From Biases to Opportunities: Leveraging Location-based-service (LBS) data for planning and policy analysis

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2025 Modeling Mobility Conference

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Outline

> Definition and Motivation

> Quantifying biases in Location-Based-Service (LBS) data
  - Data stability, sparsity, pre- and post-processing, algorithms, and socio-demographic and built environment factors

> Where opportunities lie in transportation planning and policy designs?

> Looking forward
  - Methodological directions
  - Practical whole-community effort

LBS Data: location- and time stamped

> Indicate where and when a mobile device is being sighted

LBS Data Generators

- Communications Companies
  - ATT, T-Mobile, Verizon
- App Service Providers
  - X, Instagram, Foursquare
- Vehicle Tracking on Entity Assets
  - Public and private telematics programs
- Mode-specific Location Tracking
  - Transit smartcard
  - Taxi traces
  - Ride sourcing (Uber)
  - Shared micromobility (e-bikes, e-scooters)

Data Aggregators and Distributors

- Veraset
- Spectus
- Safegraph

Data Products Sellers

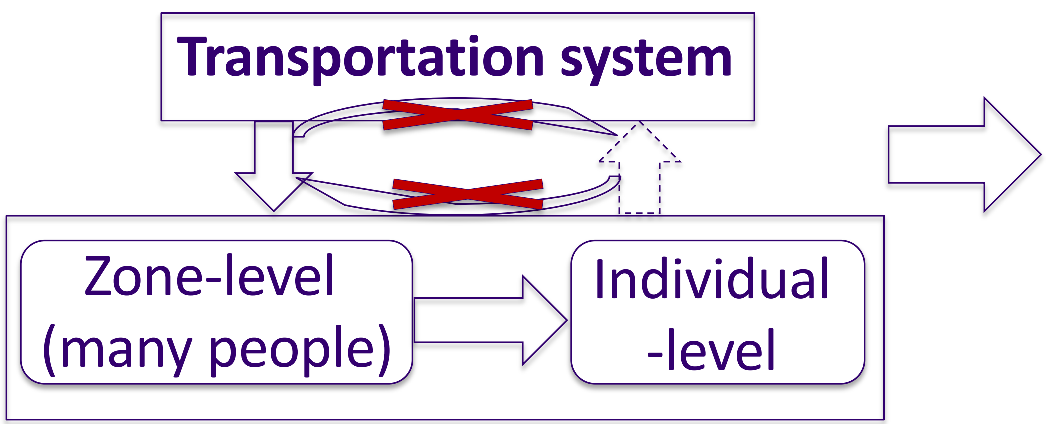
- Streetlight
- Replica

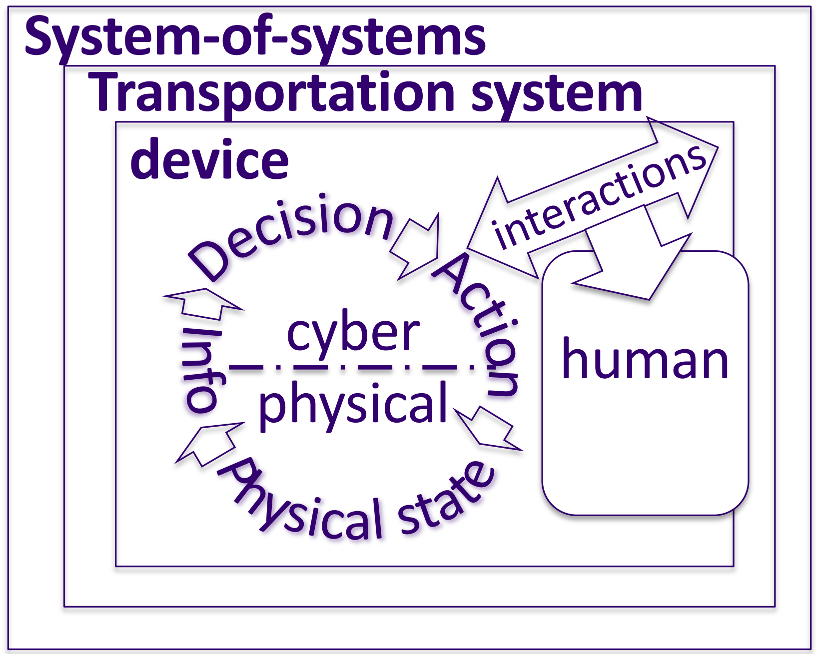
LBS Data: Key Features

> **Key features**

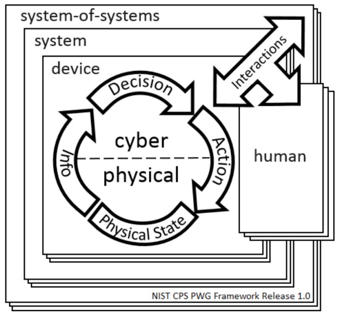
- Big: 1-10% in the U.S.; and up to 30% in some Asian countries (e.g., Singapore and South Korea) ➔ capturing diverse travel patterns
- Continuous/longitudinal: days to weeks and months and even years
- Most lack socio-demographics though

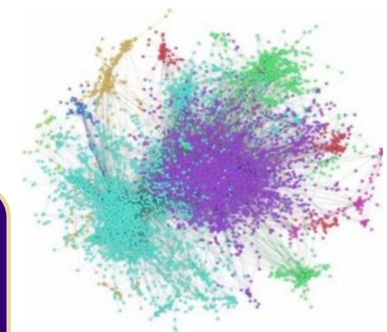
Toward smarter planning, policy designs and feedback





