Emergence of Scaling in Dockless Bike-Sharing Systems

Ruiqi Li
UrbanNet Lab
College of Information Science and Technology, BUCT

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About Me

Education

2017.01-2017.12 **Boston University**
Visiting Scholar at *Department of Physics* (H. Eugene Stanley)

2015.12-2017.01 **MIT**
Visiting Ph.D. at *Department of Civil & Environmental Engineering* (M. C. Gonzalez)

2013.09-2018.06 **Beijing Normal University**
Ph.D. in *Systems Science*

I'm a "**normal**" person graduated from a "**Normal**" university

2009.09-2013.06 **University of Electronic Science and Technology of China**
Bachelor Degree in *Computer Science*

Work

2018.07-now **Beijing University of Chemical Technology**
Associate Professor, Director of UrbanNet Lab at *Department of Computer Science*

Homepage: https://lir939.wixsite.com/lirq
Twitter: @RuiqiLii
UrbanNet Lab: https://cist.buct.edu.cn/tdcy_8719/list.htm

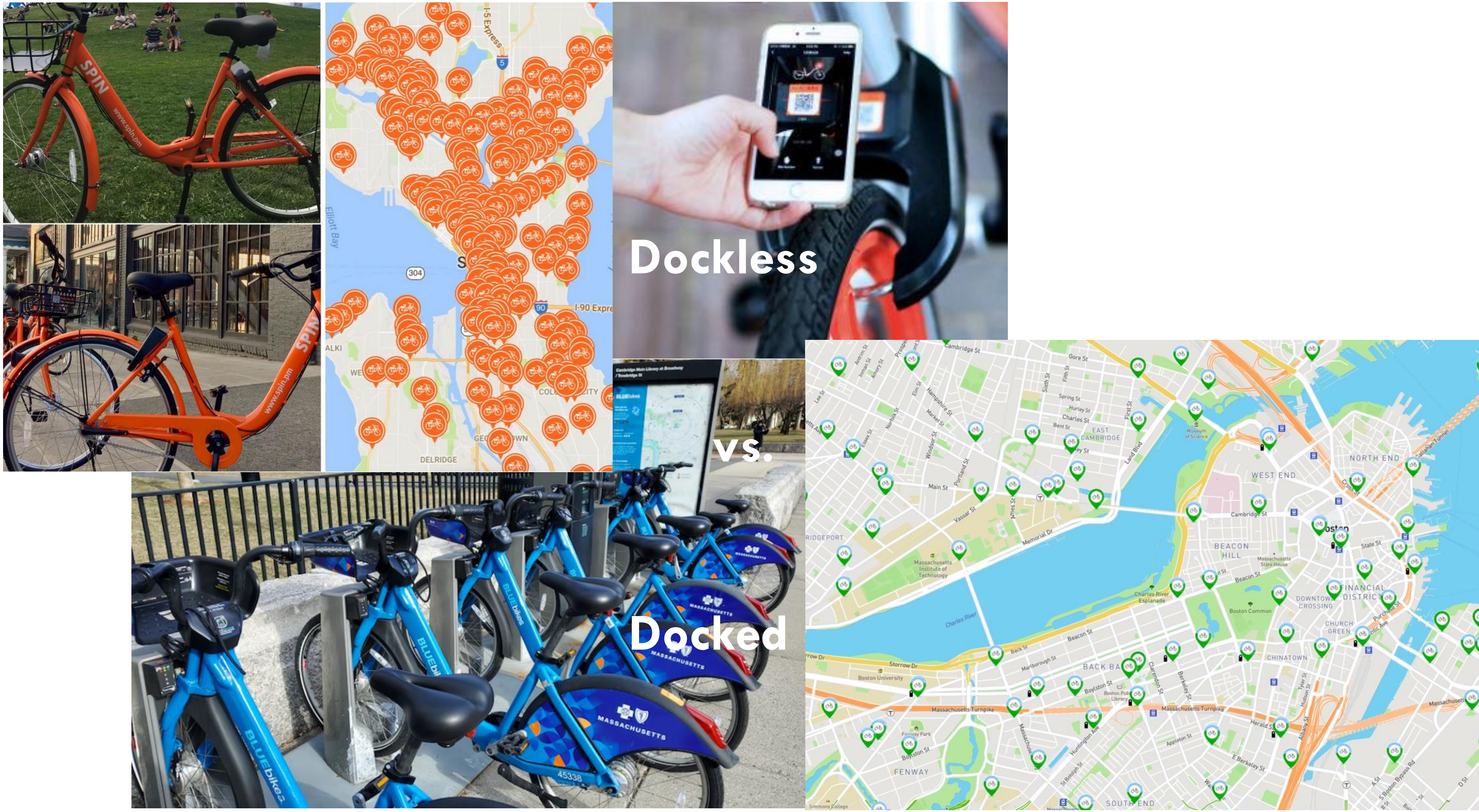
URBANNET LAB

- We are focusing on **urban computation & modeling, complex networks,** and **human mobility**

- We are aiming at gaining better understanding of urban systems and transportation systems with network science, big data, and advanced technologies.

Selected publications:

- **Ruiqi Li,** Lei Dong, Jiang Zhang*, Xinran Wang, Wenxu Wang*, Zengru Di, H. Eugene Stanley*. *Simple spatial scaling rules behind complex cities*. ***Nature Communications***, 2017, 8: 1841
- **Weiwei Gu,** Aditya Tandon, Yong-Yeol Ahn, Filippo Radicchi*. *Principled approach to the selection of the embedding dimension of networks*. ***Nature Communications***, 2021, 12: 3772
- **Ruiqi Li***, Shuai Gao, Ankang Luo, Qing Yao*, Bingsheng Chen, Fan Shang, Rui Jiang, H. Eugene Stanley*. *Gravity model in dockless bike-sharing systems within cities*. ***Physical Review E***, 2021
- **Ruiqi Li*,** Peter Richmond, Bertrand M. Roehner*. *Effect of population density on epidemics*. ***Physica A***, 2018, 510: 713-724
- **R Li***, A Luo, F Shang, L Lv*, J Fan*, G Lu, L Pan, L Tian, HE Stanley*, *Emergence of scaling in dockless bike-sharing systems*, arXiv preprint arXiv:2202.06352, 2022
- X Qiu, T Gao, Y Yang, A Luo, F Shang*, **R Li***, *Understanding urban congestion with biking traffic and routing detour ratio*, arXiv preprint arXiv:2205.08118, 2022


Dockless
vs.
Docked

MOTIVATIONS

Bike-sharing Systems have long been regarded **a critical component** towards the transition to a **greener, healthier,** and **more resilient transportation**

- saving parking space
- reduce carbon emissions & saving fossil energy (by replacing short distance motorized trips)
- improve public health (increasing fitness and reducing the stress of riders from cycling activities)

Newly emergent **Dockless Bike-sharing Systems (DBS)** give **better accessibility** and **more flexibility** to users

- It can more accurate estimate travel demands by bike & detailed riding behaviors of individuals
- Famous DBS: Mobike, Ofo, DiDi Bike, LimeBike, Spin, Ford GoBike

However, quite few attention was dedicated to

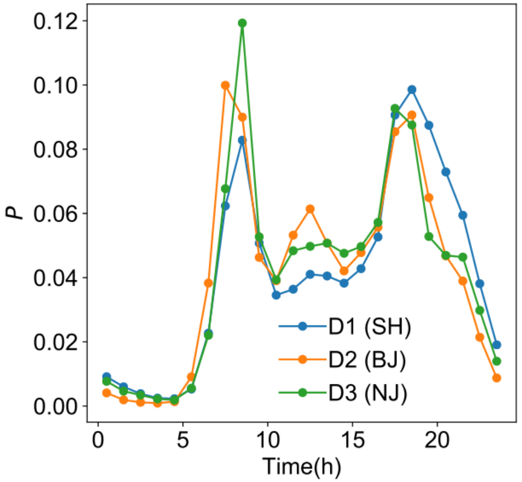
At collective level:

- (1) Is there any universal patterns behind biking traffic?
- (2) What's the relation between biking traffic and vehicle traffic?

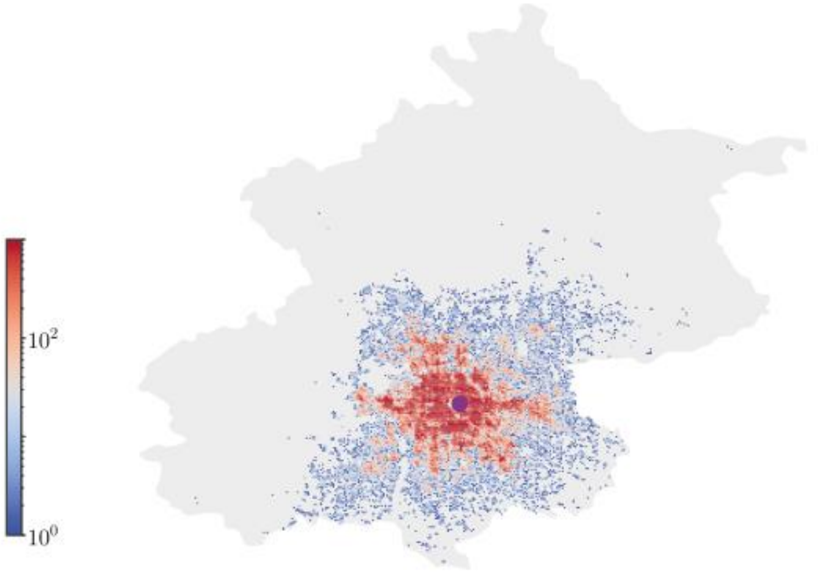
At individual level:

- (3) fundamental laws of "mobility" patterns on dockless sharing bikes (sharing conveyances)
- (4) The relationship between travelers and sharing transport conveyances

DATASETS



(a)

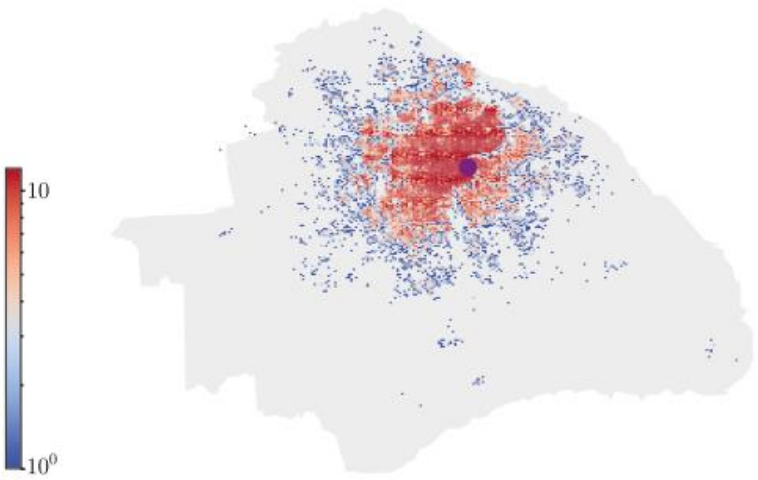


We acquired seven DBS datasets for six cities in China and one dataset for Singapore.

