displays the density of each type of other stay by hour and day, as a share of all stays for our baseline sample for the Tokyo metropolitan area in April 2019. We find that our probabilistic assignment captures 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. 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.

In Panel (A) of Figure 7, we show 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, Panel (B) of Figure 7 also reports 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). Comparing the two panels, we find that

[9] This categorization of service sectors follows 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.

Figure 7: Frequency of Non-Commuting Trips and Service-Sector Employment Shares

(A) Number of Non-Work Stays in Each Sector



(B) Number of Non-Work Stays and Employment in Each Sector

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: Panel (A): Average number of each type of other stay per day for weekdays and weekends (excluding stays at home locations) for our baseline sample of users in the metropolitan area of Tokyo in April 2019. Other stays are allocated probabilistically to each of these five categories using the shares of these service sectors in total service-sector employment, as discussed in the main text. Panel (B) reports the same information in table form, together with 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 above for the definitions of home, work and other stays.

"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 disproportionately 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 by far the most frequent, there is considerable variation in the composition of service-sector employment across the locations visited by users, with "Accommodations, Eaton and Drinking," "Finance, Real Estate, Communication, and Professional," and "Medical and Health Care" all accounting for around 10 percent or more of the total number of stays. Lastly, "Other" stays are infrequent, confirming that non-commuting trips are indeed strongly related to the availability of nontradable services.[10]

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 8, 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. This difference is even greater at the weekend, with an average distance travelled of 6.04 kilometers for other stays, which is consistent with users remaining closer to their residential locations at weekends. Given that users choose where to live and work taking into account their access to surrounding locations, this clustering of other stays closer to home highlights the relevance of these non-commuting trips for residential location decisions, as explored further in the quantitative analysis of our model below.

In Panel (B) of Figure 8, we display the distribution of distances travelled for each type of other stay separately. Comparing across the different categories, 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 these two categories of shopping and visits to bars, restaurants and cafes close to home again highlights the relevance of access to these consumption opportunities for users' residential location decisions. More generally, these differences in bilateral travel patterns for different economic activities suggest that omitting non-consumption trips not only undercounts travel journeys but can also yield misleading inference about the effects of changes in travel costs on bilateral patterns of travel, as explored more formally in later sections.

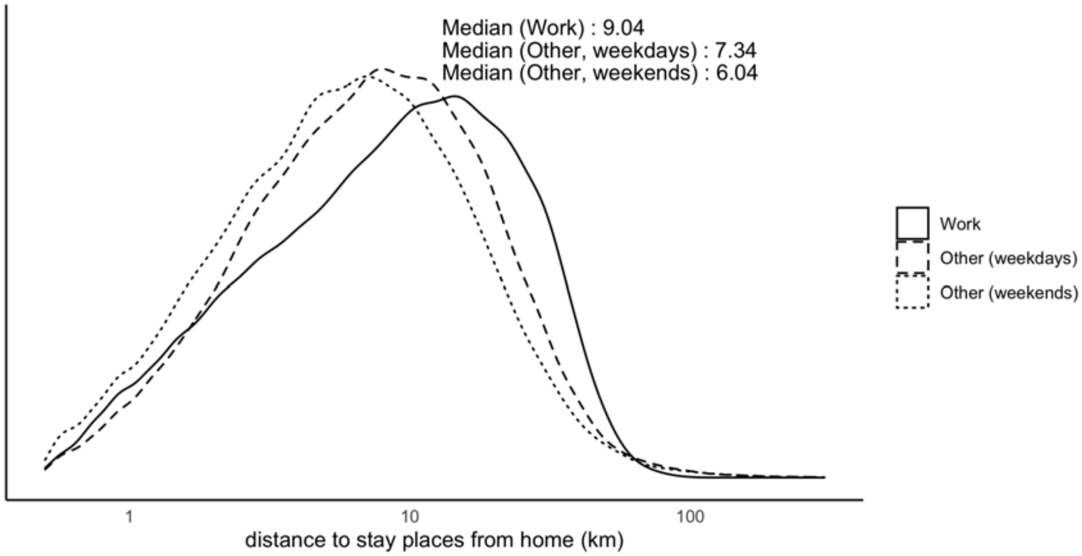
Fact 4. Trip chains. We now show that trip chains are a relevant feature of the data, in which non-commuting trips occur along the journey between home and work. In Figure 9, we use the fact that in the smartphone data we observe the sequence of stays originating from a user's home location and ending 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.

As apparent from the figure, 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 5). Nevertheless, a substantial fraction of non-commuting trips (47 percent) occur as part of commuting trips (47 percent). This pattern of results is consistent with the evidence in Davis, Dingel, Monras,

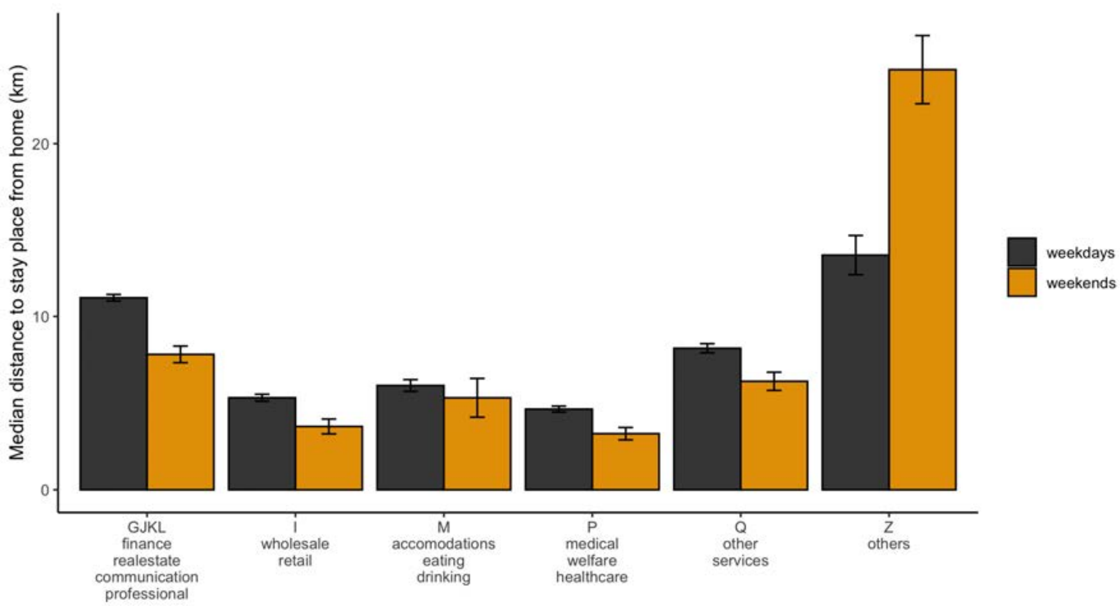
[10] Some of these non-commuting trips could include business-related trips rather than consumption trips (e.g., business meetings, procurement). In Figure A.4.2 of the online appendix, we show that business-related trips are a minor fraction (20 percent) of all non-commuting weekday trips using separate travel survey data.

