The Economics of Spatial Mobility: Theory and Evidence Using Smartphone Data[1]

Yuhei Miyauchi
Boston University

Kentaro Nakajima
Hitotsubashi University

Stephen J. Redding
Princeton University, NBER, CEPR

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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. The copyrights of all tables and figures presented in this document belong to ZENRIN DataCom CO., LTD.

Motivation

- Each day, millions of trips occur within urban areas
  - Commuting trips
  - Non-commuting trips
  - Occur as a part of a trip chain (e.g., a coffee shop on the way to work, shopping expedition)
- Trip chains induce consumption externality across space
  - Large employment or commercial districts attract consumer foot traffic
  - Relevant for firm location decisions and internal structure of the city
  - Decline of nontradable service demand in downtown during Covid-19 pandemic
- Challenges for analyzing spatial mobility
  - Lack of data
  - Lack of theoretical/empirical approach to handle high-dimensionality of travel decisions

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
  - Shows that non-commuting trips are frequent, related to nontradable service availability, occur within a trip chain, and decline during the Covid-19 pandemic

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- Develops a quantitative theoretical model of travel itinerary decision
  - Agents decide the set and sequence of destinations for consumption during a day
  - Embeds this decision to a canonical quantitative general equilibrium urban model featuring commuting
  - Develops importance sampling method for estimation / simulation to overcome high-dimensionality

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  - Embeds this decision to a canonical quantitative general equilibrium urban model featuring commuting
  - Develops importance sampling method for estimation / simulation to overcome high-dimensionality
- Shows that trip chains and consumption externality are crucial for:
  - explaining the decline of nontradable service demand in downtown during Covid-19 pandemic
  - welfare assessment of public transportation infrastructure

Related Literature

- Internal structure of cities focusing on commuting: Alonso-Mills-Muth, Fujita-Ogawa '82, Lucas-Rossi-Hansberg '02, Ahlfeldt-Redding-Sturm-Wolf '15, Allen-Arkolakis-Li '18, Monte-Redding-Rossi-Hansberg '18, Tsivanidis '19, Dingel-Tintelnot '20
- Consumption access and endogenous amenities within cities: Glaeser-Kolko-Saiz '01, Diamond '16, Couture-Gaubert-Handbury-Hurst '22, Almagro-Domínguez-Iino '21, Hoelzlein '20; Couture '16, Davis-Dingel-Monras-Morales '19, Su '22, Hausman-Samuels-Cohen-Sasson '21, Tan-Lee '21, Agarwal-Jensen-Monte '20, Allen-Fuchs-Ganapati-Graziano-Madera-Montoriol-Garriga '21
- Trip chains and shopping externality: Eaton-Lipsey '82, Fujita-Thisse '96, Ushchev-Sloev-Thisse '15; Shoag-Veuger '18, Relihan '22, Koster-Pasidis-van-Ommeren '19
- Using cell phone or smartphone data to capture spatial urban mobility: Athey-Ferguson-Gentzkow-Schmidt '21, Couture-Dingel-Green-Handbury '21, Kreindler-Miyauchi '22, Gupta-Kontokosta-Van-Nieuwerburgh '22
- High-dimensional discrete choice models: Kloek-van-Dijk '78, Ackerberg '09 (for importance sampling); Jia '08, Antras-Fort-Tintelnot '14, Thomassen-Smith-Seiler-Schiraldi '17, Arkolakis-Eckert-Shi '21, Allen-Arkolakis '21
- Spatial incidence of Covid-19 pandemic shocks: Argente-Hsieh-Lee '22, Fajgelbaum-Khandelwal-Kim-Mantovani-Schaal '21, Giannone-Paixao-Pang '22, Althoff-Eckert-Ganapati-Walsh '22

Outline

Smartphone GPS Data from Japan

- Tracks anonymised GPS location every 5 minutes (minimum) whenever phone is on
  - From 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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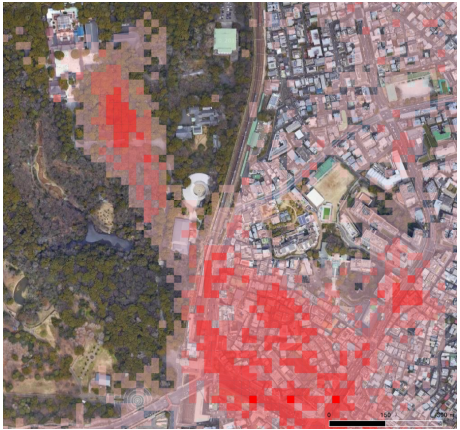
  - Other location: all other stays that are neither home nor work location
- We mostly focus on user-days in April 2019 whose:
  - first and last stays of the day is at home (to avoid overnight travelers)
  - whose workplace is assigned
  - and whose home and work is within Tokyo metropolitan area

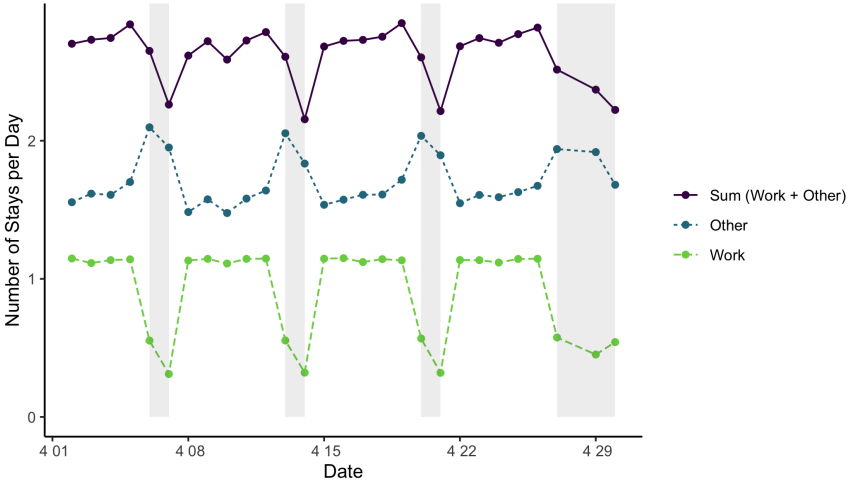
Example of Stays (around Meiji Shrine)