City	Platform	Rec.	Period(MM/DD)	Users	Bikes
Shanghai (D1)	Mobike	1.02	08/01-09/01, 2016	0.017	0.300
Beijing (D2)	Mobike	3.20	05/10-05/24, 2017	0.350	0.485
Nanjing (D3)	DiDi Bike	1.35	10/01-10/31, 2019	NA	0.060
Nanjing (D4)	Mobike	1.44	03/20-03/26, 2017	NA	0.048
Chengdu (D5)	Mobike	4.40	09/03-09/09, 2018	NA	0.275
Xi'an (D6)	Mobike	4.09	09/03-09/09, 2018	NA	0.150
Xiamen (D7)	aggregated	0.22	12/21-12/25, 2020	NA	0.053
Singapore (D8)	NA	0.30	09/11-09/17, 2017	NA	0.033

Spatial distribution of biking trips in Beijing & Shanghai

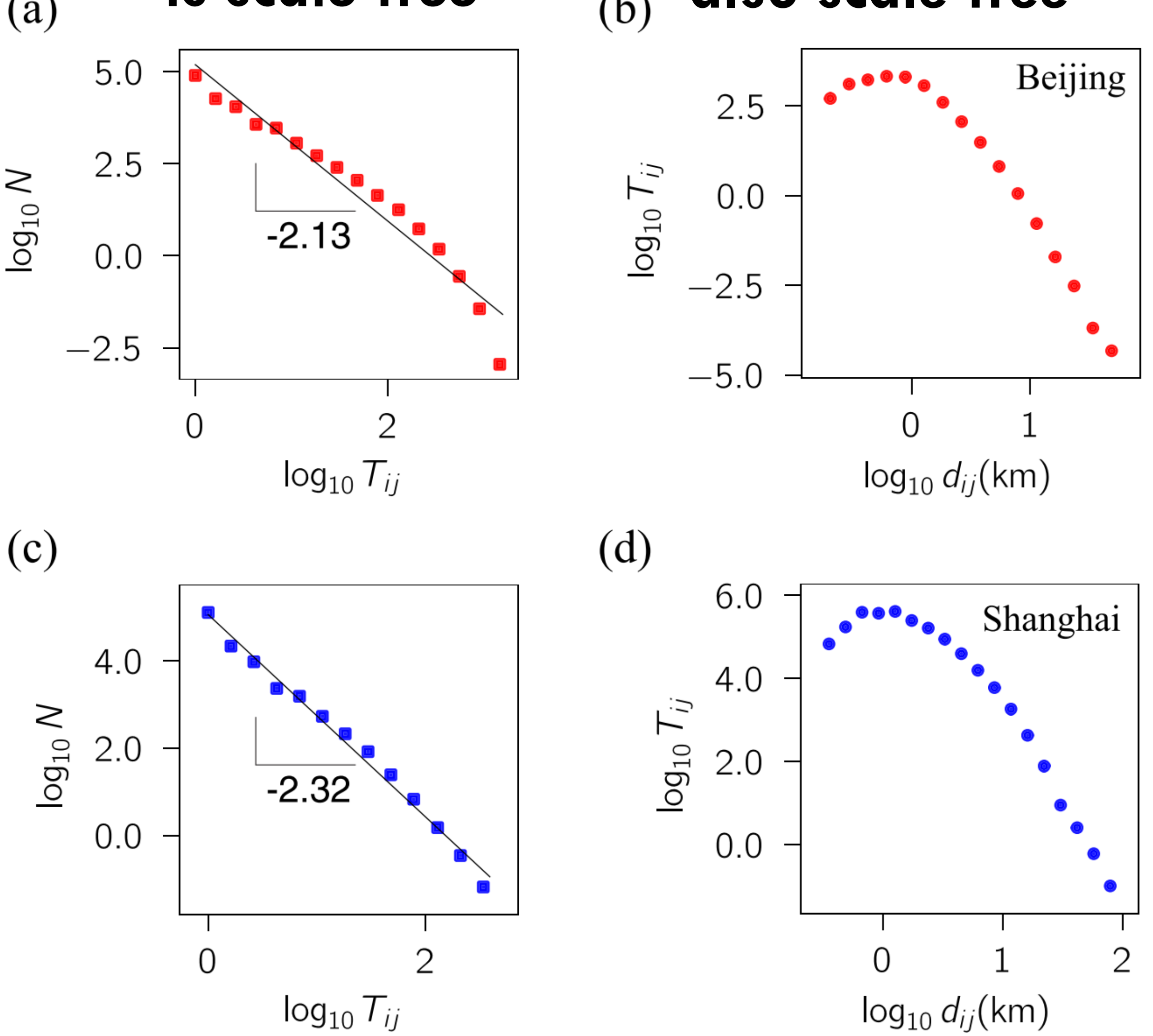
(c)

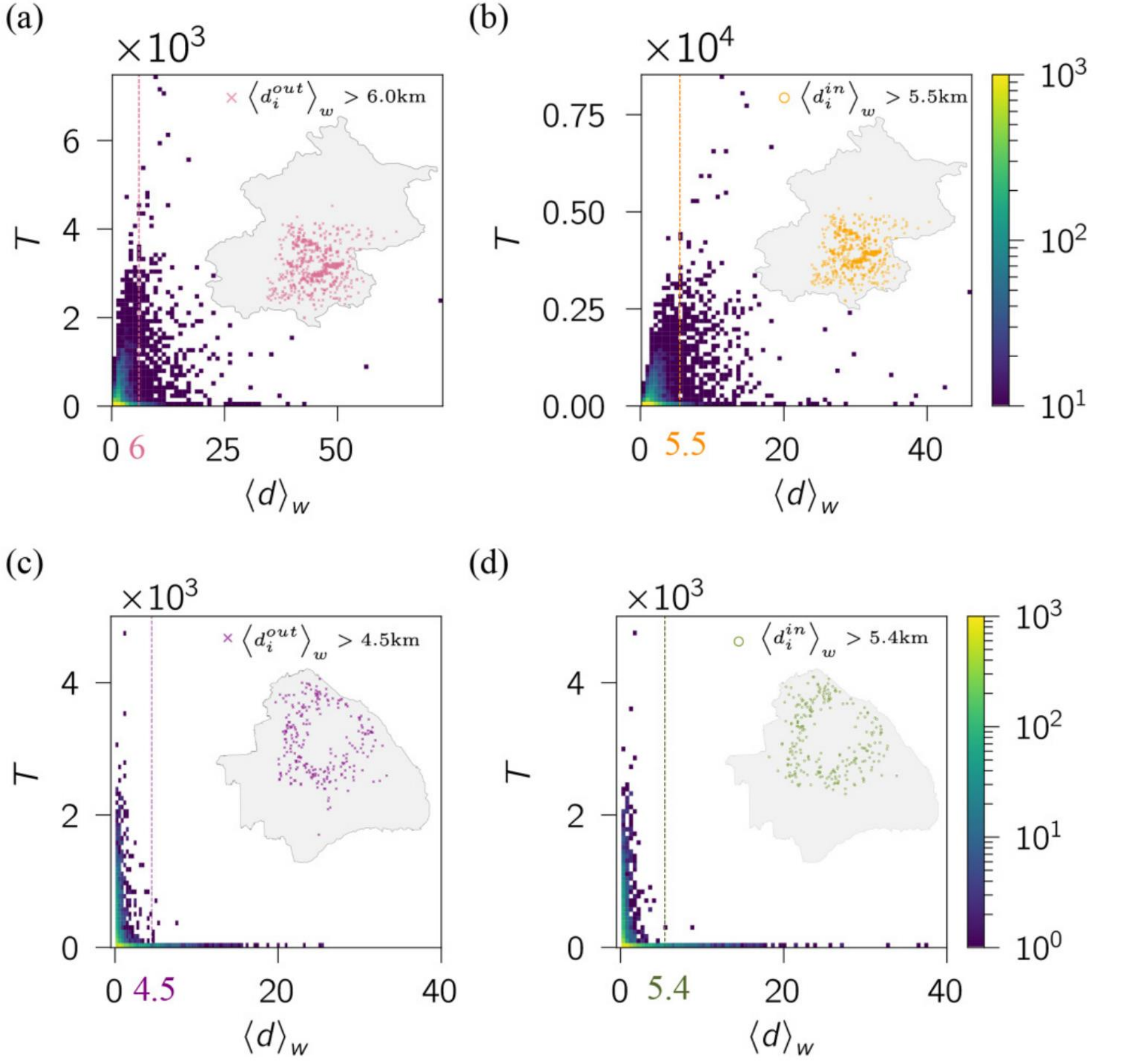


Biking traffic between locations is scale-free

Trip distance by bikes is also scale-free

Spatial distribution of long-distance biking trips





This may differ from common impressions that bikes are for short trips

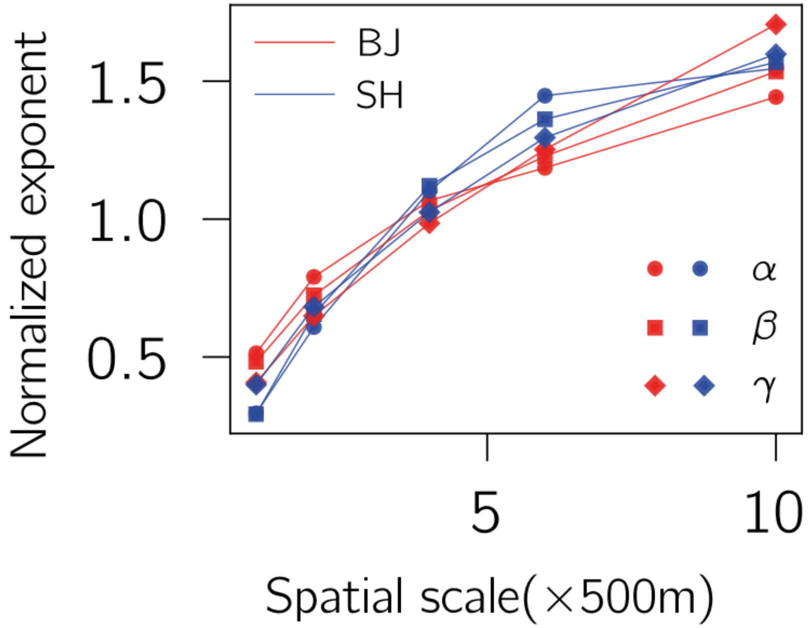
The impacts of spatial scale and population on biking traffic

