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Analyses of Ridesourcing Systems and Their Drivers' Behaviors

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Acknowledgement

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  - Hai Yang, Hong Kong University of Science and Technology
- Sponsors

Ridesourcing—"crowd-sourced" taxi services

- Ridesourcing refers to an urban mobility service that began in 2010, in which private car owners use their own vehicles to provide for-hire rides (Rayle et al., 2014).
- Transportation Network Companies (TNCs) like Uber, Lyft and Didi Chuxing provide ride-hailing apps that intelligently match participating drivers to riders. These apps are free to use but usually a commission is charged for each transaction/ride

UBER

31 m rides per day

DiDi

41 m rides per day

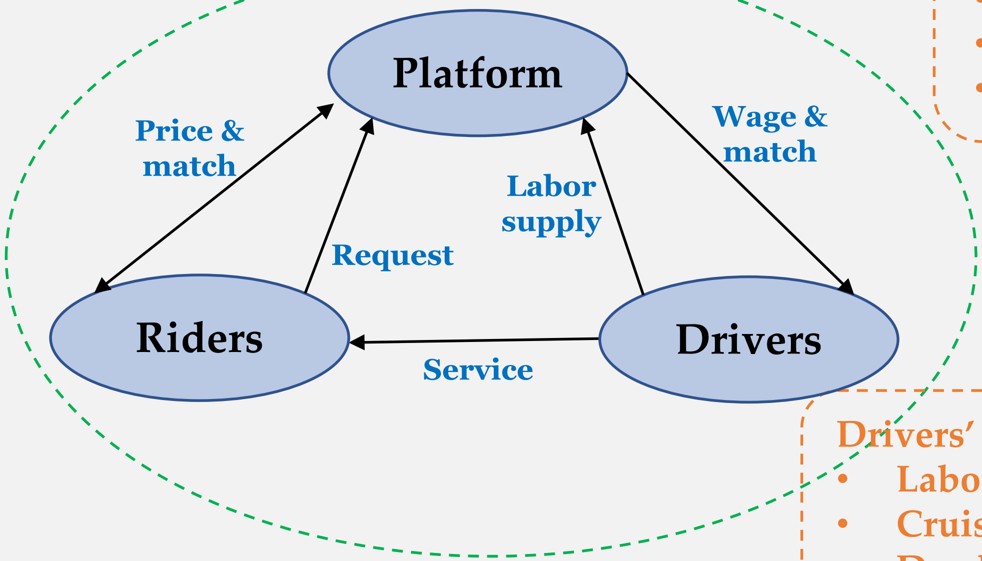
Our research program on ridesourcing

- We launched a research program in 2014 aimed at studying the operations of ridesourcing services, understanding their impacts and implications, and developing policies and strategies to guide their deployment and improve their performance
- The research findings also provide insights into the operations and management of future automated shared mobility services.

Research scope

Operations strategies

- Matching
- Pricing
- Repositioning
- Contract design
- Incentive design



Macroscopic modeling of ride-hailing systems

- Efficiency
- Regulation
- Traffic congestion

Drivers' behaviors

- Labor supply
- Cruising
- Dwelling

limos lab for innovative mobility systems

Today's plan

1 Analyses of ridesourcing systems

2 Analyses of ridesourcing driver dwelling behaviors

Controversies over congestion and competition

Vox

OPEN SOURCED RECODE THE GOODS FUTURE PERFECT THE HIGHLIGHT FIRST PERSON MORE

Uber and Lyft have admitted to making traffic worse in some US cities

npr

SIGN IN NPR SHOP

NEWS ARTS & LIFE MUSIC SHOWS & PODCASTS SEARCH

NATIONAL

Ride-Hailing Services Add To Traffic Congestion, Study Says

Uber, Lyft say they help ease traffic congestion. New study says otherwise.

Traffic in San Francisco grew worse as Uber and Lyft became more popular.

Uber and Lyft are suing New York City after it limited the length of time drivers can cruise without passengers

SCIENCE ADVANCES | RESEARCH ARTICLE

ECONOMICS

Do transportation network companies decrease or increase congestion?

Sections

The Washington Post

Democracy Dies in Darkness

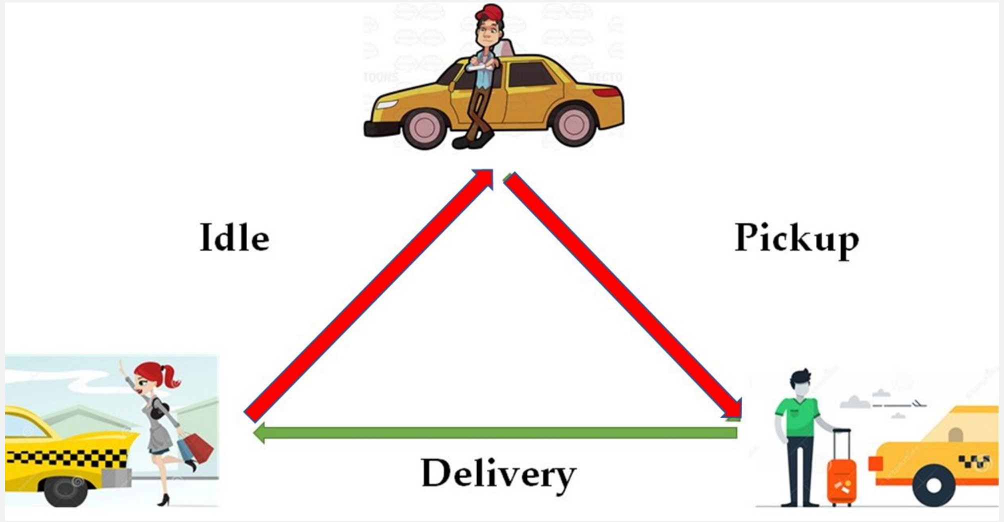
Gridlock

Uber and Lyft concede they play role in traffic congestion in the District and other urban areas

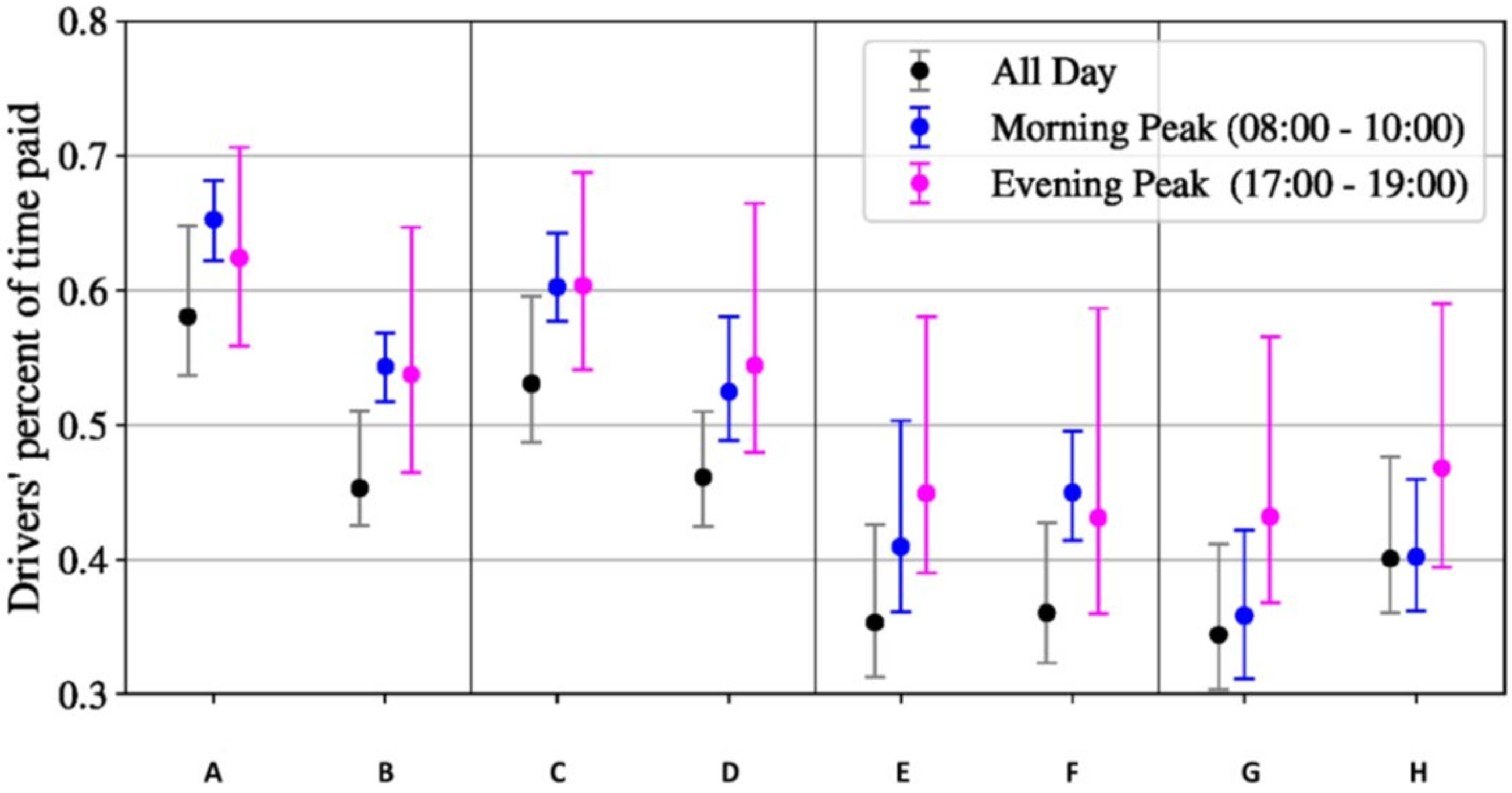
About 1 in every 15 miles driven in the District is in an Uber or Lyft, according to a study.

