Slides

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Outline 1/n

- *<Title of study>*:
  - Mobile phone data in Singapore (small densely urban city)
  - Residential vs experienced segregation
  - What is the difference?
  - What explains the difference?
- Data
  - Mobile phone GPS ping records
  - Jan–Mar 2020 (3 months/91 days)
  - Neighborhood-level census demographics & characteristics
- Segregation measures
  - Existing measures exists (Massey and Denton 1988)
  - **Exposure measure**: probability a type B individual will encounter a type W individual based on shared residential areas
  - Low exposure $\rightarrow$ high segregation

Outline 2/n

- Why it matters (aka motivation)
  - Labor market opportunities (Banerjee and Ingram 2018; Hensvik and Skans 2016)
  - Segregation worsens socioeconomic markers such as schooling, employment, and marriage (Chay et al. 2014; Chetty et al. 2016)
  - Exposure reduces discrimination (Rao 2019)
  - Exposure increases knowledge spillovers (Atkin et al. 2022)
- Revisiting segregation:
  - Segregation is usually based on census/residency (Hutchens 2001; Jones and Pebley 2014; Krivo et al. 2013; Palmer et al. 2013; Sin 2002)
  - Social mixing in a physical space
  - Experienced segregation—where I go—is different to residential segregation—where I live
  - Unsupervised learning algorithm to retrieve social clusters
  - Adapted experienced segregation measure
- Our findings:
  - Measures based on residence/census overstates experienced segregation
  - Key neighborhood amenities and travel accessibility affect segregation

Outline 3/n

- Segregation w/o accounting for day-to-day mixing is overstated:
  - Exposure based on real-time movement $>$ exposure based on residence
  - Experienced segregation $<$ wealth segregation
  - When we do not account for the choice in where people go in their day-to-day lives, segregation is overstated
- Segregation is linked to neighborhood amenities and travel access:
  - Access to transit stations linked to higher exposure of poor to wealthy
  - Travel inequity linked to higher experienced segregation
  - Parks linked to higher experienced segregation
- Asymmetries in experienced segregation:
  - Exposure of wealthy to poor much less linked to neighborhood factors than exposure of poor to wealthy

Data 1/4

- **Backbone of Data**: CITYDATA.ai GPS pings
  - Neighborhood-daily level
  - Jan–Mar 2020 (3 months, 91 days)
  - GPS pings $\longrightarrow$ O–D flows (Lee, Lim, and Shen 2021; Lim and Shen 2022)
  - Sparsity: Trim daily O–D flows + tests of representativeness (Lim and Shen 2022)
- Type: by income/wealth
  - Residence type: 1–2 room public flats vs private houses
  - House micro-transactions
- Other data: Neighborhood-level (200) characteristics
  - Age, gender, ethnic (census)
  - Neighborhood amenities (official shape files)
  - Crowd-sourced F&B POIs (OSM)
  - Travel access (from $\sim$2.5m H3-9 pairs)

Data 2/4: CITYDATA.ai GPS ping records

```
/.
├── 2020-01-01
│   ├── admiralty_subzone_sg
│   │   └── admiralty_subzone_sg_2020_01_01_deviceList.csv.gz
│   └── airport_road_subzone_sg
│       └── airport_road_subzone_sg_2020_01_01_deviceList.csv.gz
├── 2020-01-02
│   └── ...
├── ...
└── 2020-03-31
    ├── admiralty_subzone_sg
    │   └── admiralty_subzone_sg_2020_03_31_deviceList.csv.gz
    ├── airport_road_subzone_sg
    │   └── airport_road_subzone_sg_2020_03_31_deviceList.csv.gz
    └── ...
```

Example flat file:

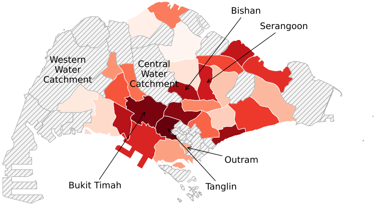
admiralty_subzone_sg_2020_01_01_deviceList.csv.gz

Hash	OS
8E545E1C31F91F777C894B3BD2C2E7D7044CC9DD	Android
40BD001563085FC35165329EA1FF5C5ECBDBBEEF	iOS
...	...
...	...
1D372C3AA0A28A5B7418A01405C621CCD523F73E	Android