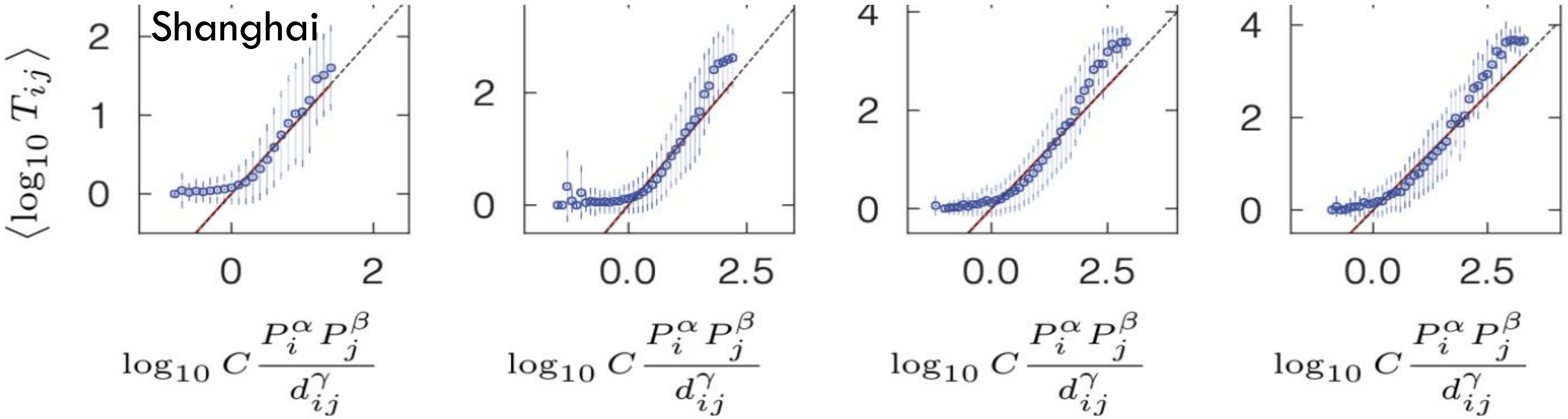
Gravity Model

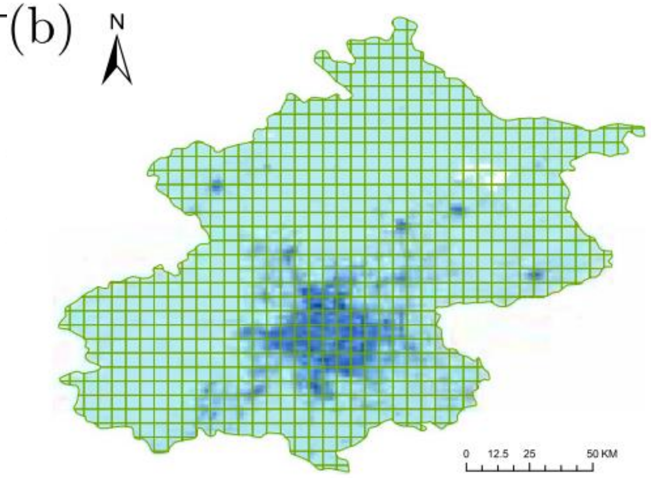
$$T_{ij} = \frac{P_i^{\alpha} P_j^{\beta}}{d_{ij}^{\gamma}}$$

TABLE I. The fitted values of parameters of the g ... nfidence interval.

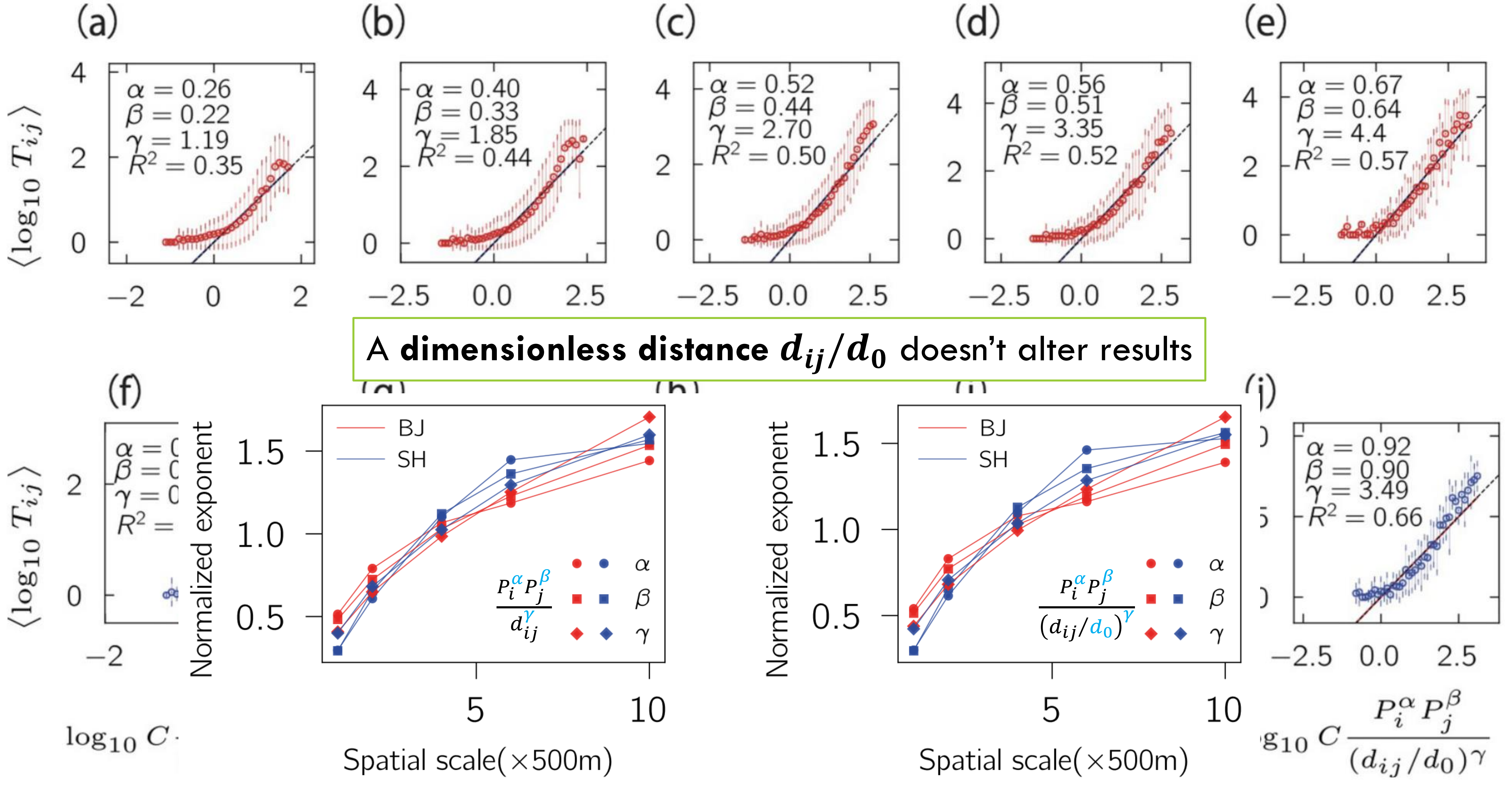
Resolutions	Shanghai α	β	γ	ng γ	C	R^2
500 m	0.18 ± 0.01	0.17 ± 0.01	0.99 ± 0.01	1.25 ± 0.02	0.2	0.35
1 km	0.37 ± 0.02	0.38 ± 0.02	1.69 ± 0.03	1.99 ± 0.04	0.07	0.45
2 km	0.67 ± 0.04	0.65 ± 0.03	2.54 ± 0.07	3.02 ± 0.08	0.03	0.54
3 km	0.88 ± 0.07	0.79 ± 0.07	3.21 ± 0.13	3.84 ± 0.18	0.03	0.58
5 km	0.94 ± 0.14	0.91 ± 0.11	3.96 ± 0.26	5.23 ± 0.36	0.07	0.67







[R. Li, et al., Gravity model in dockless bike-sharing systems within cities, PRE (2021)]

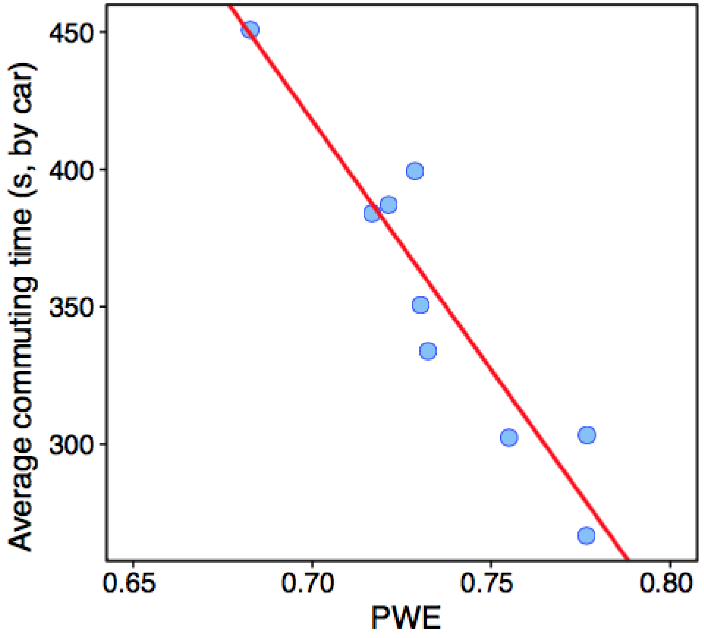

(a)
$\alpha = 0.26$
$\beta = 0.22$
$\gamma = 1.19$
$R^2 = 0.35$
(b)
$\alpha = 0.40$
$\beta = 0.33$
$\gamma = 1.85$
$R^2 = 0.44$
(c)
$\alpha = 0.52$
$\beta = 0.44$
$\gamma = 2.70$
$R^2 = 0.50$
(d)
$\alpha = 0.56$
$\beta = 0.51$
$\gamma = 3.35$
$R^2 = 0.52$
(e)
$\alpha = 0.67$
$\beta = 0.64$
$\gamma = 4.4$
$R^2 = 0.57$
$\langle \log_{10} T_{ij} \rangle$
A **dimensionless distance** d_{ij}/d_0 doesn't alter results
(f)
(j)
Normalized exponent
BJ
SH
$\frac{P_i^\alpha P_j^\beta}{d_{ij}^\gamma}$
$\frac{P_i^\alpha P_j^\beta}{(d_{ij}/d_0)^\gamma}$
α
β
γ
Spatial scale(×500m)
$\alpha = 0.92$
$\beta = 0.90$
$\gamma = 3.49$
$R^2 = 0.66$
$\log_{10} C \frac{P_i^\alpha P_j^\beta}{(d_{ij}/d_0)^\gamma}$

