Consumption Access and the Spatial Concentration of Economic Activity: Evidence from Smartphone Data[1]

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[1] "Konzatsu-Tokei (R)" Data refers to people flow data constructed from individual location information sent from mobile phones under users' consent, through applications provided by NTT DOCOMO, INC (including mapping application *Docomo Chizu NAVI*). Those data is processed collectively and statistically in order to conceal private information. Original location data is GPS data (latitude, longitude) sent every five minutes, and it and does not include information to specify individual.

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- Many urban trips are related to consumption beyond commuting
  - Bars, restaurants, coffee shops, theaters, cinemas, shopping, museums etc
  - Consumption access affects workplace and residence decisions, goods and factor demand, and equilibrium city structure
- Questions:
  - How important is consumption access for the spatial concentration of economic activity?
  - How does consumption access affect the impact of transport improvements?
  - Can consumption access explain the change of spatial demand in nontradable service during pandemic?

This Paper

- Documents patterns of commuting and non-commuting trips using new smartphone data for Japan
  - Tracks GPS location every 5 minutes (minimum) from a mapping application (whenever phone on)
  - Covers $\approx 0.5\%$ of Japanese population
  - Shows that non-commuting trips are frequent, related to nontradable service availability, occur within a trip chain, and decline during the pandemic

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  - Embed this decision to a canonical quantitative urban model of commuting
- Quantifies the role of consumption trips in spatial organization of economic activity
  - Simulate/estimate high-dimensional itinerary decision by importance sampling method
  - Consumption trips matter for agglomeration pattern and the impacts of transportation improvement
  - Shows that our model accurately predicts the spatial patterns of the reduction of nontradable service demand during the pandemic

Related Literature

- Internal structure of cities focusing on commuting
  - Alonso-Mills-Muth, Fujita-Ogawa (1982), Fujita-Krugman (1995), Lucas-Rossi-Hansberg (2002), Ahlfeldt-Redding-Sturm-Wolf (2015), Allen-Arkolakis-Li (2018), Monte-Redding-Rossi-Hansberg (2018), Owens-Rossi-Hansberg-Sarte (2020), Dingel-Tintelnot (2020)
- Consumption and amenities within cities
  - Couture (2016), Diamond (2016), Glaeser-Kolko-Saiz (2001), Davis-Dingel-Monras-Morales (2018), Couture-Gaubert-Handbury-Hurst (2019), Almagro-Domínguez-Iino (2019), Gorback (2019), Hoelzlein (2020), Allen-Fuchs-Ganapati-Graziano-Madera-Montoriol-Garriga (2020)
- Urban transport infrastructure
  - Baum-Snow (2006), Duranton-Turner (2011, 2012), Heblich-Redding-Sturm (2020), Tsivanidis (2019), Severen (2019), Allen-Arkolakis (2019), Fajgelbaum-Schaal (2019), Zarate (2021), Balboni-Bryan-Morten-Siddiqi (2021)
- Using cell phone or smartphone data to capture urban trips
  - Athey-Ferguson-Gentzkow-Schmidt (2018), Couture-Dingel-Green-Handbury (2021), Kreindler-Miyauchi (2021), Atkin-Chen-Popov (2021), Gupta-Kontokosta-Van-Nieuwerburgh (2021), Buchholz-Doval-Kastl-Matejka-Salz (2021), Barwick-Donaldson-Li-Lin-Rao (2021)
- Consumer foot traffic and agglomeration
  - Eaton-Lipscy (1982), Quinzii-Thisse (1990), Fujita-Thisse (1996), Relihan (2017), Shoag-Veuger (2018), Koster-Pasidis-van Ommeren (2019), Benmelech-Bergman-Milanez-Mukharlyamov (2019)

Outline

Smartphone GPS Data from Japan

- Tracks anonymised GPS location every 5 minutes (minimum) from a mapping app (whenever phone on)
  - One of the most popular map app in Japan (*Docomo Chizu NAVI*)
  - Each month $\approx$ 545,000 users ($\approx$ 0.5% population) and $\approx$ 1,497,000,000 GPS points

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- NTT Docomo Inc. pre-processes original GPS data points
  - Stay : no movement $\leq$ 100 meters for $\geq$ 15 minutes
  - Home location: most frequent location (defined by the groups of geographically contiguous stays) in terms of number of stays each month
  - Work location: second most frequent location, $\geq$ 600 meters from home
    - ★ Work location is not assigned for users with "unreliable" work location (e.g., if the user does not appear in work location $\geq$ 5 days; $\approx$ 30% of users) detail
  - Other location: all other stays that are neither home nor work location

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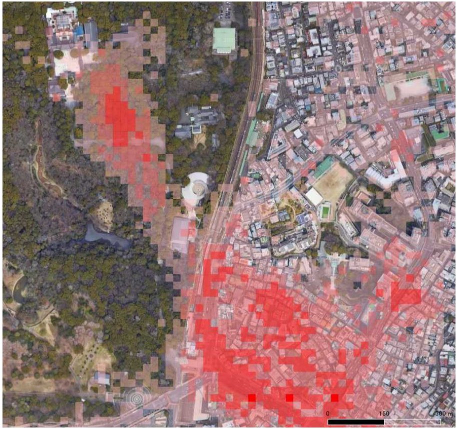
  - Other location: all other stays that are neither home nor work location
- We mostly focus on user-days in April 2019 whose:
  - first and last stays of the day is at home (to avoid overnight travelers)
  - whose workplace is assigned
  - and whose home and work is within Tokyo metropolitan area

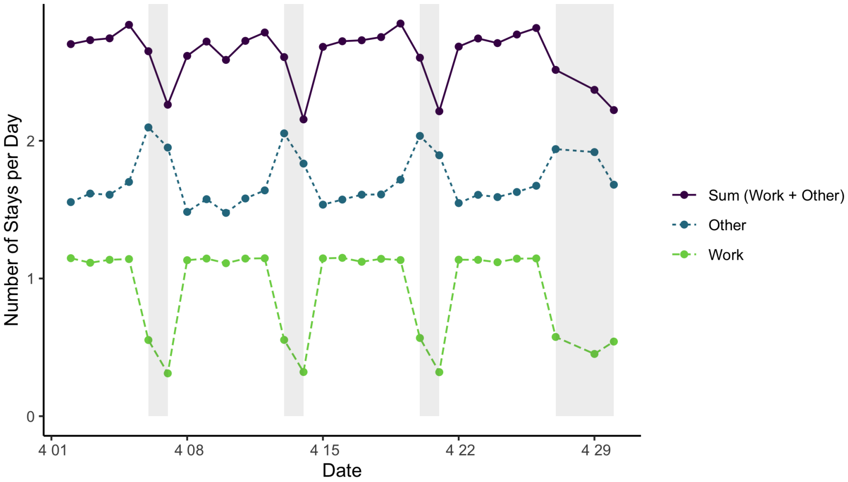
Example of Stays (around Meiji Shrine)



