Does dockless bikesharing create a competition for losers?

Hongyu Zheng[1], Kenan Zhang[2], and Yu (Marco) Nie[1]
Department of Civil and Environmental Engineering, Northwestern University
School of Architecture, Civil and Environmental Engineering (ENAC), École polytechnique fédérale de Lausanne (EPFL)

Web link to this poster

Introduction

Benefits of 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
- Low entry barrier: nasty pricing wars/massive oversupply.
- Operators struggled to properly maintain and position their fleets.
- Consumed too much public space.

Our contributions
- ❑ Propose a dynamic game framework to model the **inter-operator competition**.
- ❑ Explain why the unregulated DLB market is often **oversupplied and prone to collapse** under competition.
- ❑ Design **an effective policy to avoid the market failure.**

Dynamic game of oligopoly competition

Game: $M(\mathbb{I}, \mathbb{S}, \mathbb{T}_i|_{i\in\mathbb{I}}, u_i|_{i\in\mathbb{I}})$, Operator set: $\mathbb{I} = \{1,2,\dots,I\}$

Upper level (multi-objective optimization)
- Each operator i chooses an **action** $s_i \in \mathbb{S} = \{S_1, \dots, S_K\}$.
- Each s_i is tied to an objective, e.g., maximizing profit.
- Operator i's **set of objectives is** $\mathbb{T}_i = \{T_{i1}, \dots, T_{iK}\}$.
- Vector-valued **payoff function** $u_i: \mathbb{S}^{|\mathbb{I}|} \to \mathbb{R}^{|\mathbb{S}|}$.
- With action profile $\boldsymbol{s} = \{s_i, \boldsymbol{s}_{-i}\}$, the payoff vector $\boldsymbol{t}_i = u_i(\boldsymbol{s}) = [t_{i1}, \dots, t_{iK}]$, is determined in the lower level.

Lower level (Subgame perfect Nash equilibrium)
- Each operator i chooses tactics $\boldsymbol{y}_i$ to maximize the objective associated with its chosen upper-level action.
  - $\boldsymbol{y}_i = [B_i, f_i]$, B_i: Fleet size, f_i: Fare rate (¥/km)
  - Proper decision: $\boldsymbol{y}_i \in \mathbb{Y}_0$ if $f_i \in [0, \Gamma_f]$, $B_i \in [0, \Gamma_B]$
- Operator i's decision problem:

$$\max_{\boldsymbol{y}_i \in \mathbb{Y}_0} T_{ik}(\boldsymbol{y}_i, \boldsymbol{y}_{-i})\Big|_{s_i = S_k}$$

s.t. Equilibrium constraints,
Operational requirements.

- General Nash equilibrium (GNE):

$$T_{ik}(\boldsymbol{y}_i^*, \boldsymbol{y}_{-i}^*) \geq T_{ik}(\boldsymbol{y}_i, \boldsymbol{y}_{-i}^*), \forall \boldsymbol{y}_i \in \boldsymbol{\Omega}_i(\boldsymbol{y}_{-i}^*), \forall i \in \mathbb{I}.$$

- The GNE can be solved using a Bi-level Dual Gradient Descent (BDGD) algorithm, please see the full paper for more details.

Nash equilibrium of the dynamic game

Definition 1:
Given $\boldsymbol{s}_{-i}$ and $s_i = S_k$. Let $\boldsymbol{t}_i = u_i(\boldsymbol{s})$ and $\boldsymbol{t}'_i = u_i(\boldsymbol{s}')$ where $\boldsymbol{s} = \{s_i, \boldsymbol{s}_{-i}\}, \boldsymbol{s}' = \{s'_i, \boldsymbol{s}_{-i}\}$. If $t_{ik} \geq t'_{ik}, \forall s'_i \neq s_i$, we say s_i is a **consistent action** for operator i given $\boldsymbol{s}_{-i}$.