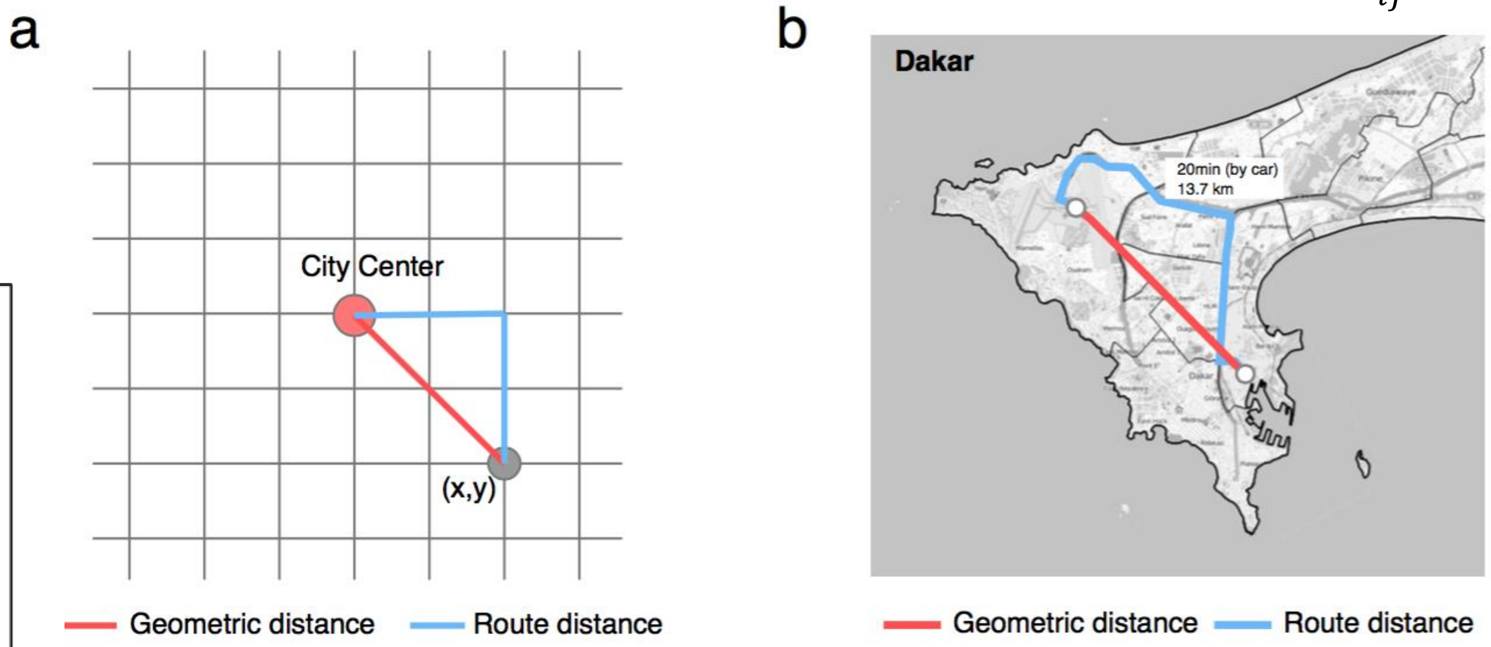
The relation between biking traffic and vehicle congestion

Population-Weighted Efficiency (PWE)

Detour Ratio $DR_{ij} = \frac{d_{ij}^{r}}{d_{ij}^{e}}$

A more comprehensive evaluation indicator on transportation efficiency



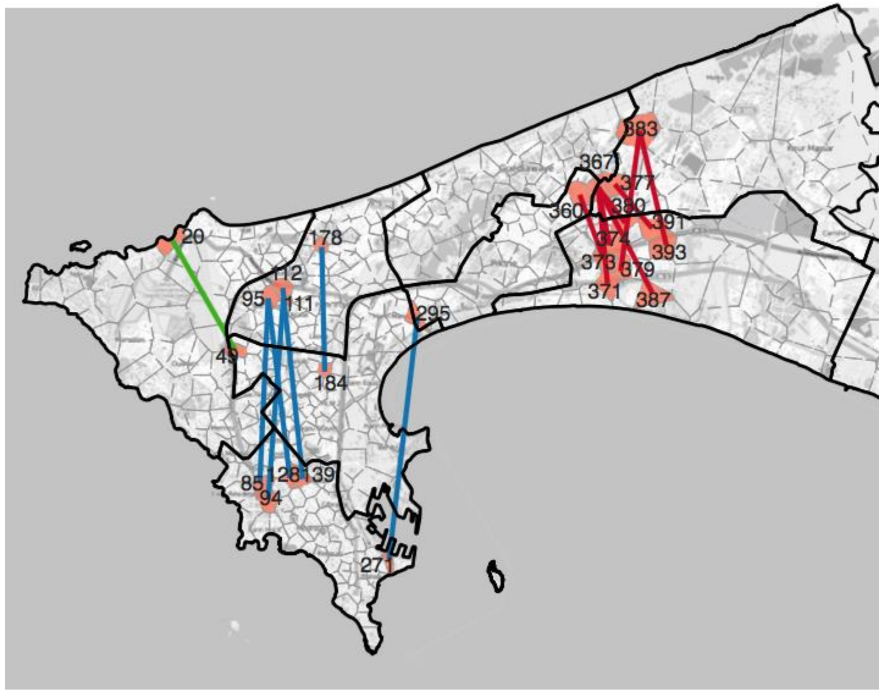


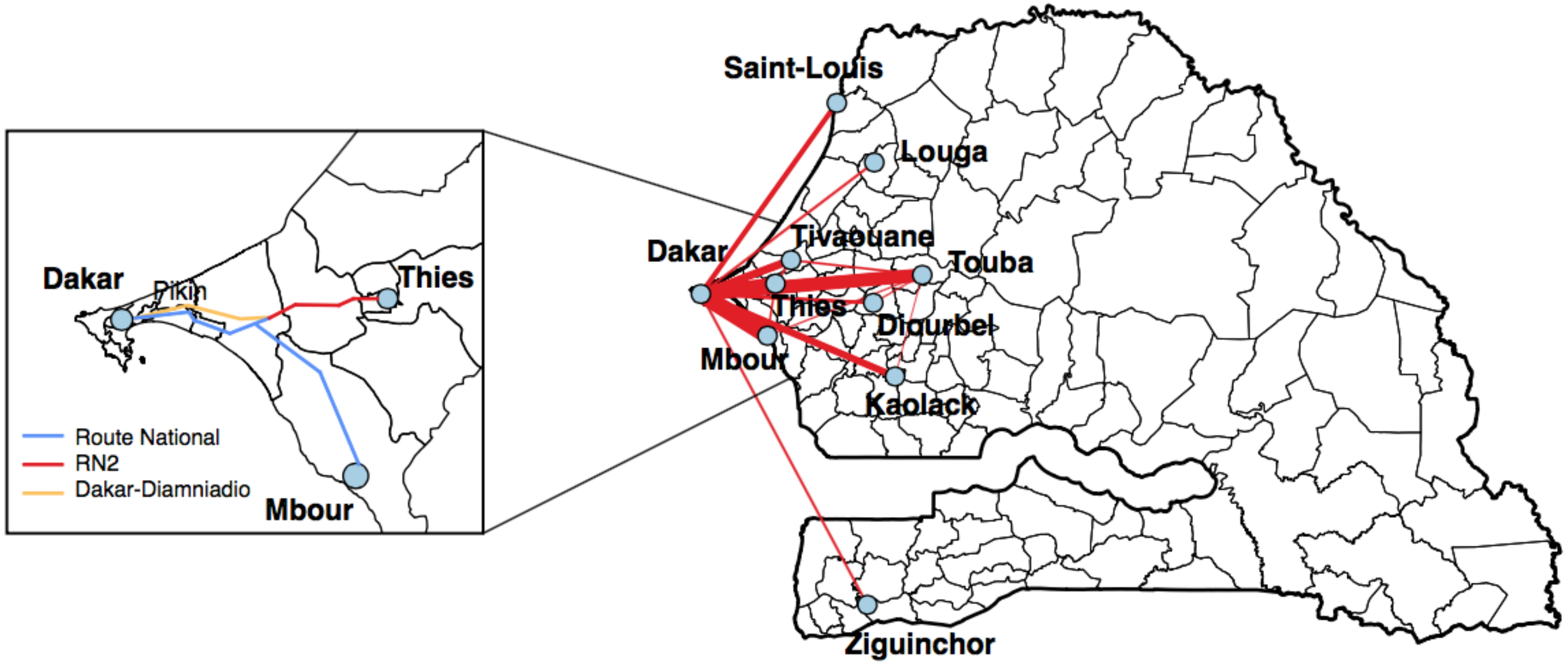
PWE of route (i, j): $\eta_{ij} = \frac{P_{ij}}{P_{tot}} \times \frac{d_{ij}^{r}}{d_{ij}^{e}}$, overall PWE: $\eta = \sum_{i,j} \eta_{ij}$

A larger value of η corresponds to a lower efficiency

[L. Dong, R. Li*, J. Zhang* & Z. Di. Scientific Reports 6:26377 (2016)]