- 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

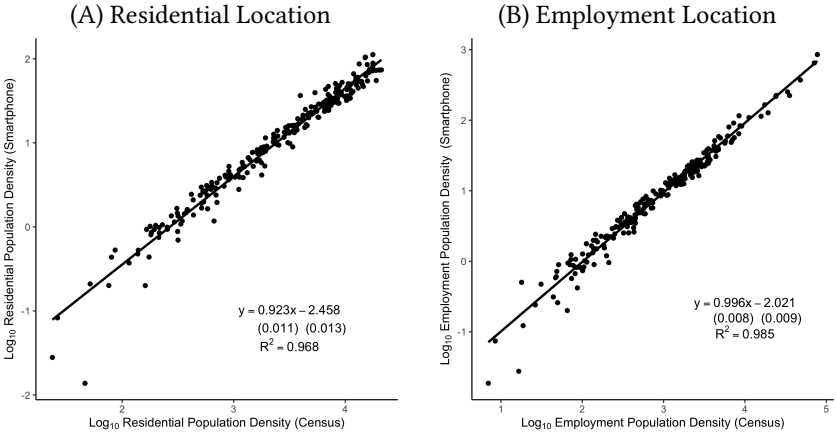
entire Tokyo metropolitan area

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

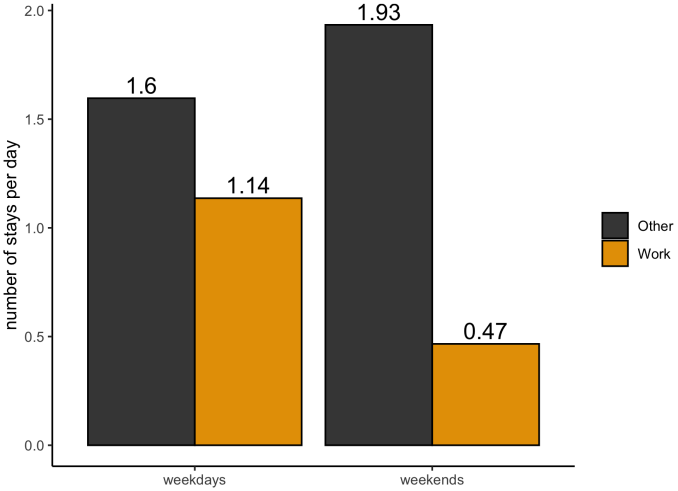
Outline

Patterns of Spatial Mobility

Document the patterns of non-commuting and commuting trips:

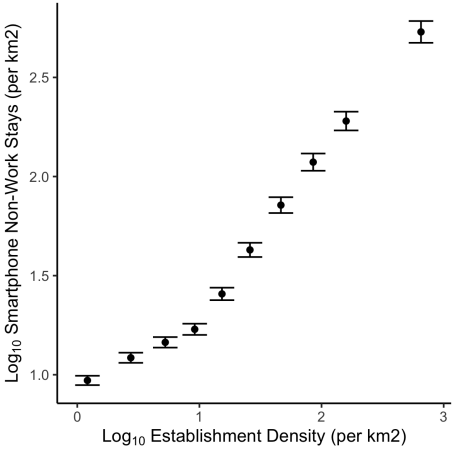
1. Non-commuting trips are frequent
2. Non-commuting trips are related to availability of non-tradable services
3. Non-commuting trips are closer to home on average than commuting trips
4. Non-commuting trips occur as a part of trip chains
5. Non-commuting and commuting trips are affected by the Covid-19 pandemic

1) Non-commuting trips are frequent



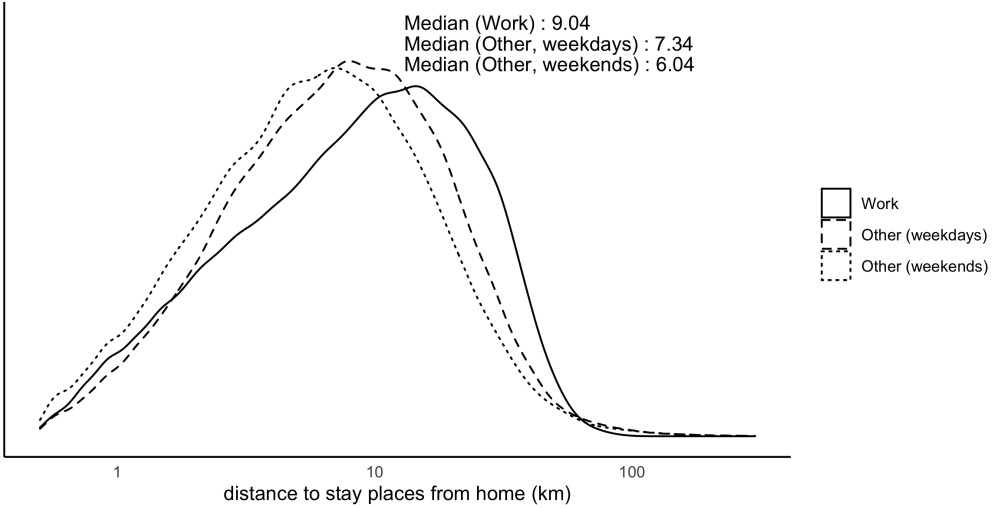
by hour travel survey

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

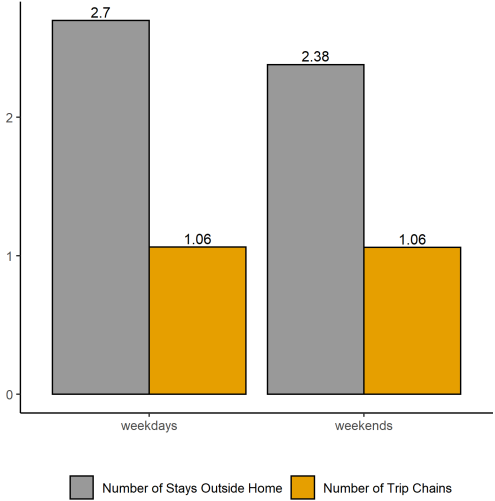


- Horizontal axis: number of establishments for nontradable services by nontradable sector