Figure 8: 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

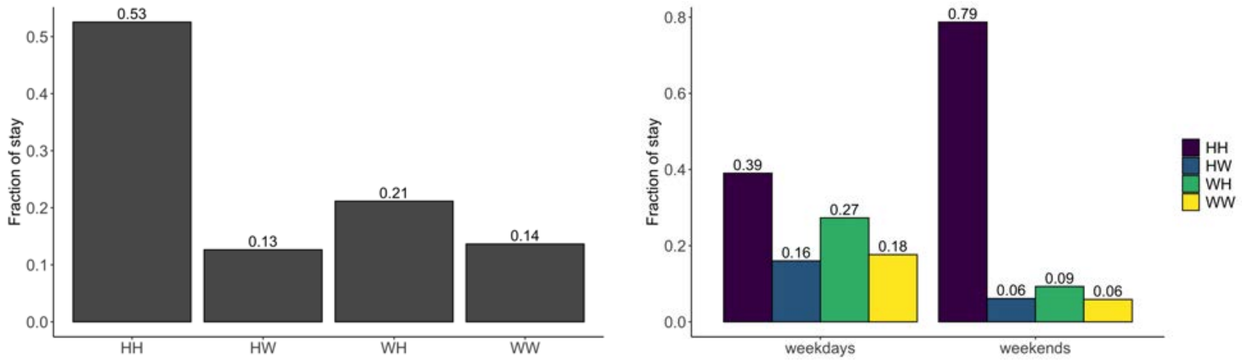


Note: Panel (A): Distributions of distance in kilometers of work locations from home location and of other stays from home locations during weekdays and weekends. Panel (B): Distributions of distance in kilometers for each type of other stay from home locations during weekdays and weekends. Distributions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

and Morales (2019), which finds that restaurant visits are affected not only by the restaurant's proximity to home but also by its proximity to work. To the extent that users face spatial frictions in travelling around the city, this has three implications that we incorporate into our quantitative analysis of the model. First, the choice of consumption location can be influenced not only by proximity to home but also by proximity to work. Second, models that abstract from consumption access can ascribe too much weight to workplace access, because they do not take into account that the choice of workplace can be influenced by access to surrounding consumption possibilities. Third, users

Figure 9: Fractions of Different Types of Other Stays on Round Trips from Home

(A) Aggregating across Weekdays and Weekends (B) Separately for Weekdays and Weekends



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.

choice of residence depends on the joint distribution of consumption and workplace access, taking into account that consumption trips can occur as part of the journey between home and work.

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 within the city. We show that the model rationalizes the reduced-form features of the smartphone data established above. In Section 5 below, we use the model to quantify the contributions of travel access and the residual of amenities in explaining the observed spatial concentration of economic activity. In Section 6, we show how the model can be used to undertake counterfactuals for the impact of transport improvements. We demonstrate that the omission of consumption access leads to an underestimation of the welfare gains from these transport improvements and distorted predictions for their impact on bilateral patterns of travel throughout the city. The derivations for all theoretical results in this section are reported in Section B of the online appendix.

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.[11] 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) 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:

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

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.

[11] In our theoretical analysis, we assume for simplicity a continuous measure of workers in the model, 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) following Dingel and Tintelnot (2020).

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 ($a_{i,g}(\omega)$).[12] 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 ($P^S_{j(k)}$ 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, travel cost component includes 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 in a tractable way, 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:

$$d_{ni\{j(k)r(k)\}} = \exp(-\kappa^W \tau^W_{ni}) \prod_{k \in K^S} \exp(-\kappa^S_k \tau^S_{nij(k)r(k)}). \tag{2}$$

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^W_{ni}) and the commuting cost parameter (κ^W), where overall commuting travel time is the sum of the travel time incurred in each direction:

$$\tau^W_{ni} = \tau_{ni} + \tau_{in}. \tag{3}$$

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 ($\tau^S_{nij(k)r(k)}$) and the consumption travel cost parameter (κ^S_k). 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):

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

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.[13]

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, consumption location $j(k)$ and route $r(k)$

[12] Although 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.

[13] While we capture the relative importance of each non-traded sector using its expenditure share, the frequency of trips can also differ across non-traded sectors, as shown in Figure 7. In Section C.1 of the online appendix, we explicitly incorporate this additional type of heterogenegity and show that the model is isomorphic up to a reinterpretation of the parameters κ^S_k. Therefore, all of our counterfactual results are unaffected by this extension of the model except for the interpretation of the estimated κ^S_k.

for non-traded service k are drawn from the following independent Fréchet distributions:

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

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.[14]

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 $r(k)$ for non-traded service k is given by:

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

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 route preferences, 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:

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

[14] 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_{ig}^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).

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

$$d^S_{nij(k)} = \mathbb{E}_{nij(k)}\left[\delta_{nij(k)r(k)}(\omega)\right] = \vartheta^R_k \left[\sum_{r' \in \mathbb{R}} T^R_{r'(k)} \exp(-\theta^R_k \kappa^S_k \tau^S_{nij(k)r'(k)})\right]^{\frac{1}{\theta^R_k}} \tag{8}$$

where $\vartheta^R_k \equiv \Gamma\left(\frac{\theta^R_k - 1}{\theta^R_k}\right)$ 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 $j(k)$ for non-traded service k that maximizes the contribution to indirect utility (1) from consuming that non-traded service, taking into account the expected travel costs across alternative routes:

$$\gamma_{nij(k)}(\omega) = \left[P^S_{j(k)} / \left(q_{j(k)}(\omega)\right)\right]^{-\alpha^S_k} d^S_{nij(k)}, \qquad k \in K^S. \tag{9}$$

where $d^S_{nij(k)}$ is the expected travel cost across these alternative routes from equation (8) above.[15]

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

$$\lambda^S_{j(k)|ni} = \frac{T^S_{j(k)} \left(P^S_{j(k)}\right)^{-\theta^S_k} \left(d^S_{nij(k)}\right)^{\frac{\theta^S_k}{\alpha^S_k}}}{\sum_{\ell \in N} T^S_{\ell(k)} \left(P^S_{\ell(k)}\right)^{-\theta^S_k} \left(d^S_{ni\ell(k)}\right)^{\frac{\theta^S_k}{\alpha^S_k}}}, \qquad k \in K^S, \tag{10}$$

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 $P^S_{j(k)}$ and their average quality $T^S_{j(k)}$ in the numerator); expected travel costs (as determined by $d^S_{nij(k)}$ 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. Therefore, both residence n and workplace i affect expected travel costs to consume non-traded service k in location $j(k)$.

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:

$$\mathbb{S}_{nik} \equiv \mathbb{E}_{nik}\left[\gamma_{nij(k)}\right] = \vartheta^S_k \left[\sum_{\ell \in N} T^S_{\ell(k)} \left(P^S_{\ell(k)}\right)^{-\theta^S_k} \left(d^S_{ni\ell(k)}\right)^{\frac{\theta^S_k}{\alpha^S_k}}\right]^{\frac{\alpha^S_k}{\theta^S_k}}, \qquad k \in K^S. \tag{11}$$

[15] Although 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.

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

Using the property that idiosyncratic quality is independently distributed across the non-traded sectors, we can also compute the expected overall contribution to utility from consuming all types of non-traded services. This expectation corresponds to an overall measure of consumption access for residence n and workplace i and depends on the travel-time weighted average of destination characteristics across all types of non-traded services:

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

We show below that the model's gravity equation predictions provide a good approximation to the observed data on consumption trips and can be used to estimate consumption access in a theory-consistent way.

4.4 Workplace Choice

We next turn to the worker's choice of workplace, given this expected 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 ($\mathbb{S}_{ni}$):

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

where $d_{ni}^W \equiv \exp(-\kappa^W \tau_{ni}^W)$ is the component of travel cost for commuting trips 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:

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

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:

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

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 ($\mathbb{S}_{ni}$):

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

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

We show below that the model's gravity equation predictions also provide a good approximation to the observed data on commuting trips, and can be used to estimate overall travel access in a theory-consistent way, taking into account consumption access.