- Each grid is about 20 meter by 20 meter
- Measure location at a fine level of spatial disaggregation
- Track the movement of users through the park to the shrine

entire Tokyo metropolitan area

Stays by Day



- Work and non-work stays display expected patterns on weekdays v. weekends

Validation of Home and Workplace Population Density

- Each dot: municipality in greater Tokyo metropolitan area
- Approximate log-linear relationships between smartphone and census measures of residence and workplace employment probabilities

residence by demographics | workplace by industry | commuting probability

Outline

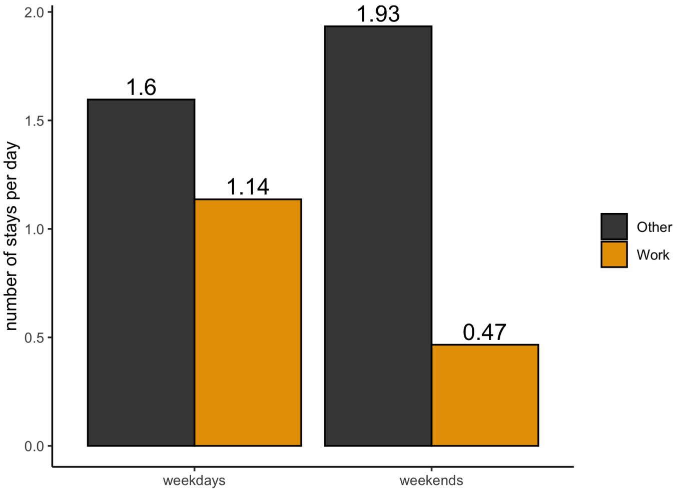
Reduced-form Evidence

- Define a non-commuting trip as a trip to a stay that is neither a user's home location nor her work location

- Establish the following properties of non-commuting trips

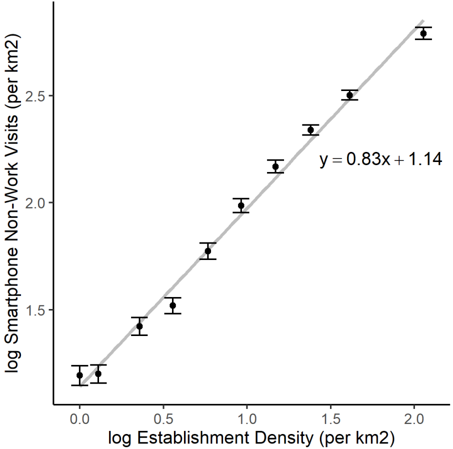
  1. Non-commuting trips are frequent
  2. Non-commuting trips are related to availability of non-tradable services
  3. Non-commuting trips are closer to home on average than commuting trips
  4. Non-commuting trips occur as a part of trip chains
  5. Non-commuting trips are affected by pandemics

1) Non-commuting trips are frequent



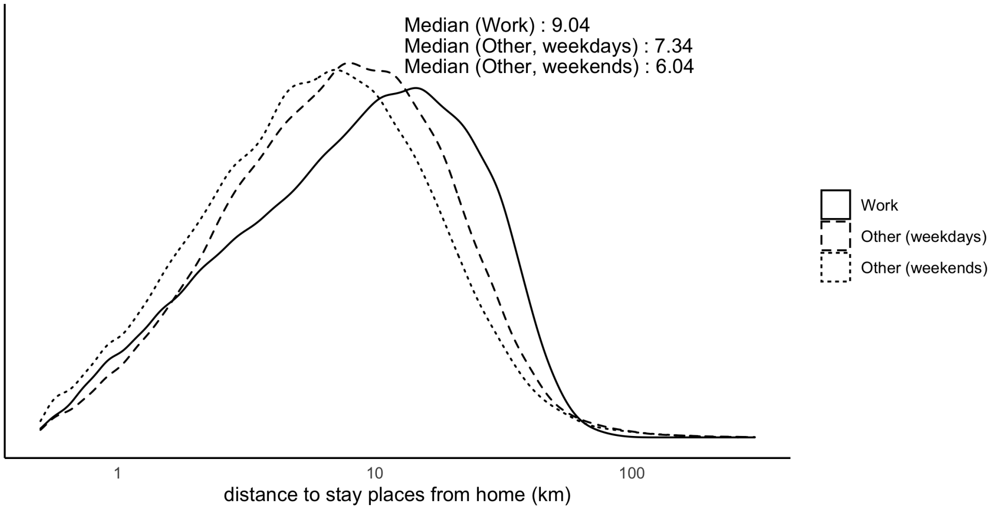
by date by hour travel survey

2) Non-commuting trips are related to availability of non-tradable services

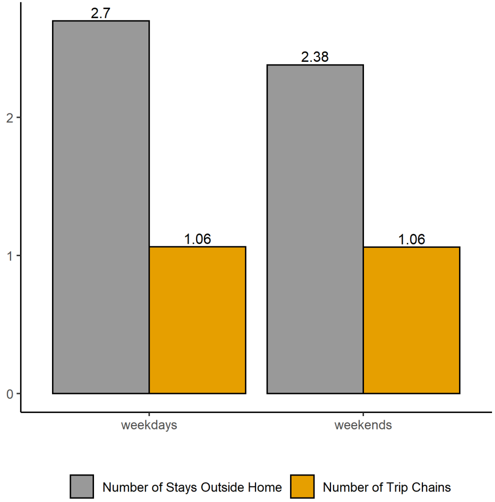


- Horizontal axis: number of establishments for nontradable services by nontradable sector

3) Non-commuting trips are closer to home than commuting trips



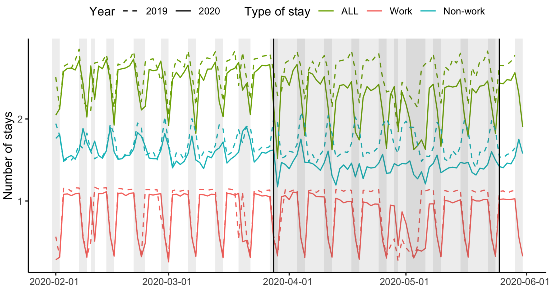
4) Non-commuting trips occur as a part of trip chains



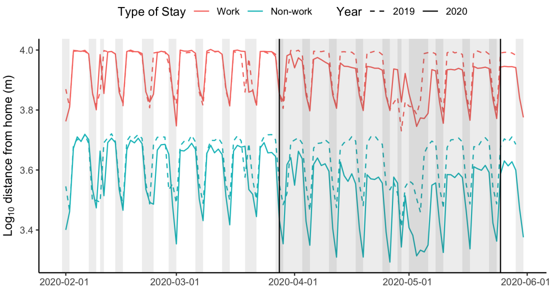
- Trip chains $\equiv$ a sequence of stays starting and ending at home by weekdays and weekends

5) Non-commuting and commuting trips are affected by pandemics

(A) Number of Stays per Day



(B) Median Distance of Stays from Home



- On March 28, 2020, an "emergency order" has been announced in Tokyo prefecture
- People are "encouraged" to stay at home unless "absolutely necessary"
- Temporarily lifted on May 25, 2020

