



Introduction to on-demand and shared mobility

■ École polytechnique fédérale

Our lab

Members

Head



Postdoc





PhD





Visiting



Lab for human-oriented mobility eco-system

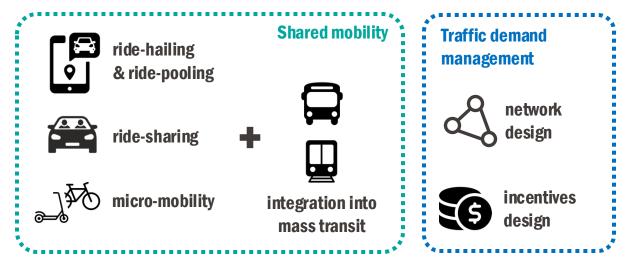
At HOMES, we develop human-centric solutions to emerging mobility challenges.



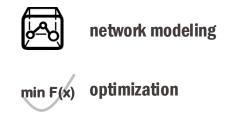
Our lab

HOMES

Topics



Methodologies





game theory



data-driven & learning

Our lab

- Courses
 - CIVIL 324 (BA6) Urban public transport systems
 - transit system and on-demand service design
 - CIVIL 477 (MA2) Transportation network modeling & analysis
 - traffic assignment and network equilibrium
- Student projects
 - Routing, choice modeling, incentives design, and network analysis
 - Learning and data-driven analyses on travel behaviors
 - Simulation of on-demand mobility and meal-delivery
 - Analysis of carpooling and bikesharing on EPFL campus (with Mobility Office)



HOMES @ EPFL





Agenda

- Basics
- Matching
- Operations
- Regulations



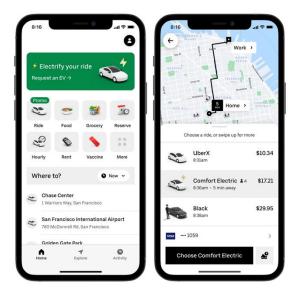
What is on-demand and shared mobility

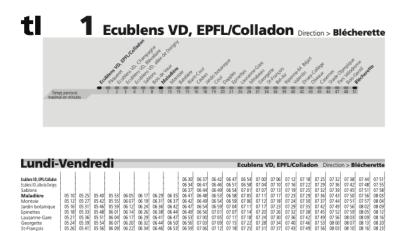
- "On-demand" means...
 - the service can be requested at any time and any location

Rel-Air

Riponne-M. Béian

• there is no fixed schedule or route (e.g., bus and train)





book a Uber trip

bus route and schedule

What is on-demand and shared mobility

- "Shared" means...
 - trips are served by a dedicated fleet of vehicles
 - you share the vehicle with someone, but not necessarily in the same trip



"sharing" in a narrow sense

"sharing" in a broad sense

Putting "on-demand" and "shared" together...

ride-hailing

- taxi
- e-hailing
- ride-pooling
- micro-transit





micromobility

- bike-sharing
- scooter-sharing

ride-sharing

carpooling





(on-demand) car-sharing











Pursuits

- get to my destination asap
- price is reasonable
- trip is comfortable



Costs

- trip fare
- waiting and in-vehicle time
- detours in shared trips







Pursuits

- high hourly earning
- short search time
- equal dispatch opportunity
-



Costs

- operation cost
- other job opportunity
- fatigue after long work hours
-





DRIVER



Pursuits

- high profit
- dispatch efficiency
- large market share
- reliable supply
- ...



Costs

- payment to drivers
- incentives to passengers
- operation cost
- ...





