How many are too many?
Analyzing dockless bikesharing systems with a parsimonious model.

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Introduction

Dockless bikesharing (DLB) system:

- Healthy, environment friendly, affordable, flexible.

Spectacular rise since 2015

- Fleet size grew 10,000 folds in 2.5 years in China.
- Ridership reached 70 million per day in 2018.

Regulation challenges

- Nasty pricing wars and massive oversupply.
- Consumed much of the public space.
- Operators struggled to properly maintain and position their fleets.

Our contribution

- ❑ Take the **regulator's perspective**.
- ❑ Capture the **interdependence between bikesharing and other modes.**
- ❑ Joint **fleet sizing and pricing** decision.
- ❑ Strive for a better **balance between tractability and realism.**

Basic model

Passenger demand Q_b

- Consider a city where people only travel by three modes
- Travel cost:

Walking: $c_w = \frac{\mu}{v_w} l$

Biking via DLB: $c_b = \left(f_b + \frac{\mu}{v_b}\right) l + \mu a$

Driving (motorized modes): $c_d = \left(f_d + \frac{\mu}{v_d}\right) l + \tau$

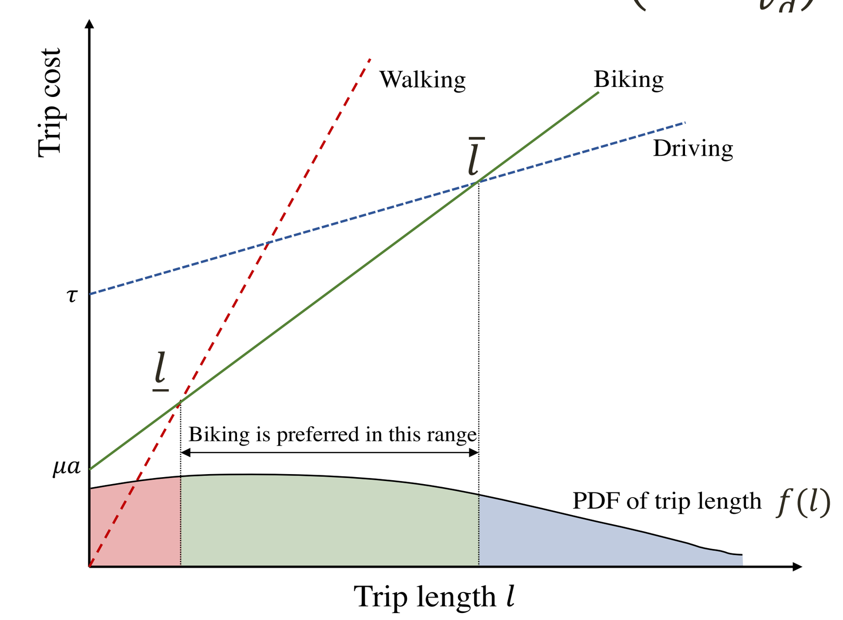

Fig.1 Illustration of mode split in a simplified mobility market.

Demand for biking: $Q_b = Q_0(F(\bar{l}) - F(\underline{l}))$

Bike supply (#idle bikes n)

Platform variables: bike fleet size B and fare rate f_b.

- The conservation of total bike time:

$$\underbrace{n}_{\text{Total parking time of idle bikes}} + \underbrace{\frac{Q_0}{v_b}\int_{\underline{l}}^{\bar{l}} x\,\mathrm{d}F(x)}_{\text{Total trip duration of occupied bikes}} + \underbrace{\alpha \frac{L}{v_r} Q_b}_{\text{Rebalancing time}} = B$$

Access time a

$$a = \frac{\delta}{v_w}\sqrt{\frac{A}{\tilde{n}}}$$

δ: parameter determined by city's geometry

A: the area of city

$\tilde{n}$: #unique bike locations

- its density is a function of the density of idle bikes, i.e ., $\frac{\tilde{n}}{A} = z\left(\frac{n}{A}\right)$. (unique location function)

Rebalancing

Each bike trip on average generates α rebalancing trips and results in a loss of σ unique locations.

$$\frac{\alpha Q_b}{\sigma Q_b} = \frac{n}{\tilde{n}} \rightarrow \sigma = \frac{\alpha \tilde{n}}{n}$$

The average rebalancing distance between a bike to be rebalanced and the nearest replenishment location:

$$L = \delta \sqrt{\frac{A}{\sigma Q_b}} = \delta \sqrt{\frac{n}{\tilde{n}} \frac{A}{\alpha Q_b}}$$

Proposition 1:
Given a bike fleet size B and a fare rate f_b, the equilibrium defined in the base model always has a solution.