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)):

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

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

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

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:

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

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

An implication of our extreme value assumption for idiosyncratic amenities is that expected utility conditional on choosing a given residence is the same across all residences in the city and equal to expected utility for the city as a whole. The intuition is as follows. On the one hand, a lower price of floor space or higher travel access raises utility for a given realization of idiosyncratic amenities (b), which raises the expected utility in a residence. On the other hand, a lower price of floor space or higher travel access attracts workers with lower realizations for idiosyncratic amenities, which reduces the expected utility in a residence. With a Fréchet distribution for idiosyncratic amenities, these two effects exactly offset one another, such that expected utility conditional on choosing a given residence is the same across all residences in the city. In the open-city specification, population mobility ensures that this common expected utility is equal to the reservation level of utility in the wider economy.

The residential choice probabilities (17) highlight that the attractiveness of a residential location depends not only on its own characteristics but also on its access to surrounding employment and consumption possibilities. In our quantitative analysis below, we use these residential choice probabilities to decompose the observed spatial 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. We show that workers' observed choices of residence, workplace and consumption can be used to reveal their relative valuations of these locations and compute measures of travel access that hold throughout this entire class of quantitative urban models.

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:

$$H_{n,U} = \frac{\alpha^H E_n R_n}{Q_n}, \tag{19}$$

where $R_n = \lambda_n^B \bar{L}$ is the measure of residents in location n and $\bar{L}$ is total city population; E_n is expected income in residence n, and the subscript U denotes the residential demand for floor space (as opposed to the commercial demand, which is characterised below). 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}):

$$E_n = \sum_{i \in N} \lambda_{i|n}^W E_{ni}, \tag{20}$$

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

4.6 Production

When we undertake counterfactuals in our quantitative analysis below, 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.[16] Together these assumptions imply that profits are zero in each location in which a tradable good or non-tradable service is produced:

$$\begin{aligned} P_i^T &= \frac{1}{A_{i,k}} w_{i,k}^{\beta^T} Q_i^{1-\beta^T}, \qquad 0 < \beta^T < 1, \qquad k \in K/K^S, \\ P_{i(k)}^S &= \frac{1}{A_{i,k}} w_{i,k}^{\beta^S} Q_i^{1-\beta^S}, \qquad 0 < \beta^S < 1, \qquad k \in K^S, \end{aligned} \tag{21}$$

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 ($\tilde{L}_{i,k}$):

$$H_{i,k} = \begin{cases} \frac{1-\beta^T}{\beta^T} \left(\frac{P_i^T A_{i,k}}{Q_i} \right)^{\frac{1}{\beta^T}} \tilde{L}_{i,k}, & k \in K/K^S \\ \frac{1-\beta^S}{\beta^S} \left(\frac{P_{i(k)}^S A_{i,k}}{Q_i} \right)^{\frac{1}{\beta^S}} \tilde{L}_{i,k}, & k \in K^S, \end{cases} \tag{22}$$

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

We allow productivity ($A_{i,k}$) in equations (21) and (22) 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 equation (21). In general,

[16] In 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 (27) below).

the wage per efficiency unit ($w_{i,k}$) differs across both sectors and locations in equation (21), 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:

$$P_i^T = 1 \qquad \forall\, i \in N. \tag{23}$$

4.7 Market Clearing

The price for each type of non-traded service k in each location j ($P^S_{j(k)}$ 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:

$$P^S_{j(k)} A_{j,k} \left(\frac{\tilde{L}_{j,k}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{j,k}}{1-\beta^S} \right)^{1-\beta^S} = \alpha^S_k \sum_{n \in N} R_n \sum_{i \in N} \lambda^S_{j(k)|ni} \lambda^W_{i|n} E_{ni}, \qquad k \in K^S, \tag{24}$$

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 $\lambda^S_{j(k)|ni}$ 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:

$$L_{j,k} = \sum_{n \in N} \lambda^W_{jk|n} R_n, \qquad k \in K, \tag{25}$$

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 $\lambda^W_{jk|n}$ 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):

$$H_i = H_{i,U} + \sum_{k \in K} H_{i,k}. \tag{26}$$

4.8 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 ($P^S_{i(k)}$), the route choice probabilities ($\lambda^S_{r(k)|nij(k)}$), the conditional consumption probabilities ($\lambda^S_{j(k)|ni}$), the conditional commuting probabilities ($\lambda^W_{ik|n}$), the residence probabilities (λ^B_n), 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 seven equilibrium variables are determined by the system of seven equations given by the land market clearing condition for each location (26), the labor market clearing condition for each location (25), the non-traded goods market clearing condition for each location and service sector (24), the conditional consumption probabilities (10), the conditional commuting probabilities (14), the residence probabilities (17), and the population mobility condition that equates expected utility in the city (18) to the reservation level of utility in the wider economy ($\bar{U}$). Given these seven equilibrium variables, we can solve for all other endogenous variables of the model.

4.9 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.[17] We thus obtain:

$$A_{i,k} = a_{i,k} \left(\frac{L_i}{K_i} \right)^{\eta^W} \tag{27}$$

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 the same across all sectors.

Agglomeration in Residents. 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 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:[18] We therefore have:

$$B_n = b_n \left(\frac{R_n}{K_n} \right)^{\eta^B} \tag{28}$$

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. Following Combes, Duranton, and Gobillon (2019) and Epple, Gordon, and Sieg (2010), 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:

$$H_i = M_i^{\mu} K_i^{1-\mu}, \qquad 0 < \mu < 1. \tag{29}$$

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:

$$\mathbb{P} M_i = \mu Q_i H_i, \tag{30}$$

[17] We 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.

[18] As 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 $\mathbb{P}$ is the common user cost of building capital. Using the construction technology (29) to substitute for building captial (M_i) in this equilibrium condition (30), we obtain a constant elasticity supply function for floor space as in Saiz (2010), with the inverse supply function given by:

$$Q_i = \psi_i H_i^{\frac{1-\mu}{\mu}} \tag{31}$$

where $\psi_i = \mathbb{P} K_i^{\frac{\mu-1}{\mu}} / \mu$ depends solely on geographical land area (K_i) and parameters. Furthermore, cost minimization and zero profits also imply that the following zero-profit condition holds:

$$Q_i = \left(\frac{\mathbb{P}}{\mu}\right)^{\mu} \left(\frac{\tilde{Q}_i}{1-\mu}\right)^{1-\mu}, \tag{32}$$

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 (27), (28) and (31).

5 Quantitative Analysis

In this section, we use our theoretical model to quantify the contributions of workplace access and consumption access to the observed uneven spatial distribution of economic activity. 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 consumption access and 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.

5.1 Estimation Procedure

We begin by discussing the estimation and calibration of the model's parameters. Our estimation proceeds 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, and finally, we calibrate the remaining parameters of the model using the observed data and central values from the existing empirical literature. In Table 1, we summarize the estimated and calibrated parameters, before discussing each of these estimation steps in turn.

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

In our first step, we calibrate the parameters governing idiosyncratic heterogeneity in commuting, consumption and residence choices (θ^W, θ_k^S and 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).

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) estimate 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) estimate 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.1.1 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 any model is necessarily an abstraction, we find a strong positive relationship between the model's predictions and the observed data.

Table 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 consumtpion 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 developed in the text of Section 5.1.

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 estimated 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.1.2 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, as summarized in Table 1. Lastly, we solve for the implied expenditure share parameter for traded goods (α^T), using $\alpha^T = 1 - \alpha^H - \sum_{k \in K^S} \alpha_k^S$, as also summarized in Table 1.