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

- 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

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

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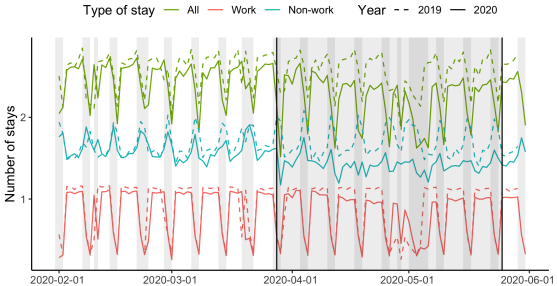
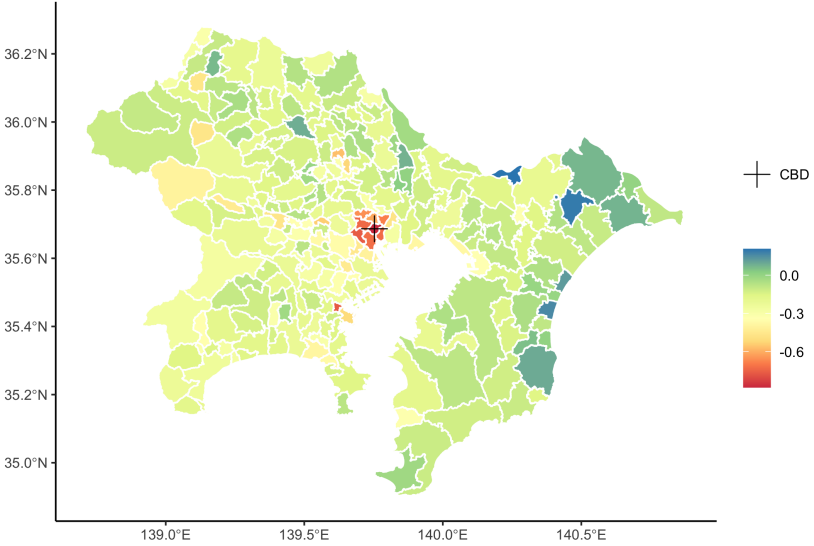
(A) Number of Stays per Day



(B) Median Distance of Stays from Home

trip chains

5) Reduction of foot traffic in downtown during pandemic



Outline

Travel Itinerary Decisions

- Develop a model of agents' travel itinerary decisions
- Two steps:
  1. Given residential location, decide workplace and employment sector given wages, commuting cost, and anticipated consumption access
  2. Given residential and employment locations, decide a set and sequence of consumption locations separately for workdays and non-workdays
- Solve the problem backward
- Later: embed this decision into a GE framework with residential location decision

Consumption Travel

- 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
  - $C(I)$: set of destinations excluding workplace j
- In each destination, a bundle of nontradable services is provided at (amenity-adjusted) price index P_n

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  - $C(I)$: set of destinations excluding workplace j
- In each destination, a bundle of nontradable services is provided at (amenity-adjusted) price index P_n
- Agent ω chooses I_ω that maximizes the indirect utility:

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

  - σ: elasticity of substitution
  - $\epsilon_{\omega I}$: idiosyncratic preference shock
  - $\tau_{I|hj}$: total iceberg travel cost; embrace travel cost saving through trip chains (i.e., $\tau_{\{1,2\}|hj} < \tau_{\{1\}|hj}\tau_{\{2\}|hj}$)

Consumption Travel Choice Probability

- 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

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

- Expected utility from consumption access given home h and workplace j:

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

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

Commuting

- Indirect utility with work j and sector $k \in T, S$ (tradable and nontradable) given home h:

$$U_{jk\omega|h} = w_{jk} \tilde{\mathbb{A}}_{hj}^{\alpha^S} \left(\tau_{hj}^W\right)^{-1} \epsilon_{jk\omega|h}^W$$

  - α^S: expenditure share for nontradable services
  - w_{jk}: wage; τ_{hj}^W: commuting cost; $\epsilon_{jk\omega|h}^W$: idiosyncratic preference (Fréchet with dispersion θ)

- Anticipated consumption access:

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

  - ξ: probability of going to work during the day

- Probability of choosing (j, k) given h:

$$\Omega_{jk|h} = \frac{\left(w_{jk} \tilde{\mathbb{A}}_{hj}^{\alpha^S} \left(\tau_{hj}^W\right)^{-1}\right)^{\phi}}{\sum_{j'} \sum_{k' \in \{T,S\}} \left(w_{j'k'} \tilde{\mathbb{A}}_{hj'}^{\alpha^S} \left(\tau_{hj'}^W\right)^{-1}\right)^{\phi}}$$

Simulating Travel Itinerary Choice

- Challenge for estimation and simulation: high-dimensionality of denominator of $\Lambda_{I|hj}$

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

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  1. Draw R itineraries $\{I_r\}$ from auxiliary distribution $F_{hj}(\cdot)$, obtain empirical distribution $\mathcal{E}_{I|hj}$ on $\mathcal{I}_{hj}^R \subset \mathcal{I}_{hj}$
  2. Weight each draw by the likelihood ratio between $F_{hj}(I)$ and $\Lambda_{I|hj}$

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

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- 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 finite-sample properties

Simulating Consumption Access

- Using simulated $\Lambda^*_{I|hj}$, we can construct consumption access $\mathbb{A}^*_{hj}$:

$$\mathbb{A}^*_{hj} = \varrho \left[\left(\sum_{n \in C(I)} P_n^{1-\sigma} \right)^{-\frac{1}{1-\sigma}} \tau^{-1}_{I|hj} \right]^{\theta} / \Lambda^*_{I|hj}$$