LBS Data: Opportunities for Transportation Planning and Policy Designs





Sensing

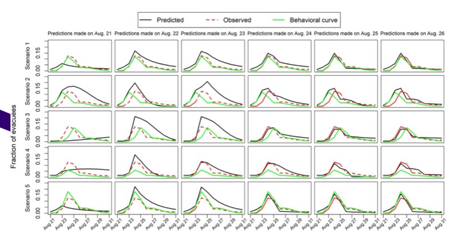
Measurement

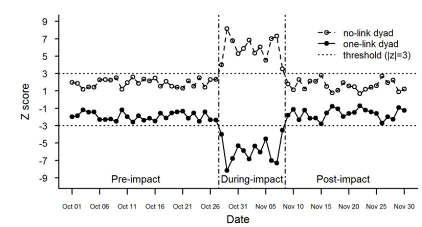
Monitoring

Learning

Management

cyber physical





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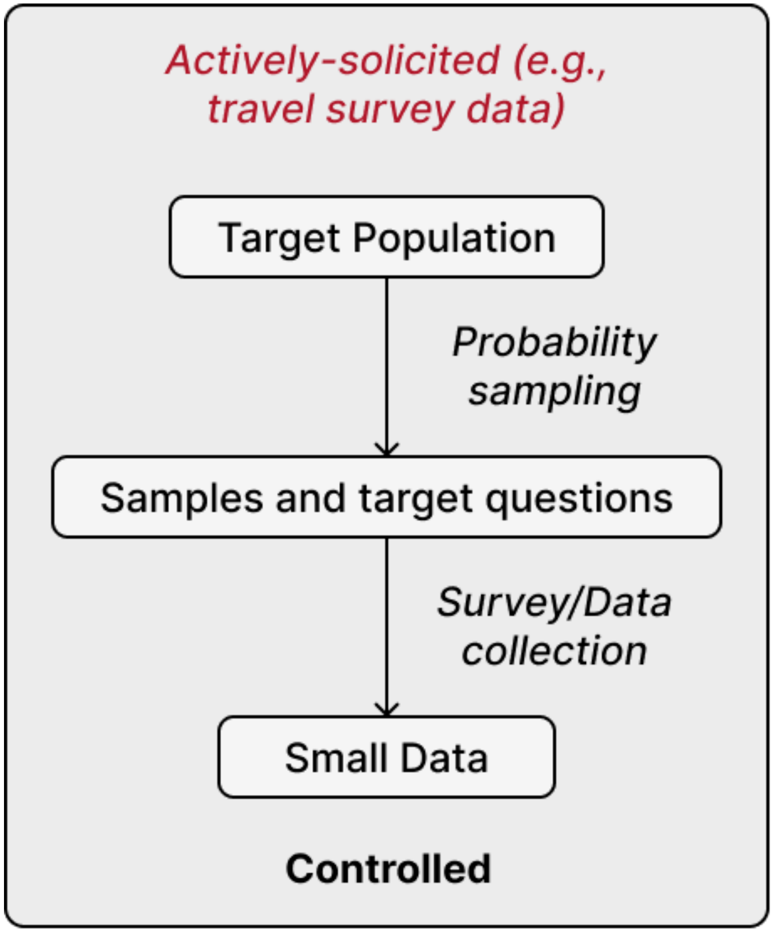
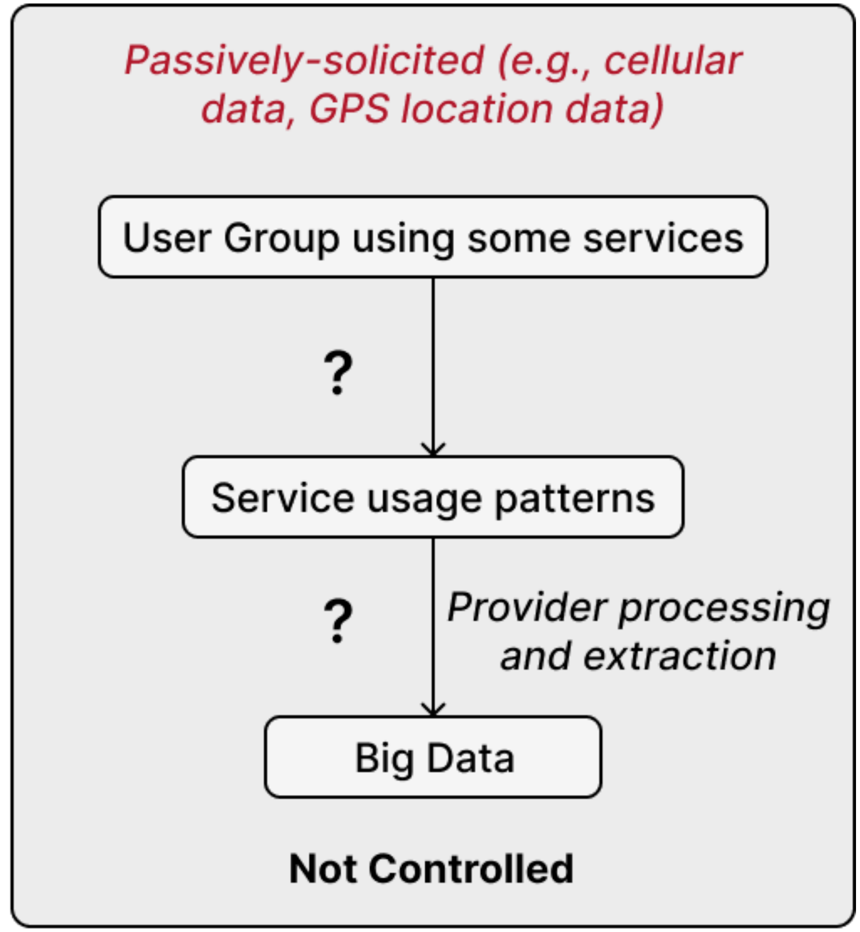
Lack of transparency on the data is the No.1 concern



Active Data Generation



Passive Data Generation

Table 1. An example HTS (left) and LBS dataset (right)

Actively-generated HTS data						
Date	Departure Time	Arrival Time	Departure Census Tract[1]	Arrival Census Tract[1]	Trip Purpose	Main Travel Mode
2020-01-02	7:00 AM	7:45 AM	53033006100	53033005300	Work	Bus
2020-01-02	12:00 PM	12:20 PM	53033005300	53033005200	Lunch	Walk
2020-01-02	12:45 PM	1:10 PM	53033005200	53033005300	Work	Walk
2020-01-02	4:30 PM	4:50 PM	53033005300	53033005100	Recreation	Bus
2020-01-02	5:50 PM	6:40 PM	53033005100	53033006100	Home	Bus

[1] HTS collects lat and long information for every trip origin and destination, which are then converted to census tracts.