Empty miles

- In-service miles driven by ridesourcing vehicles without a passenger
  - Ghost or zombie miles if automated vehicles
- Empty miles generate additional traffic demand, contributing to congestion
  - On a typical weekday, ridesourcing contributes 20% vehicle-miles-traveled in San Francisco (SFMTA, June 2017). Roughly 50% of them are empty

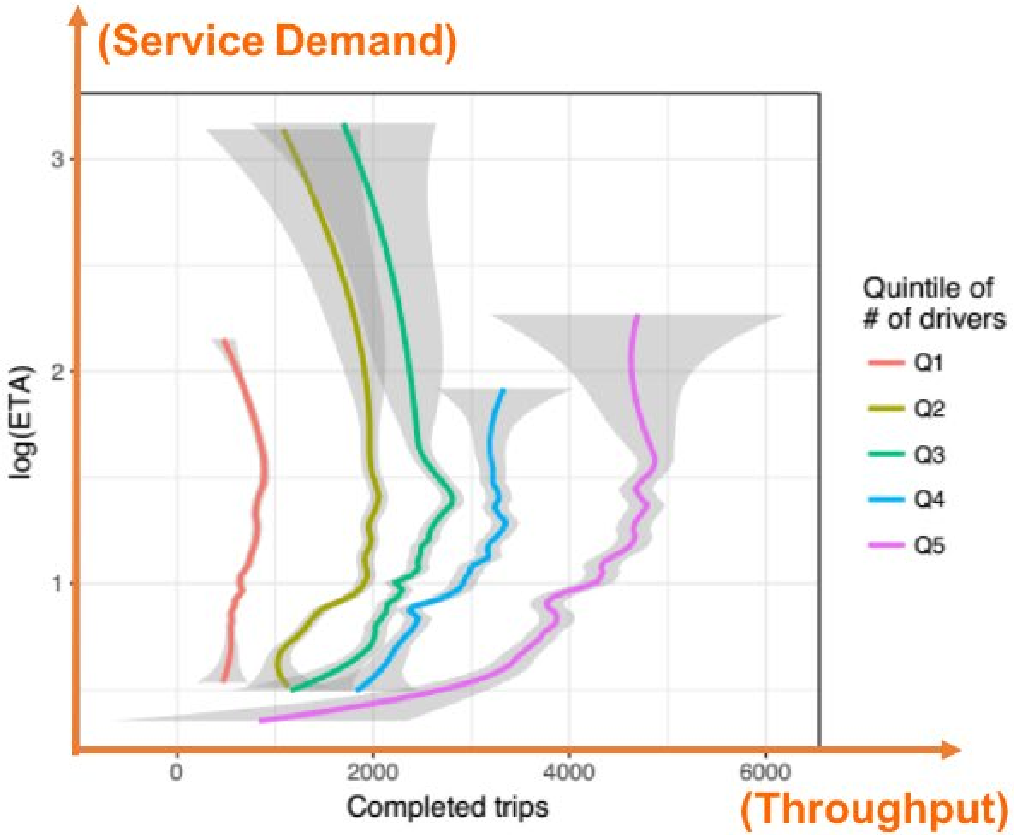


Substantial empty time (mileage) exists within the system

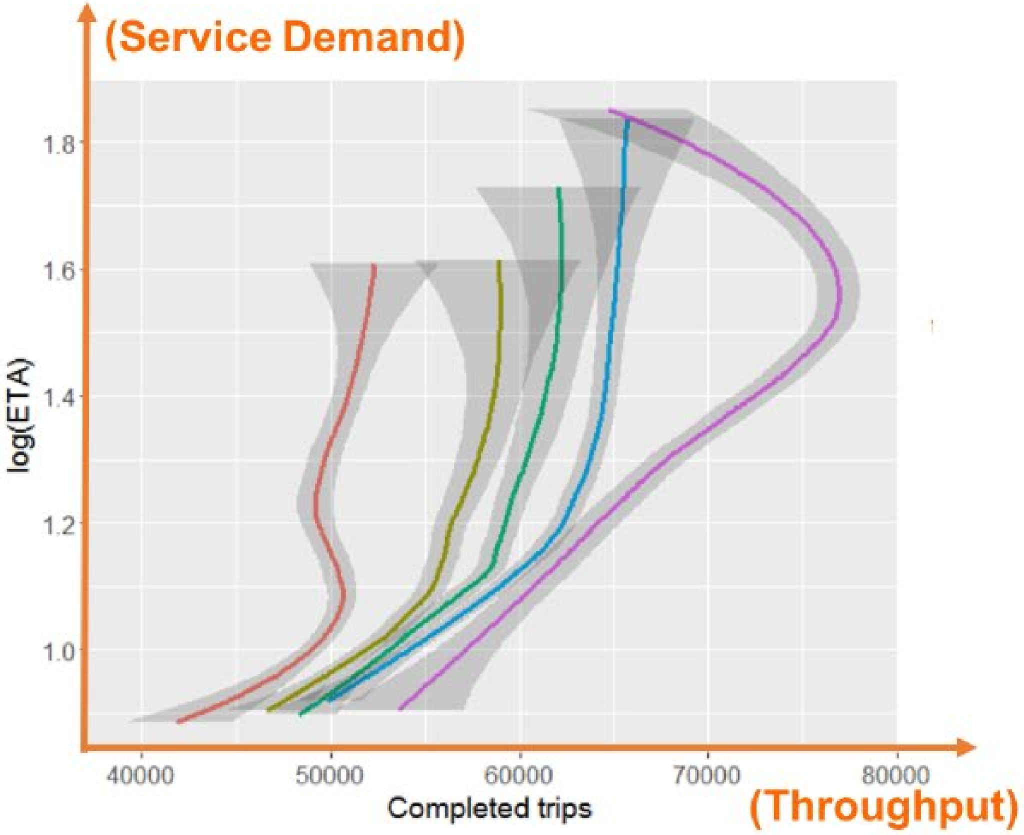


Daily average utilization rate varies substantially in practice, ranging from 34% to 58%

Worse yet, loss of efficiency as the system becomes busier …



Uber - New York City
(Castillo et al., 2018)



DiDi - Chengdu

Causes for loss of efficiency: matching failures

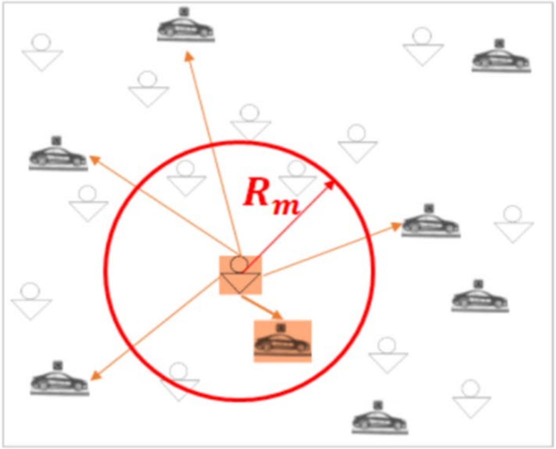


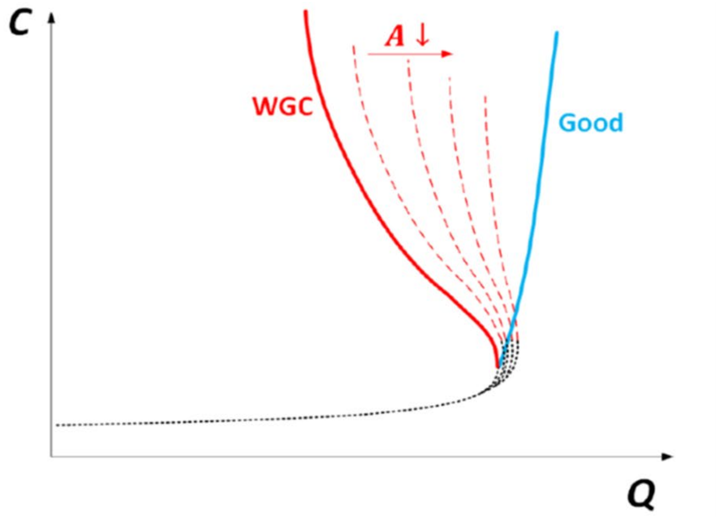
	Idle	Pickup	Delivery
$N =$ Total Number of Vehicles	N^v +	N^m +	N^d