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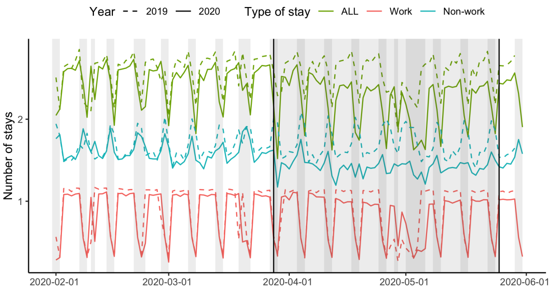

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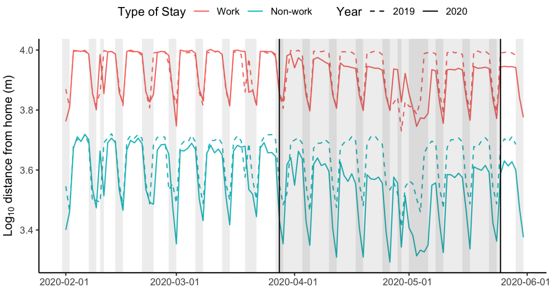

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- ↓ in non-commuting & commuting stays (10-20%) and distance traveled table
- Noncommuting stays ↓ in downtown areas, ↑ in suburban areas detail

Outline

Model

- Develop a quantitative urban model to examine the role of access to consumption of nontradable services in spatial organization of economic activity

- Two elements:

  1. Agents' itinerary decisions (sequence of trip destinations) given home and work locations
  2. Embed this decision to a canonical quantitative urban model of commuting

Itinerary Decision

- Multiple locations in the city: $N \equiv \{1, \ldots, n\}$
- An agent with home location $h \in N$ and work location $j \in \{N, \emptyset\}$ decide consumption itinerary I
  - $j = \emptyset$ for non-workday or non-employed
  - $I \in \mathcal{I}_{hj}$: a (non-empty) ordered subset of N, must include j

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  - $I \in \mathcal{I}_{hj}$: a (non-empty) ordered subset of N, must include j
- In each destination, a bundle of nontradable services is provided at (amenity-adjusted) price index P_n
  - Agents allocate consumption amount across visiting locations under CES utility with EoS σ
- The agent chooses I_ω such that:

$$I_\omega = \max_{I \in \mathcal{I}_{hj}} \left(\sum_{n \in I} P_n^{1-\sigma} \right)^{-\frac{1}{1-\sigma}} T_{I|hj}^{-1} \epsilon_{\omega I}$$

  - $T_{I|hj}$: total iceberg travel cost
  - $\epsilon_{\omega I}$: idiosyncratic preference shock
  - $T_{I|hj}$ embrace travel cost saving through trip chains; e.g., allow for $T_{\{1,2\}|hj} < T_{\{1\}|hj} T_{\{2\}|hj}$

Itinerary Decision

- Assume that $\epsilon_{\omega I}$ follows i.i.d. Fréchet distribution with dispersion parameter θ
- The probability that agents choose itinerary I is given by

$$\Lambda_{I|hj} = \frac{\left[\left(\sum_{n\in I} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{I|hj}^{-1}\right]^{\theta}}{\sum_{\ell\in\mathcal{I}_{hj}}\left[\left(\sum_{n\in \ell} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{\ell|hj}^{-1}\right]^{\theta}}$$

- We define consumption access as the inverse of the expected price index net of travel cost and idiosyncratic itinerary shock given agents home h and work j:

$$\mathbb{A}_{hj} = \varrho\left[\sum_{\ell\in\mathcal{I}_{hj}}\left(\sum_{n\in\ell} P_n^{1-\sigma}\right)^{-\frac{\theta}{1-\sigma}}\left(T_{\ell|hj}\right)^{-\theta}\right]^{-\frac{1}{\theta}}$$

- Challenge: high-dimensionality of $\mathcal{I}_{hj} \Rightarrow$ importance sampling method

General Equilibrium

Embed itinerary decision into a canonical GE urban model (e.g., Ahlfeldt et al 2015; Tsivanidis 2019) detail

- Production
  - Two sectors: tradables and nontradables
  - Cobb-Douglas production function with labor and floor space
  - Perfect competition for tradables, monopolistic competition & free entry for nontradables
- Agents decide home location, work location, and sector based on wages, rents, residential amenity, commuting cost, and anticipated consumption access
  - Assume exogenous probability of going to workplaces, $\xi = 5/7$ in baseline
- Labor market clearing $\Rightarrow$ wages
- Floor space market clearing $\Rightarrow$ rents
- Goods market clearing $\Rightarrow$ nontradable prices
- Amenity and productivity spillovers

Outline

Simulating Consumers' Itinerary Choice

- Itinerary choice probability:

$$\Lambda_{I|hj} = \frac{\left[\left(\sum_{n \in I} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{I|hj}^{-1}\right]^{\theta}}{\sum_{\ell \in \mathcal{I}_{hj}} \left[\left(\sum_{n \in \ell} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{\ell|hj}^{-1}\right]^{\theta}}$$

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$$\tilde{\Lambda}_{I|hj} = \frac{\mathcal{E}_{I|hj}\Lambda_{I|hj}/F_{hj}(I)}{\sum_{\ell\in\mathcal{I}_{hj}^R}\mathcal{E}_{\ell|hj}\Lambda_{I|hj}/F_{hj}(\ell)} = \frac{\mathcal{E}_{I|hj}\left[\left(\sum_{n\in I} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{I|hj}^{-1}\right]^{\theta}/F_{hj}(I)}{\sum_{\ell\in\mathcal{I}_{hj}^R}\mathcal{E}_{\ell|hj}\left[\left(\sum_{n\in \ell} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{\ell|hj}^{-1}\right]^{\theta}/F_{hj}(\ell)}$$

where $\mathcal{I}_{hj}^R$ is a subset of $\mathcal{I}_{hj}$ sampled in Step 1.

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where $\mathcal{I}_{hj}^R$ is a subset of $\mathcal{I}_{hj}$ sampled in Step 1.