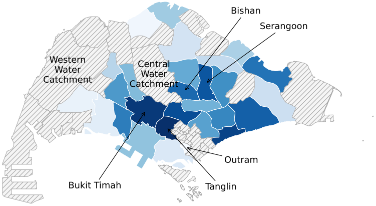
O-D panel

- Infer home using most frequent appearance
- Inter-neighborhood presence $\longrightarrow$ O-D flows

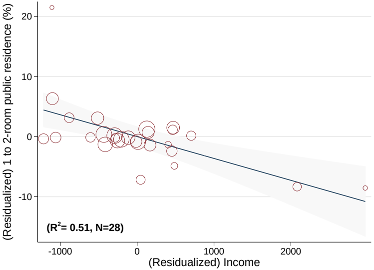
Residence type 1/2

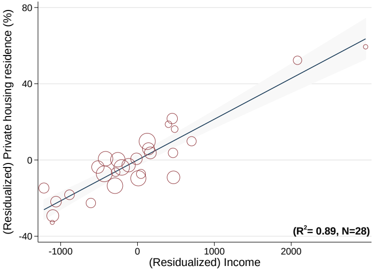


(a) Income

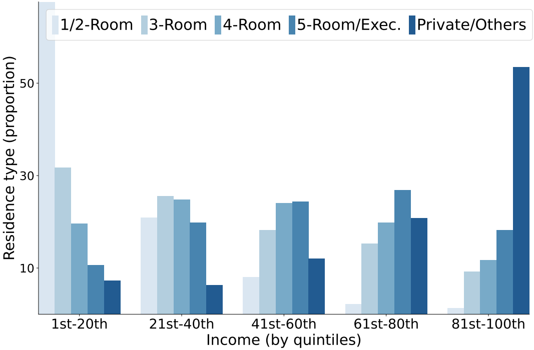


(b) Private residence





Residence type 2/2



Proxying income with residence type

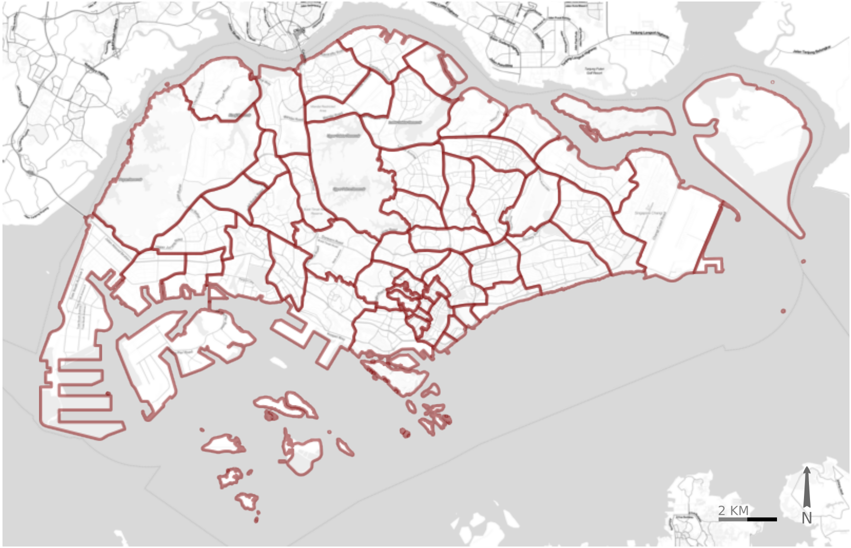
Residence type

- Proportion of residents living in 1–2-room public highrise flats (HDB)
- Residence data available at $\sim$200 neighborhood level
- L = public 1–2 rm residents
- H = private housing residents

Geography

- **5 regions**
- 55 census areas
- $\approx$ 300 subzones
- $\approx$ 200 neighbourhoods ($\approx 1 km^2$)

Geography



- 5 regions
- **55 census areas**
- $\approx$ 300 subzones
- $\approx$ 200 neighbourhoods ($\approx 1 km^2$)