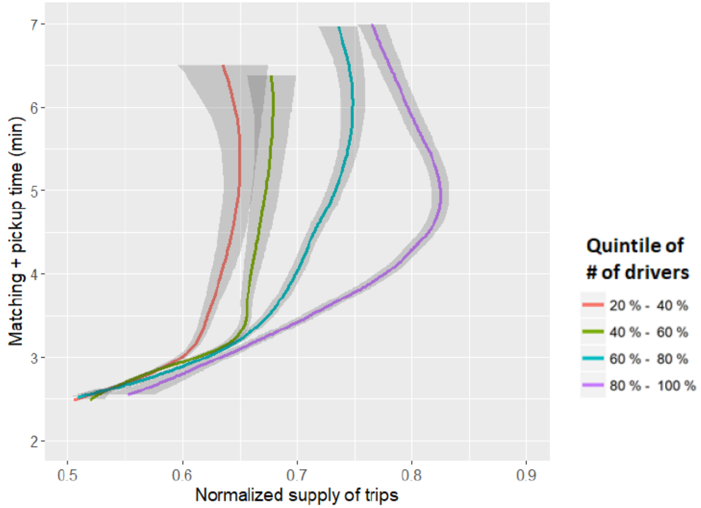
Quick Commitment — "Wild Goose Chases"

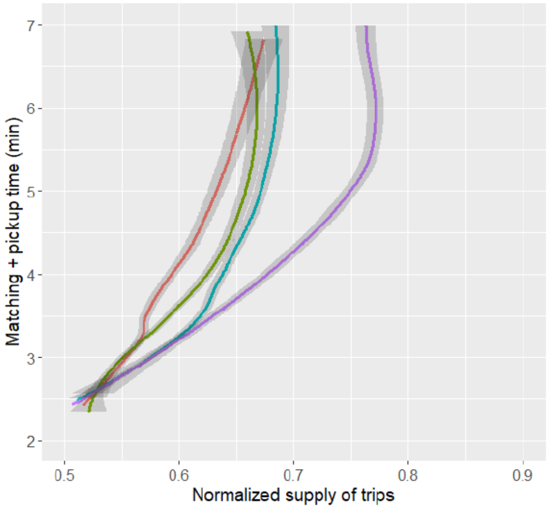
Indiscriminate Matching — "Countryside Delivery"

Adaptively adjusting matching radius solves "wild goose chases"*



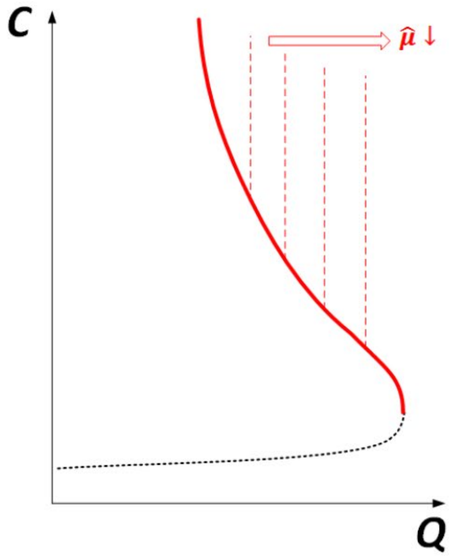


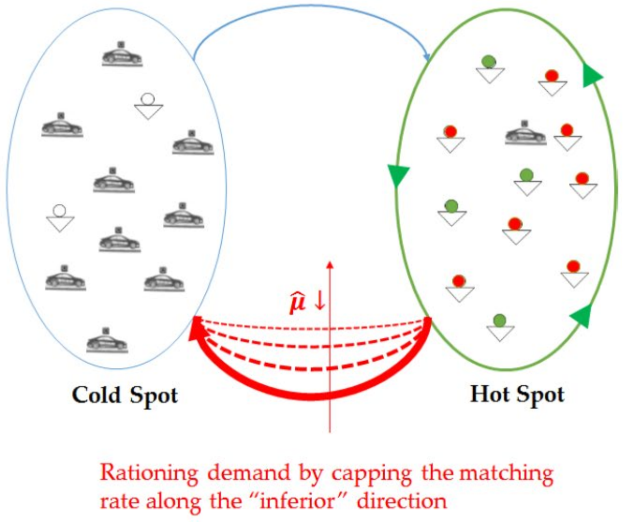


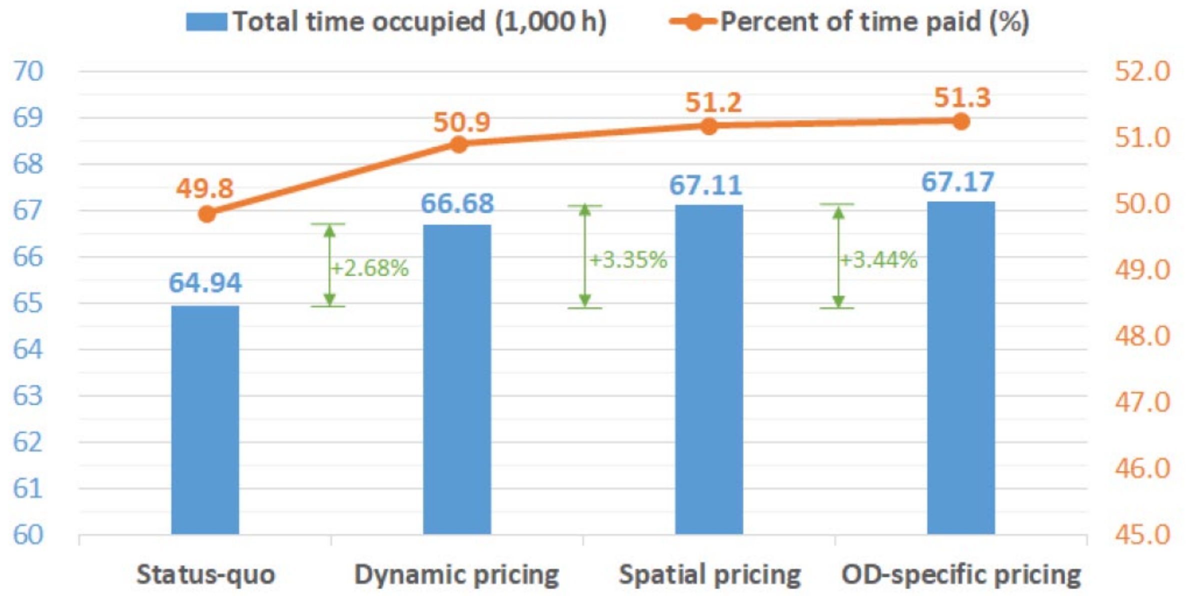


*Xu, Z., Yin, Y. and Ye, J. (2020) On the supply curve of ride-hailing systems. Transportation Research Part B, 132, 29-43.

Differentiated matching or pricing solves "countryside deliveries"*



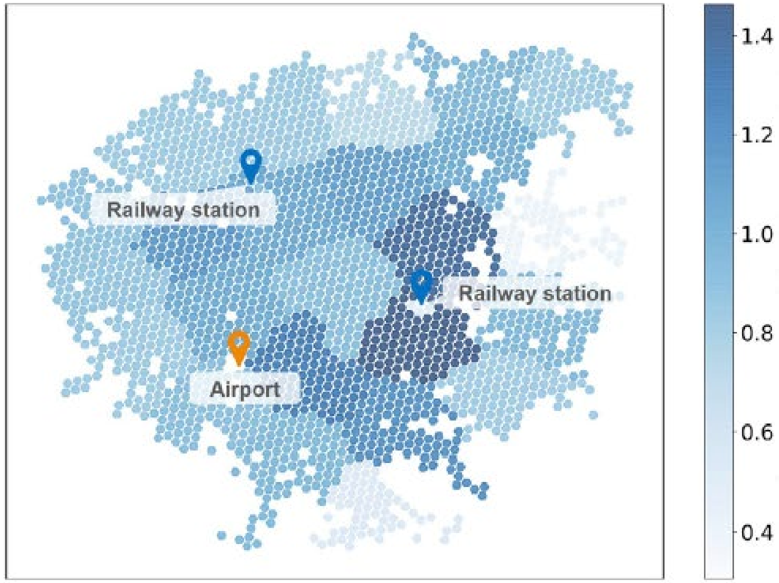




*Xu, Z., Yin, Y., Chao, X., Zhu, H. and Ye, J. (2021) A generalized fluid model for ride-hailing systems. Transportation Research Part B, 150, 587-605.