- Any $F_{hj}(\cdot)$ with common support as $\Lambda_{I|hj}$ ensures $\tilde{\Lambda}_{I|hj} \to \Lambda_{I|hj}$ as $R \to \infty$; in practice "myopic sequential choice" has good approximation detail

Estimation Procedure

- Parametrize travel cost as:

$$T_{I|hj} = \eta^{|I|} \exp\left(\rho D_{I|hj}\right)$$

  - η: iceberg cost of stopping at one location
  - ρ: semi-elasticity of travel cost with respect to travel time
  - $D_{I|hj}$: total travel time to follow itinerary I from home location h involving work location j ($D_{I|hj} = D_{hI_1} + \sum_{i=1,\ldots,|I|-1} D_{I_i I_{i+1}} + D_{I_{|I|} h}$)

- Estimation procedure:

  1. Estimate parameters relevant for consumption itinerary choice $\{\theta, \sigma, \rho, \eta, \{P_n\}\}$
  2. Calibrate GE parameters

Estimate parameters for consumption itinerary choice $\{\theta, \sigma, \rho, \eta, \{P_n\}\}$

1. Estimate consumption location choice *conditional on visiting only one location* by PPML:

$$\Lambda^{\text{single}}_{\{n\}|h\varnothing} = \frac{P_n^{-\theta} D_{\{n\}|h\varnothing}^{-\rho\theta}}{\sum_{\ell \in N} P_\ell^{-\theta} D_{\{\ell\}|h\varnothing}^{-\rho\theta}}.$$

   - Identifies $\rho\theta$ and $\{P_n^{\theta}\}$

2. Calibrate ρ from existing value-of-time estimates (Couture 2016; Couture et al 2019):
   - Identifies θ and $\{P_n\}$

3. Estimate σ using the relationship between estimated price index P_n and number of varieties (proxied by number of nontradable establishments M_{nS}):

$$\log P_n - \log p_n = \beta_0 + \beta_1 \log M_{nS} + \epsilon_n$$

   where p_n is the observed variety-specific price (use official food price index); $\beta_1 = -1/(\sigma - 1)$; instrument M_{nS} by number of establishments in 1980

4. SMM to estimate η targeting the average number of stays per day

Estimate parameters for consumption itinerary choice: Results

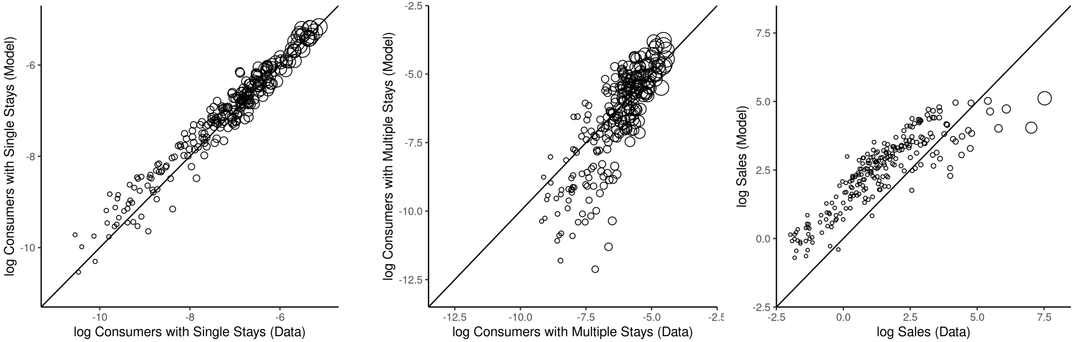
- Spatial unit: 240 municipalities in Tokyo metropolitan area
- Draw 100 importance samples for each home-work
- Assume maximum number of stays per day = 5

Parameters	Value	Source / Target
ρ	1.62	Value of time (Couture, Gaubert, Handbury, Hurst 2020)
θ	1.93	Gravity equation (conditional on single location visit)
σ	5.82	Gravity equation (conditional on single location visit) and number of establishments
η	4.86	Average number of stays per day

Model Fit

(i) targeted moments

(ii) untargeted moments



Calibration of General Equilibrium Parameters

Parameter	Description	Value	Source
ϕ	dispersion of Fréchet shocks for residence and workplace choice	1.22	Commuting gravity equation
α^S	expenditure share for nontradable sector	0.6	Data
α^H	expenditure share for residential floor space	0.25	Data
α^T	expenditure share for tradable sector	0.15	Data
ξ	probability of going to workplaces	0.71	5 days / week
β^S	labor share in production for nontradable sector	0.8	Data
β^T	labor share in production for tradable sector	0.8	Data
η^W	elasticity of production spillover in tradable sector	0.17	$\beta^S/(\sigma-1)$
η^B	elasticity of residential amenity spillover	0	Ahlfeldt-Pietrostefani (2019) (Conservative)
μ	share of capital for floor space production	0.75	Ahlfeldt et al (2015)

Outline

Counterfactual Simulations

Answer following questions about the quantitative role of consumption access through counterfactuals:

1. How does consumption access affect the impact of transport improvements?
2. Can our model explain the change of peoples' movement patterns during pandemic?

other counterfactuals to change travel cost

Transportation Infrastructure

- Assess impacts of public transit that was developed in Tokyo metropolitan areas after 1980 map
- Counterfactuals to remove these public transit (increase of travel time)

Transportation Infrastructure

- Assess impacts of public transit that was developed in Tokyo metropolitan areas after 1980 map
- Counterfactuals to remove these public transit (increase of travel time)
  - Second row: omit consumption access ($\alpha^S = 0$)
  - Third row: assume that agents have to go home for every destination
  - Recalibrate the model for each scenario
- The table shows the following regression coefficients ($\times$ 100) and the aggregate changes of welfare

$$\Delta \log L_n = \beta \log L_n + \epsilon_n, \quad \Delta \log R_n = \beta \log R_n + \epsilon_n$$

	Δ Employment Concentration (%)	Δ Residence Concentration (%)	Δ Welfare (%)	Δ Welfare Relative to Baseline (%)
(1) Baseline	-2.3	-1.9	-7.9	100
(2) No Consumption Trips	-1.7	-1.5	-6.6	84
(3) No Trip Chains	-2.0	-1.7	-7.3	92

Transportation Infrastructure

- Assess impacts of public transit that was developed in Tokyo metropolitan areas after 1980 map
- Counterfactuals to remove these public transit (increase of travel time)
  - Second row: omit consumption access ($\alpha^S = 0$)
  - Third row: assume that agents have to go home for every destination
  - Recalibrate the model for each scenario
- The table shows the following regression coefficients ($\times$ 100) and the aggregate changes of welfare

$$\Delta \log L_n = \beta \log L_n + \epsilon_n, \quad \Delta \log R_n = \beta \log R_n + \epsilon_n$$

	Δ Employment Concentration (%)	Δ Residence Concentration (%)	Δ Welfare (%)	Δ Welfare Relative to Baseline (%)
(1) Baseline	-2.3	-1.9	-7.9	100
(2) No Consumption Trips	-1.7	-1.5	-6.6	84
(3) No Trip Chains	-2.0	-1.7	-7.3	92

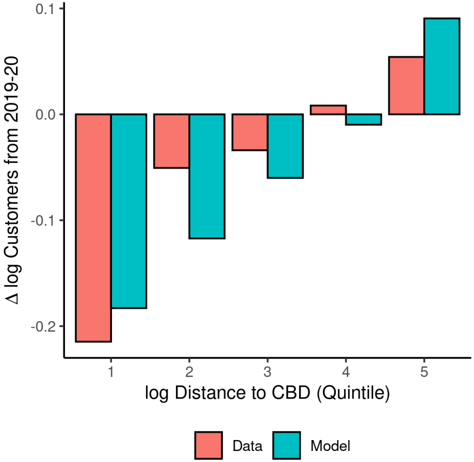
- Omitting consumption access and/or trip chains leads to underestimation of the effects on spatial concentration and welfare gains from transportation improvement