Definition 2:
Given $\boldsymbol{s}_{-i}$. Let $\boldsymbol{t}_i = u_i(\boldsymbol{s})$ and $\boldsymbol{t}'_i = u_i(\boldsymbol{s}')$ where $\boldsymbol{s} = \{s_i, \boldsymbol{s}_{-i}\}, \boldsymbol{s}' = \{s'_i, \boldsymbol{s}_{-i}\}$. If, $\forall s'_i \neq s_i$, we have $t_{ik} \geq t'_{ik}$, $\forall k = 1, \dots, K$ and at least one inequality holds strictly, then s_i is a **dominant action** for operator i given $\boldsymbol{s}_{-i}$.

Definition 3: Given an oligopoly game $M(\mathbb{I}, \mathbb{S}, \mathbb{T}_i|_{i\in\mathbb{I}}, u_i|_{i\in\mathbb{I}})$, an action profile $\boldsymbol{s}$ is a **Nash equilibrium under weak preference (NEWP) / under strong preference (NESP)** if for $\forall i \in \mathbb{I}$, s_i is a consistent/strong action given $\forall \boldsymbol{s}_{-i}$.

- NEWP ensures that every operator is content with its chosen action (still with flexibility to change).
- No one will change its action in an NESP (more stable).

Demand-supply equilibrium of a DLB market

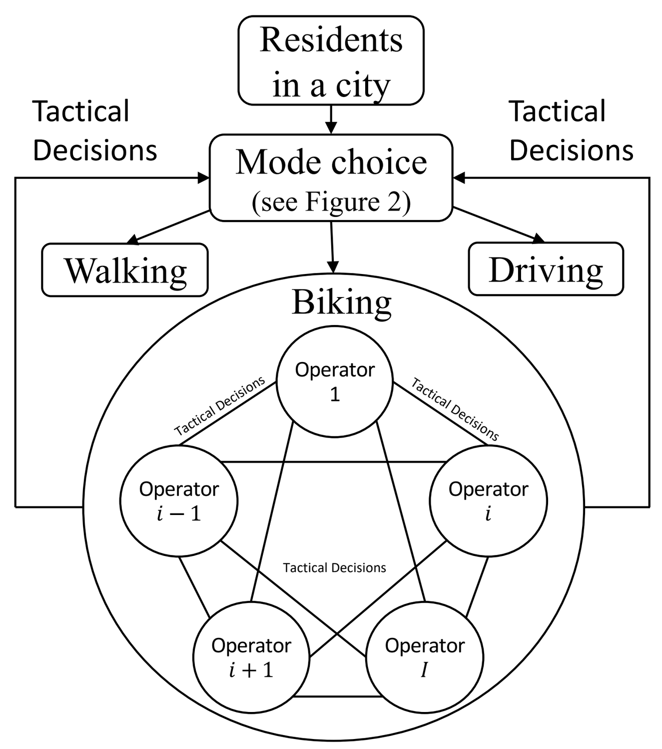

Fig.1 Bikesharing market with I operators.

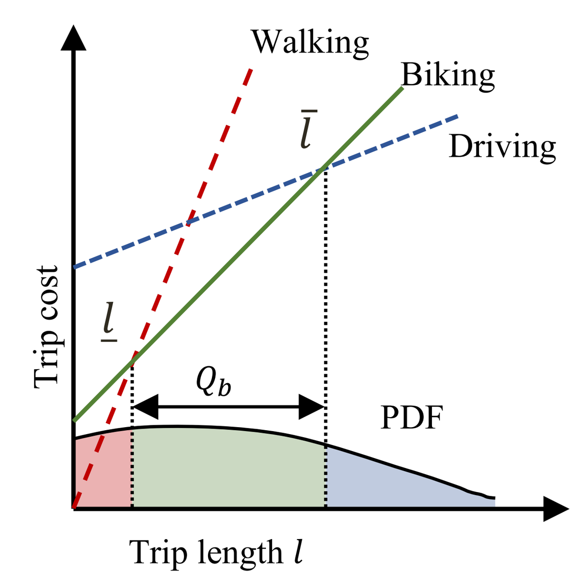

Fig.2 Mode split by trip length.