- For stability of simulation, use I that is most frequently drawn in auxiliary distribution

Estimation

- Parametrize travel cost for non-commuting travel as:

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

  - η: iceberg cost of stopping at an additional location
  - ρ: semi-elasticity of travel cost with respect to travel time (i.e., value of time)
  - $D_{I|hj}$: total travel time to follow itinerary I minus the direct round trip to workplaces $(D_{hj} + D_{jh})$

- Parametrize travel cost for commuting travel as:

$$\tau_{hj}^{W} = \exp\left(\rho\left(D_{hj} + D_{jh}\right)\right)$$

- Estimate $\{\eta, \rho, \theta, \sigma, \phi, \{P_n\}, \{w_{nk}\}\}$ through GMM

GMM Procedure

1. Given $\{\eta, \rho\}$, estimate $\{\theta, \sigma, \phi, \{P_n\}, \{w_{nk}\}\}$:
   1. Estimate $\{P_n\}$ and θ from destination choice *conditional on visiting only one location* by PPML:

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

   2. Estimate σ using the estimated price index:

$$\log P_n - \log p_n = \beta_0 + \frac{1}{1-\sigma} \log M_{nS} + \epsilon_n$$

      - p_n: variety-specific price (use official food price index)
      - M_{nS}: number of nontradable establishments; instrumented by the same value in 1980
   3. Estimate $\{w_{jk}\}$ and ϕ from commuting gravity equations (with simulated $\tilde{\mathbb{A}}_{hj}$):

$$\Omega_{jk|h} = \frac{w_{jk}^{\phi} \tilde{\mathbb{A}}_{hj}^{\phi\alpha^S} \exp(-\rho\phi\left(D_{hj} + D_{jh}\right))}{\sum_{j'} \sum_{k' \in \{T,S\}} w_{j'k'}^{\phi} \tilde{\mathbb{A}}_{hj'}^{\phi\alpha^S} \exp(-\rho\phi\left(D_{hj'} + D_{j'h}\right))}$$

2. Estimate $\{\eta, \rho\}$ by GMM with moments: (1) number of stays per day (use simulated and observed $\Lambda_{I|hj}$; for η) and (2) variance of residential income (for ρ)

Estimate parameters for consumption itinerary choice: Results

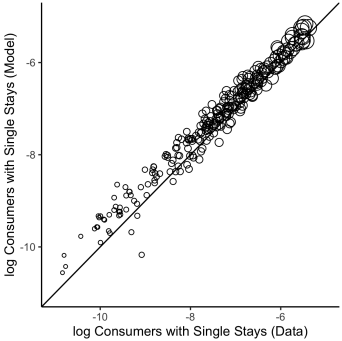
- Spatial unit: 240 municipalities in Tokyo metropolitan area
- Draw 200 importance samples for each home-work
- Assume maximum number of stays per day = 5

Parameters	Values	Estimated Parameters
σ	5.3	Elasticity of substitution
θ	4.5	Dispersion of Fréchet shocks for travel itinerary choice
ϕ	3.04	Dispersion of Fréchet shocks for workplace choice
ρ	0.69	Travel cost per hour
η	2.1	Travel cost of stopping at a location
Parameters	Values	Calibrated Parameters
ξ	0.71	Fraction of workdays
α^S	0.6	Expenditure share of nontradable sector

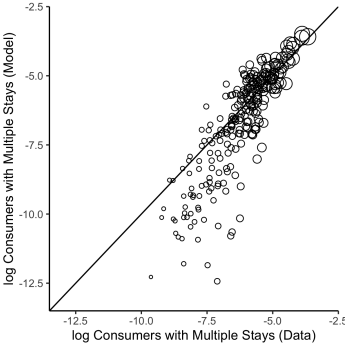
- Visiting an additional location is equivalent to $\log(\eta)/\rho \approx 1$ hours of additional travel

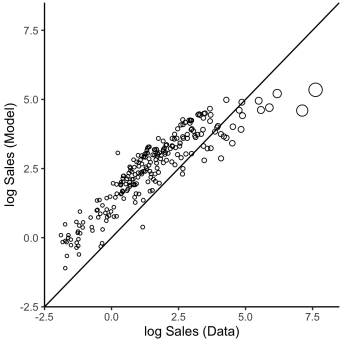
Model Fit

(i) targeted moments



(ii) untargeted moments





Outline

General Equilibrium

Embed itinerary decision into a canonical GE urban model (e.g., Ahlfeldt et al '15; Tsivanidis '19) 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 based on rents, residential amenity, and anticipated workplace and consumption access
- Labor market clearing $\Rightarrow$ wages
- Floor space market clearing $\Rightarrow$ rents
- Goods market clearing $\Rightarrow$ nontradable prices
- Amenity and productivity spillovers

Calibration of General Equilibrium Parameters

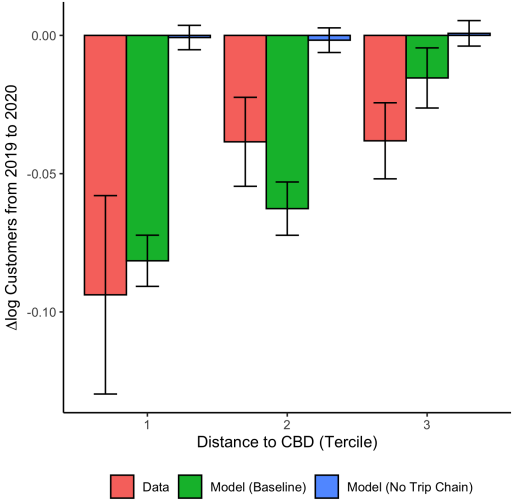
Parameter	Description	Value	Source
α^H	expenditure share for residential floor space	0.25	Data
β^S	labor share in production for nontradable sector	0.8	Data
β^T	labor share in production for tradable sector	0.8	Data
η^W	elasticity of production spillover in tradable sector	0.19	$\beta^S/(\sigma-1)$
η^B	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