Repositioning of platform-controlled fleets to further address spatial demand-supply imbalance to reduce empty miles.*

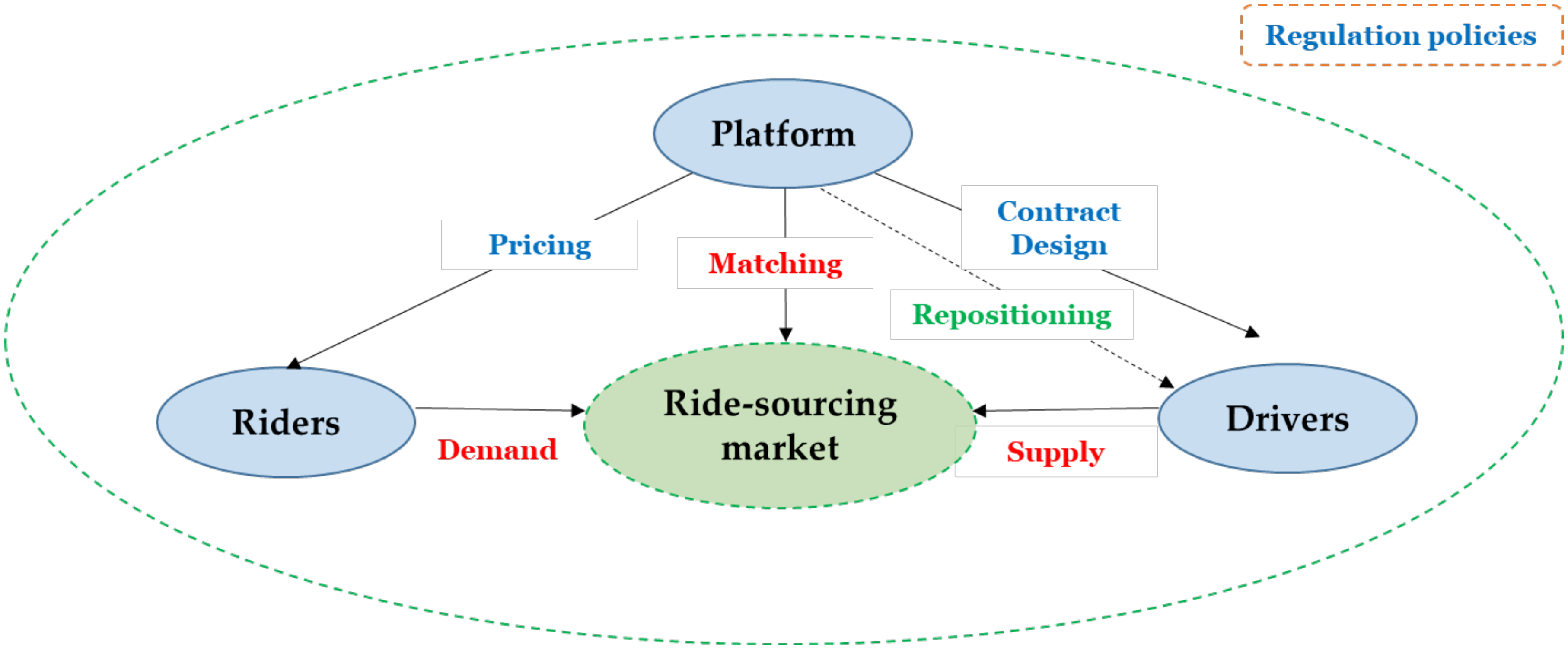
(a) Hourly trip demand



(b) Ratios of trip arrival and completion rates

* Dong, T., Luo, Q, Xu, Z., Yin, Y. and Wang, J. (2024) Strategic driver repositioning in ride-hailing networks with dual sourcing. Transportation Research Part C, 158, 104450.

There is a limit for such improvements due to the spatial asymmetry and temporal variation of passenger demand



Regulation remains the most powerful tool to address the congestion concern of ridesourcing services

An uneven playing field: taxi vs. ridesourcing

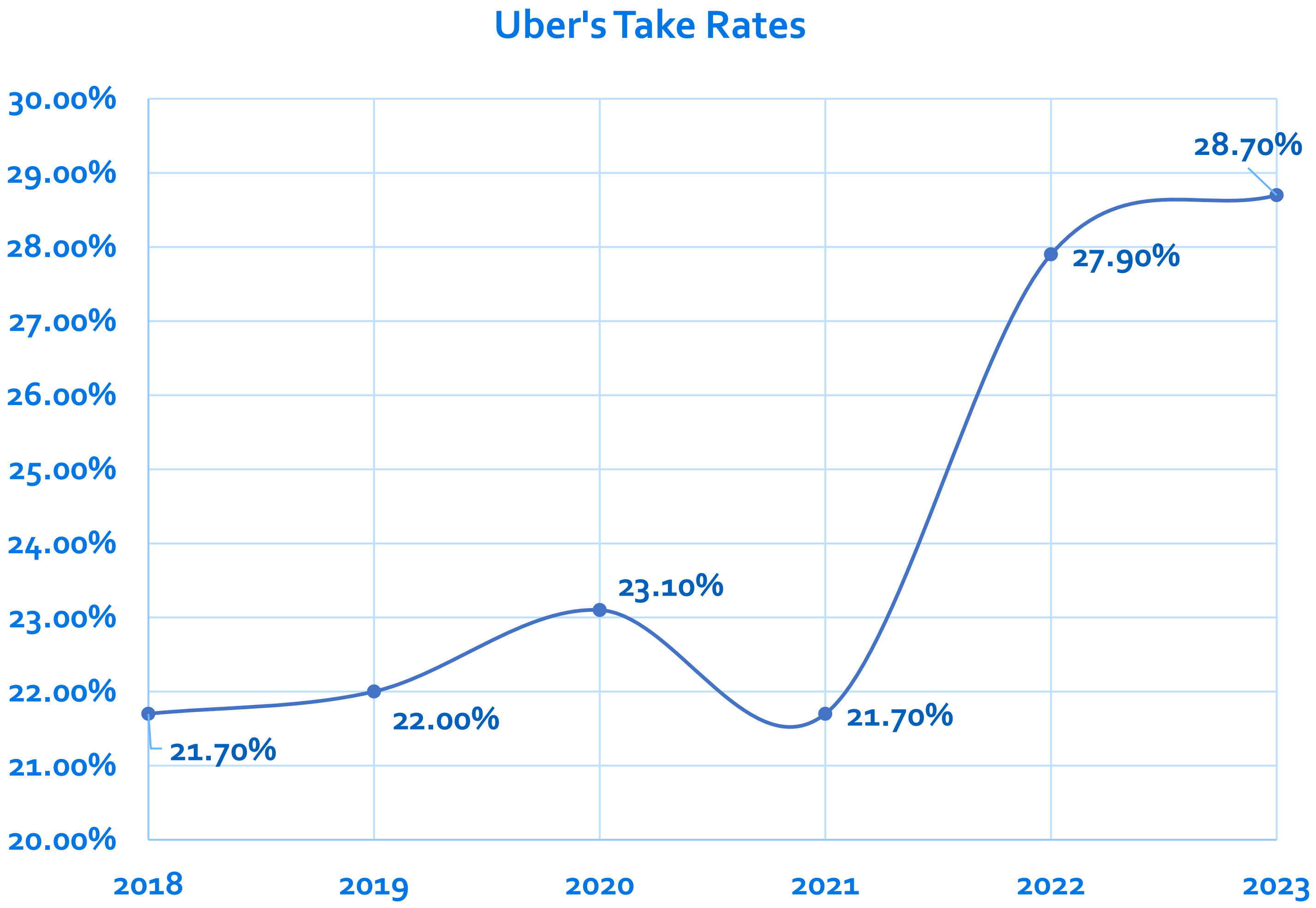
- The taxi industry is heavily regulated through quantity and price controls, while TNCs initially entered the market with minimal oversight compared to taxis.
- Over time, governments have introduced regulations for ridesourcing services, including requirements for driver background check, insurance, and safety measures. However, these regulations are generally less restrictive than those imposed on traditional taxis.
- Regulations in the U.S.
  - Quantity: New York City imposed a cap in 2018, later lifting it in 2023 for new vehicles, provided they are electric or wheelchair-accessible
  - Congestion charge: New York City, Chicago
  - Minimum wage: Seattle, New York City, California

Capping commission

- Capping the commission alone has potential to increase social welfare*
- The policy can have different granularity levels. The cap may be imposed per trip, unit distance or time, and can vary with respect to location or even time of day**
- When congestion is high, congestion surcharge can be imposed to internalize congestion externality***

* Zha, L., Yin, Y. and Yang, H. (2016) Economic analysis of ride-sourcing markets. Transportation Research Part C, 71, 249-266.
Ke, J., Li, X., Yang, H., and Yin, Y. (2022) Pareto-efficient solutions and regulations of congested ride-sourcing markets with heterogeneous demand and supply. Transportation Research Part E, 102483.
** Zha, L., Yin, Y. and Xu, Z. (2018) Geometric matching and spatial pricing in ride-sourcing markets. Transportation Research Part C, 92, 58-75.
Zha, L., Yin, Y., Du, Y. (2018) Surge pricing and labor supply in the ride-sourcing market. Transportation Research Part B, 117, Part B, 708-722.
***Vignon, D., Yin, Y. and Ke, J. (2021) Regulating ridesourcing services with product differentiation and congestion externality. Transportation Research Part C, 127, 103088.