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 probabilities and the observed route choice in our smartphone data: HH, WW, HW, WH. 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:

$$\lambda_{r(k)|nij(k)}^R = \frac{\exp(-\phi_k^R \tau_{nij(k)r(k)}^S) \xi_{r(k)}^R \exp(u_{nij(k)r(k)}^R)}{\zeta_{nij(k)}^R}, \tag{33}$$

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).[19] The estimated semi-elasticity of travel time (ϕ_k^R) in equation (33) 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"; "Accommodation, 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 $r(k) = HH$. This pattern of results implies a high average preference for consuming non-traded services from home, rather than consuming them from work, or on the route between home and work, which is consistent with the reduced-form evidence in Figure 9 in Section 3.

[19]In robustness checks, we find a similar pattern of results if we instead estimate this choice probability using the multinomial logit model.

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

$$\tilde{d}_{nij(k)}^S \equiv \left(d_{nij(k)}^S\right)^{1/\kappa_k^S} = \vartheta_k^R \left[\sum_{r'\in\mathbb{R}} \xi_{r'(k)}^R \exp(-\phi_k^R \tau_{nij(k)r'(k)}^S)\right]^{\frac{1}{\phi_k^R}}, \tag{34}$$

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 procedure, 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 (33) above. We are not required 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 ($\tilde{d}_{nij(k)}^S \equiv \left(d_{nij(k)}^S\right)^{1/\kappa_k^S}$) from equation (34) 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 procedure below. We are not required to separate out the contributions of $1/\kappa_k^S$ and $d_{nij(k)}^S$ to the overall value of adjusted expected travel costs ($\tilde{d}_{nij(k)}^S$).

Table 2: Estimation Results for Route Choice

Dependent Variable:	Route Choice Probability				
	Finance realestate communication professional	Wholesale retail	Accomodations eating drinking	Medical welfare healthcare	Other services
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Travel Time (Hours)	-0.312***	-0.269***	-0.264***	-0.297***	-0.271***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dummy (HW)	-1.58***	-1.66***	-1.75***	-1.67***	-1.61***
	(0.010)	(0.010)	(0.009)	(0.011)	(0.012)
Dummy (WH)	-1.04***	-1.16***	-1.10***	-1.23***	-1.12***
	(0.009)	(0.010)	(0.009)	(0.011)	(0.010)
Dummy (WW)	-1.03***	-1.13***	-1.30***	-1.09***	-1.09***
	(0.009)	(0.009)	(0.008)	(0.010)	(0.011)
Fixed-effects					
Home-Work-Consumption Location	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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 (33) 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 shown in Figure 9 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. Standard errors in parentheses are clustered at the level of the combination of residence, workplace, and consumption location.

5.1.3 Estimating the Consumption Location Choice and Consumption Access ($\mathbb{S}_{ni}$) (Step 3)

In our third step, we estimate the consumption location choice 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, can be written as:

$$\lambda_{j(k)|ni}^{S} = \frac{\xi_{j(k)}^{S} \left(\tilde{d}_{nij(k)}^{S}\right)^{-\phi_k^S} \exp\left(u_{nij(k)}^{S}\right)}{\zeta_{ni,k}^{S}}, \tag{35}$$

where $\tilde{d}_{nij(k)}^{S}$ is our estimated adjusted expected travel costs from equation (34) in the previous step; and $u_{nij(k)}^{S}$ is a stochastic error that captures idiosyncratic determinants of consumption travel costs.

In a conventional gravity equation, travel flows are determined for a bilateral pair of locations. In contrast, in our extended gravity equation (35), 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 (34) to consume non-traded service k in location $j(k)$ depends on both residence n and workplace i.[20]

We estimate this extended gravity equation (35) 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 Thibault 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 (35) 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:

$$\xi_{j(k)}^{S} = T_{j(k)}^{S} \left(P_{j(k)}^{S}\right)^{-\theta_k^S}. \tag{36}$$

Third, the estimated residence fixed effect in equation (35) corresponds to the denominator in the conditional consumption probability in equation (10) and captures the overall attractiveness of residence n in terms of its travel-time weighted access to all consumption locations $\ell(k)$ for service k:

$$\zeta_{ni,k}^{S} = \sum_{\ell \in N} T_{\ell(k)}^{S} \left(P_{\ell(k)}^{S}\right)^{-\theta_k^S} \left(\tilde{d}_{ni\ell(k)}^{S}\right)^{-\phi_k^S}. \tag{37}$$

From these estimated fixed effects, we recover a theoretically-consistent estimate of consumption access for each type of non-traded service ($\mathbb{S}_{nik}$). 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 ($\left(\tilde{d}_{ni\ell(k)}^{S}\right)^{-\phi_k^S}$) across locations, and using our calibrated values of θ_k^S and α_k^S, we obtain our baseline estimate of consumption access:

$$\mathbb{S}_{ni} = \prod_{k \in K^S} \Gamma\left(\frac{\theta_k^S/\alpha_k^S - 1}{\theta_k^S/\alpha_k^S}\right) \left[\sum_{\ell \in N} \xi_{\ell(k)}^{S} \left(\tilde{d}_{ni\ell(k)}^{S}\right)^{-\phi_k^S}\right]^{\frac{\alpha_k^S}{\theta_k^S}}. \tag{38}$$

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: $\mathbb{S}_{ni} = \prod_{k \in K^S} \left[\Gamma\left(\frac{\theta_k^S/\alpha_k^S - 1}{\theta_k^S/\alpha_k^S}\right)\right] \left(\zeta_{ni,k}^{S}\right)^{\frac{\alpha_k^S}{\theta_k^S}}$. As sample size becomes sufficiently

[20] In the international trade literature, extended gravity arises from third-country effects, where for example the probability that a firm exports from the US to France depends on whether it also exports to Germany (as in Morales, Sheu, and Zahler 2019). In our model of consumption trips, there are two inter-linked third-location effects. The probability of travelling from residence n to consumption location $j(k)$ for service k depends on workplace i, while the probability of travelling from workplace i to consumption location $j(k)$ also depends on residence n.

large, these two sets of estimates of consumption access converge asymptotically towards one another if the model is a correct specification of the data generating process, as shown in an international trade context in Thibault (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.3 of the online appendix.

In Table 3, we report the results of estimating the consumption extended gravity equation (35) 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.2 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.

Table 3: Estimation Results for Consumption Location Choice

Dependent Variable:	Consumption Location Choice Probability				
	Finance realestate communication professional	Wholesale retail	Accomodations eating drinking	Medical welfare healthcare	Other services
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log $\tilde{d}^S_{nij(k)}$	-1.15***	-1.12***	-1.09***	-1.19***	-1.08***
	(0.040)	(0.036)	(0.035)	(0.038)	(0.036)
Fixed-effects					
Home and Work Location Pairs	Yes	Yes	Yes	Yes	Yes
Consumption Location	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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 (35) 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 ($\tilde{d}^S_{nij(k)}$) 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.

As 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.4.1 in Section D.4 of the online appendix, we find substantially smaller semi-elasticities with respect to travel times 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 for the consumption gravity equation incorporating route choice than this alternative specification, as evident from the smaller Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC) than in Panel (B) of Table D.4.1. This pattern of results is consistent with the idea that 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.