Covid-19 Pandemic

- Use our model to predict the change of peoples' movement patterns during pandemic
- 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 ($\{R_n, L_n, P_n, w_n, Q_n\}$)
- Compare against the model where agents visit only one consumption location from home

Model accurately predicts decline of consumer foot traffic in downtown

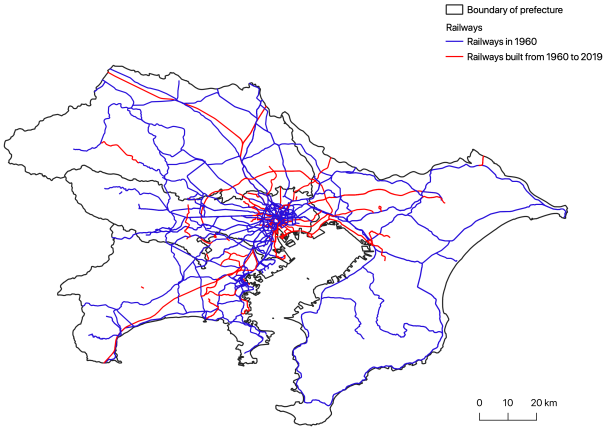


fit to other moments | comparison to GE | alternative calibration to "Model (No Trip Chain)"

Outline

Transportation Infrastructure

- Assess impacts of public transit that was developed in Tokyo metropolitan areas after 1960
- Counterfactuals to remove these public transit (increase of travel time)



Transportation Infrastructure

- Evaluate change in residential welfare:

$$\mathbb{E}[\max_h U_{h\omega}] = \varrho^R \left[\sum_h B_h^\theta Q_h^{-\theta\alpha^H} \left(\sum_{j'} \sum_{k' \in \{T,S\}} \left(w_{j'k'} \tilde{\mathbb{A}}_{hj'}^{\alpha^S} \left(\tau_{hj'}^W \right)^{-1} \right)^\phi \right)^{\theta/\phi} \right]^{1/\theta}$$

	Δ Welfare (%)	Relative to Baseline (%)
(1) Baseline	-7.4	100
(2) No Consumption Trips	-5.8	78
(3) No Trip Chains (Single Consumption Location from Home)	-6.0	81
(4) No Trip Chains (All Consumption Locations from Home)	-6.5	88

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

changes of GE variables

Outline

Conclusions

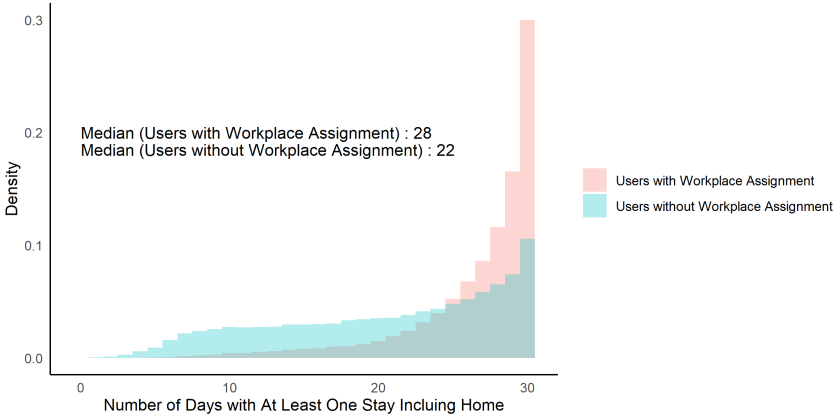
- We analyze spatial mobility using smartphone data and a new model of travel itinerary
- We develop the importance sampling method to overcome high-dimensionality issue
  - Can be applied to other applications such as bundled product and store choice, establishment location choices, import choices, shipping route choices, ...
- We show that accurately capturing patterns of spatial mobility is crucial for assessing mobility shocks such as Covid-19 pandemic and transportation infrastructure improvement