Passively-generated LBS data			
Time	Latitude	Longitude	Location Accuracy (m)
2020-01-02 7:13:30	42.824731	-71.115226	65
2020-01-02 7:29:11	42.837882	-71.057814	20
2020-01-02 11:11:31	42.851232	-70.913241	12
2020-01-02 13:10:22	42.858141	-70.913241	5
2020-01-02 18:32:38	42.823326	-71.112916	10

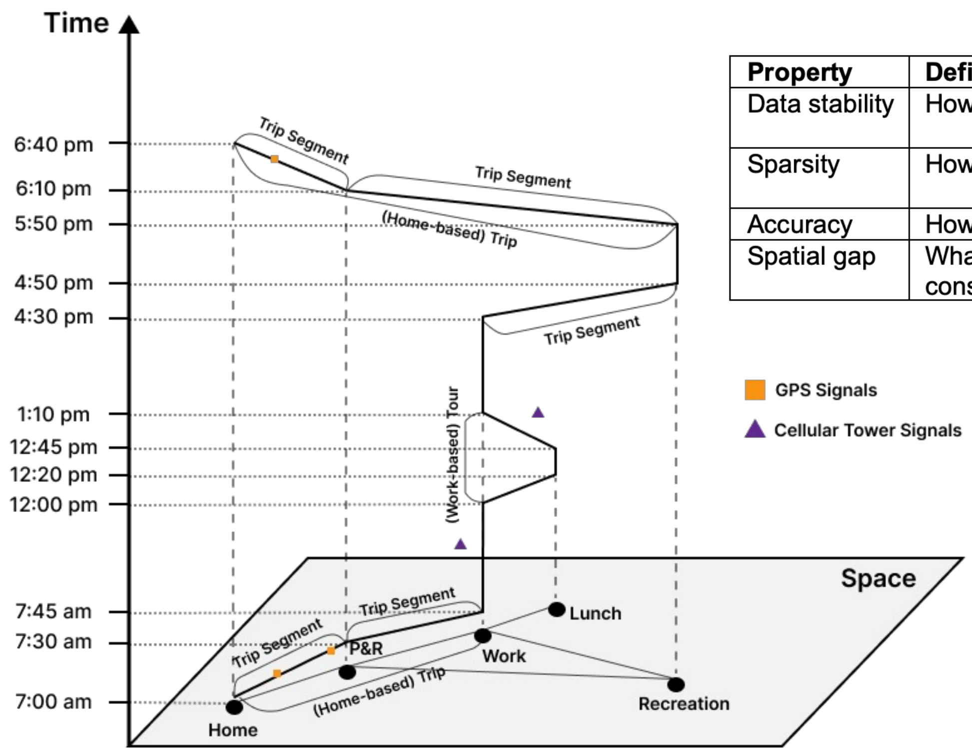


Table 3. Properties of LBS Data

Property	Definition	Metric
Data stability	How stable is the LBS data over time?	Number of devices per time period Number of records per person per day
Sparsity	How temporally sparse is the LBS data?	Intra-day occupancy Inter-day occupancy
Accuracy	How spatially accurate is the LBS data?	Locational accuracy in meters
Spatial gap	What is the spatial gap (in km) between consecutive observations?	Jumping distance in kilometers

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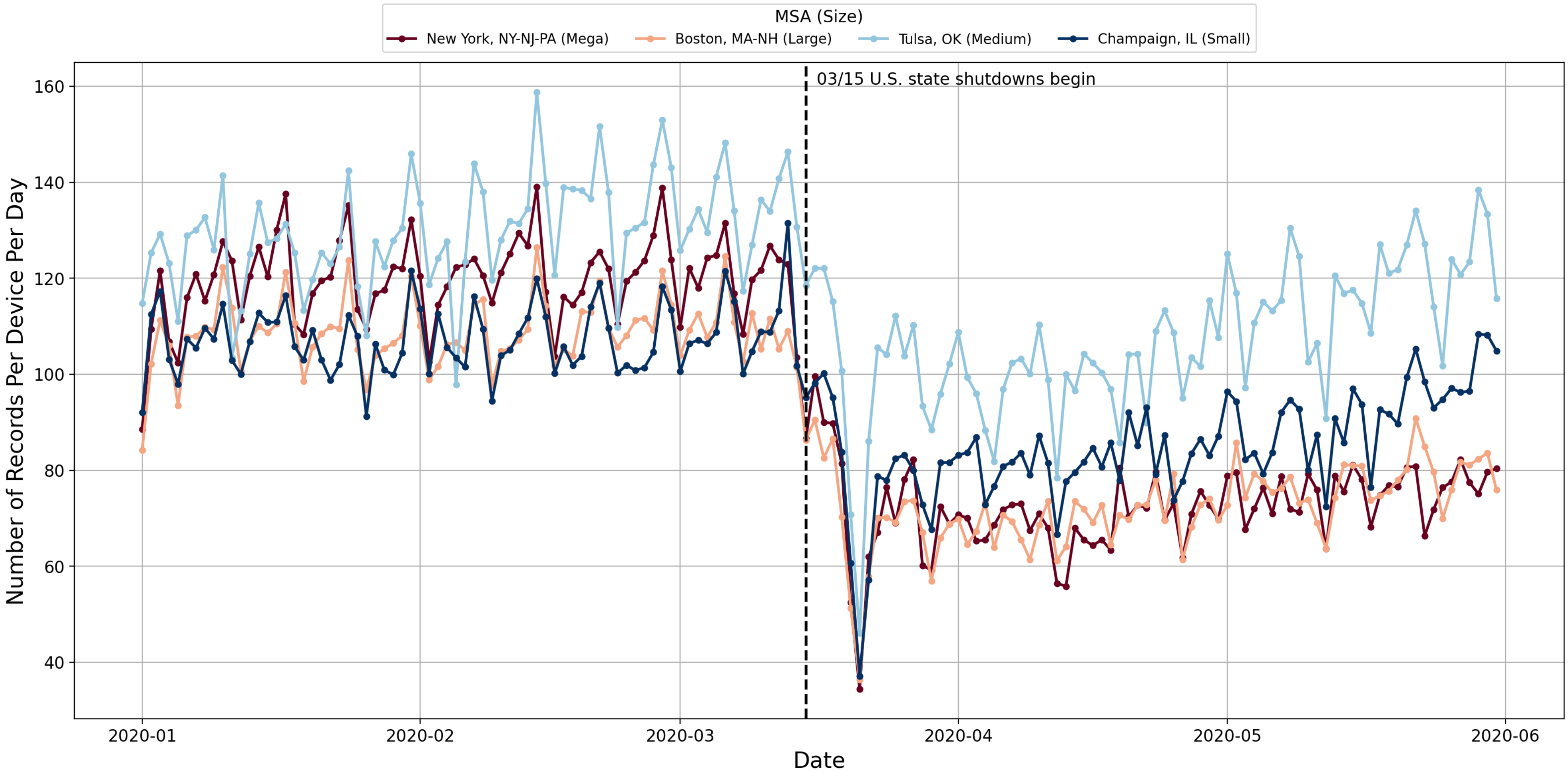
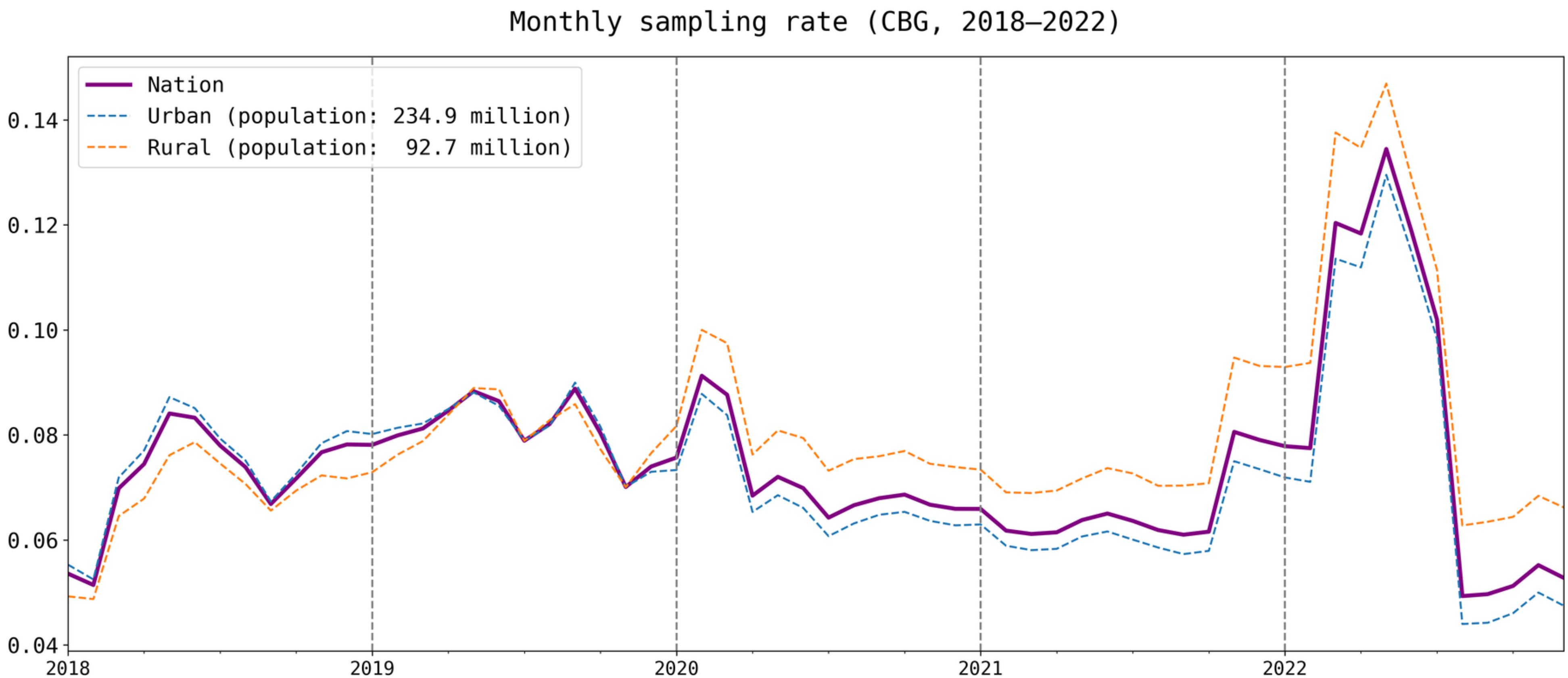
A sample of 11 metro regions in U.S.