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

In our fourth step, we estimate the workplace choice 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 the conditional commuting probabilities (14) and (15), the probability that a worker commutes from residence n to workplace i can be written as the following extended gravity equation:

$$\lambda_{i|n}^{W} = \frac{\xi_i^W \exp\left(-\phi^W \tau_{ni}^W\right) \left(\mathbb{S}_{ni}\right)^{\theta^W} \exp\left(u_{ni}^W\right)}{\zeta_n^W}, \tag{39}$$

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

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 (39), 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 (39) 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 (39) 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 (39) captures the average attractiveness of workplace i across sectors in terms of its wage ($w_{i,g}$) and productivity draws ($T_{i,g}^W$) in equation (14), such that:

$$\xi_i^W = \sum_{m \in K} T_{i,m}^W w_{i,m}^{\theta^W}. \tag{40}$$

Third, the estimated residence fixed effect (ζ_n^W) in equation (39) 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:

$$\zeta_n^W = \sum_{\ell \in N} \sum_{m \in K} T_{\ell,m}^W w_{\ell,m}^{\theta^W} \exp\left(-\phi^W \tau_{n\ell}^W\right) \left(\mathbb{S}_{n\ell}\right)^{\theta^W}. \tag{41}$$

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 (ζ_i^W) weighted using the estimated bilateral travel costs ($\exp\left(-\phi^W \tau_{ni}^W\right)$) across locations, and using our calibrated value of θ^W, we obtain our baseline estimate of travel access:

$$\mathbb{A}_n = \Gamma\left(\frac{\theta^W - 1}{\theta^W}\right) \left[\sum_{\ell \in N} \xi_\ell^W \exp\left(-\phi^W \tau_{n\ell}^W\right) \left(\mathbb{S}_{n\ell}\right)^{\theta^W}\right]^{\frac{1}{\theta^W}}. \tag{42}$$

Second, using the estimated residence fixed effects (ζ_n^W) and our calibrated value of θ^W, we obtain another estimate of workplace access: $\mathbb{A}_n = \Gamma\left(\frac{\theta^W-1}{\theta^W}\right)\left(\zeta_n^W\right)^{\frac{1}{\theta^W}}$. 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 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.3 of the online appendix.

In Table 4, we present the results of estimating the commuting extended gravity equation (35). We include the commuting travel time, consumption access from the previous step ($\mathbb{S}_{n\ell}$) 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 workers' consumption location choices are more responsive to travel time than their workplace location choices. In Section D.2 of the online appendix, we report a specification check in which 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.

As a specification check, we re-estimated the commuting gravity equation excluding the consumption access term model ($\log\left(\mathbb{S}_{n\ell}\right)^{\theta^W}$). As shown in Table D.4.2 in Section D.4 of the online appendix, we find a larger semi-elasticity of commuting flows with respect to travel time when consumption access is omitted (-0.649 instead of -0.617). This downward bias arises because the estimated consumption access term $\log\left(\mathbb{S}_{n\ell}\right)^{\theta^W}$ tends to be larger for the commuting pairs with longer distances, which gives rise to a downward omitted variables bias when this term is omitted. Furthermore, we find a better model fit with the commuting gravity equation incorporating consumption access than with 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 distances 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.

Table 4: Estimation Results for Workplace Choice

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

Note: Results of estimating the commuting probability (39) 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 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 share of land in construction costs of $\mu = 0.75$ following Epple, Gordon, and Sieg (2010) and Combes, Duranton, and Gobillon (2019). 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). In existing empirical estimates of residential agglomeration, consumption access is typically omitted, because of the absence of readily-available data on consumption trips. Our estimates of consumption access are positively correlated with the density of residents and indeed consumption trips provide one mechanism and microfoundation for residential agglomeration forces. Therefore, one would expect estimated residential agglomeration forces to be smaller after controlling for consumption access. We present some empirical evidence consistent with this view in our counterfactuals below, when we compare our model's predictions for the opening of a subway line in the city of Sendai to the observed impact of the opening of the subway line in the data.

5.2 Quantifying the Contributions 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. We start by re-writing the residential choice probabilities (17) in the following form:

$$\left(\lambda_n^B\right)^{1/\theta^B} Q_n^{\alpha^H} = \mathbb{B}_n \mathbb{A}_n, \tag{43}$$

where $\mathbb{B}_n$ is a composite amenities parameter for residence n 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 ($\bar{U}$):

$$\mathbb{B}_n \equiv B_n \left(T_n^B\right)^{1/\theta^B} \left(P_n^T\right)^{-\alpha^T} \left(\bar{U}/\vartheta^B\right)^{-1} \tag{44}$$

In these residential choice probabilities (43), we observe the share of residents (λ_n^B) and the price of floor space (Q_n), and we estimated travel access ($\mathbb{A}_n$) from Steps 1-4 above (equation (42)). Therefore, we can use these residential choice probabilities (43) 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. The left-hand side of these residential choice probabilities (43) corresponds to a summary measure of the relative attractiveness of locations. If we observe a location that has relatively many 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 this 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, as implemented in the international trade literature in Eaton, Kortum, and Kramarz (2004). We estimate an ordinary least squares (OLS) regression of each of the components on the right-hand side of the residential choice probabilities (43) on the summary measure of the relative attractiveness of locations from the left-hand side:

$$\ln \mathbb{A}_n = c_0^A + c_1^A \ln\left(\left(\lambda_n^B\right)^{1/\theta^B} Q_n^{\alpha^H}\right) + u_{nt}^A, \tag{45}$$
$$\ln \mathbb{B}_n = c_0^B + c_1^B \ln\left(\left(\lambda_n^B\right)^{1/\theta^B} Q_n^{\alpha^H}\right) + u_{nt}^B,$$

Noting that OLS is a linear estimator with mean zero residuals, and using the residential choice probabilities (43), 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 of the residential choice probabilities. 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 (39), but omitting the consumption access term ($\log\left(\mathbb{S}_{n\ell}\right)^{\theta^W}$):

$$\mathbb{A}_n^{\text{nocons}} = \Gamma\left(\frac{\theta^W - 1}{\theta^W}\right)\left[\sum_{\ell \in N} \xi_\ell^W \exp\left(-\phi^W \tau_{n\ell}^W\right)\right]^{\frac{1}{\theta^W}}, \tag{46}$$

where ϕ^W and ξ_ℓ^W are the estimated travel time coefficient and workplace fixed effects from the extended commuting gravity equation (39). Using this measure of travel access without consumption trips ($\mathbb{A}_n^{\text{nocons}}$) in equation (43), we can recover a corresponding measure of amenities without consumption trips ($\mathbb{B}_n^{\text{nocons}}$), and implement our variance decomposition in equation (45) above.[21]

Table 5 reports the results of these variance decompositions for our model including consumption trips (Panel A) and the special case excluding consumptiont 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 ($\tilde{Q}_n$) 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 ($Q_n^{\alpha^H}\left(\lambda_n^B\right)^{1/\theta^B}$), with a contribution of 56 percent compared to 44 percent. In contrast, when we consider a conventional quantitative urban model excluding

[21] As a robustness check, Panel (B) of online appendix Table D.4.3 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.

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. One implication of these findings is that a substantial component of the variation in conventional measures of residential amenities may reflect unobserved differences in the geography of access to consumption opportunities. A key advantage of our smartphone GPS data is that allows us to measure and quantify the relative importance of these consumption trips. Once we incorporate this information on consumption trips, we find that the contribution from the residual of residential amenities declines substantially. A second implication of these findings is that workplace access ($\mathbb{A}_n^{\text{nocons}}$) is far from perfectly correlated with overall travel access incorporating consumption trips ($\mathbb{A}_n$), such that we find a much smaller contribution from travel access when we restrict attention to commuting information alone.

Table 5: Decomposition of Variation in the Relative Attractiveness of Locations ($\log\left[\left(\lambda_n^B\right)^{1/\theta^B} Q_n^{\alpha^H}\right]$) into the Contributions of 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		
$\log Q_n^{\alpha^H}\left(\lambda_n^B\right)^{1/\theta^B}$	0.566***	0.434***
	(0.049)	(0.049)
Observations	201	201
R^2	0.403	0.284
Panel B: No Consumption Trips		
$\log Q_n^{\alpha^H}\left(\lambda_n^B\right)^{1/\theta^B}$	0.373***	0.627***
	(0.036)	(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 (45). 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.