Thank You

Appendix

Number of Days with Stays with and without Workplace Assignment

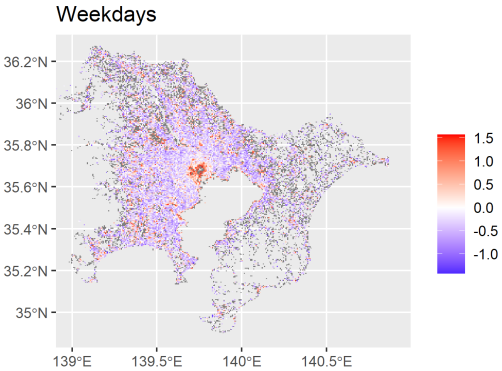
go back

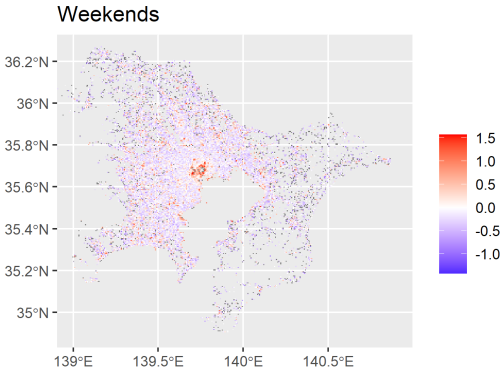


- Many devices with missing workplace assignments are not used every day

Log Difference of Day- and Night-time Population

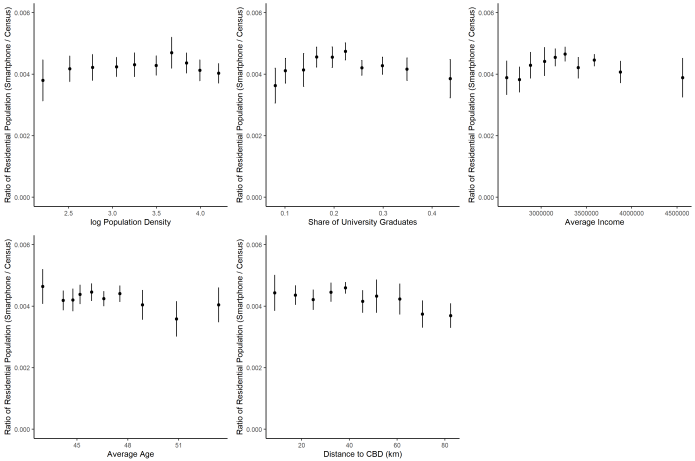
go back





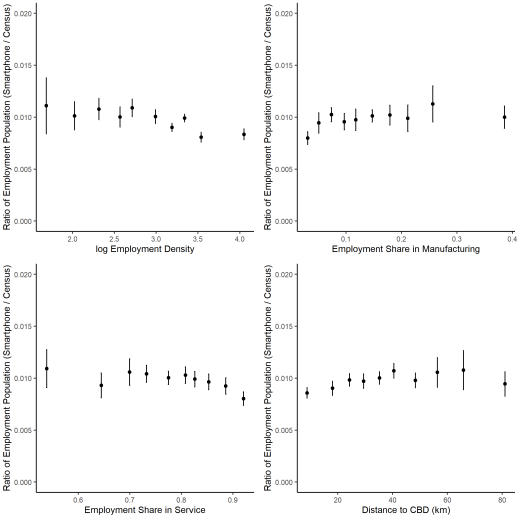
- Log Difference between Day-time and Night-time population is greater during weekdays than during weekends

Coverage of Smartphone Users by Residential Location back



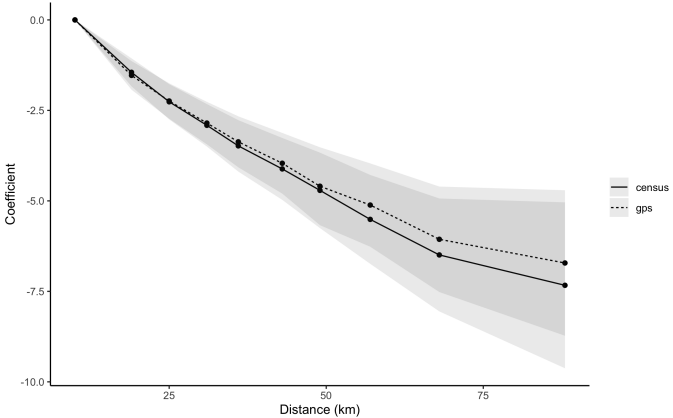
- Divide municipalities into 10 strata (23 wards in central Tokyo aggregated into one unit)

Coverage of Smartphone Users by Employment Location back



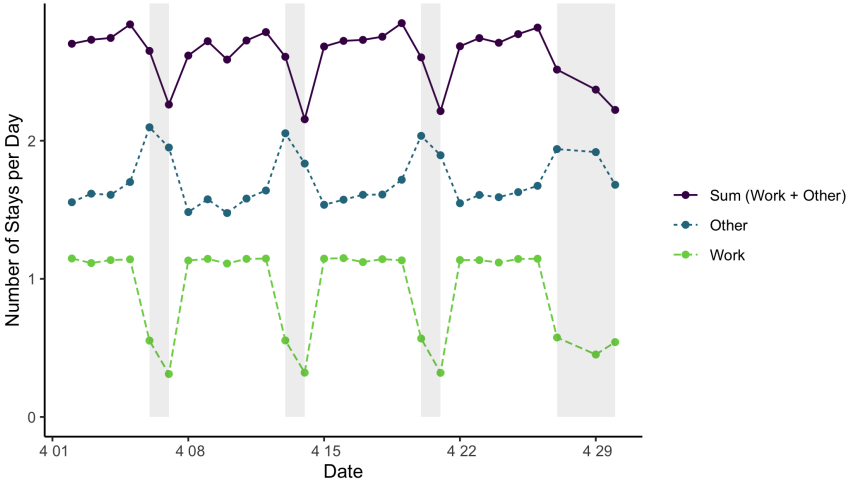
Validation of Commuting Flows go back

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



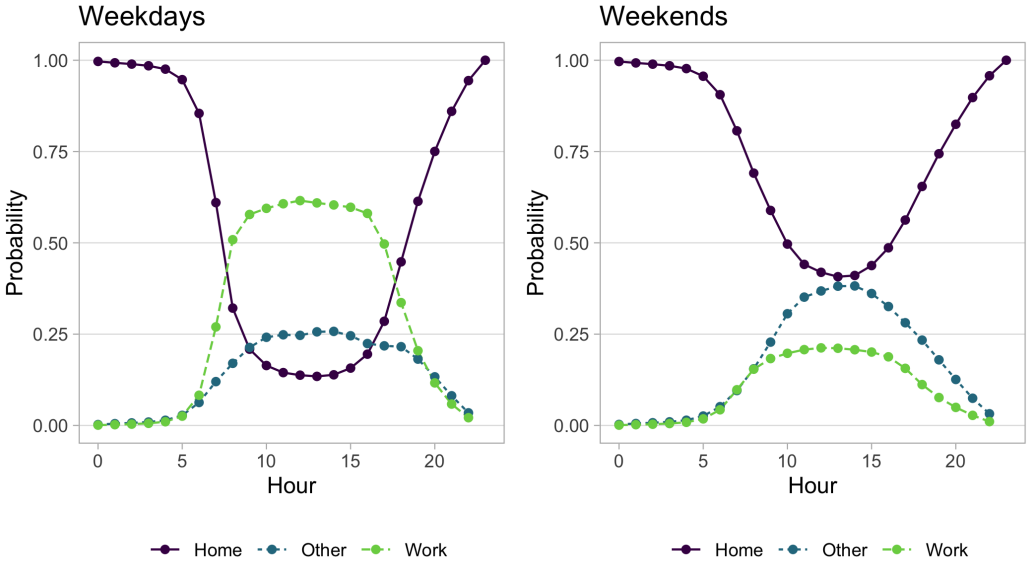
- Gravity regression including workplace fixed effects, residence fixed effects and indicator variables for distance grid cells