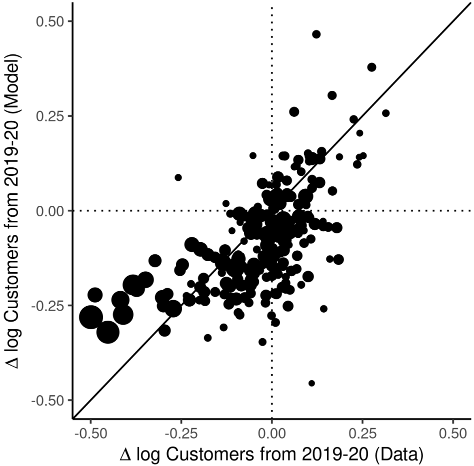
Pandemic

- Can our model explain the change of peoples' movement patterns during pandemic by the change of limited set of structural parameters?

- Estimate the "short-run effect" of "emergency order" from 3/28-5/25 in 2020
  - Calibrate the baseline model using April 2019 data
  - Change two parameters:
    1. ρ (value of time): use April 2020 data to fit the gravity equation of consumption travel conditional on visiting only one location (fix θ)
    2. ξ (probability of going to work): change as observed in the data (No effect on productivity or labor supply)
  - Run counterfactuals without changing GE objects ($\{P_n, w_n, R_n, L_n, Q_n\}$)

Model accurately predicts change of spatial nontradable service demand





additional statistics map

Outline

Conclusions

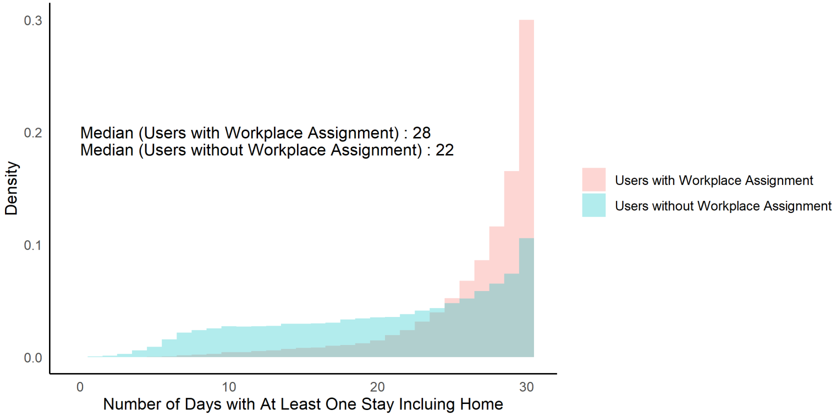
- What explains the spatial organization of economic activity in cities?
  - Traditional theories emphasize commuting between workplace and residence
  - Many urban trips are related to consumption beyond commuting
- We use smartphone data to provide new evidence on the prevalence and characteristics of non-commuting trips
- We develop a quantitative spatial model to examine the implications of consumption access for the spatial organization of economic activity
  - Consumption trips matter for agglomeration pattern and the impacts of transportation improvement
  - Model accurately predicts the change of spatial travel patterns during the pandemic

Thank You

Appendix

Number of Days with Stays with and without Workplace Assignment

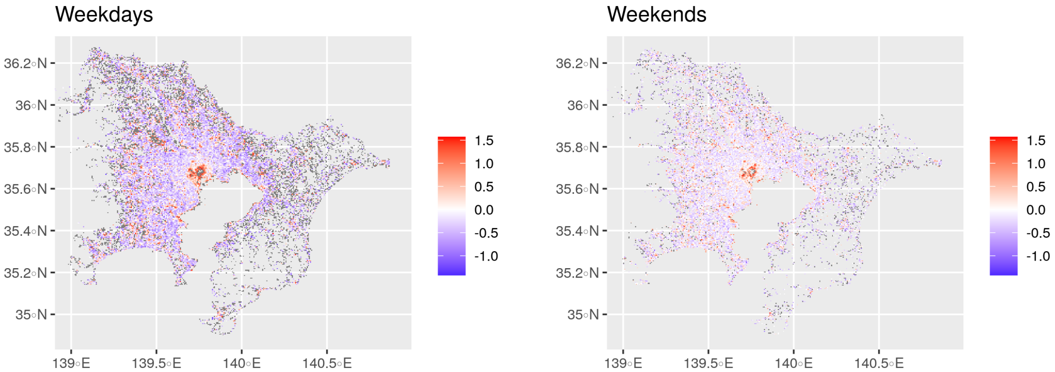
go back



- Many devices with missing workplace assignments are not used every day

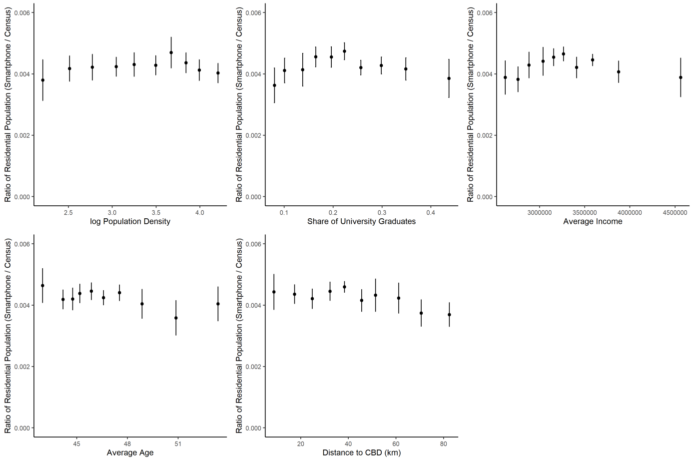
Log Difference of Day- and Night-time Population

go back



- Log Difference between Day-time and Night-time population is greater during weekdays than during weekends

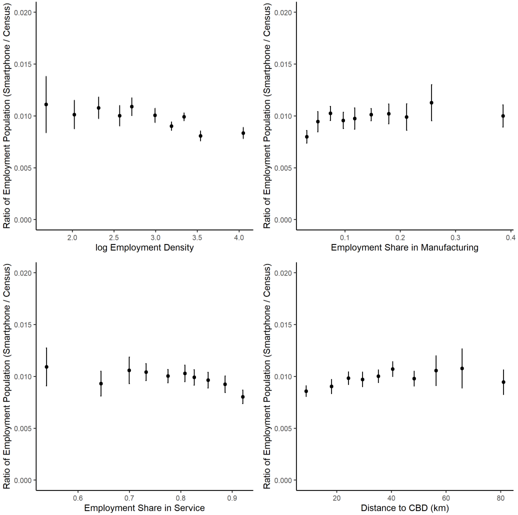
Coverage of Smartphone Users by Residential Location back



- Divide municipalities into 10 strata (23 wards in central Tokyo aggregated into one unit)