6 Counterfactuals

In this section, we use our theoretical framework to undertake counterfactuals for changes in travel costs to provide further evidence on the role of consumption trips in shaping the spatial distribution of economic activity. In Section 6.1, we introduce the system of equations for undertaking these counterfactuals. In Section 6.2, we examine the contribution of consumption trips towards agglomeration by undertaking a counterfactual in which we assume no travel costs for commuting and consumption trips, thus eliminating the spatial frictions in commuting or consumption. In Section 6.3, we examine the role of consumption trips in shaping the welfare effects of transport infrastructure improvements by undertaking a counterfactual for the construction of a new subway line.

6.1 Counterfactual Equilibrium

In this section, we introduce the system of equations that we use to solve for a counterfactual equilibrium. This system of equations can be solved using either the observed initial travel shares (as in the conventional exact-hat algebra approach of Dekle, Eaton, and Kortum 2007) or using the initial travel shares predicted by the estimated model (as in the covariate-based approach of Dingel and Tintelnot 2020). In our baseline specification, we use this covariate-based approach to address concerns about granularity and the resulting potential for overfitting using the exact-hat algebra approach. In Section G.5 of the online appendix, we report a robustness test 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 each case, we rewrite the counterfactual equilibrium conditions of the model in terms of the initial travel shares and endogenous variables and the counterfactual changes in these endogenous variables. 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.[22] 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 (α^H, α^T, $\{\alpha_k^S\}$, $\{\theta_k^S\}$, θ^W, θ^B, κ^W, κ^S, η^B, η^W, β^S, β^T, μ), assumed changes in travel cost $\{\hat{d}_{ni}^W, \hat{d}_{nij(k)}^S\}$, and the initial travel shares and endogenous variables ($\{\lambda_{ig|n}^W, \lambda_{j(k)|ni}^S, \lambda_n^B\}$, $\{H_{j,k}, H_{n,U}\}$, $\{E_{ni}\}$), we solve for the counterfactual equilibrium by solving the following system of equations, as derived in Section E of the online appendix.

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

$$\hat{\lambda}_{ig|n}^W = \frac{\hat{w}_{i,g}^{\theta^W} \left(\hat{d}_{ni}^W\right)^{\theta^W} \hat{\mathbb{S}}_{ni}^{\theta_W}}{\sum_{\ell \in N} \sum_{m \in K} \hat{w}_{\ell,m}^{\theta^W} \left(\hat{d}_{n\ell}^W\right)^{\theta^W} \hat{\mathbb{S}}_{n\ell}^{\theta_W} \lambda_{\ell m|n}^W}, \tag{47}$$

$$\hat{\lambda}_{j(k)|ni}^S = \frac{\left(\hat{P}_{j(k)}^S\right)^{-\theta_k^S} \left(\hat{d}_{nij(k)}^S\right)^{\theta_k^S}}{\sum_{\ell \in N} \left(\hat{P}_{\ell(k)}^S\right)^{-\theta_k^S} \left(\hat{d}_{ni\ell(k)}^S\right)^{\theta_k^S} \lambda_{\ell(k)|ni}^S}. \tag{48}$$

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 the own commuting shares ($\hat{\lambda}_{nT|n}^W$) and own consumption shares ($\hat{\lambda}_{n(k)|ni}^S$):

$$\hat{\mathbb{A}}_n = \left[\hat{w}_{n,g}^{\theta^W} \left(\hat{d}_{nn}^W\right)^{\theta^W} \hat{\mathbb{S}}_{nn}^{\theta_W} / \hat{\lambda}_{ng|n}^W\right]^{\frac{1}{\theta^W}}, \tag{49}$$

for some $g \in K$, and

$$\hat{\mathbb{S}}_{ni} = \prod_k \left[\left(\hat{P}_{n,k}^S\right)^{-\theta_k^S} \left(\hat{d}_{nin(k)}^S\right)^{\theta_k^S} / \hat{\lambda}_{n(k)|ni}^S\right]^{\frac{\alpha_k^S}{\theta_k^S}}. \tag{50}$$

[22] It 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).

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

$$\hat{\lambda}_n^B = \frac{\hat{\mathbb{A}}_n^{\theta^B} \hat{Q}_n^{-\alpha^H \theta^B} \hat{B}_n^{\theta^B}}{\sum_{\ell \in N} \hat{\mathbb{A}}_\ell^{\theta^B} \hat{Q}_\ell^{-\alpha^H \theta^B} \hat{B}_n^{\theta^B} \lambda_\ell^B}. \tag{51}$$

(iii) Changes in commercial and residential floor space demand From equations (21) and (22), the changes in commercial floor space in each sector ($\hat{H}_{i,g}$) are given by:

$$\hat{H}_{i,g} = \frac{\hat{w}_{i,g} \hat{\tilde{L}}_{i,g}}{\hat{Q}_i}, \tag{52}$$

where the change in labor input adjusted for effective units of labor ($\hat{\tilde{L}}_{i,g}$) can be expressed as:

$$\hat{\tilde{L}}_{i,g} = \frac{1}{\hat{w}_{i,g}} \frac{\sum_{n \in N} E'_{ni} \lambda'^W_{ig|n} \lambda^{B'}_n}{\sum_{n \in N} E_{ni} \lambda^W_{ig|n} \lambda^B_n}. \tag{53}$$

From equation (19), the changes in residential floor space ($\hat{H}_{i,U}$) satisfy:

$$\hat{H}_{i,U} = \frac{\hat{E}_i \hat{\lambda}_i^B}{\hat{Q}_i}, \tag{54}$$

where the counterfactual residential income E'_n is given by equation (20):

$$E'_n = \sum_{i \in N} E'_{ni} \lambda'^W_{i|n}, \tag{55}$$

and the changes of commuting-pair specific income $\hat{E}_{ni}$ satisfy:

$$\hat{E}_{ni} = \frac{\hat{\mathbb{A}}_n}{\hat{\mathbb{S}}_{ni}}. \tag{56}$$

(iv) Changes in the price of floor space From equation (31), 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:

$$\hat{Q}_i = \hat{H}_i^{\frac{1-\mu}{\mu}}, \tag{57}$$

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 ($\hat{H}_{i,U}$):

$$\hat{H}_i = \frac{H_{i,U} \hat{H}_{i,U} + \sum_{k \in K} H_{i,k} \hat{H}_{i,k}}{H_{i,U} + \sum_{k \in K} H_{i,k}}. \tag{58}$$

(v) Changes in endogenous productivities and amenities From equations (27) and (28), the changes in endogenous productivities ($\hat{A}_{i,k}$) and amenities ($\hat{B}_n$) as a result of agglomeration forces satisfy:

$$\hat{A}_{i,k} = \hat{L}_i^{\eta^W}, \tag{59}$$

$$\hat{B}_n = \hat{R}_n^{\eta^B}. \tag{60}$$

(vi) Changes in nontraded goods prices From equation (24), the changes in non-traded goods prices ($\hat{P}_{j,k}$) satisfy:

$$\hat{P}^S_{j(k)} = \frac{1}{\hat{A}_{j,k}\hat{\tilde{L}}^{\beta^S}_{j,k}\hat{H}^{1-\beta^S}_{j,k}} \frac{\sum_{n,i\in N} E'_{ni}\lambda'^S_{j(k)|ni}\lambda'^W_{i|n}\lambda'^B_n}{\sum_{n,i\in N} E_{ni}\lambda^S_{j(k)|ni}\lambda^W_{i|n}\lambda^B_n}. \tag{61}$$