Stays by Day go back

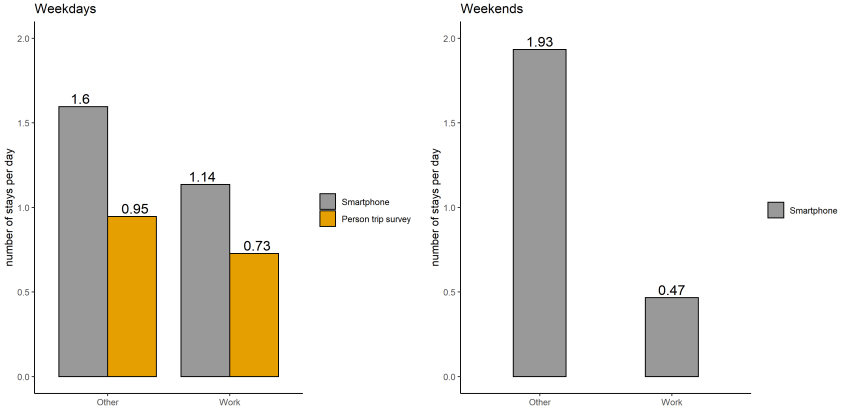


- Work and non-work stays display expected patterns on weekdays v. weekends

Stay by Hour go back

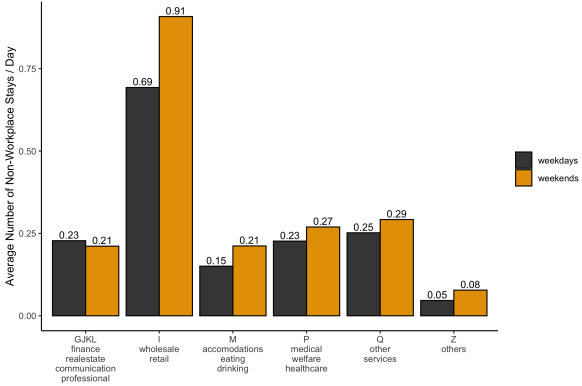


Frequency of Stays | Smartphone vs. Travel Survey go back



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

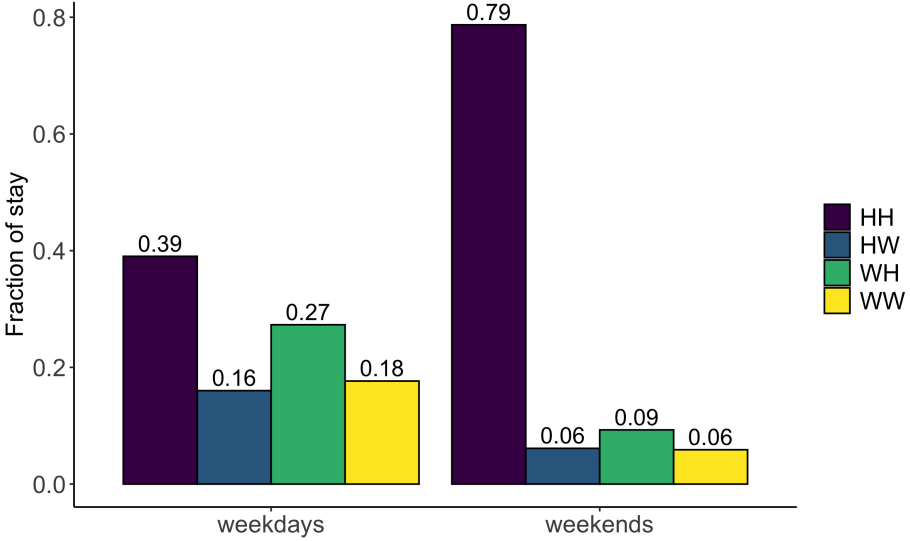
go back



- 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."

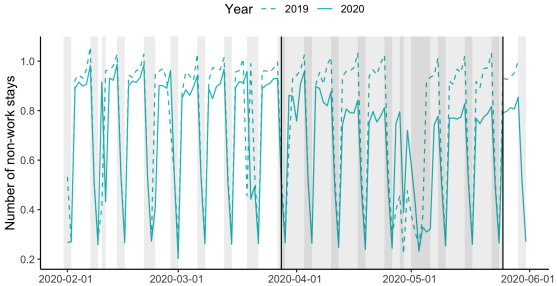
Trip Chains | Weekdays vs. Weekends

go back

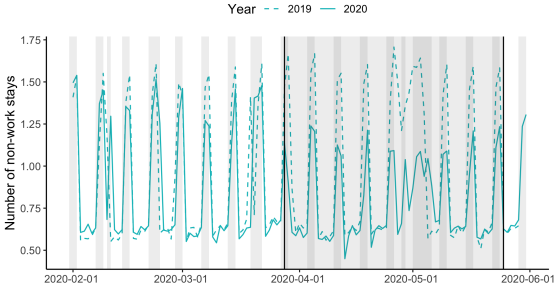


5) Non-commuting trips an trip chains during pandemics go back

(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)

General Equilibrium: Agents' Residential Location Choice

- Indirect utility with home h:

$$U_{h\omega} = B_h Q_h^{-\alpha^H} \left(\sum_{j'} \sum_{k \in \{T,S\}} \left(w_{j'k} \tilde{\mathbb{A}}_{hj'}^{\alpha^S} \left(\tau_{hj'}^W \right)^{-1} \right)^{\phi} \right)^{1/\phi} \epsilon_{h\omega}^R$$