Geography

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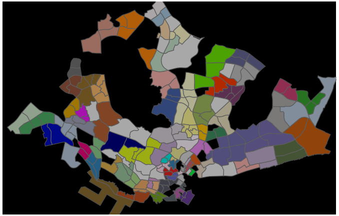
- $\approx$ **200 neighbourhoods** ($\approx 1 km^2$)

Retrieving Social Clusters 1/4

Resident (Census planning area)

Real-time (social clusters)

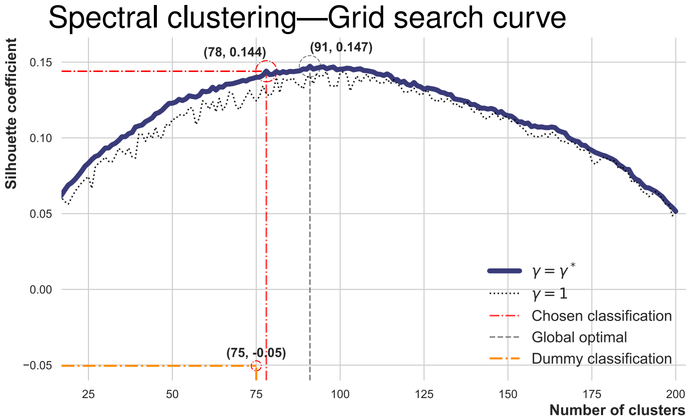


- Social clusters = clusters of neighborhoods where people are more likely to visit
- Clustering to study urban mobility & behavior (Di Clemente et al. 2018; Wang et al. 2018)

1. GPS pings $\longrightarrow$ O-D flows
2. O–D flows $\longrightarrow$ Distance matrix (Adachi et al. 2020; Tolbert and Sizer 1996)
3. Distance matrix $\longrightarrow$ Affinity matrix
4. Affinity matrix $\longrightarrow$ Spectral clustering (Pedregosa et al. 2011)

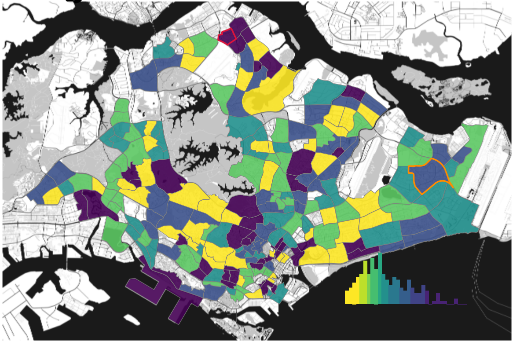
- Residential boundaries $\neq$ social boundaries

Retrieving Social Clusters 2/4



- Unsupervised
- Silhouette score
- Search over K = number of clusters
- Search over γ = coefficient in rbf kernel
- Preferred: K = 78

Retrieving Social Clusters 3/4



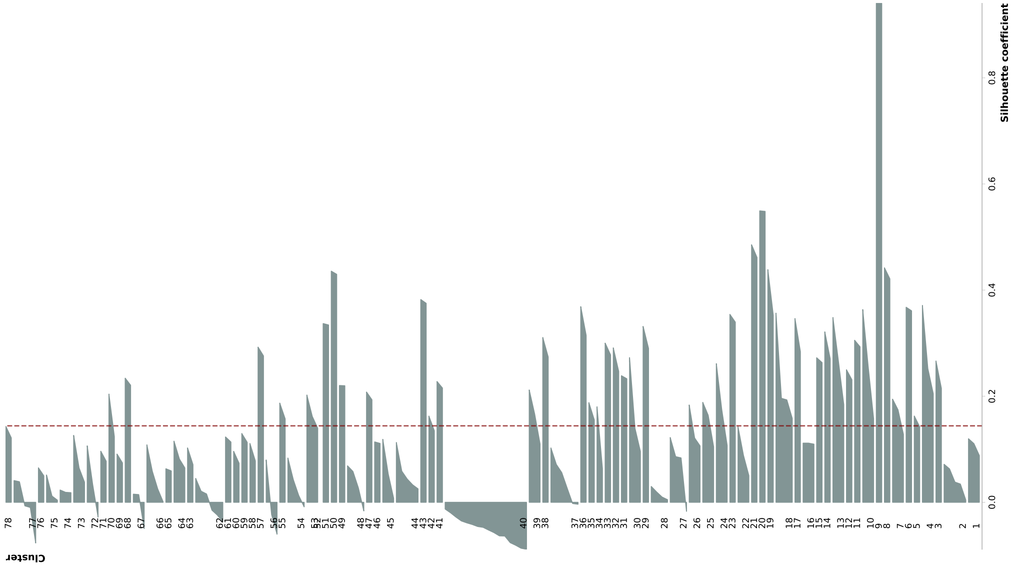
Evaluating clusters via silhouette score