Proposition 2:
The number of idle bikes n strictly increases with the fleet size B.

System design problems

Profit maximization

$$\max_{B, f_b} \; R = \underbrace{f_b Q_0 \int_{\underline{l}}^{\bar{l}} x\,\mathrm{d}F(x)}_{\text{Total revenue}} - \underbrace{\beta_0 B}_{\text{Purchase \& maintenance cost}} - \underbrace{\beta_1 \alpha L Q_b}_{\text{Rebalancing cost}}.$$

s.t. Equilibrium constraints, $B \geq 0, f_b \geq 0$

Proposition 3: Suppose a DLB operator aims to maximize profit while maintaining a stable level of service, i.e., a constant access time.

- ✓ **A higher rebalancing speed v_r always leads to a greater profit.**
- ✓ The **optimal fare rate f_b^* with a lower rebalancing speed dominates that with a higher rebalancing speed** in the strong set order.

Ridership maximization:

$$\max_{B, f_b} \; Q_b \;\; \text{s.t. Equilibrium constraints, } B \geq 0, f_b \geq 0$$

Social welfare maximization (system cost minimization)

$$\min_{B, f_b} \; \text{DLB operator's cost + Walking/Biking/Driving cost}$$
$$\text{s.t. Equilibrium constraints, } B \geq 0, f_b \geq 0$$

Case study

Data

Full sampled DLB trip records from a large DLB operator in Chengdu, China (43 days, 15,367,275 trips in total)

- #DLB bikes: 1.1 million (09/2018).
- Fleet cap: 0.6 million (05/2019); 0.45 million (05/2020).

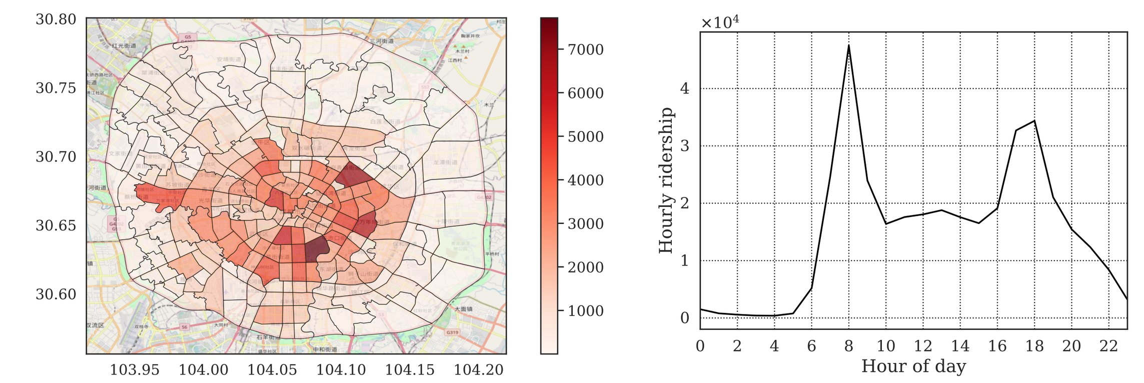

Fig.2 Spatial and temporal distribution of trip records.

Specification of unique bike location function

Trips are sliced in time intervals (30 mins) and subareas (240)

- #Idle bikes n: If one bike is parked within a space-time slot, record its location.
- #Unique bike locations $\tilde{n}$: For each space-time slot, apply DBSCAN (MinPts=2, ε=10m).

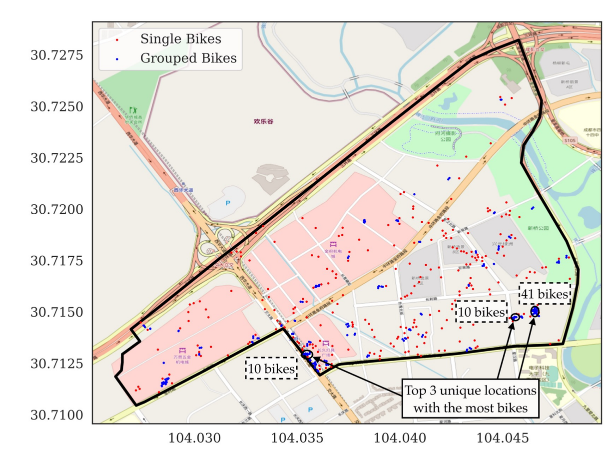

Fig.3 Illustration of clustering results. (474 bikes→322 unique locations)