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

$$\Omega_h^R = \frac{\left(B_h Q_h^{-\alpha^H} \right)^{\phi} \sum_{j'} \sum_{k \in \{T,S\}} \left(w_{j'k} \tilde{\mathbb{A}}_{hj'}^{\alpha^S} \left(\tau_{hj'}^W \right)^{-1} \right)^{\phi}}{\sum_{h'} \left(B_{h'} Q_{h'}^{-\alpha^H} \right)^{\phi} \sum_{j'} \sum_{k \in \{T,S\}} \left(w_{j'k} \tilde{\mathbb{A}}_{h'j'}^{\alpha^S} \left(\tau_{h'j'}^W \right)^{-1} \right)^{\phi}}$$

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

$$P_i^T = \frac{1}{A_{iT}} w_{iT}^{\beta^T} Q_i^{1-\beta^T}, \qquad 0 < \beta^T < 1$$

- 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:

$$H_i = H_i^U + \sum_{k \in \{T,S\}} H_{ik}$$

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

- Nontradeable service market clearing:

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

go back

Practical Choice of Auxiliary Distribution for Importance Sampling

go back

The proposed itinerary I is simulated in the following order:

1. For each h and j, randomly generate the total number of stays, $|I|$, and the number of stays that agents make up to the stay at workplace (if any), ι, from the observed distribution in the data.
2. Determine the i-th location n_i starting from $i = 1$.
   - If the i-th location of the day is at workplace (i.e., $i = \iota$), set the stay location as $n_i = j$.
   - If the i-th location of the day is not at workplace, assume that agents choose the location myopically without considering subsequent stays. Namely, denoting the itinerary up to $(i-1)$-th stay by I_{i-1}, we sample n_i following the probability:

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

3. Repeat Step 2 for $i = 1, \ldots, |I|$.

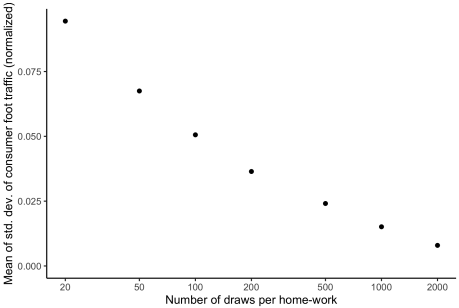
Finite-Sample Properties of Importance Sampling

go back

(A) Finite-Sample Bias

Number of draws per home-work	10th pctl	25th pctl	50th pctl	75th pctl	90th pctl
20	0.84	0.88	0.93	0.98	1.00
50	0.88	0.93	0.96	0.99	1.01
100	0.92	0.95	0.97	0.99	1.01
200	0.94	0.96	0.98	0.99	1.00
500	0.97	0.98	0.99	1.00	1.00
1000	0.99	0.99	1.00	1.00	1.00
2000	1.00	1.00	1.00	1.00	1.00

(B) Finite-Sample Variance



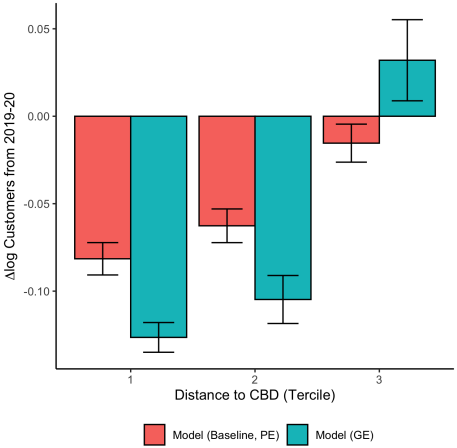
Covid-19 Counterfactual: Fit to Other Moments

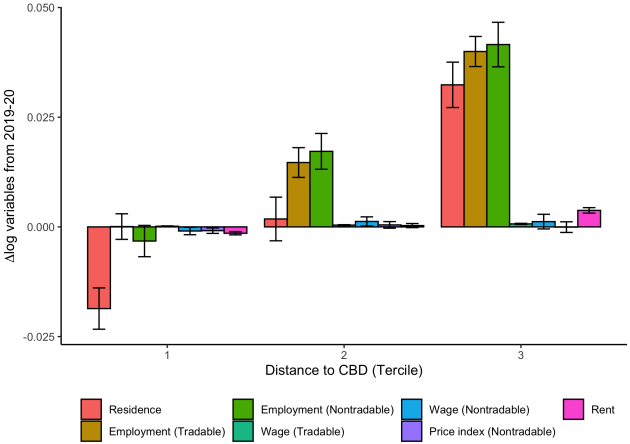
go back

	(1) Data	(2) Model (Baseline)	(3) Model (No Trip Chain)
(a) Targeted Moments			
(a-1) Δ log probability of work stay per day	-0.04	-0.04	-0.04
(a-2) Δ gravity coefficient conditional on visiting only one location	-0.27	-0.27	-0.27
(b) Untargeted Moments			
(b-1) Δ log number of nonwork stay per user-day	-0.06	-0.08	0.00
(b-2) Δ log number of nonwork stay per user-day given workdays	-0.04	-0.07	0.00
(b-3) Δ log number of nonwork stay per user-day given non-workdays	-0.10	-0.09	0.00
(b-4) Δ log median distance to nonwork stays from home	-0.19	-0.19	-0.06

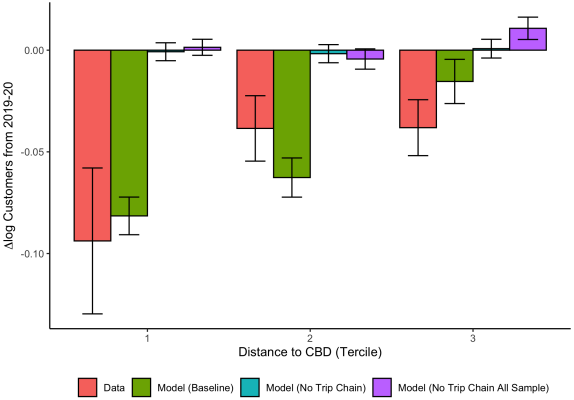
Covid-19 Counterfactual: General Equilibrium

go back





Covid-19 Counterfactual: Alternative Calibration to Model (Gravity) go back



Transportation Counterfactual: General Equilibrium Variables

go back