Application of PWE: identifying efficient routes



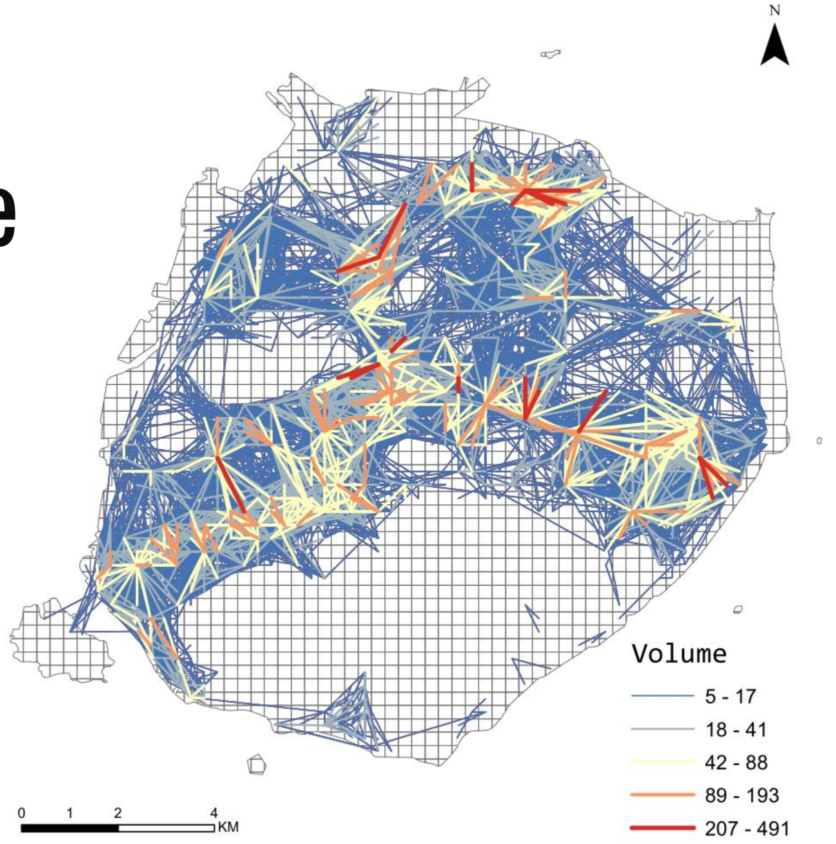


[L. Dong, R. Li*, J. Zhang* & Z. Di. Scientific Reports 6:26377 (2016)]

Biking-Weighted Efficiency & Vehicle Traffic Congestion

Biking-Weighted Efficiency: $\frac{T_{ij}}{T} \times \boldsymbol{indicator}$

$T = \sum_{i,j} T_{ij}$, T_{ij} is the biking traffic from location i to j



$\boldsymbol{indicator}$: detour ratio (d_r/d_e) Vehicle congestion (t_{jam}/t_{free})

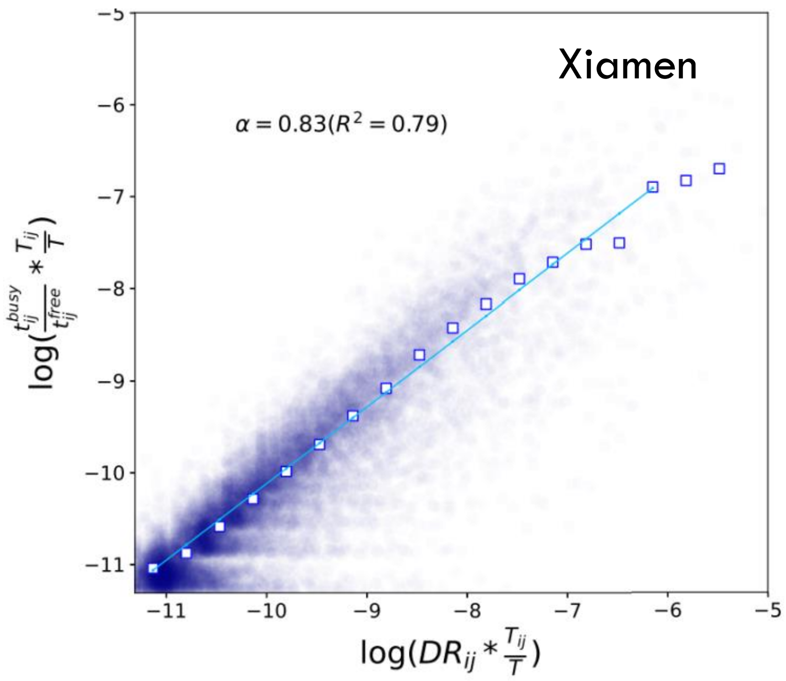
First 100 routes with largest PWE value with different criterion

Travel time during rush hours are queried from Amap API

[X. Qiu, T. Gao, Y. Yang, A. Luo, F. Shang* & R. Li*. Understanding urban congestion with biking traffic and routing detour ratio. 2022, arXiv: 2205.08118]

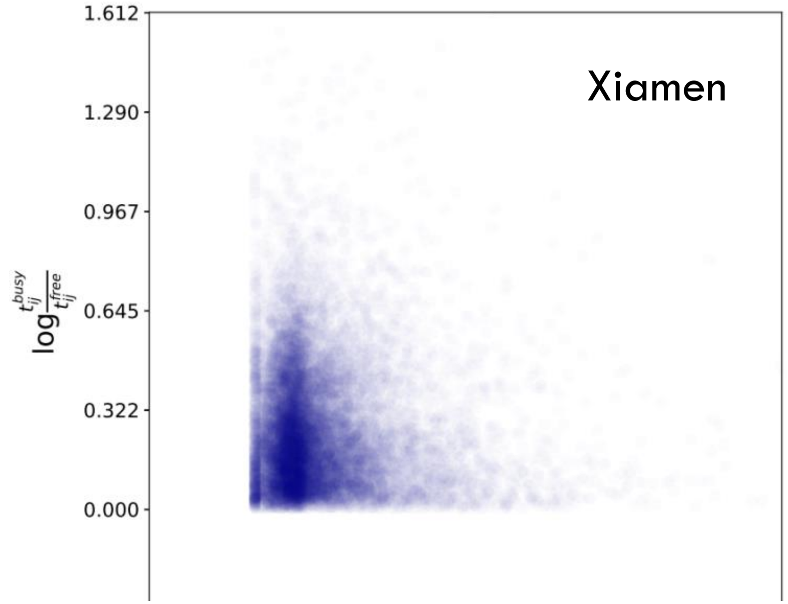
[Understanding urban congestion with biking traffic and routing detour ratio. 2022, arXiv: 2205.08118]

Relation between the PWE and congestion at the route level



$$\left(\frac{T_{ij}}{T}\cdot\frac{t_{ij}^{busy}}{t_{ij}^{free}}\right) \propto \left(\frac{T_{ij}}{T}\cdot\frac{r_{ij}}{d_{ij}}\right)^{\alpha}$$

$$\Rightarrow \frac{t_{ij}^{busy}}{t_{ij}^{free}} \propto \left(\frac{T_{ij}}{T}\right)^{\alpha-1}\left(\frac{r_{ij}}{d_{ij}}\right)^{\alpha}$$

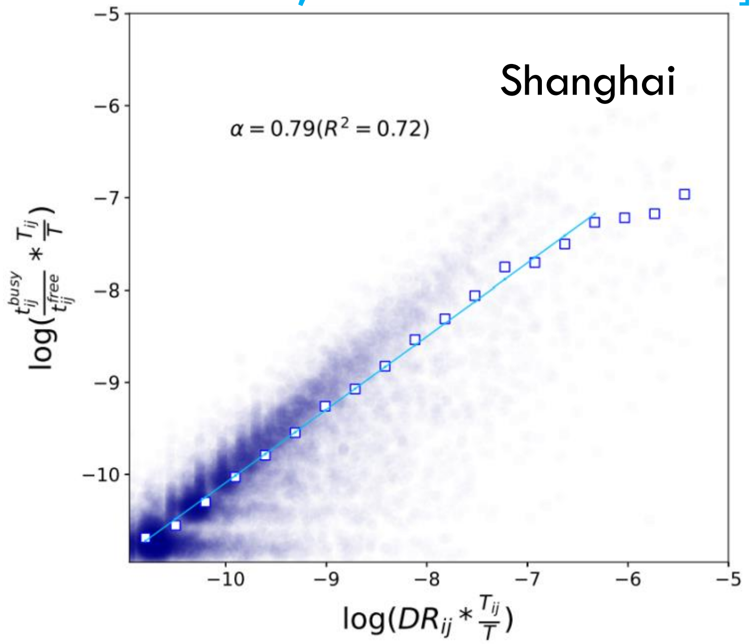


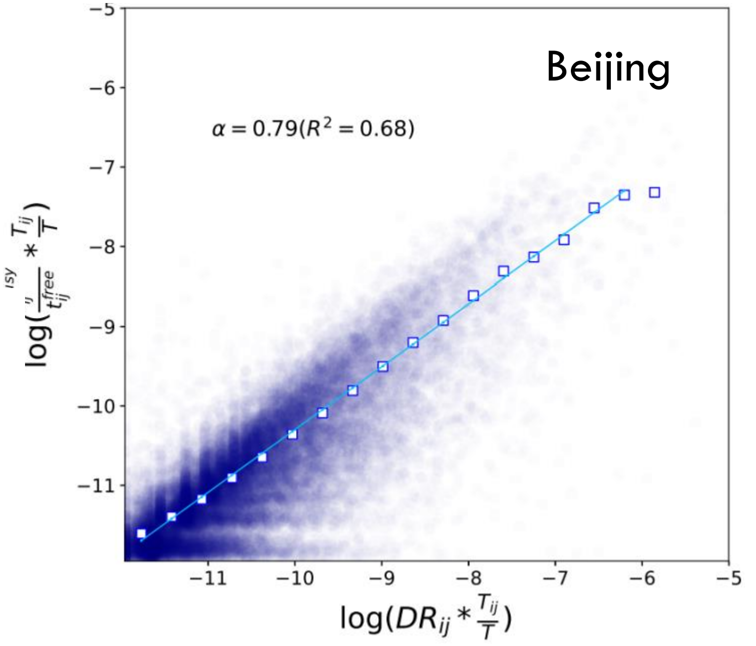
According to BPR function:

$$t_{ij} = \left(1+\eta\left(\frac{V_{ij}}{C_{ij}}\right)\right)^{\beta} \times t_{ij}^{free},$$

Here, V_{ij} is the vehicle volume on route (i, j)