Coverage of Smartphone Users by Employment Location

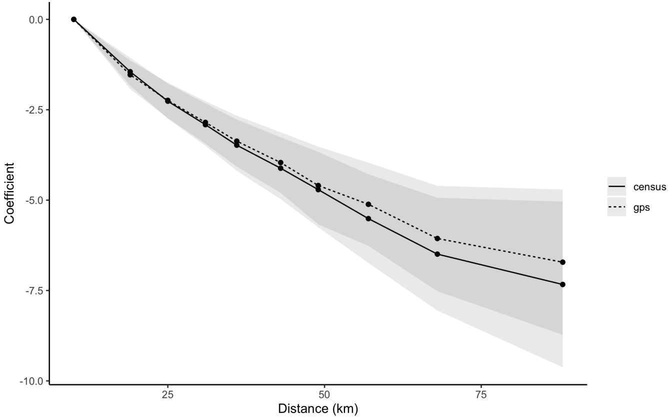
back



Validation of Commuting Flows

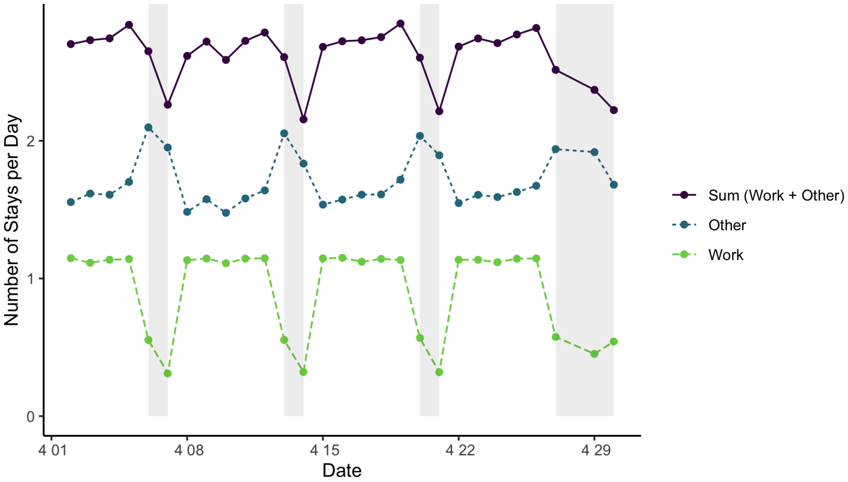
go back

- Commuting probabilities decay at a similar rate with distance in smartphone and census data



- Gravity regression including workplace fixed effects, residence fixed effects and indicator variables for distance grid cells

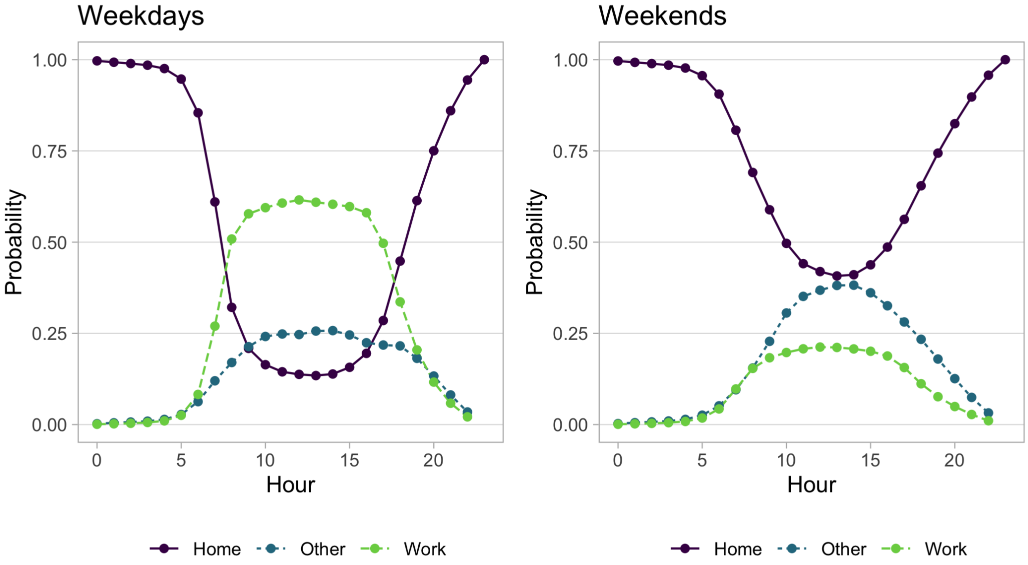
Stays by Day go back



- Work and non-work stays display expected patterns on weekdays v. weekends

Stay by Hour

go back



Frequency of Stays | Smartphone vs. Travel Survey

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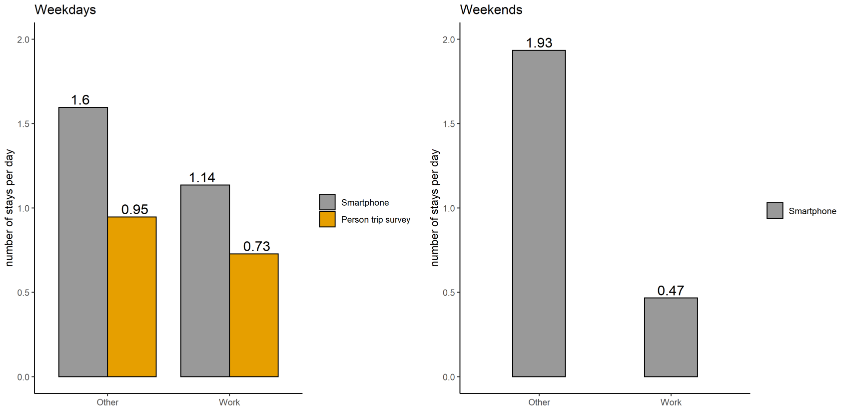
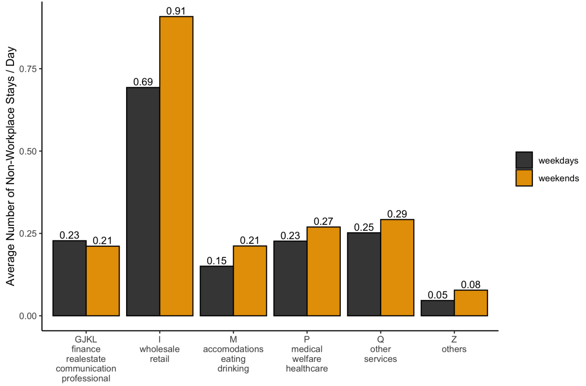