(viii) Changes in Wages From the zero-profit condition (21), the changes in wages in each sector and location with positive production ($\hat{w}_{i,k}$) are given by:

$$\hat{w}_{i,k} = \left(\frac{\hat{A}_{i,k}\hat{P}^S_{i(k)}}{\hat{Q}_i^{1-\beta^S}}\right)^{1/\beta^S}. \tag{62}$$

We solve this system of equations (47)-(62), 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 ($\hat{\lambda}^W_{ig|n}$, $\hat{\lambda}^S_{j(k)|ni}$, $\hat{\mathbb{A}}_n$, $\hat{\mathbb{S}}_n$, $\hat{\lambda}^B_n$, $\hat{H}_{i,g}$, $\hat{H}_{i,U}$, $\hat{\tilde{L}}_{i,g}$, $\hat{Q}_i$, $\hat{A}_{i,k}$, $\hat{B}_n$, $\hat{P}^S_{i(k)}$, $\hat{w}_{i,k}$), 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:

$$\widehat{\mathbb{E}[u]} = \left[\sum_{\ell\in N} \lambda^B_\ell \hat{B}^{\theta^B}_\ell \hat{\mathbb{A}}^{\theta^B}_\ell \hat{Q}_\ell^{-\alpha^H\theta^B}\right]^{\frac{1}{\theta^B}}, \tag{63}$$

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

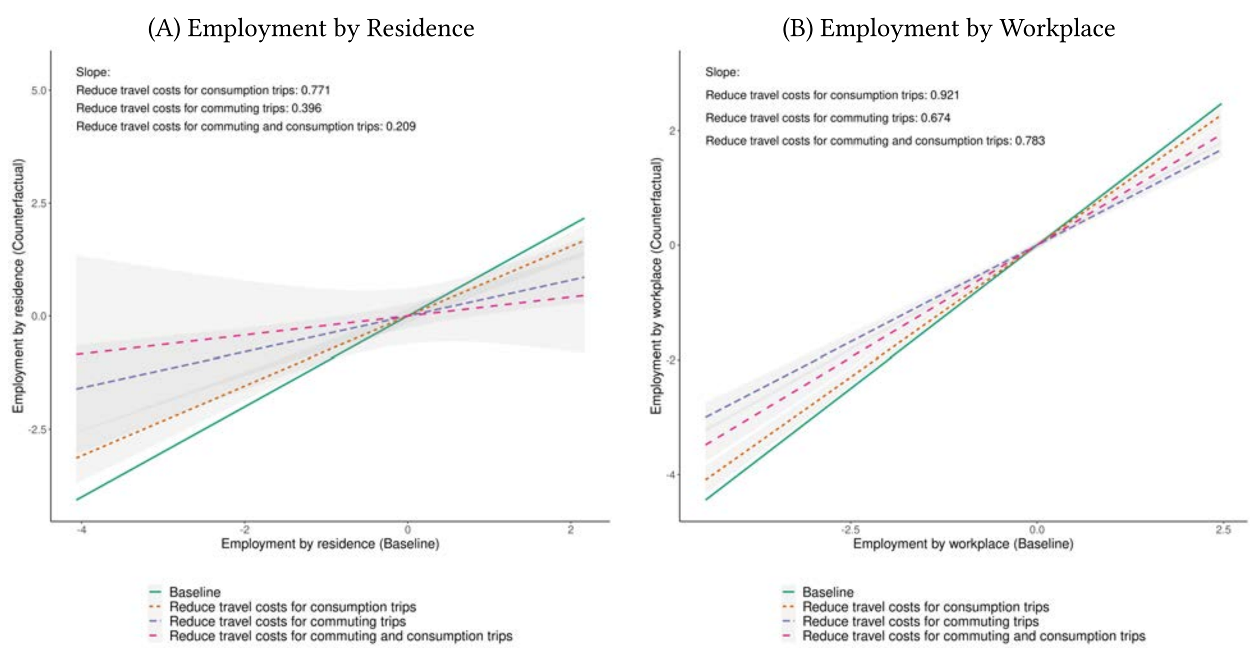
As discussed above, conventional quantitative urban models without consumption trips correspond to a special case of our model, in which $\alpha^S_k = 0$ for all $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda^S_{j(k)|ni} = 0$ and $\mathbb{S}_{ni} = 1$. In this special case, the change in expected utility ($\widehat{\mathbb{E}[u]}$) as a result of the change in travel costs continues to be given by equation (63), but the change in travel access ($\hat{\mathbb{A}}_n$) reduces to the change in workplace access ($\hat{\mathbb{A}}^{\text{nocons}}_n$). Therefore, if one assumes no consumption trips, whereas in reality they occur, there are two sources of bias in these counterfactual predictions for the impact of changes in travel costs. First, the general equilibrium predictions of the model for the changes in all endogenous variables (such as the price of floor space, the probability of working in each location and the probability of living in each location) are in general different with and without consumption trips. The reason is that these consumption trips change the relative attractiveness of locations as workplaces and residences (because of their differential access to other locations for consumption) and change relative factor demand across locations (through travel from each location to consume non-traded goods in other locations). Second, even if the general equilibrium predictions for all other endogenous variables were the same, abstracting from consumption trips would lead to a systematic understatement of the welfare gains from reductions in travel costs. The reason is that these reductions in travel costs lower the costs of consumption trips and raise consumption access ($\hat{\mathbb{S}}_{ni} > 1$), which in turn increases travel access ($\hat{\mathbb{A}}_n > 1$), and hence raises expected utility in equation (63). Intuitively, the special case of the model without consumption trips undercounts the travel journeys that benefit from the reduction in travel costs, which leads to an understatement of the welfare gains from this reduction in travel costs.

6.2 Travel Costs and the Spatial Concentration of Economic Activity

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 reducing 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 ($\kappa^S_k = \phi^S_k\alpha^S_k/\theta^S_k > 0$), 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. We use the parameter values from Table 1, with the agglomeration parameters given by $\eta^B = 0.08$ and $\eta^W = 0.15$. In Table F.0.1 in Section F of the online appendix, we report robustness tests using alternative values for these agglomeration parameters.

In Figure 10, 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.

Figure 10: 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 1, with the agglomeration parameters given by $\eta^B = 0.08$ and $\eta^W = 0.15$. In Table F.0.1 in Section F of the online appendix, we report robustness tests using alternative values for these agglomeration parameters.

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 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.