No direct cap or control exists on commission, i.e., the “take rate”



Uber Driver Salary in 2024

	Annual Salary	Monthly Pay	Weekly Pay	Hourly Wage
75th Percentile	$48,102	$4,009	$925	$23
Average	$39,402	$3,284	$758	$19
25th Percentile	$32,702	$2,725	$629	$16

Minimum wage

- California: $16.00 per hour
- Washington: $16.28 per hour
- New York City: $15.00 per hour

Key Takeaway

- Despite owning no vehicles, TNCs operate like a traditional cab company, which, if unregulated, would set prices and fleet size to maximize their profit. If the taxi market is regulated, there is a need to regulate ridesourcing as well.
- Commission regulation and congestion charge appear promising to increase social welfare

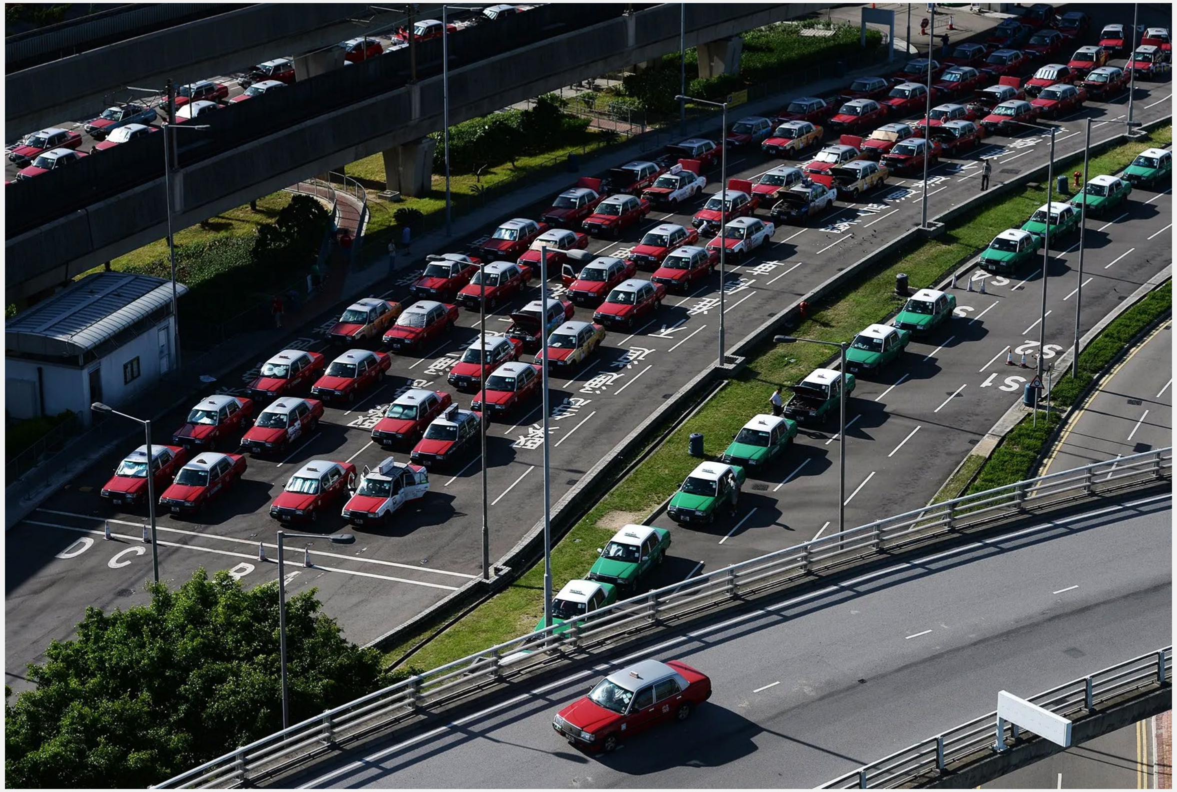
Today's plan

1 Analyses of ridesourcing systems

2 Analyses of ridesourcing driver dwelling behaviors

Driver dwelling at transportation terminals

Transportation terminals are hotspots for ridesourcing market and are often plagued by oversupply, long waiting time and poor management



TRAVEL NEWS

Uber drivers see long wait times for airport pickup requests

TECH

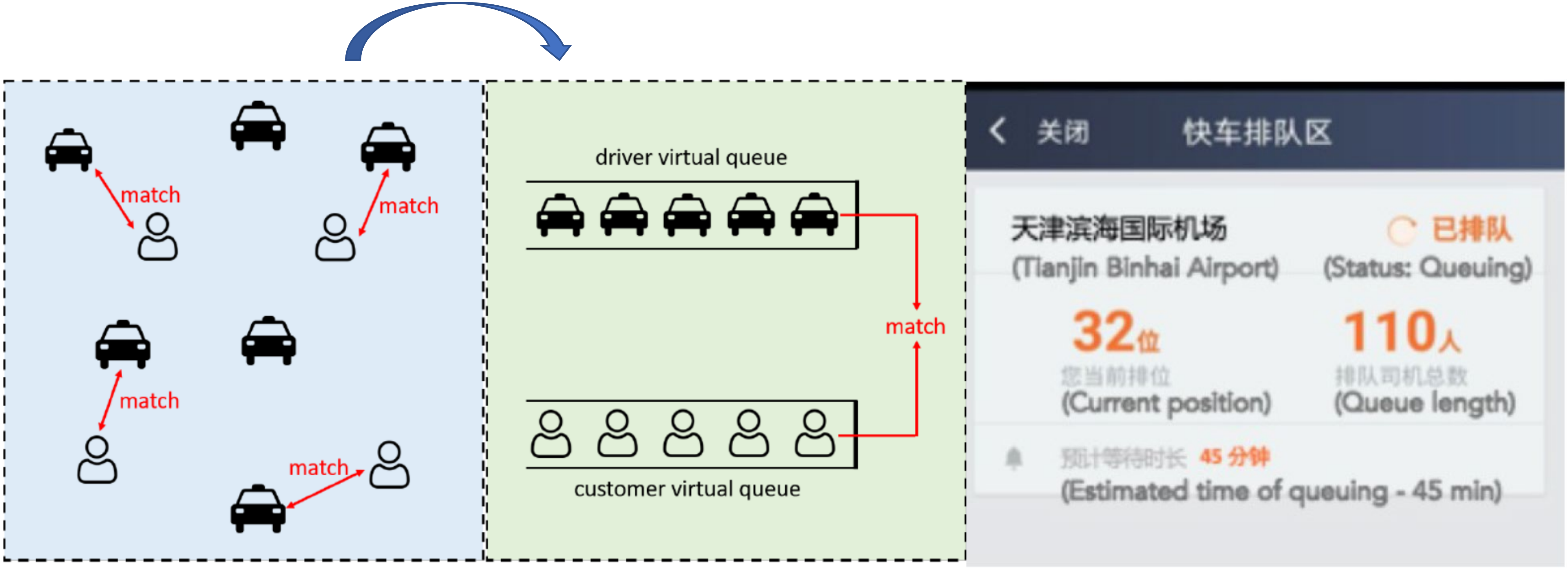
Uber, Lyft drivers at SFO doing lots of waiting, less driving