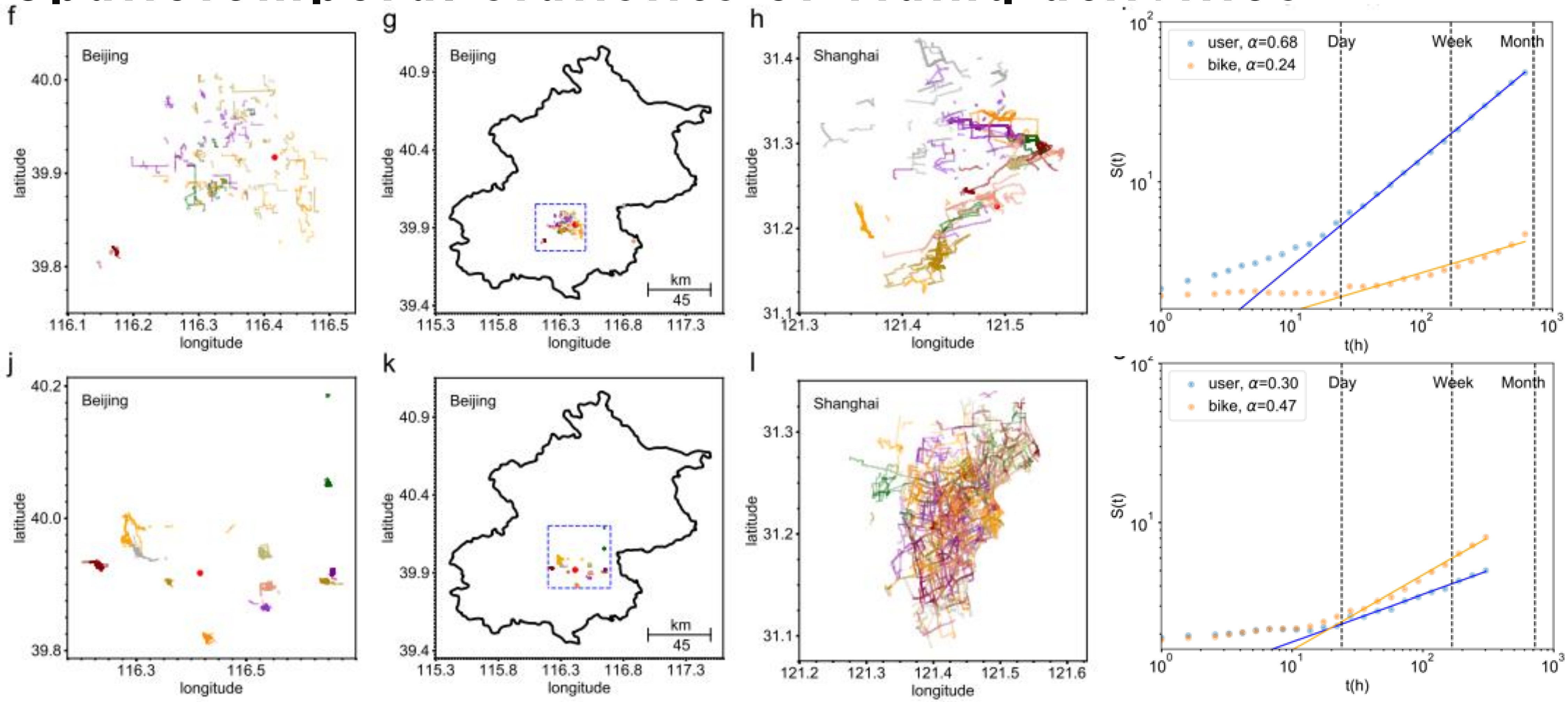
$$\frac{t_{ij}^{busy}}{t_{ij}^{free}} = \left(1+\eta\left(\frac{V_{ij}}{C_{ij}}\right)\right)^{\beta} = \left(\frac{T_{ij}}{T}\right)^{\alpha-1} \times DR_{ij}^{\alpha}.$$





Scaling behavior on the choice behaviors of choosing which bike to ride

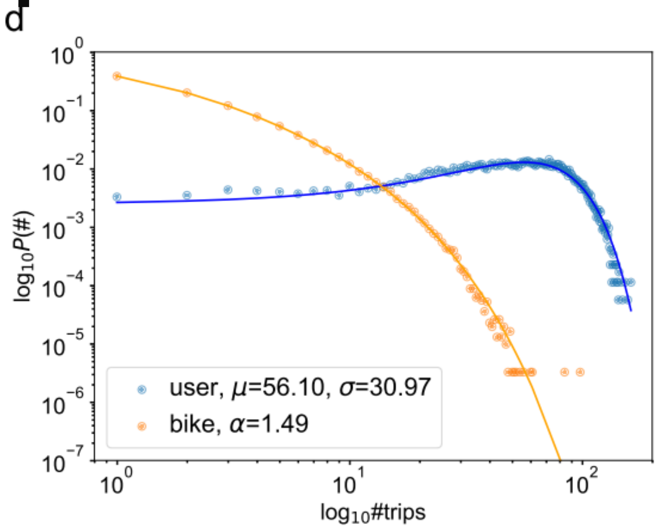
Spatiotemporal statistics of riding activities



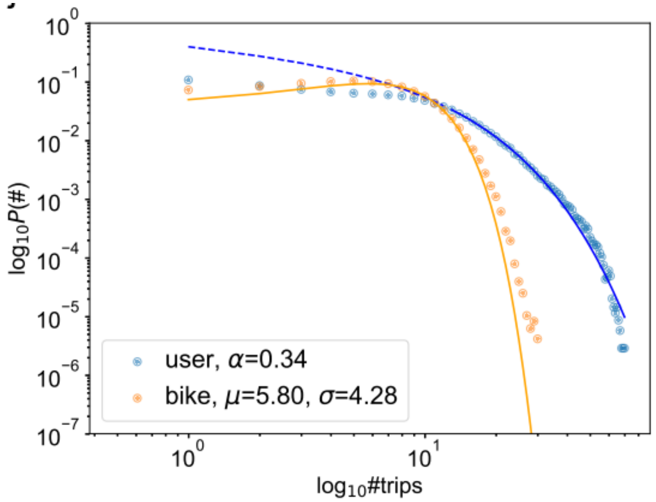
Trajectories of 10 most active bikes (up) and riders (bottom), which are different within and across cities

Different and even paradoxical collective mobility patterns on travelers and bikes

Shanghai



Beijing

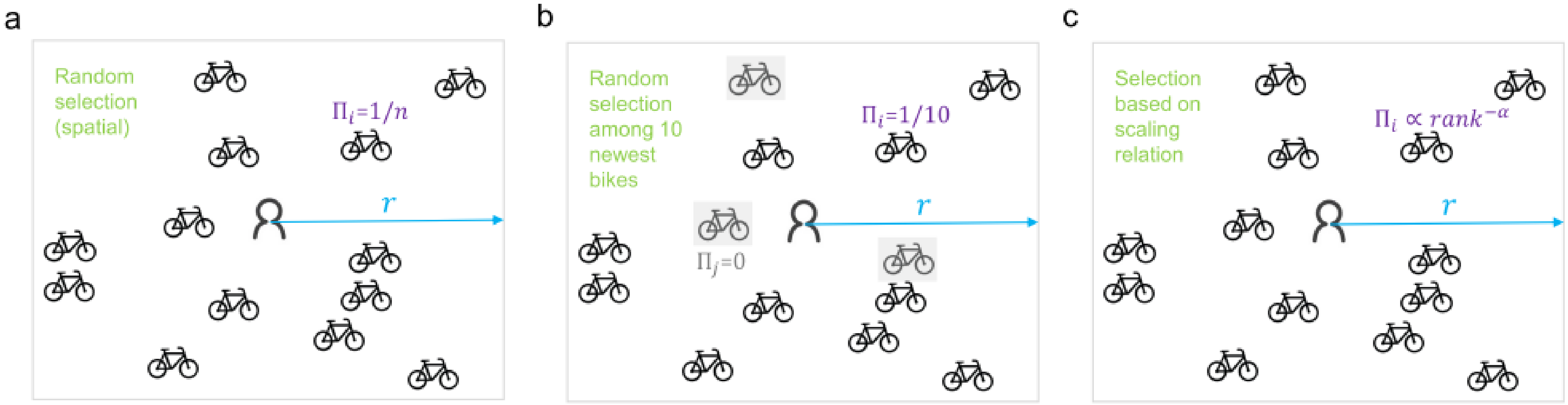


What's the underlying connection?

Choice behaviors should be central to such connection

And what might affect the choice on choosing which bike to ride?

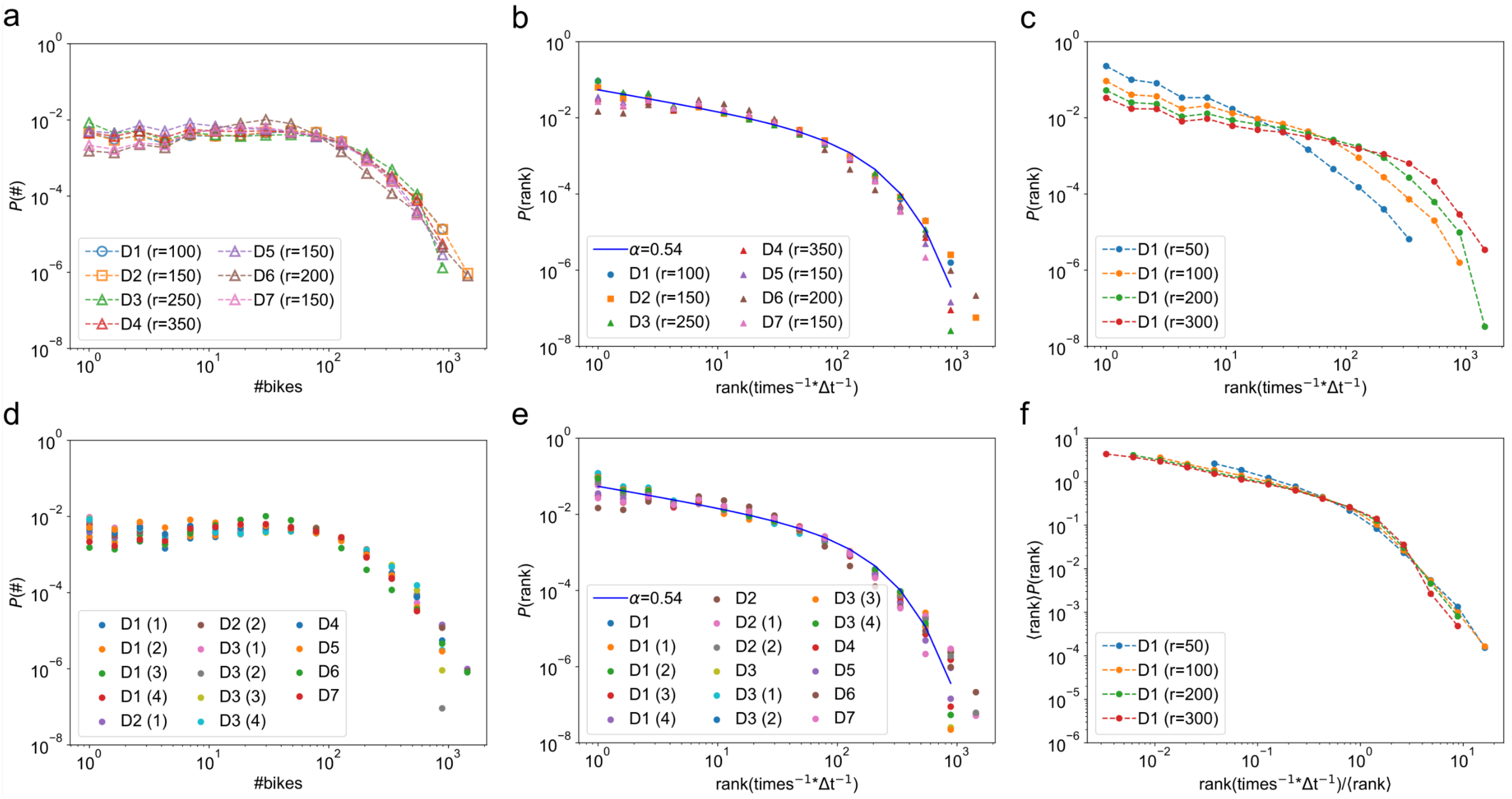
- Spatial scale
- The number of available bikes
- The conditions of bike
- The urgency of a trip
- If the user is picky or not
- …