(Rousseeuw 1987)

$$s_i = \frac{b_i - a_i}{\max\{a_i, b_i\}} \in [-1, 1]$$

- b_i = mean intra-cluster distance
- a_i = mean inter-cluster distance
- Denominator normalizes score to [-1,1]
- 400% better than dummy classifications

Retrieving Social Clusters 4/4



Quantifying social segregation 1/2: Residential Exposure (L to H)

$$E_a^{LH} = \frac{1}{|\mathcal{L}_a|} \sum_{i \in \mathcal{L}_a} s_{c(i)}^H \qquad (1)$$

- Residential exposure of type L to type H (traditional measure)
  (Athey et al. 2020; Massey and Denton 1988)
- $|\cdot|$ = size
- $s_{c(i)}^H$ = share of H in individual i's census unit c (eg neighborhoods)
- E = prob. that L physically come into contact with H (Massey and Denton 1988)
- a = census planning area of neighborhoods

Quantifying social segregation 2/2: Real-time Exposure (L to H)

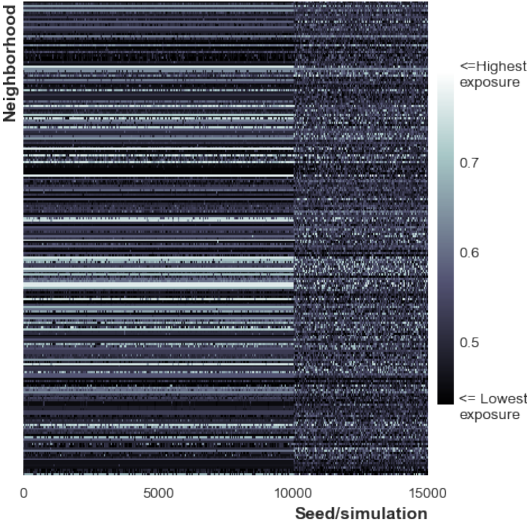
$$\tilde{E}_a^{LH} = \frac{1}{|\tilde{\mathcal{L}}_a|} \sum_{i \in \tilde{\mathcal{L}}_a} \tilde{s}_{c(i)}^{H} \tag{2}$$

- Real-time exposure is analogous— $\tilde{\cdot}$ denotes measures imputed using GPS pings
- Eg $\tilde{s}_{c(i)}^{H}$ imputed using flows from GPS pings:

$$\tilde{n}_d^L = \sum_d \underbrace{\pi_{od} \cdot \underbrace{\pi_o^L \cdot Devices_o}_{\text{share of devices imputed as type L}}}_{\text{share of imputed L-type that visit d}}$$

- a = social cluster of neighborhoods (from spectral clustering)

Real-time Exposure: Sensitivity of clustering



- Testing sensitivity of spectral clustering
- Spectral clustering uses K-means, which is sensitive to (pseudo-random) init.
- Iterations 0–99,999: Different init. for social clusters
- Iterations 10,000–15,000: Different init. for dummy clusters

Quantifying Experienced Segregation 1/2

Wealth segregation: $$s_d = \underbrace{\frac{2}{3}}_{\substack{\text{norm.}\\ \text{constant}}} \sum_q \underbrace{\left|\pi_{dq} - \frac{1}{4}\right|}_{\substack{\text{disparity =}\\ \text{deviation from}\\ \text{equal distr.}}} \in [0,1] \quad \text{(Morales et al. 2019)} \tag{3}$$