As SF fares dry up, drivers vie for spots in airport lots, lengthy wait

Uber dodges questions about driver waiting area chaos near OR Tambo Airport

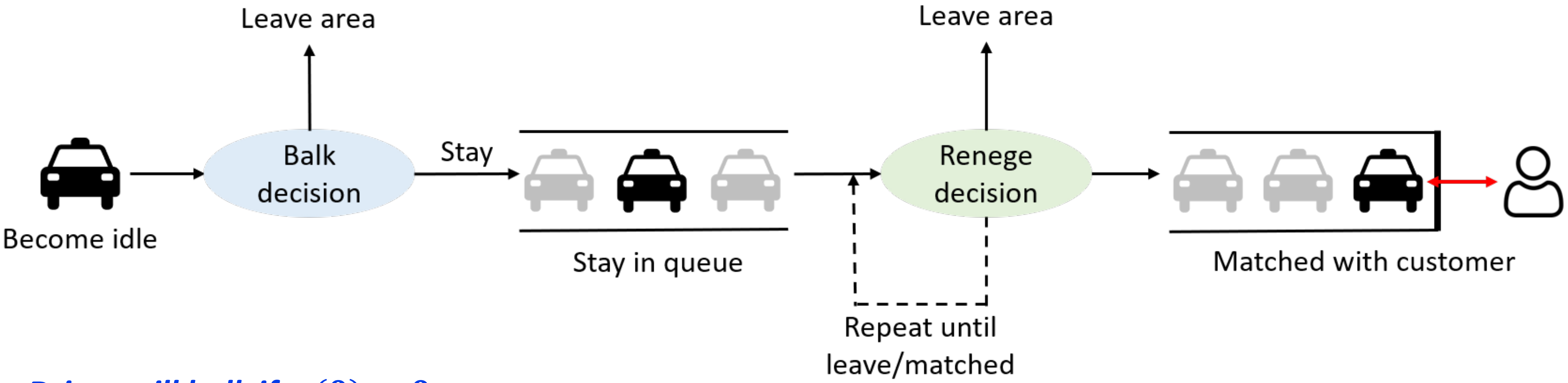
Hanno Labuschagne 2 November 2023

Understanding drivers' dwelling behaviors is crucial for efficient management of driver queue

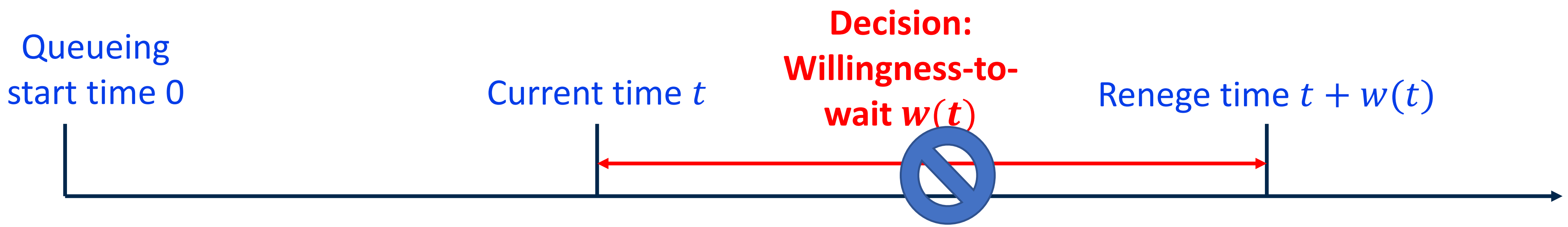


A Natural Experiment Conducted by Didi at Tianjin Airport (May 21–27, 2018)

Drivers' terminal dwelling as a queueing process

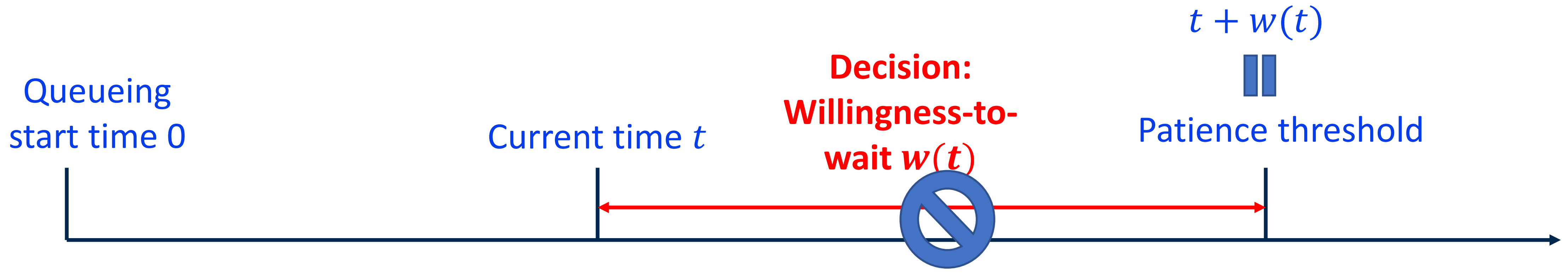


Driver will balk if $\boldsymbol{w(0) = 0}$



Matching probability: pdf $f(t)$ and cdf $F(t)$ defined on $[0, +\infty)$

Conventional paradigm



Matching probability: pdf $f(t)$ and cdf $F(t)$ defined on $[0, +\infty)$

When joining a queue, drivers compare perceived matching reward with the cost of waiting time to determine their patience threshold. During waiting, their willingness to wait (WTW) decreases at a rate of 1, i.e., $\frac{dw(t)}{dt} = -1$

Driver's utility function of choosing WTW w at time t

pdf of matching | Utility of match | Cost of waiting | Sunk cost effect

$$U(w|t) = \frac{1}{1-F(t)}\left(\int_0^w f(t+\tau)[v_R - v_w(t+\tau) - v_s^R(t)]d\tau \right.$$
$$\left. +(1-F(t+w))[v_o - v_w(t+w) - v_s^o(t)]\right)$$

Probability of reneging | Utility of outside option | Cost of waiting | Sunk cost effect

$$v_R > v_o$$

Model configuration

Waiting time cost

$$v_w(t+w) = k_w(t+w) + k_l(t+w)^2$$

k_l signals risk attitude on time loss domain, i.e., $k_l > 0$ for risk-aversion; $k_l = 0$, risk-neutral and $k_l < 0$, risk-seeking

RICHARD THALER
(Nobel Laureate, 2017)

Sunk cost effect as per the mental accounting theory (Thaler, 1985)

$$v_s^R(t) = k_s t(C - v_R)$$
$$v_s^o(t) = k_s t(C - v_o)$$

$k_s \geq 0$ signals the scale of sunk cost effect; C is a large constant to ensure the cost is positive. Note that $v_s^R(t)$ and $v_s^o(t)$ both increase with t and $v_s^R(t) \leq v_s^o(t)$, suggesting that being matched amortizes the sunk waiting time better

Driver's decision on WTW w at time t

Utility function:

$$U(w|t) = \frac{1}{1-F(t)}\left(\int_0^w f(t+\tau)[v_R - k_w(t+\tau) - k_l(t+\tau)^2 - k_s t(C - v_R)]d\tau \right.$$
$$\left. +(1-F(t+w))[v_o - k_w(t+w) - k_l(t+w)^2 - k_s t(C - v_o)]\right)$$

$$\hat{w}(t) = \underset{w\geq 0}{\operatorname{argmax}}\, U(w|t)$$

If $\hat{w}(0) = 0$, the driver would balk from the queue

If $t > 0$ and $\hat{w}(t) = 0$, the driver would renege from the queue at time t

Properties of $\widehat{w}(t)$

$$\frac{f(t+\widehat{w}(t))}{1-F(t+\widehat{w}(t))} = \frac{k_w + 2k_l(t+\widehat{w}(t))}{(v_R - v_o)(1+k_s t)}$$

Observations

- If $k_s = 0$ (no mental accounting), $t + \widehat{w}(t) =$ constant, regardless of t (conventional model of patience time), i.e. $\frac{d\widehat{w}(t)}{dt} = -1$

- If $k_s > 0$ (with mental accounting), $t + \widehat{w}(t)$ increases with t (sunk cost causes postponement of reneging), i.e.,

$$\frac{d\widehat{w}(t)}{dt} > -1$$

Matching methods may interact with mental accounting

$$\frac{f(t+\hat{w}(t))}{1-F(t+\hat{w}(t))} = \frac{k_w + 2k_l(t+\hat{w}(t))}{(v_R - v_o)(1+k_s t)}$$

Random matching (exponentially distributed matching time)

$$f(t) = \frac{1}{t_m} e^{-\frac{t}{t_m}}$$

Expected matching time

$$\hat{w}(t) = \frac{t_m^{-1}(1+k_s t)(v_R - v_o) - k_w}{2k_l} - t$$

Mental accounting increases willingness to wait

Deterministic matching (approximation to the virtual queuing system)

$$f(t) = \mathbb{I}(t = t_m)$$

$$\hat{w}(t) = t_m - t$$

Mental accounting has no impact

Balking and reneging

	$\hat{w}(0) = 0$	$\hat{w}(t)$ given no balking
Matching method	*balking condition*	*reneging time*
Random matching	$k_w \geq \frac{v_R - v_0}{t_m}$	$t_r = \frac{t_m^{-1}(v_R - v_0) - k_w}{2k_l - t_m^{-1}k_s(v_R - v_0)}$ *if* $2k_l - t_m^{-1}k_s(v_R - v_0) > 0$ $t_r = \infty$ *otherwise*
Deterministic matching	$k_w \geq \frac{v_R - v_0 - k_w t_m^2}{t_m}$	*no renege, all matched at* $t = t_m$

Furthermore, for random matching, $t_r > t_m$ *if* $(v_R - v_0)(t_m^{-1} + k_s) - k_w - 2k_l t_m > 0$

Hypothesis 1: Willingness to wait

Controlling for market conditions and exogenous factors, drivers' willingness-to-wait in the queue decreases at a rate slower than one.