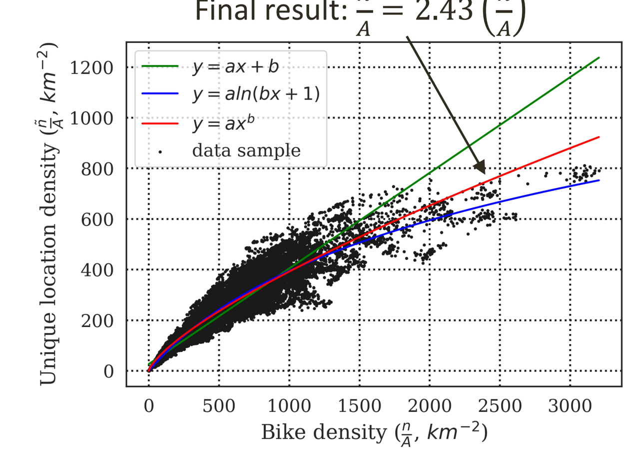

Fig.4 Empirical data and fitted functions.

Counterfactual scenarios

Table 1: DLB system performances: (i) profit maximization; (ii) ridership maximization with non-negative profit; and (iii) social optimum; (iv) the status quo.

Scenarios	i	ii	iii	iv
Price (¥/km)	1.782	**0.135**	0.015	0.416
#bike	75,578	**138,144**	151,496	**600,000**
Access time (min)	1.04	0.84	0.82	0.48
Average trip distance (km)	0.95	1.40	1.47	1.26
Utilization ratio	4.62%	7.39%	7.45%	1.45%
Ridership	26,603	**52,583**	**55,357**	49,904
Social welfare	57,583	**94,405**	**94,884**	74,052
Profit	39,222 (87%)	**0 (0%)**	-9,587 (-810%)	-10,498 (-40%)
Maintain cost	4,307 (10%)	7,874 (79%)	8,635 (730%)	34,199 (131%)
Rebalancing cost	1,352 (3%)	2,055 (21%)	2,135 (180%)	2,463 (9%)
Revenue	44,883 (100%)	9,929 (100%)	1,182 (100%)	26,165 (100%)

Scenario (ii) delivers a more balanced performance:

- an affordable price to maintain revenue neutrality
- ridership and social welfare close to system optimum
- a much smaller fleet than what is currently deployed

Options of a regulator

- **Regulator:** maximize bike ridership or social welfare by restricting either the price or the fleet size.
- **Operator:** maximize profit or ridership regardless of the regulations.

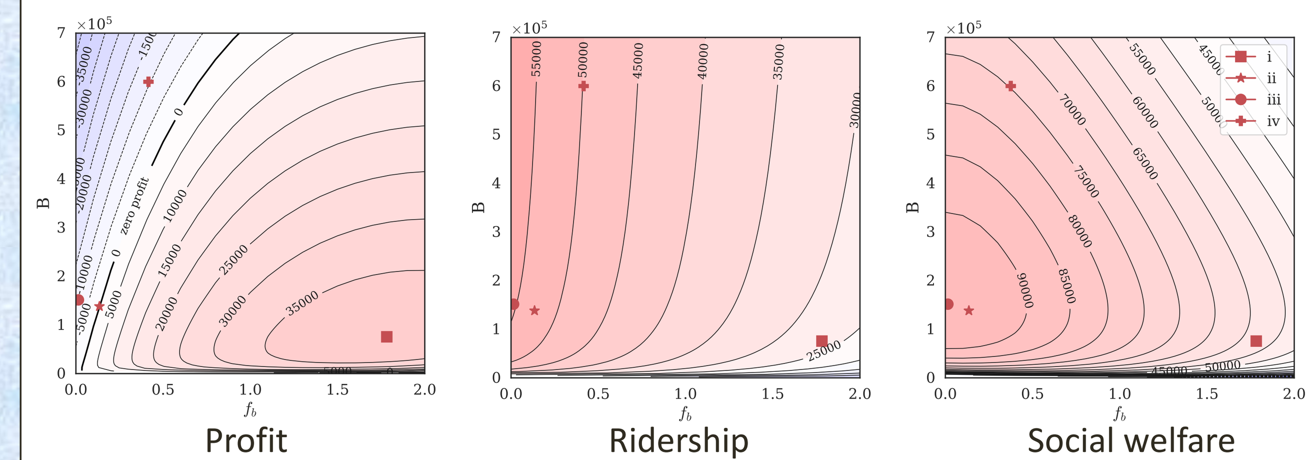

Fig.5 Operator's profit, ridership and social welfare at different prices and fleet sizes.