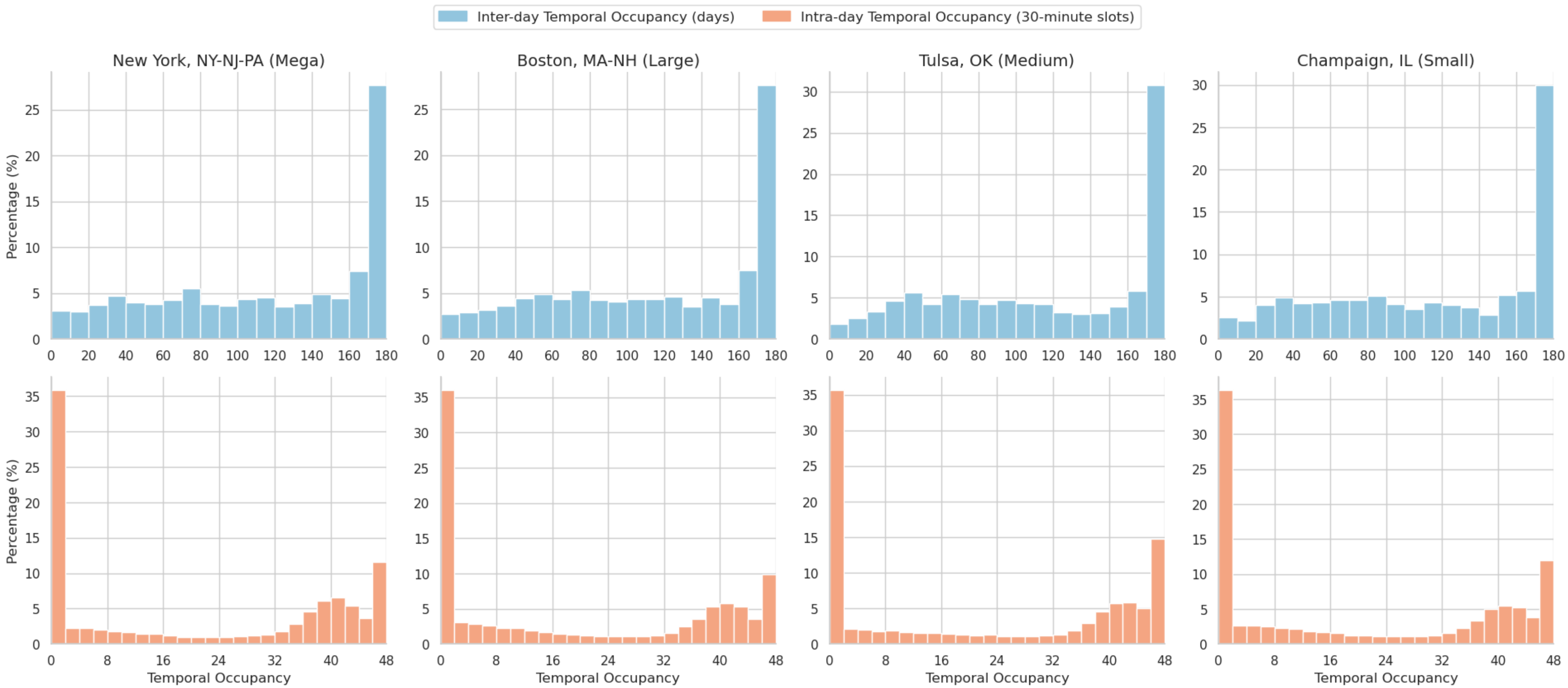
MSA Type	MSA Name	Population	Sampling rate[1] (%)	Study sample size[2]	Population density (pp/sq. m^2)
Mega	*New York-Newark-Jersey City, NY-NJ-PA*	*22,432,947*	*4.8*	*15,992*	*2,934.9*
	Los Angeles-Long Beach-Anaheim, CA	12,872,322	4.2	15,000	2,652.9
Large	*Boston-Cambridge-Newton, MA-NH*	*4,900,550*	*6.1*	*10,000*	*1,405.7*
	Seattle-Tacoma-Bellevue, WA	4,034,248	4.6	10,000	687.3
	Baltimore-Columbia-Towson, MD	2,844,510	10.1	10,000	1,090
Medium	*Tulsa, OK*	*1,034,123*	*10.6*	*10,000*	*164.8*
	Fresno, CA	1,171,617	7.5	10,000	170.4
	Tyler, TX	233,479	11.7	10,000	262.5
Small	*Champaign-Urbana, IL*	*236,514*	*7.9*	*10,000*	*155.6*
	Sebring-Avon Park, FL	105,618	10.0	10,000	103.8
	Cheyenne, WY	100,984	8.1	9,008	37.5