Hypothesis 2: Balking

Controlling for expected matching time and market conditions, drivers are more likely to balk during the implementation of the virtual queuing system

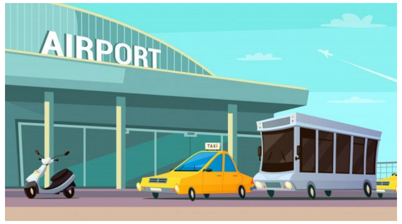
Service data from Tianjin, China

Timeline:

Pre-experiment: 4 weeks	Experiment week	Post-experiment: 4 weeks

Locations:

Treatment location



Metropolitan airport

Control locations

Railway station

City subcenter

Contents: idle driver trajectories, demand condition and weather

Size: 47,548 drivers, 506,515 trajectories

Descriptive statistics

Variable	Location	Mean/Percentage
DRIVER_ENTRY_TYPE	all	73.6% involuntary; 26.4% voluntary
	airport	70.7% involuntary; 29.3% voluntary
	railway station	77.9% involuntary; 22.1% voluntary
	city subcenter	73.6% involuntary; 26.4% voluntary
DWELL_TIME	all	9.72; involuntary 8.48; voluntary 13.16
	airport	15.33; involuntary 12.65; voluntary 21.79
	railway station	6.73; involuntary 6.12; voluntary 8.20
	city subcenter	6.41; involuntary 6.21; voluntary 6.96
BALK	all	39.2% balk; involuntary 45.4%; voluntary 45.7%
	airport	36.9% balk; involuntary 45.7%; voluntary 6.5%
	railway station	51.5% balk; involuntary 59.4%; voluntary 31.0%
	city subcenter	35.3% balk; involuntary 36.8%; voluntary 31.8%

Estimating Willingness to Wait

- "Death" event: renege from queue
- Weibull survival model

$$S(T) = \exp(-\int_0^T p t^{p-1} \exp(\beta^T \boldsymbol{x}_t)\, dt)$$

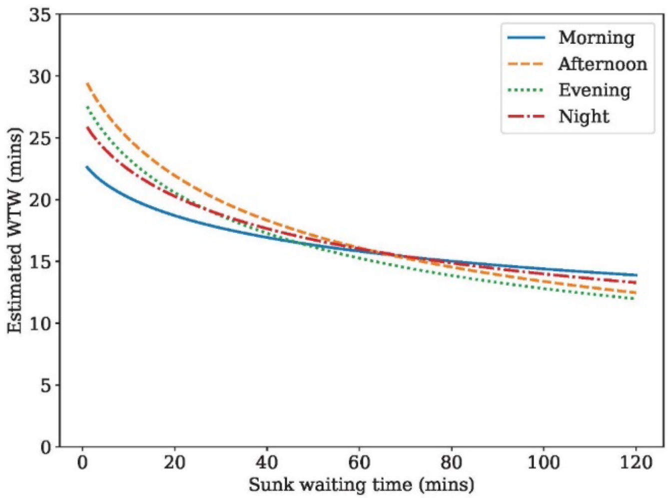
- Parameterization of the survival function

$$\begin{aligned}\boldsymbol{\beta} \cdot \mathrm{x_i}(\mathbf{t}) = & \beta_1 \cdot \mathtt{LOC\_ACCESS\_RATE}_{it} + \beta_2 \cdot \mathtt{NBHD\_ACCESS\_RATE}_{it} + \boldsymbol{\beta}_3 \cdot \mathtt{CANCEL\_COUNT}_{it} \\ & + \boldsymbol{\beta}_4 \cdot \mathtt{REJECT\_COUNT}_{it} + \boldsymbol{\beta}_5 \cdot \mathbf{X_{it}} + \eta_i.\end{aligned}$$

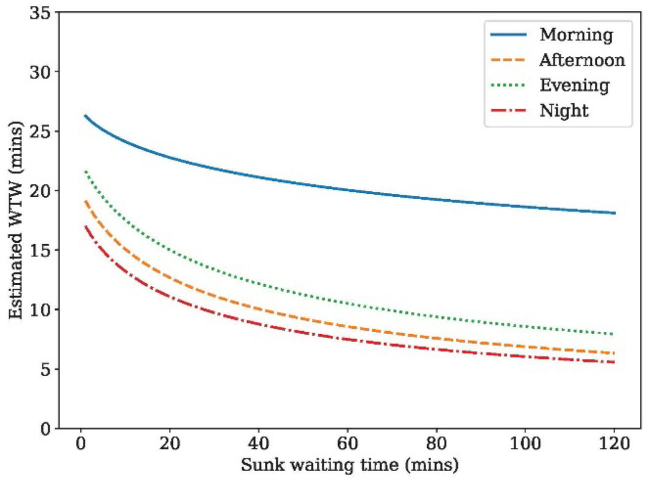
- WTW

$$\widehat{w}(T) = \frac{\int_t^\infty S(t)}{S(T)} = \frac{1}{p} (\exp(\beta^T \boldsymbol{x}_t))^{-\frac{1}{p}} \Gamma(\frac{1}{p}, \exp(\beta^T \boldsymbol{x}_t) t^p)$$

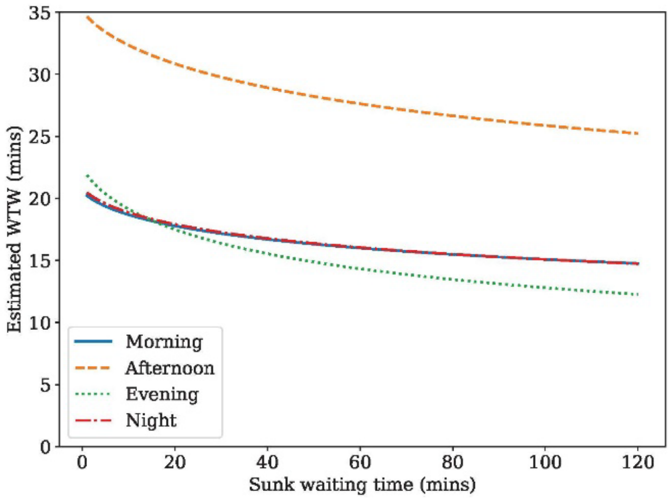
Estimated WTW



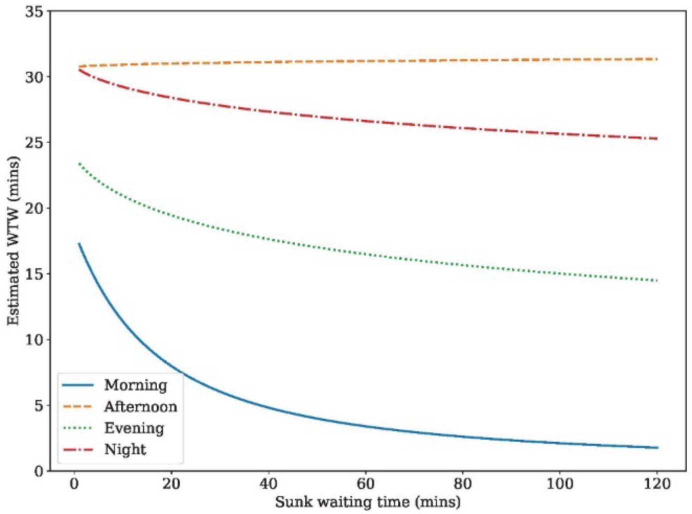
Involuntary drivers (weekdays)



Involuntary drivers (weekends)