Demand
- Travel cost:
  - Walking: $c_w = \frac{\mu}{v_w} l$
  - Biking via DLB: $c_b = \left(f + \frac{\mu}{v_b}\right) l + \mu a$
  - Driving (motorized modes): $c_d = \left(f + \frac{\mu}{v_d}\right) l + \tau$

Total demand for biking: $Q = \bar{Q}(G(\bar{l}) - G(\underline{l}))$

Ridership of Operator i: $Q_i = \frac{n_i}{\sum_{j\in\mathbb{I}} n_j} Q - \sum_{j\in -i} k_{ij}(f_i - f_j)$

- n_i: #idle bikes of Operator i.
- k_{ij}: competition factor, which captures the amount of ridership shifted between Operator i and j.

Supply

The conservation of total bike time:

$$n_i + \frac{1}{v_b}\frac{Q_i}{Q}\bar{Q}\int_{\underline{l}}^{\bar{l}} x dG(x) + \alpha\frac{L_i}{v_r}Q_i = B_i$$

Total parking time of idle bikes; Total trip duration of occupied bikes; Rebalancing time

Average trip fare

$$f = \frac{\sum_{i\in\mathbb{I}} Q_i f_i}{\sum_{i\in\mathbb{I}} Q_i}$$

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., $\frac{\tilde{n}}{A} = z\left(\frac{\sum_{i\in\mathbb{I}} n_i}{A}\right)$, which is calibrated in Zheng et al. (2023)

Rebalancing
- Each bike trip on average generates α rebalancing trips.
- Please refer to Zheng et al. (2023) for the calculate method of average rebalancing distance.

Performance
- Profit = Revenue – Property cost – Rebalancing cost.
- Social welfare = system cost without DLB – system cost with DLB

Case study

Data
Full sampled DLB trip records from a large DLB operator in the city center of Chengdu, China (43 days, 15,349,358 trips in total)
- #DLB bikes: 1.1 million (09/2018).
- Fleet cap: 0.6 million (05/2019); 0.45 million (05/2020).

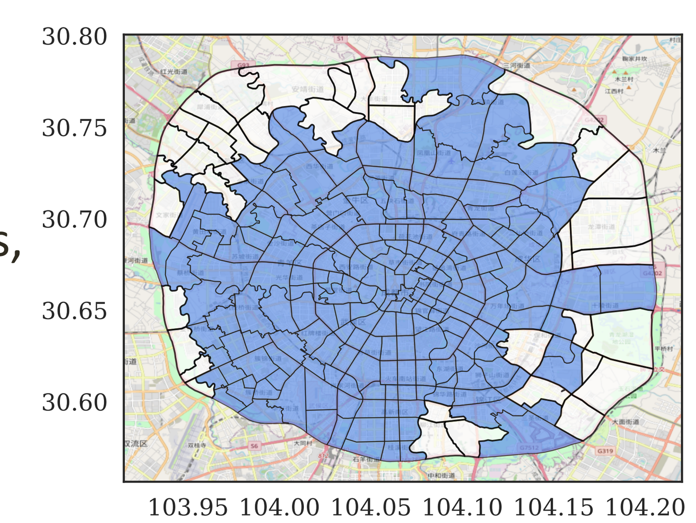

Fig.3 Chengdu's city center (colored area) considered for the case study.

Game settings
- Action set $\mathbb{S} = \{\mathrm{p}, \mathrm{r}\}$, where p is profit-maximization and r is ridership-maximization with a profit target $\overline{\Pi_i}$.
- Operator set $\mathbb{I} = \{1, 2\}$

Outcomes of a DLB duopoly competition
- Market always settles at the only NESP. No rational operator will unilaterally commit to profit maximization.
- Performance: zero profit, low social welfare.