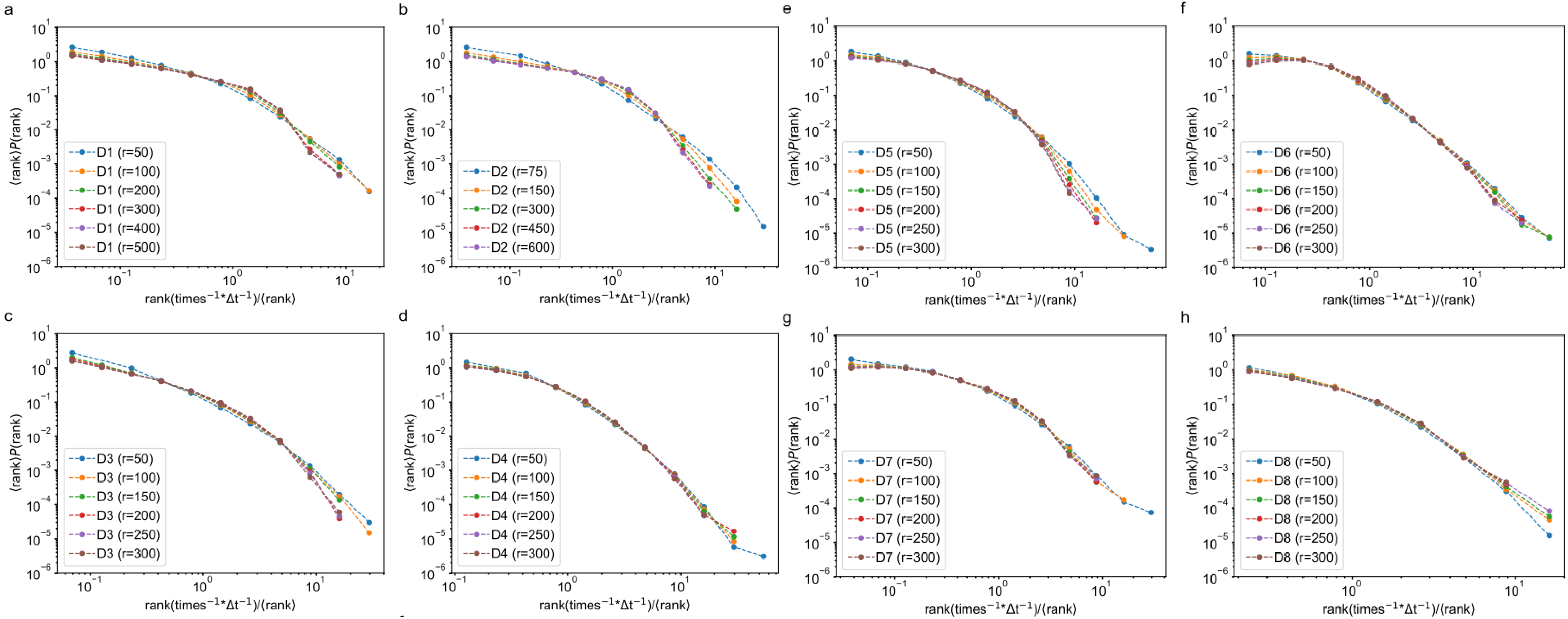


Emergence of Scaling during Selection Process

The spatial scale of two cities are different

Such patterns are quite stable over time (e.g., during each week)





a
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D1 (r=50)
D1 (r=100)
D1 (r=200)
D1 (r=300)
D1 (r=400)
D1 (r=500)
b
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D2 (r=75)
D2 (r=150)
D2 (r=300)
D2 (r=450)
D2 (r=600)
e
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D5 (r=50)
D5 (r=100)
D5 (r=150)
D5 (r=200)
D5 (r=250)
D5 (r=300)
f
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D6 (r=50)
D6 (r=100)
D6 (r=150)
D6 (r=200)
D6 (r=250)
D6 (r=300)
c
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D3 (r=50)
D3 (r=100)
D3 (r=150)
D3 (r=200)
D3 (r=250)
D3 (r=300)
d
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D4 (r=50)
D4 (r=100)
D4 (r=150)
D4 (r=200)
D4 (r=250)
D4 (r=300)
g
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D7 (r=50)
D7 (r=100)
D7 (r=150)
D7 (r=200)
D7 (r=250)
D7 (r=300)
h
⟨rank⟩P(rank)
rank(times^{-1}*Δt^{-1})/⟨rank⟩
D8 (r=50)
D8 (r=100)
D8 (r=150)
D8 (r=200)
D8 (r=250)
D8 (r=300)

KS distance between the generated distribution and empirical one of bikes

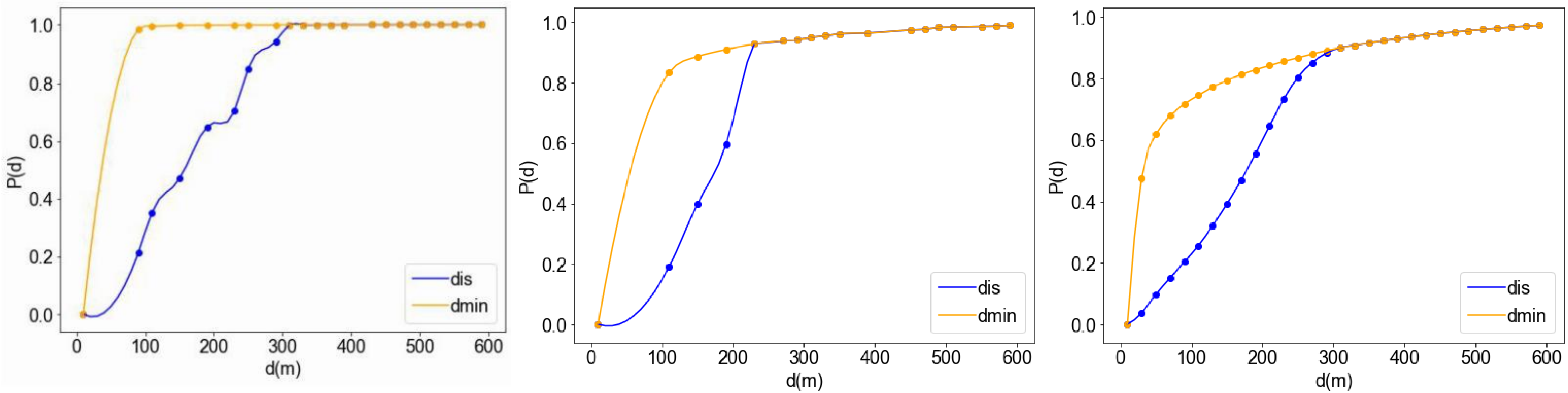
Nanjing	#trips	$\langle d \rangle$	gyration	revisitation	longest trip
(i) Random (non-spatial)	0.2301	0.0493	0.7865	**0.0485**	0.0930
(ii) Random (spatial, r=100 m)	0.1426	0.0283	0.4737	0.3283	0.0614
(iii) $times^{-1}$ (top10, r=100 m)	0.2623	0.0255	0.4795	0.3075	0.0949
(iv) $times^{-1}\Delta t^{-1}$ (top10, r=100 m)	0.1583	0.0418	0.4764	0.3595	0.0861
(v) $times^{-1}\Delta t^{-1}$ (top10, r=250 m)	0.0980	0.0214	**0.4209**	0.1663	0.0380
(vi) $times^{-1}\Delta t^{-1}$ (r=250 m)	**0.0693**	**0.0167**	0.4305	0.3007	**0.0236**

Supplementary Table 5. The KS distance between the generated distributions of bikes and the empirical one in Nanjing (D3). In D3, as there is no user ID provided, thus we have to treat the user of each trip as a new individual and apply the discovered scaling behaviour in Fig. 4b in the main text. It is slightly strange that the most unrealistic non-spatial random selection works the best on the revisitation indicator (see the fourth column of the table). For all other indicators, the The choice model vi that incorporates the discovered scaling behaviour outperforms other models. Across all three cities (D1-D3), the choice model vi generally over-performs others (see Table 1 in the main text and Supplementary Table 3). The smallest ones are highlighted in bold, and the second smallest are highlighted by underlines.