- Wealth quartile inferred by origin neighborhood & house microtransactions
- π_{dq} is proportion of visitors to neighborhood d from wealth quartile q:

$$\pi_{dq} = \frac{\overbrace{\sum_o \pi_{od} \cdot \mathbf{1}\{q_o = q\} \cdot Devices}^{\text{devices in wealth quartile q from o to d}}}{\sum_o \pi_{od} \cdot Devices}$$

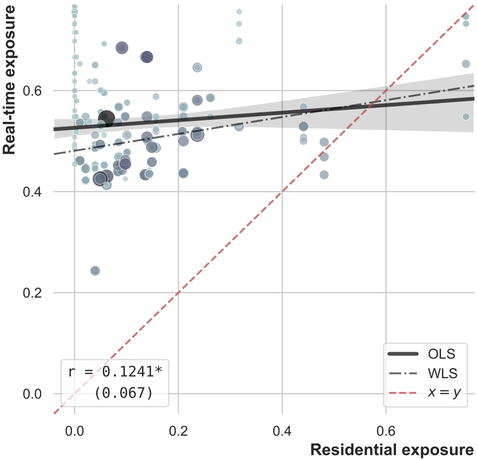
Quantifying Experienced Segregation 2/2

$$\textbf{Experienced segregation: } s_o = \underbrace{\frac{2}{3}}_{\text{norm. constant}} \sum_q \underbrace{\left| \pi_{oq} - \frac{1}{4} \right|}_{\text{disparity = deviation from equal distr.}} \in [0, 1] \quad \text{(Morales et al. 2019)} \tag{4}$$

- π_{oq} is the probability that someone from o will be exposed to someone from wealth quartile q
- Experienced segregation = where I go *And* where other people go

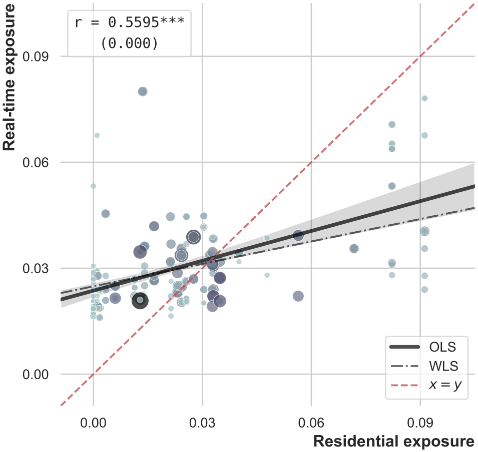
$$\pi_{oq} = \sum_d \underbrace{\pi_{od}}_{\text{prob. of flow from o to d}} \cdot \underbrace{\pi_{dq}}_{\text{prob. visitor from d is from wealth quartile q}}$$

Social segregation is overstated?



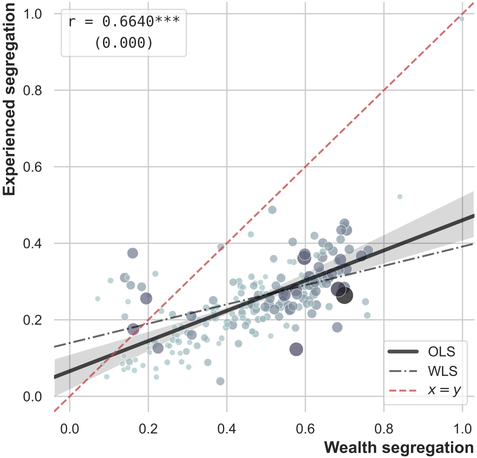
- Parity plot—Real-time vs residential
- **Poor to wealthy**
- Real-time exposure of poor to wealthy is higher than residential exposure of poor to wealthy

Social segregation is overstated?