RIVER



Pursuits

- max social welfare
- min traffic congestion
- equity and accessibility
-



Instruments

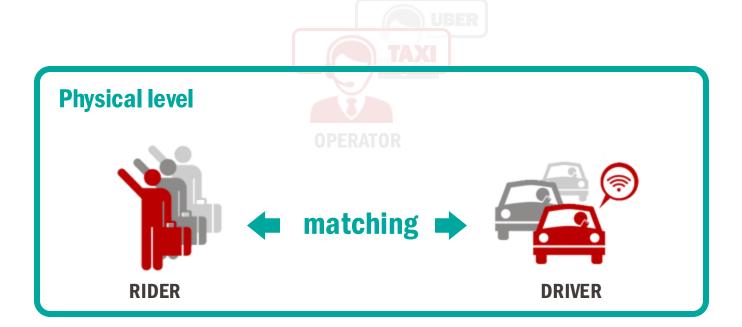
- subsidy and tax
- regulation and incentive mechanism
- ...





RIVER







street-hailing



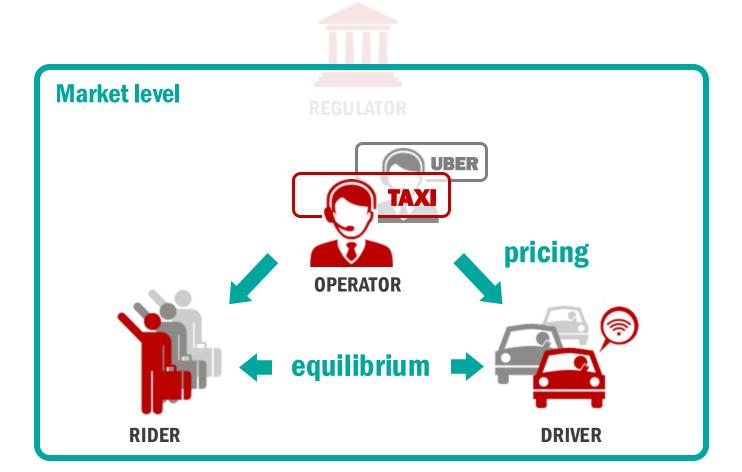
e-hailing



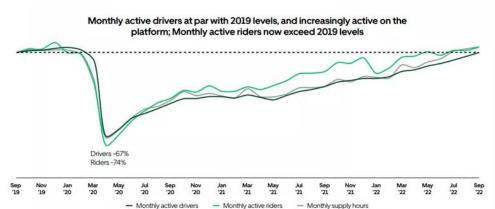
taxi stand



Ride-sharing with meeting point

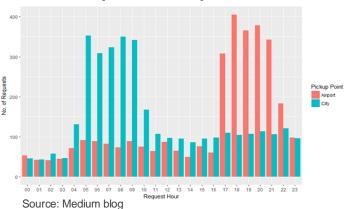


Active riders and drivers

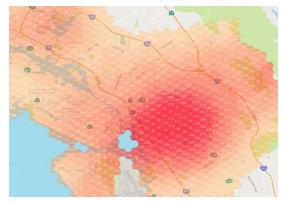


Source: Uber

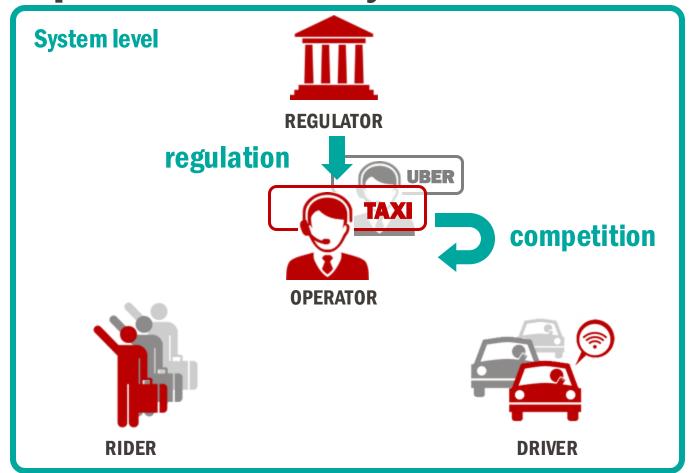
Temporal demand pattern

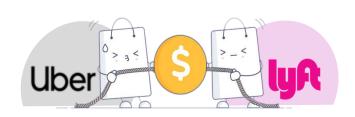


Peak-hour surge pricing

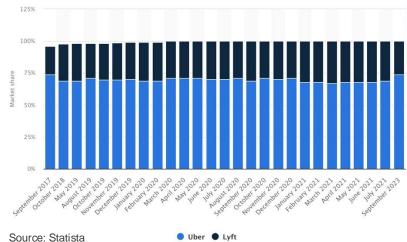


Source: Uber





U.S. market share





Multi-homing drivers



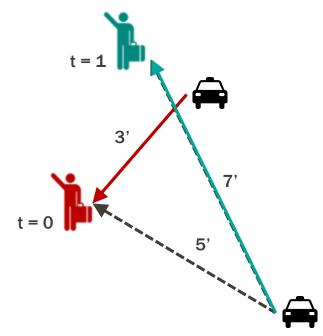
Driver protest for higher payment



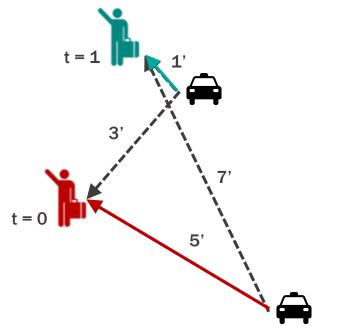
Questions?

Next topic: Matching

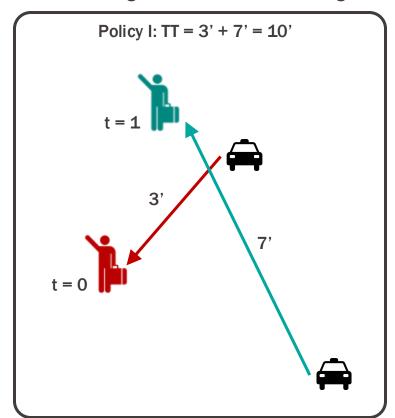
- How to dispatch drivers to picking up riders
 - Policy I: Instant matching
 - riders are first-come-first-served
 - riders are match to the closest driver