Operator 1 \ Operator 2	$s_2 = \mathrm{p}$ (Maximizing profit)	$s_2 = \mathrm{r}$ (Maximizing ridership without deficit)
$s_1 = \mathrm{p}$ (NEWP)	6850, 20274 6850, 20274 56180	-117, 9539 0, 39387 62868
$s_1 = \mathrm{r}$	0, 39387 -117, 9539 62868	0, 23336 0, 23336 57122 (The only NESP)

Table 1: System performance. In each cell, the first and second rows report the payoff vectors for Operator 1 and 2, respectively, where the first/second element is its profit (¥/hr)/ridership (trips/hr), and the third row reports social welfare (¥/hr).

Role of regulation
- Fleet cap can avoid the market failure and improve social welfare and profitability.

Operator 1 \ Operator 2	$s_2 = \mathrm{p}$ (Maximizing profit)	$s_2 = \mathrm{r}$ (Maximizing ridership with no budget constraint)
$s_1 = \mathrm{p}$	10274, 19516 10274, 19516 60037	5398, 12605 -6552, 39273 69480
$s_1 = \mathrm{r}$	-6552, 39273 5398, 12605 69480	-6176, 28056 -6176, 28056 69741

All action profiles are NEWP

Table 2: System performance in a duopoly dynamic game with a fleet cap = 61803 for each operator.

Sensitivity of profitability to the number of operators
- A relatively mature market with profit-maximizing operators.

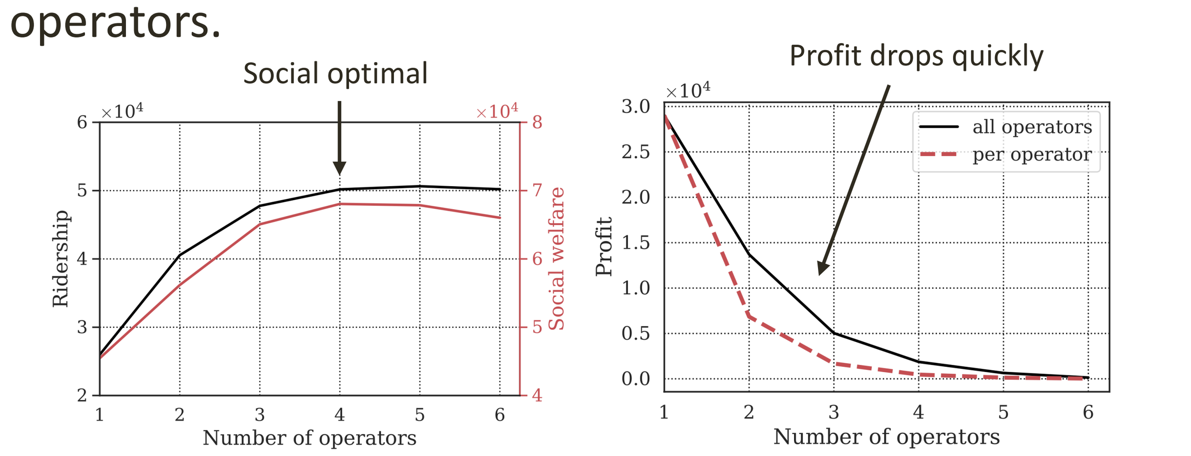

Fig. 4 System performance metrics in an oligopoly market with different numbers of profit-maximizing operators.

Takeaway messages
- ➢ **If one DLB operator wants to dominate the market, the others must do the same.**
  - Fleet cap can avoid the trap in which everyone is competing to lose more money.
- ➢ **Profit plunges with #operators if focusing on making money.**

References: Zheng H., Zhang K., Nie Y., Yan P., and Qu Y. (2023). How many are too many? Analyzing dockless bikesharing systems with a parsimonious model. Transportation Science, 0(0). Published online.

Zheng H., Zhang K., and Nie Y. (2023). Does dockless bikesharing create a competition for losers? *Available at SSRN: http://dx.doi.org/10.2139/ssrn.4613247.* Under review in Management Science.