- Parity plot—Real-time vs residential
- **Wealthy to poor**
- Real-time exposure of wealthy to poor is (mostly) higher than residential wealthy to poor
- Asymmetric—(im)parity less clear than poor to wealthy

Experienced segregation



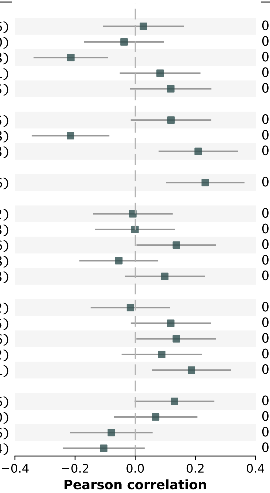
- Parity plot—Experienced vs wealth segregation
- Experienced segregation is lower than wealth segregation

Correlates of Residuals 1/n

- We describe the factors that correlate with lower segregation based on our measure of real-time exposure and experienced segregation
- Residualise real-time measures using their residential counterparts
- Reporting correlates of residuals with neighborhood factors
- Factors that stand out:
  - National parks
  - F&B
  - Travel access

Real-time exposure—Poor to Wealthy

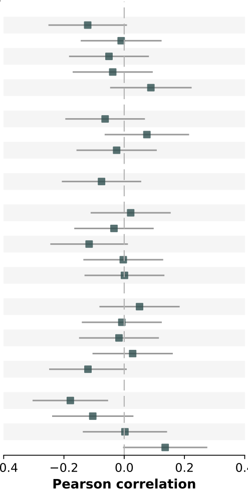
Variable	Est.(95% Conf. Int.)	P-value	N
Age group			
Age group 0–9	0.03(-0.11 to 0.16)	0.69	213
Age group 10–19	-0.04(-0.17 to 0.10)	0.59	213
Age group 20–39	-0.21(-0.34 to -0.08)	0.0***	215
Age group 40–64	0.08(-0.05 to 0.21)	0.22	215
Age group > 65	0.12(-0.02 to 0.25)	0.08*	212
Ethnic mix			
% majority ethnic	0.12(-0.02 to 0.25)	0.08*	215
% minority ethnic x	-0.22(-0.34 to -0.08)	0.0***	198
% minority ethnic y	0.21(0.08 to 0.33)	0.0***	215
Gender mix			
% female	0.23(0.10 to 0.36)	0.0***	215
Amenities			
Libraries	-0.01(-0.14 to 0.12)	0.91	219
Supermarkets	-0.00(-0.13 to 0.13)	0.99	219
National parks	0.14(0.00 to 0.26)	0.04**	219
Sport facilities	-0.05(-0.19 to 0.08)	0.42	219
Tourist attractions	0.10(-0.03 to 0.23)	0.14	219
Food & beverage			
Hawkers	-0.02(-0.15 to 0.12)	0.81	219
Restaurants	0.12(-0.01 to 0.25)	0.08*	218
Cafes	0.14(0.00 to 0.26)	0.04**	218
Bars & pubs	0.09(-0.05 to 0.22)	0.19	218
Fast-foods	0.19(0.06 to 0.31)	0.0***	218
Travel access			
Transit stations	0.13(-0.00 to 0.26)	0.05**	219
Transit time	0.07(-0.07 to 0.20)	0.33	201
Driving (4w) time	-0.08(-0.22 to 0.06)	0.26	197
Travel inequity	-0.10(-0.24 to 0.04)	0.14	197



- Neighborhoods w/ more “young people” have lower exposure
- Ethnic mix matters
- Neighborhoods with more parks have more exposure