[1] Sampling rate is the ratio of number of unique devices with an inferred home location located in the area divided by the area's population. [2] Study sample size is the size of the data used for the analysis in this paper.

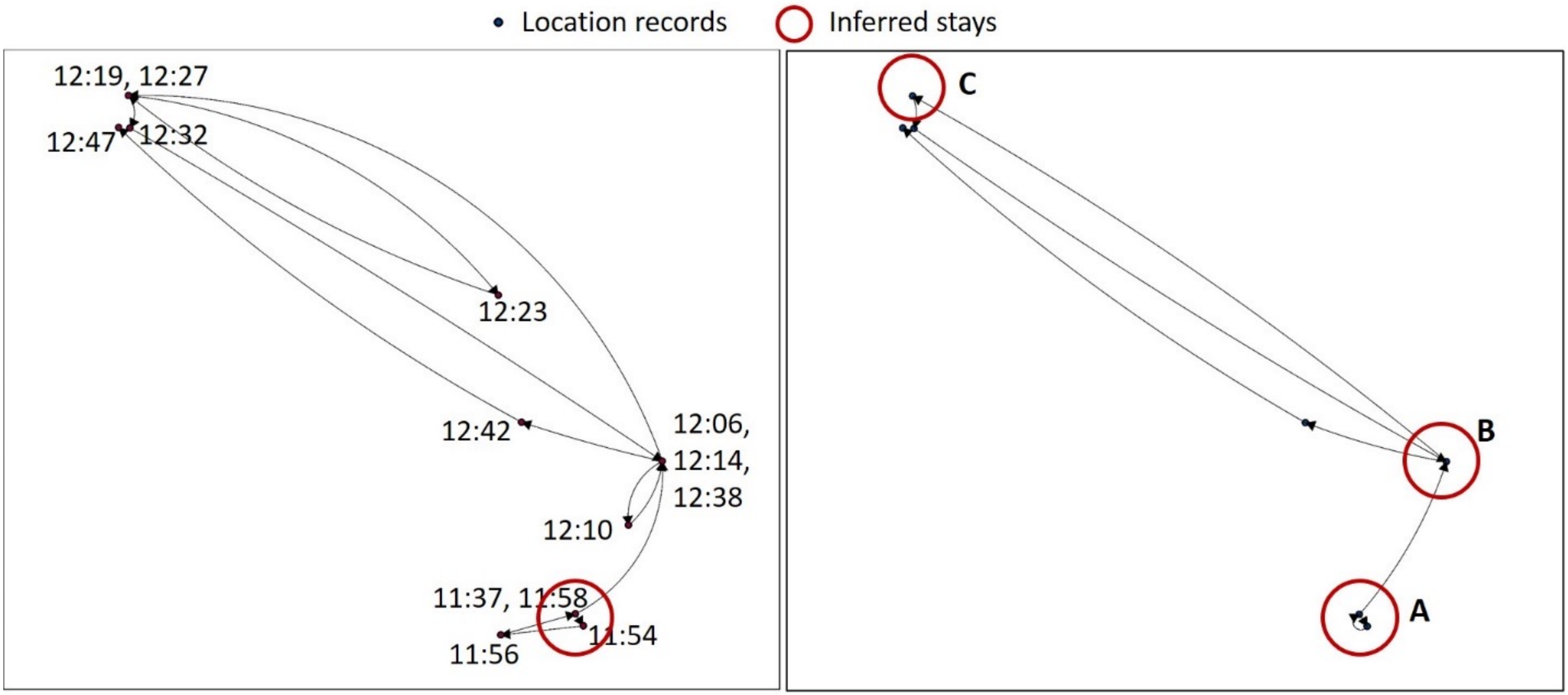

MSA (Size)
New York, NY-NJ-PA (Mega)
Boston, MA-NH (Large)
Tulsa, OK (Medium)
Champaign, IL (Small)
03/15 U.S. state shutdowns begin
Number of Records Per Device Per Day
160
140
120
100
80
60
40
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
Date