Non-commuting trips by destination sectors of non-tradable services

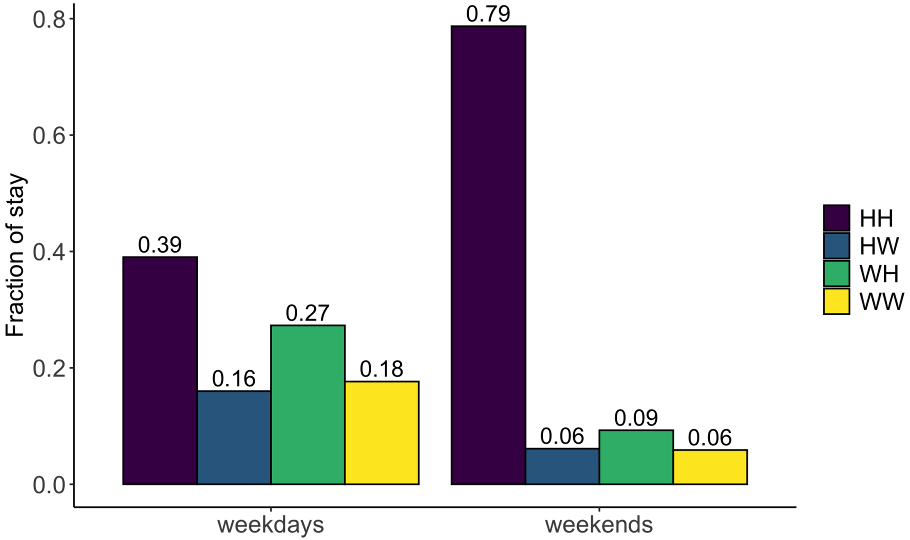
go back



- For each 500 meter grid cell, compute the employment share of each service sector in total service sector employment using separate economic census data
- If a non-commuting trip to a grid cell is observed, we allocate that trip to a service sector probabilistically using the shares of sectors in service employment in that grid cell
- If no service-sector employment in the mesh, assign "Z Others."

Trip Chains | Weekdays vs. Weekends

go back

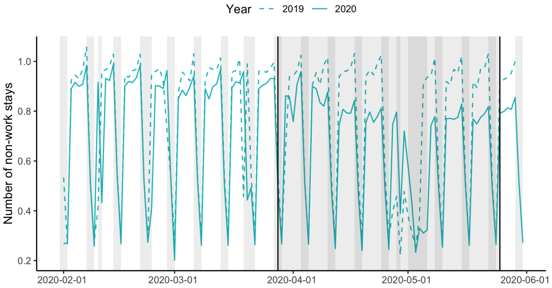


5) Non-commuting trips are affected by pandemics

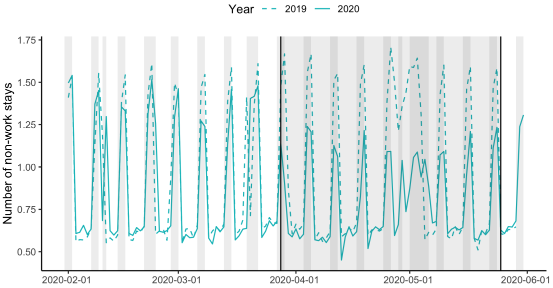
	Type of Stay	All	Weekday	Non-Weekday
(A): Percentage Change of Number of Stays per Day 2019-2020				
(1)	All	−13.3	−10.3	−20.3
(2)	Work	−6.4	−10.7	−1.4
(3)	Non-work	−16.7	−10.0	−24.6
(B): Percentage Change of Median Distance of Stays from Home 2019-2020				
(4)	Work	−0.7	−1.2	−0.4
(5)	Non-work	−3.2	−2.8	−4.3

5) Non-commuting trips are affected by pandemics

(C) Non-Work Stays within Work Trip Chain

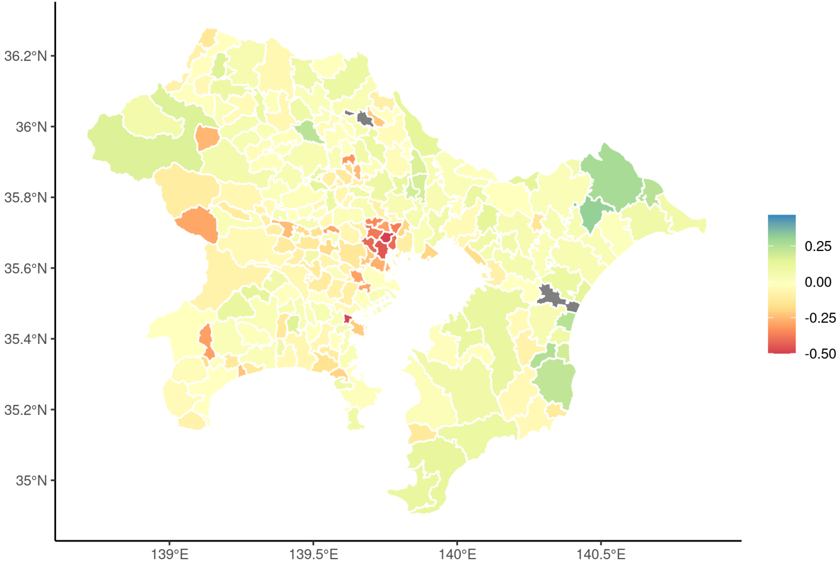


(D) Non-Work Stays outside Work Trip Chain



- During weekdays, reduction of non-commuting stays through work trip chains (Panel C)
- During weekends, reduction of non-commuting stays outside work trip chains (Panel D)

Reduction of foot traffic in downtown during pandemic



Agents' Residential and Workplace Choice

- Sectors: $k \in T, S$ for tradable goods and nontradable services
- Indirect utility with home h, work j and sector k:

$$U_{hjk\omega} = w_{jk} B_h \tilde{\mathbb{A}}_{hj}^{\alpha^S} Q_h^{-\alpha^H} T_{hj}^W \epsilon_{hjk\omega}^W$$

- Anticipated consumption access:

$$\tilde{\mathbb{A}}_{hj}^{\alpha^S} = \xi \mathbb{A}_{hj}^{\alpha^S} + (1-\xi)\, \mathbb{A}_{h\emptyset}^{\alpha^S}$$

  - ξ is the probability of going to work during the day

- Assuming the Fréchet distribution for $\epsilon_{hjk\omega}^W$, probability of choosing (h, j, k) is:

$$\Omega_{hjk} = \frac{\left(w_{jk} B_h Q_h^{-\alpha^H} \tilde{\mathbb{A}}_{hj}^{\alpha^S} \tau_{hj}^W\right)^{\phi}}{\sum_{h',j'} \sum_{k \in \{K,S\}} \left(w_{j'k'} B_h Q_{h'}^{-\alpha^H} \tilde{\mathbb{A}}_{h'j'}^{\alpha^S} \tau_{h'j'}^W\right)^{\phi}}$$

Production: Nontradable Sector

- Monopolistic competition + free entry
- Marginal cost for a firm is given by

$$c_i = \frac{1}{a_{iS}} w_{iS}^{\beta^S} Q_i^{1-\beta^S},$$

- Firms have to pay f_i^S unit of output to enter, determine entry as:

$$M_{iS} = \frac{1}{f_{iS}} \frac{1}{\sigma - 1} \left(\frac{L_{iS}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{iS}}{1 - \beta^S} \right)^{1-\beta^S}$$