Real-time exposure—Wealthy to Poor

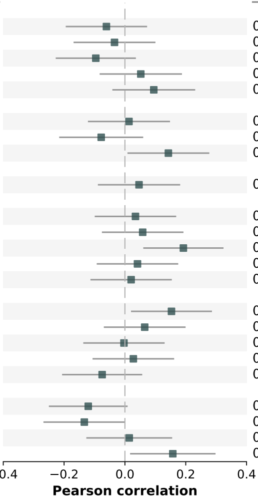
Variable	Est.(95% Conf. Int.)	P-value	N
Age group			
Age group 0–9	-0.12(-0.25 to 0.01)	0.07*	213
Age group 10–19	-0.01(-0.14 to 0.12)	0.88	213
Age group 20–39	-0.05(-0.18 to 0.08)	0.46	215
Age group 40–64	-0.04(-0.17 to 0.10)	0.58	215
Age group > 65	0.09(-0.05 to 0.22)	0.19	212
Ethnic mix			
% majority ethnic	-0.06(-0.20 to 0.07)	0.35	215
% minority ethnic x	0.08(-0.06 to 0.21)	0.29	198
% minority ethnic y	-0.03(-0.16 to 0.11)	0.71	215
Gender mix			
% female	-0.08(-0.21 to 0.06)	0.27	215
Amenities			
Libraries	0.02(-0.11 to 0.15)	0.75	219
Supermarkets	-0.03(-0.17 to 0.10)	0.62	219
National parks	-0.12(-0.25 to 0.02)	0.08*	219
Sport facilities	-0.00(-0.14 to 0.13)	0.96	219
Tourist attractions	0.00(-0.13 to 0.13)	0.99	219
Food & beverage			
Hawkers	0.05(-0.08 to 0.18)	0.45	219
Restaurants	-0.01(-0.14 to 0.13)	0.91	218
Cafes	-0.02(-0.15 to 0.12)	0.8	218
Bars & pubs	0.03(-0.11 to 0.16)	0.68	218
Fast-foods	-0.12(-0.25 to 0.01)	0.07*	218
Travel access			
Transit stations	-0.18(-0.30 to -0.05)	0.01***	219
Transit time	-0.10(-0.24 to 0.03)	0.14	201
Driving (4w) time	0.00(-0.14 to 0.14)	0.97	197
Travel inequity	0.14(-0.00 to 0.27)	0.05*	197



- More transit stations—lower exposure

Experienced segregation

Variable	Est.(95% Conf. Int.)	P-value	N
Age group			
Age group 0–9	-0.06(-0.19 to 0.08)	0.38	210
Age group 10–19	-0.03(-0.17 to 0.10)	0.62	210
Age group 20–39	-0.10(-0.23 to 0.04)	0.16	212
Age group 40–64	0.05(-0.08 to 0.19)	0.45	212
Age group > 65	0.09(-0.04 to 0.23)	0.17	209
Ethnic mix			
% majority ethnic	0.01(-0.12 to 0.15)	0.85	212
% minority ethnic x	-0.08(-0.22 to 0.06)	0.27	195
% minority ethnic y	0.14(0.01 to 0.27)	0.03**	212
Gender mix			
% female	0.05(-0.09 to 0.18)	0.5	212
Amenities			
Libraries	0.03(-0.10 to 0.17)	0.61	216
Supermarkets	0.06(-0.08 to 0.19)	0.39	216
National parks	0.19(0.06 to 0.32)	0.0***	216
Sport facilities	0.04(-0.09 to 0.17)	0.54	216
Tourist attractions	0.02(-0.11 to 0.15)	0.76	216
Food & beverage			
Hawkers	0.15(0.02 to 0.28)	0.02**	216
Restaurants	0.07(-0.07 to 0.20)	0.34	215
Cafes	-0.00(-0.14 to 0.13)	0.96	215
Bars & pubs	0.03(-0.11 to 0.16)	0.68	215
Fast-foods	-0.07(-0.21 to 0.06)	0.27	215
Travel access			
Transit stations	-0.12(-0.25 to 0.01)	0.07*	216
Transit time	-0.13(-0.27 to 0.01)	0.06*	198
Driving (4w) time	0.01(-0.13 to 0.15)	0.84	194
Travel inequity	0.16(0.02 to 0.29)	0.02**	194



- Parks
- Hawkers
- Travel inequity

Discussion

Are flows pro-social?

- Social exposure zones can capture daily trip hops
- Trip hops constitute an important form of interaction where individuals share physical activity space

  (Athey et al. 2020; Cagney et al. 2020)

Discussion

Experiential vs. physical segregation

- GPS and geolocation data allows us to incorporate the fact that segregation is also behavioural and mobility choices
- Real-time based measures of exposure and segregation based on experience are lower than their residential counterparts

  (Athey et al. 2020)
- Segregation is more than where we live
- What does this say about housing policies that uses quotas to socially integrate?

Dicussion

The bigger (areal) picture

- Why do environmental/areal factors matter?
- Where we live matters

  (hence all the lit. on neighborhood choices, e.g., Agostinelli et al. 2021; Ferreira and Wong 2022)
- Zip code > genetic code?
- Singapore: highly connected + densely urban + mix of urban planning + social policy = consciously created common spaces. What does this say about physical vs. experiential segregation and how it relates to other holistic health & population outcomes?

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