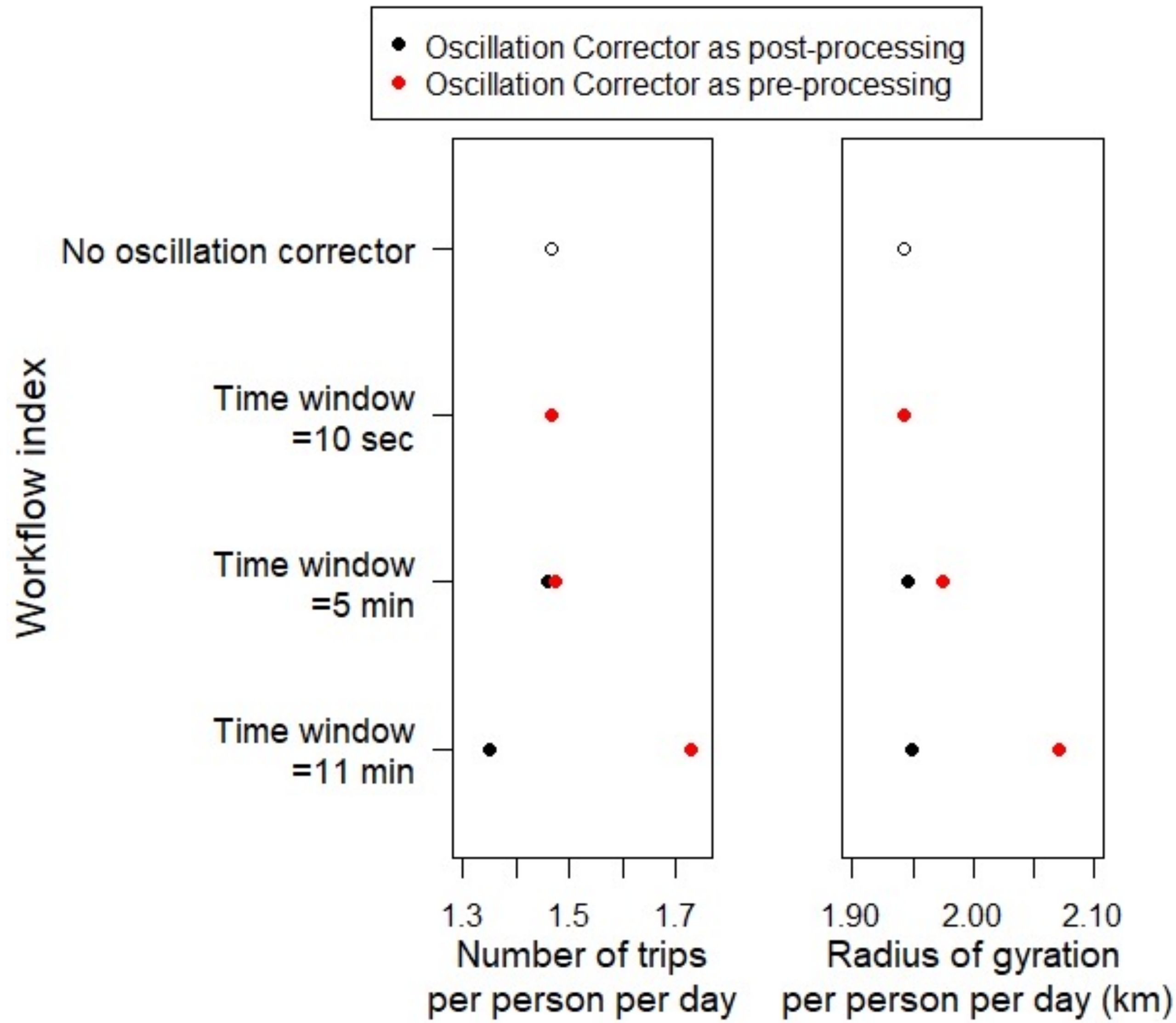
Li et al. (2024) "Understanding the bias of mobile location data across spatial scales and over time: A comprehensive analysis of SafeGraph data in the United States. Plos One. January 19th.

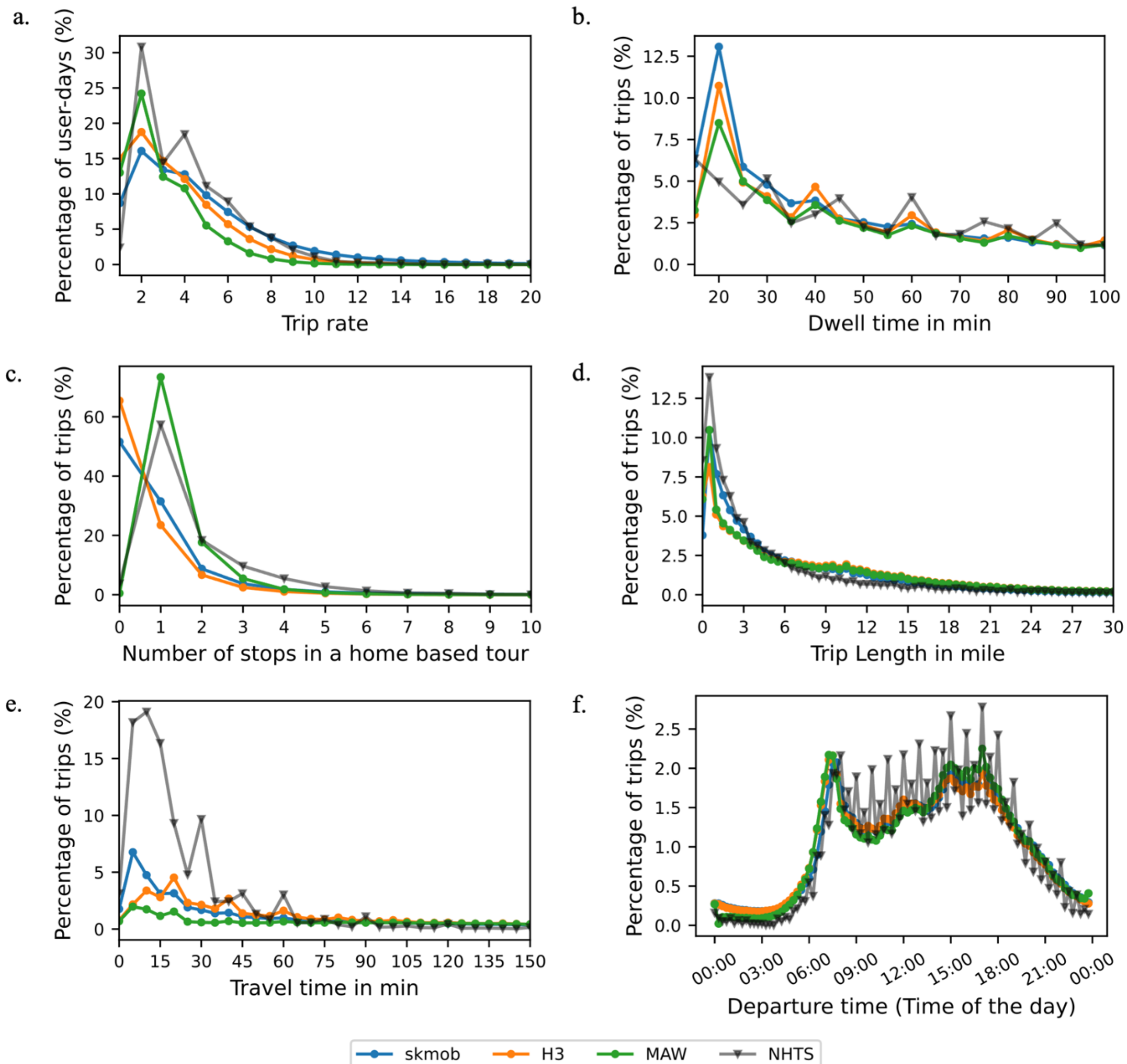


Inter-day Temporal Occupancy (days)
Intra-day Temporal Occupancy (30-minute slots)
New York, NY-NJ-PA (Mega)
Boston, MA-NH (Large)
Tulsa, OK (Medium)
Champaign, IL (Small)
Percentage (%)
Temporal Occupancy