- Price index is given by

$$P_i = p_i \left(M_{iS} \right)^{\frac{1}{1-\sigma}} = \frac{1}{A_{iS}} w_{iS}^{\beta^S} Q_i^{1-\beta^S},$$

where

$$A_{iS} = \tilde{a}_{iS} \left(L_{iS} \right)^{\frac{\beta^S}{\sigma - 1}} \left(H_{iS} \right)^{\frac{1-\beta^S}{\sigma - 1}}$$

Production: Tradable sector

- Tradable good produced using labor and floor space in each location i according to constant returns to scale technology under perfect competition

$$P_i^T = \frac{1}{A_{i,k}^T} w_i^{\beta^T} Q_i^{1-\beta^T}, \qquad 0 < \beta^T < 1$$

- Tradable good is costlessly traded and chosen as the numeraire

$$P_i^T = P^T = 1 \qquad \text{for all} \qquad i \in N$$

- Marshallian externality:

$$A_{iT} = a_{iT} \left(\frac{L_{iT}}{K_i} \right)^{\eta^W}$$

Floor Space Supply

- Land is owned by absentee landlord
- Perfectly competitive developers supply floor space for residential and business purposes in each location
- The inverse supply function for floor space is

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

  - H_i: total floor space in location i
  - ψ_i: exogenous characteristics of land space
  - $1 - \mu$: share of land used for floor space construction

Endogenous Amenity

- Amenity of location n endogenously depends on the residential density

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

where R_n is the total measure of residents in location n.

Market Clearing

- Floor space market clearing:

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

  - $H_{i,U}$: residential floor space consumption
  - $H_{i,k}$: commercial floor space allocated for sector k

- Nontradeable service market clearing:

$$P_{nS} A_{nS} \left(\frac{L_{nS}}{\beta^S} \right)^{\beta^S} \left(\frac{H_{nS}}{1-\beta^S} \right)^{1-\beta^S} = \alpha^S \sum_{h,j,k} \sum_{I} w_{jk} \Omega_{hjk} \tilde{\Lambda}_{I|jh} \Psi_{n|I}$$

go back

Practical Choice of Auxiliary Distribution for Importance Sampling go back

1. For each h and j, randomly sample (1) total number of stays and (2) number of stays before and after the stop to workplace j (if any) from the observed distribution in the data.

2. Determine the i-th location n_i starting from $i = 1$. When the i-th location of the day is at workplace (j), set the stay location n_i such that $n_i = j$. When the i-th location of the day is not at workplace, assume that agents myopically choose the first location without considering subsequent stays. Namely, denoting the itinerary up to $(i-1)$-th stay by I_{i-1}, we sample n_i from the following distribution:

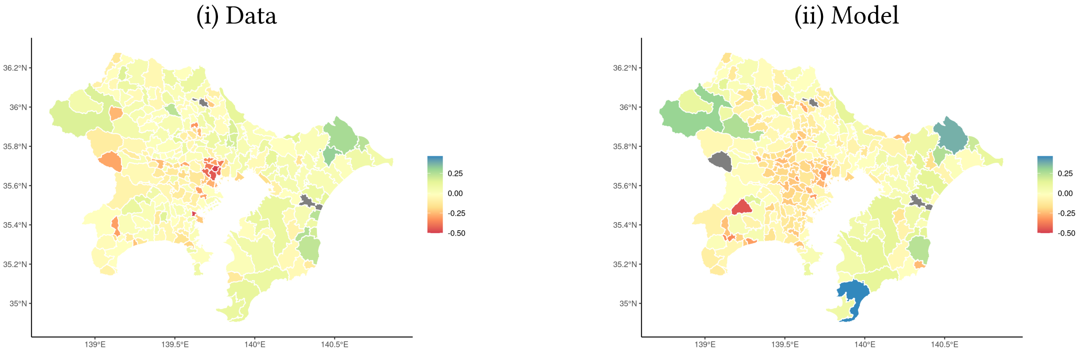
$$\Pi_{n_i}^{i} = \frac{\left[\left(\sum_{n \in \{n_i, I_{i-1}\}} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{\{n_i, I_{i-1}\}|hj}^{-1}\right]^{\theta}}{\sum_{\ell \in N}\left[\left(\sum_{n \in \{\ell, I_{i-1}\}} P_n^{1-\sigma}\right)^{-\frac{1}{1-\sigma}} T_{\{\ell, I_{i-1}\}|hj}^{-1}\right]^{\theta}}$$

3. Repeat Step 2 for all stops.

Fit to Targeted and Untargeted Moments

	Data	Model
(i) targeted moments		
(1) Δ log number of work stay per user-day	-0.06	-0.06
(2) Δ Gravity coefficient conditional on visiting only one location	-0.27	-0.27
(ii) untargeted moments		
(1) Δ log number of total stay per user-day	-0.08	-0.11
(2) Δ log number of nonwork stay within work trip chains	-0.19	-0.22
(3) Δ log number of nonwork stay outside work trip chains	-0.10	-0.11
(4) Δ log median log distance to nonwork destinations within work trip chains	-0.28	-0.31
(5) Δ log median log distance to nonwork destinations outside work trip chains	-0.21	-0.19

Model predicts the reduction of nontradable service demand in downtown



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Counterfactuals: Travel Cost and Spatial Concentration

- Counterfactually decrease travel time for commuting, consumption travel, and both, by 20%

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$$\Delta \log L_n = \beta \log L_n + \epsilon_n, \quad \Delta \log R_n = \beta \log R_n + \epsilon_n$$

	Δ Employment Concentration (%)	Δ Residence Concentration (%)
(1) Decrease Only Commuting Time	-6.5	-9.7
(2) Decrease Only Consumption Travel Time	2.7	3.2
(3) Decrease All Travel Time	-3.7	-6.6

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- Commuting time $\downarrow \Rightarrow$ more dispersion (e.g., Baum-Snow 2007; Tsivanides 2019; Heblich, Redding, Sturm 2021)
- Consumption travel time $\downarrow \Rightarrow$ *more concentration*
  - Complementarity between work locations and consumption trips through trip chains
  - Lower consumption travel cost makes downtown workplaces more attractive due to consumption access $\uparrow$

Counterfactuals: Trip Chains and Spatial Concentration

- Counterfactually shut down trip chains
  - First row: Assume that agents cannot make detour for consumption trips on the way to work
  - Second row: Assume that agents have to go home for every destination

	Δ Employment Concentration (%)	Δ Residence Concentration (%)
(1) Only Shut Down Trip Chains through Work	-3.9	-1.3
(2) Shut Down All Trip Chains	-5.2	-1.8

- Trip chains leads to agglomeration (e.g., Eaton-Lipscy 1982, Fujita-Thisse 1996)

Map of Public Transit in Tokyo Metropolitan Area