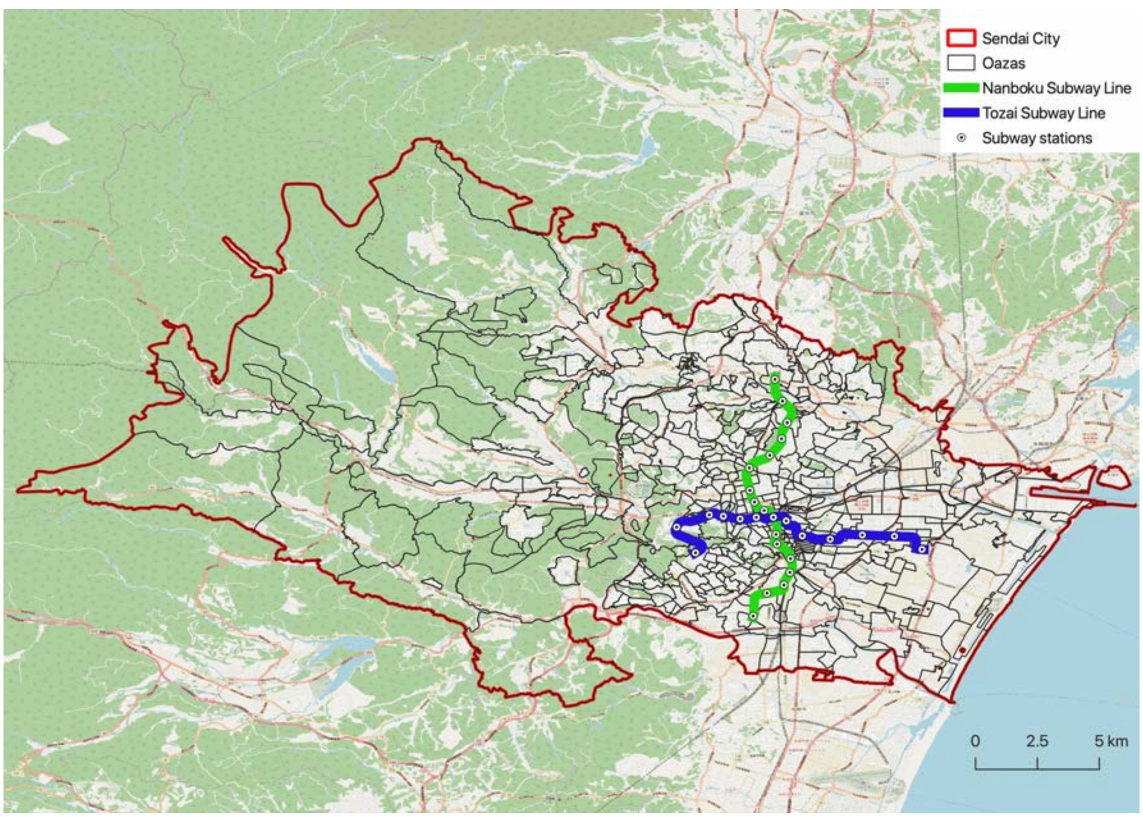
In our third counterfactual of halving the travel costs for both commuting and consumption trips, we find that the regression slope of counterfactual employment by workplace is 0.78, such that the spatial inequality of employment by workplace decreases by 22 percent ($= 1 - 0.78$). Interestingly, this 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.

6.3 Transportation Infrastructure

In our second set of counterfactuals, we examine the role of consumption access in shaping the impact of transport infrastructure improvements. In particular, we use our smartphone data and quantitative model to evaluate the impact of the construction of a new subway (underground) line in the city of *Sendai*. Before the construction of this new line, there had been 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, as shown in Figure 11.

Figure 11: Map of the City of *Sendai*



We use our model to undertake counterfactuals for the impact of this new subway line. Our goals are twofold. First, we show that our counterfactual predictions closely align with the observed changes in land prices, residents, and travel access before and after the subway opening. Since we calibrate the model using only the observed smartphone data before the subway opening, these results indicate that our model has *ex ante* predictive power for evaluating the impact of transport infrastructure improvements. Second, we use our counterfactuals to evaluate the welfare gains from the opening of the new subway line. We find that these welfare gains are substantially underestimated by omitting consumption trips, in part because of the resulting undercounting of trips. These results are consistent with the view that that existing quantitative urban models that focus on commuting may underestimate the welfare gains from transport infrastructure improvements, because they abstract from all the other types of trips that occur within urban areas and benefit from the resulting reduction in travel costs.

In Section 6.3.1, 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 6.3.2, 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.

6.3.1 Difference-in-Difference Effects of Tozai Subway Line

We start by analyzing how the Tozai Subway Line has changed urban landscape of the city of Sendai using our smartphone data and land price data. Our analysis is based on the following difference-in-difference regression:

$$\Delta \log Y_n = c_0 + c_1 T_n + u_n, \tag{64}$$

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 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 and the procedure developed in Section 5.1 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 when estimating the effective change in travel time, as discussed in Appendix G.1.[23]

In Panel (A) of Table 6, we present the results of estimating equation (64) 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

[23] We use the same parameters as in Table 1, except for ϕ^W and ϕ_k^S, which we re-estimate from our extended consumption and commuting gravity equations for the city of Sendai, as discussed in Section G.2 of the online appendix.

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

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 (64) 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.[24]

As an additional specification check, we estimate the same reduced-form regressions for the same sample period, 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

[24]In 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 (28)) 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.

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.

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***	0.311	0.054***	0.004
	(0.014)	(0.210)	(0.008)	(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***	0.300***	0.073***	0.000
	(0.010)	(0.032)	(0.008)	(0.000)
Observations	370	370	370	370
R^2	0.197	0.191	0.199	

Note: Results of estimating the difference-in-difference regression (64) 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.

6.3.2 Welfare Gains from the Tozai Subway Line

Having shown that the model is quantitatively successful in rationalizing the observed change in the spatial distribution of economic activity following the opening of the Tozai Subway Line, we now use the model to evaluate the welfare impact of the opening of this new subway line for our baseline closed-city specification.

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 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 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 $k \in K^S$, $\alpha^T = 1 - \alpha^H$, $\lambda^S_{j(k)|ni} = 0$ 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.[25] 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 the option of 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, Redding, and Sturm (2020). However, 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.

Naturally, there a number of caveats worthy of discussion. A full cost-benefit analysis would involve a comparison of the net present value of these welfare gains from the transport infrastructure improvement to the construction costs, the net present value of operating profits or losses, and the net present value of maintenance costs. Nevertheless, for a marginal project for which the net present values of these benefits and costs lie close to one another, an underestimate of the increase in the flow of expected utility from a transport infrastructure of 47 percent because of abstracting from

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

consumption trips could well be consequential for making the case for that transport improvement.

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 an unprecedented level of detail 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.

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 use the model's gravity equations for commuting and consumption trips to estimate the relative valuation that users place on different locations and construct theoretically-consistent measures of travel access. We next use the model's residential choice probabilities to show that travel access is about as important as the residual of residential amenities in explaining the relative attractiveness of locations, 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 the impact of changes in travel costs on the spatial distribution of economic activity. In a first set of counterfactuals, we eliminate spatial frictions for commuting and consumption trips, and show that both sets of spatial frictions make substantial contributions to the concentration of economic activity. In a second set of counterfactuals, we evaluate the impact of the construction of new transport infrastructure on the spatial distribution of economic activity. We show that abstracting from consumption trips leads to a substantial underestimate of the welfare gains from a transport infrastructure improvement (because of the undercounting of trips) and leads to a distorted picture of changes in travel patterns within the city (because of the different geography of commuting and non-commuting trips).

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

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翻訳和文

本研究は、経済活動の集積を理解する上で消費アクセスが果たす役割について、新たな理論と証拠を提供するものである。本研究では，ユーザーの位置情報を 5 分ごとに記録したスマートフォンのデータと，サービス業の事業所の位置情報を示す経済センサスのデータを組み合わせて，東京圏における通勤および非通勤移動を測定した。その結果，非通勤移動は通勤者の移動に比べて頻度が高く，自宅に近接しており，非貿易サービスの利用可能性と強く関連し，移動の連鎖が生じていることがわかった。次に、これらの定型的事実を踏まえて、通勤移動と非貿易サービスを利用するための移動を組み込んだ定量的な都市モデルを開発した。モデルの構造を利用して理論的に導出された、各地点における移動アクセスを推定し、居住者や地価の変動を説明する上で、消費アクセスが職場アクセスに比べても一定の貢献をしていることを示した。また、移動費用の変化についての反実仮想分析を行ったところ、消費トリップを除外すると、交通インフラ改善による厚生利益が大幅に過小評価され、それによる都市内の移動パターンの変化が歪められてしまうことがわかった。