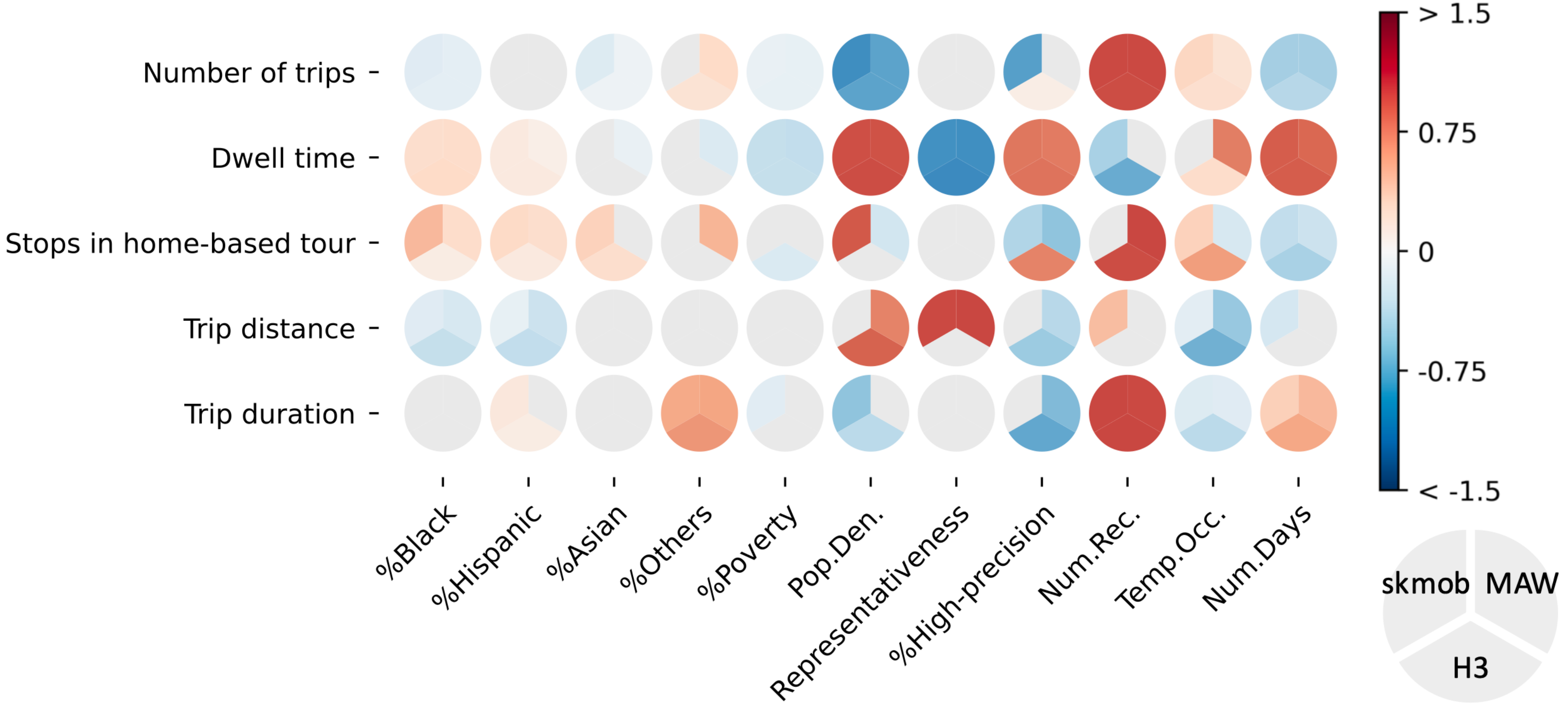


Location records
Inferred stays
12:19, 12:27
12:47
12:32
12:23
12:42
12:06,
12:14,
12:38
12:10
11:37, 11:58
11:54
11:56
C
B
A


Oscillation Corrector as post-processing
Oscillation Corrector as pre-processing
Workflow index
No oscillation corrector
Time window =10 sec
Time window =5 min
Time window =11 min
1.3
1.5
1.7
Number of trips per person per day
1.90
2.00
2.10
Radius of gyration per person per day (km)



a.
Percentage of user-days (%)
Trip rate
b.
Percentage of trips (%)
Dwell time in min
c.
Percentage of trips (%)
Number of stops in a home based tour
d.
Percentage of trips (%)
Trip Length in mile
e.
Percentage of trips (%)
Travel time in min
f.
Percentage of trips (%)
Departure time (Time of the day)
skmob
H3
MAW
NHTS


Number of trips
Dwell time
Stops in home-based tour
Trip distance
Trip duration
%Black
%Hispanic
%Asian
%Others
%Poverty
Pop.Den.
Representativeness
%High-precision
Num.Rec.
Temp.Occ.
Num.Days
> 1.5
0.75
0
-0.75
< -1.5
skmob
MAW
H3

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Where do opportunities lie?

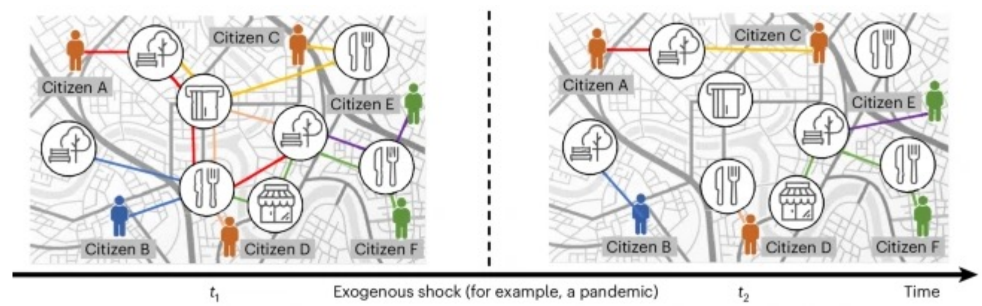
> Aiding National Household Travel Survey (NHTS) data

– Emerging modes of transportation



> Analysis of travel patterns by population segments

– Equity
– Job-housing balance
– Access to services
– Exposure to noise and pollutions
– Community resilience and adaptations



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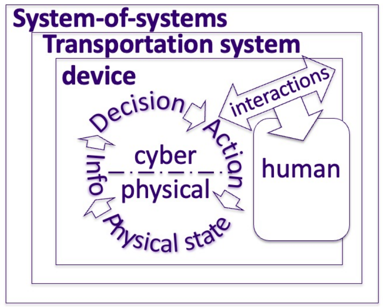
Where do opportunities lie?