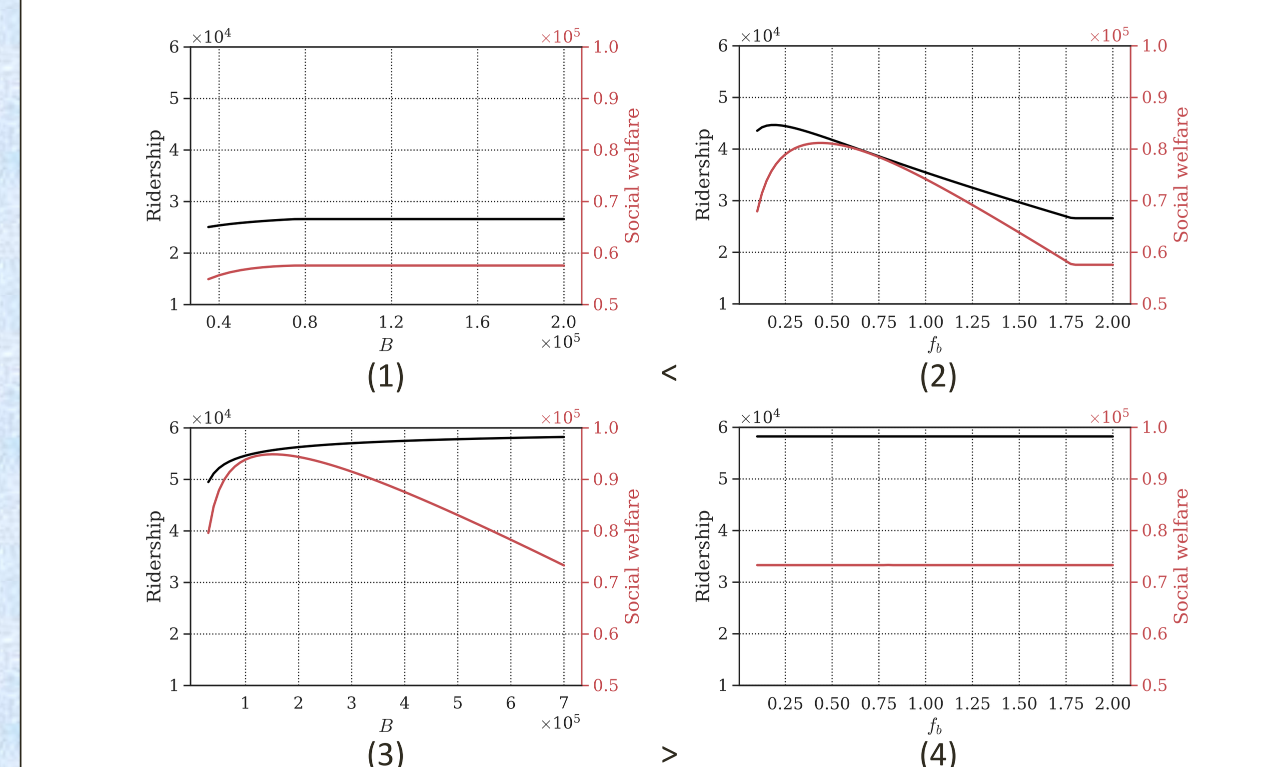

Fig.6 Ridership and social welfare achieved when the operator maximizes profit (1,2) or ridership (3,4). In fleet control (1,3), price optimized with fleet size less than B. In price control (2,4), fleet size optimized with price less than f_b.

Conclusions

- ➢ Current fleet cap set by Chengdu (450,000) should be **cut by roughly two thirds** in order to avoid severe oversupply and waste.
- ➢ **Maximizing ridership with non-negative profit** delivers more balanced outcomes.
- ➢ **The choice of regulator policy depends on the operator's objective:**
  - If its focus is profit, limiting price is more effective. Between ¥ 0.2 and ¥ 0.4 per km for Chengdu.
  - If it aims to grow ridership for a dominant market position, then fleet size limit is a better strategy.

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