A simulation platform

We build a simple/primary simulation platform to evaluate the situation **if there's no bike rebalancing at all**

The latter two figures show the additional distance needed to find a bike in Shanghai (left), Beijing (middle), and Nanjing (right) on a nearest basis (orange lines) or a empirical choosing process and criteria (blue lines)

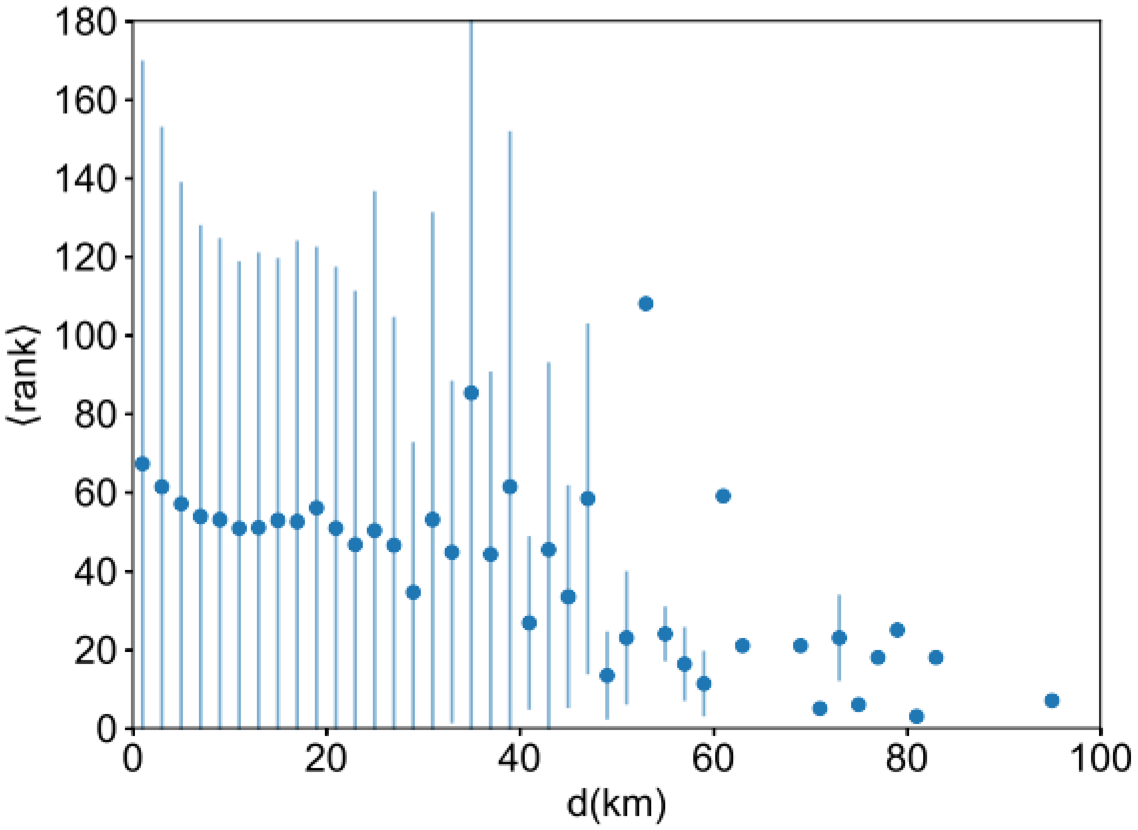


Thanks for your time !

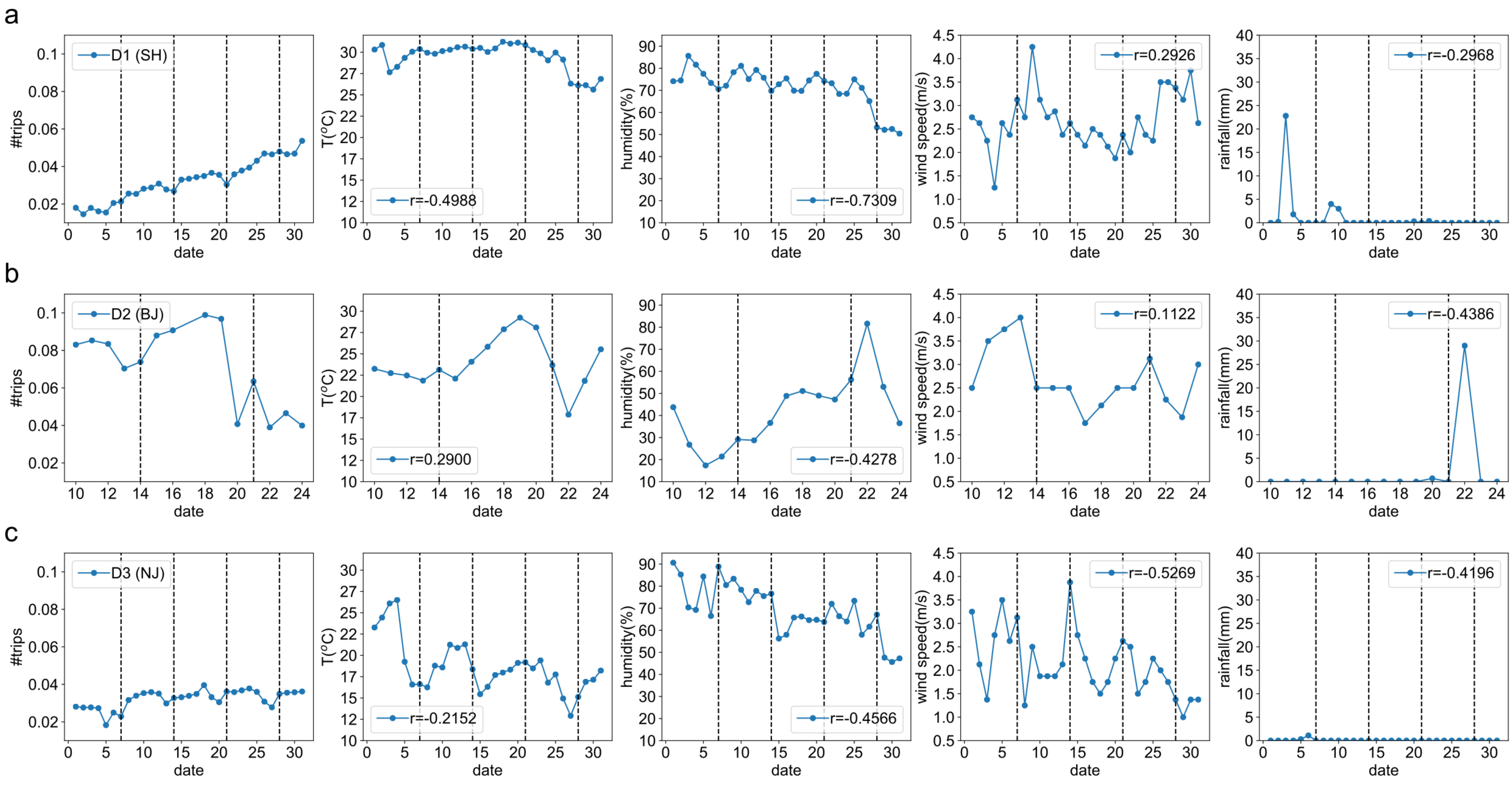
lir@buct.edu.cn

@RuiqiLii

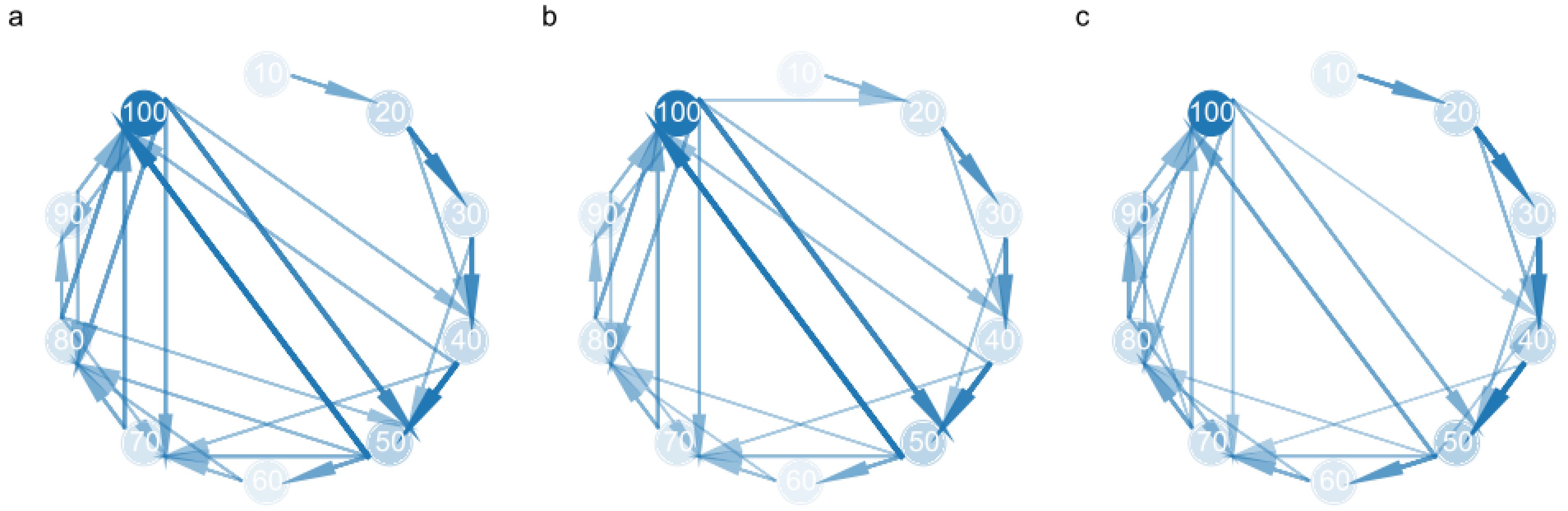
Better city Better life



Supplementary Figure 8: The average rank of bikes got selected for trips with increasing trip length in Shanghai (D1). It is clear that for longer distance trips, the average rank value of bikes got selected is smaller (i.e., the composite condition of the bike is better). Error bars mean standard deviation.



a
b
c
D1 (SH)
D2 (BJ)
D3 (NJ)
#trips
T(^oC)
humidity(%)
wind speed(m/s)
rainfall(mm)
date
r=-0.4988
r=-0.7309
r=0.2926
r=-0.2968
r=0.2900
r=-0.4278
r=0.1122
r=-0.4386
r=-0.2152
r=-0.4566
r=-0.5269
r=-0.4196



Supplementary Figure 9: The dynamics of the ranking of bikes. At each hour, we calculate the rank of the bike within the searching range that is consistent with Fig. 4a in the main text for each city. The rank value of each bike is categorised into ten levels: first ten percent (indicated by the "10" in the node, i.e., the newest ones), up to 90-100 percent ("100", the most unwanted ones). We observe a clear descending trend, but much less a "reviving" ascending trend. And the patterns are similar across cities. For clarity, we only show the top 30% of edges with the highest volume, and the color of the node denotes the self-loop volume. The results are obtained from the first day of the data as an example. **a**, Shanghai (D1); **b**, Beijing (D2); **c**, Nanjing (D3).