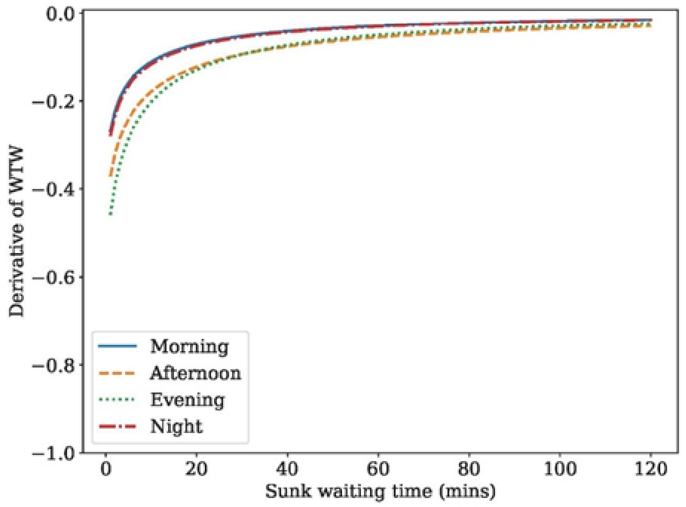


Voluntary drivers (weekdays)

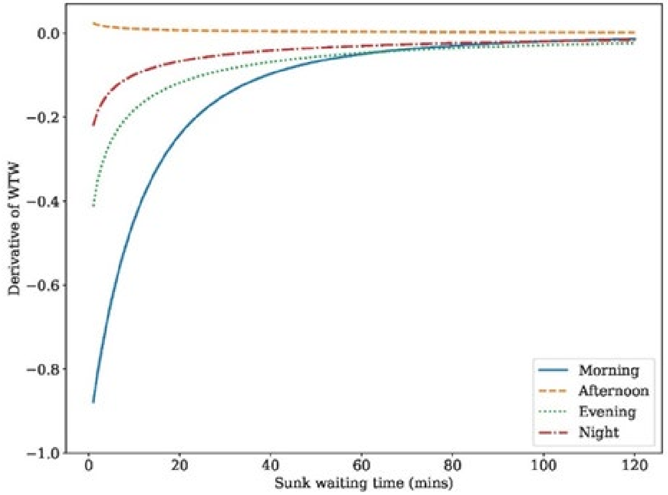


Voluntary drivers (weekends)

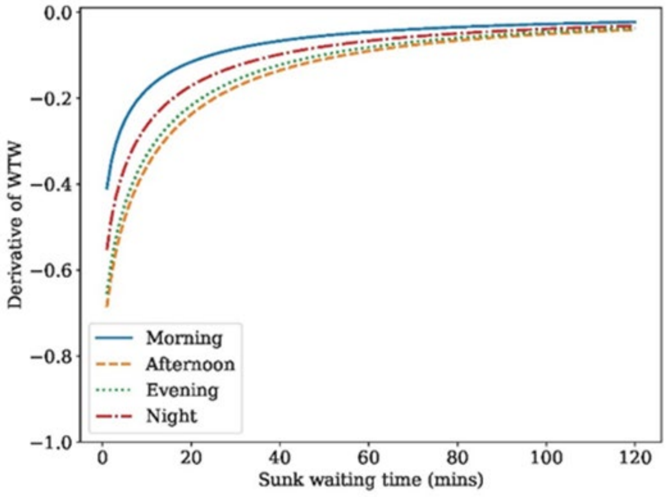
$\frac{d\hat{w}(t)}{dt} > -1$, supporting Hypothesis 1 and suggesting drivers influenced by "sunk-cost fallacy"



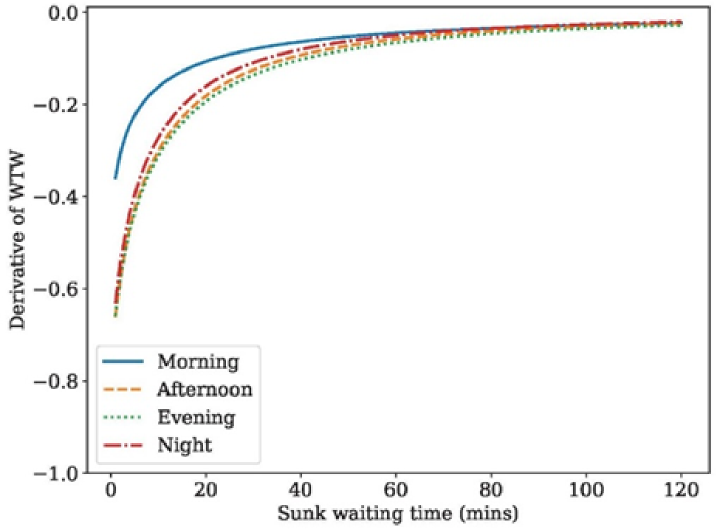
Involuntary drivers (weekdays)



Involuntary drivers (weekends)



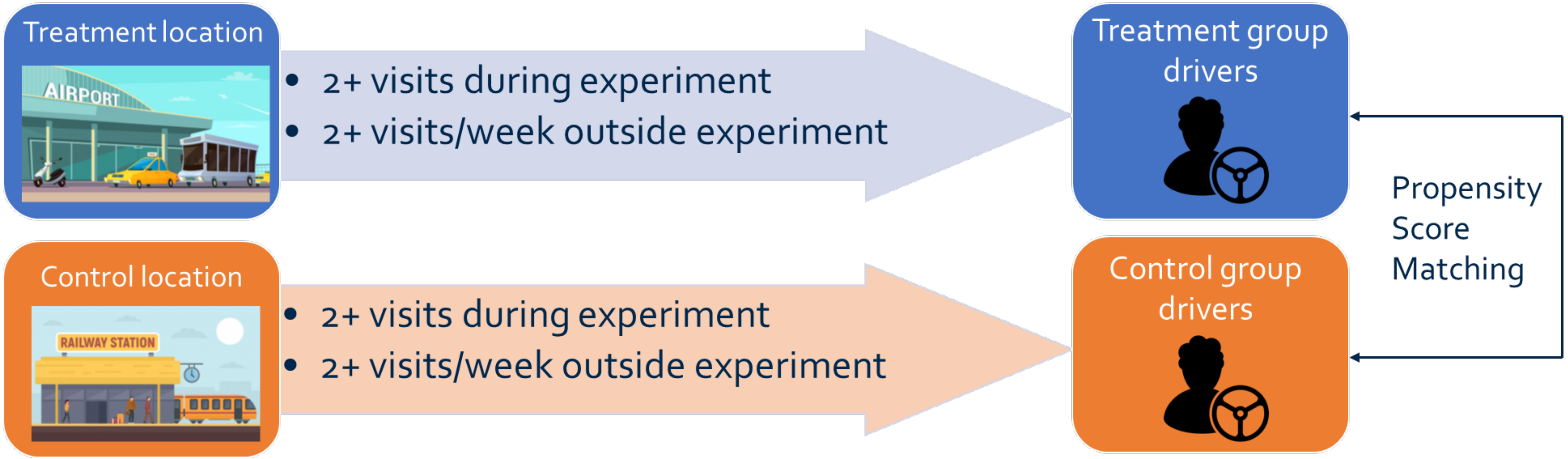
Voluntary drivers (weekdays)



Voluntary drivers (weekends)

Difference-in difference to investigate the impact of the virtual queuing system on balking

$$\text{Probit}(\texttt{balk}_{it}) = \beta_1 \cdot \texttt{TREATMENT}_{it} + \beta_2 \cdot \texttt{GROUP}_{it} + \beta_3 \cdot \texttt{TREATMENT}_{it} \times \texttt{GROUP}_{it} + \beta_4 \cdot \texttt{AVG\_WAIT}_{it} + \beta_5 \cdot \mathrm{X}_{it} + \eta_i + \epsilon_{it}$$



The implementation reduces balking, contradicting Hypothesis 2

Control location	Railway station	City subcenter
ATE	-2.048*	-2.477*

$^{*}p < 0.05$

Our new hypothesis: Drivers engage in matching probability weighting under random matching. They tend to overestimate the likelihood of less desirable outcomes while underestimating the likelihood of more desirable ones, leading to a higher likelihood of balking than anticipated.

Key Takeaway

- Drivers are boundedly rational when dwelling at transportation terminals
  - They take sunk waiting time into account when making decisions
  - They may engage in probability weighting
- Overlooking the sunk-cost effect can lead to underestimating congestion in idle driver queues and overestimating the platform profits
- Virtual queueing system does not necessarily reduce idle driver queues
  - Tradeoff: it reduces balking, thereby increasing queue entry. On the other hand, it prevents drivers from suffering the sunk-cost fallacy, which can help reduce the idle driver queue, if drivers have a high degree of mental accounting and a lower degree of risk aversion
- Platforms should invest in understanding drivers' risk aversion and measuring the sunk-cost effect to determine whether to adopt a more randomized matching strategy or a more deterministic one

Thank You !

QUESTIONS?

Liu, T., Xu, Z., Keppo, J. Yin, Y. and Zhu, H. (2024) Bounded rationality in ride-sourcing drivers' dwelling at transportation terminals: a behavioral queueing analysis.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5050040