> Next-generation travel demand management program

– Real-time and context-aware;

– Personalized;

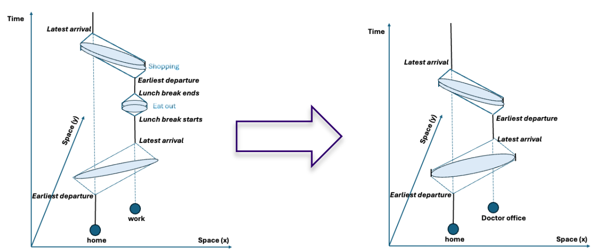
– Trajectory-aware



> LBS as foundational data for micro-simulation of travel patterns

– HTS Survey data ➔ fusion of small (HTS) and big (LBS);

– Trip-based model ➔ activity-based model ➔ digital twin



Simulated travel patterns that continuously evolve in response to internal and external shocks

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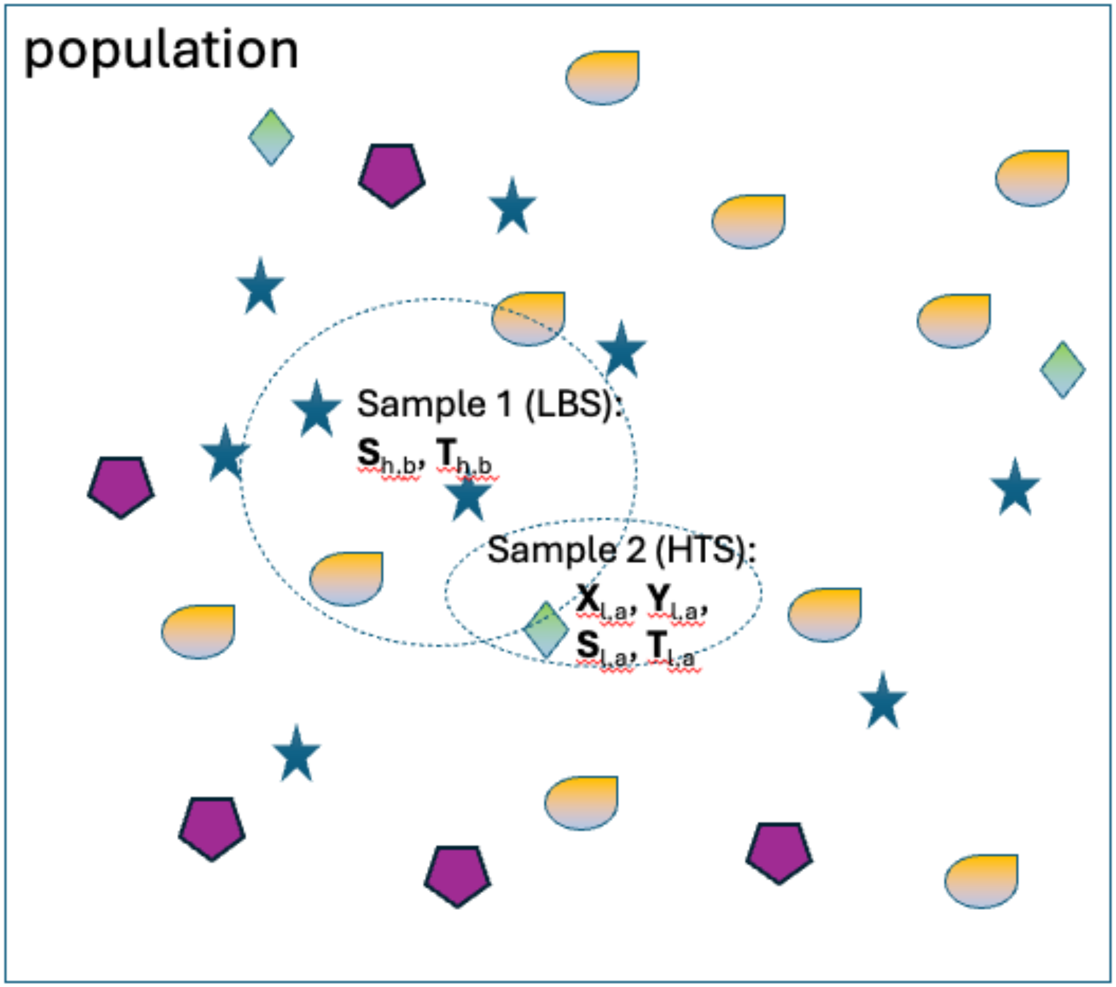
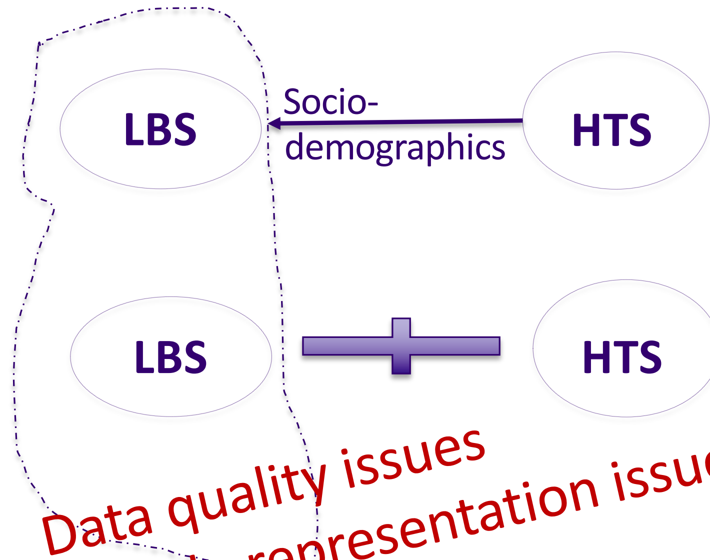
LBS Data Pre-processing

> Removing oscillations;
> Imputation of missing data;
> Inferring stays and trips;
> Inferring trip purposes and stay types;
> Inferring mode of transportation

From Biased Samples to Population





Data quality issues

Sample representation issues

CAPTURE PROBABILITY

Practical aspects

> Journals and funding sponsors shall require reporting of the characteristics of the data used in the study;
> Sensitivity analyses shall be conducted with respect to how trips and modes are detected;
> We shall compile a list of open-source data sources as benchmarks;
> Better, a central registry shall be established for all studies using big data for planning related analysis;

Thank you!

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