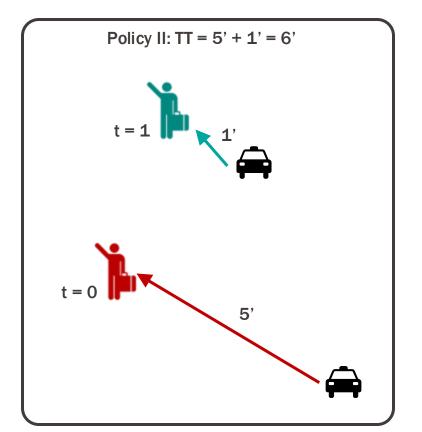


- How to drivers to picking up riders
 - Policy II: Batch matching
 - consolidate requests over a matching interval into a batch
 - match riders and drivers to minimize the total pickup time

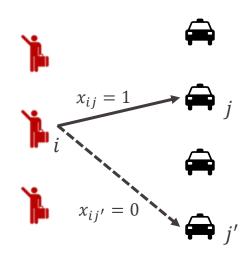


Advantage of batch matching





- Mathematical formulation of batch matching
 - Set of riders: $I = \{1, ..., N\}$
 - Set of drivers: $J = \{1, ..., M\}, M \ge N$
 - Matching indicator: $x_{ij} \in \{0,1\}, i \in I, j \in J$
 - Pickup time: $t_{ij} \in R_+, i \in I, j \in J$



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min	$\sum_{ij} t_{ij} x_{ij}$	Objective: min total pickup time
	$\sum_j x_{ij} = 1$,	Constraint: all riders are matched
	$\sum_i x_{ij} \leq 1$,	Constraint: each driver at most serves one rider
	$x_{ij} \in \{0,1\}.$	Feasibility: binary matching decision

- Mathematical formulation of batch matching
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 - Pickup time: $t_{ij} \in R_+, i \in I, j \in J$

$$\min_{x} \quad \sum_{ij} t_{ij} x_{ij}$$

$$s.t. \quad \sum_{j} x_{ij} = 1,$$

$$\sum_{i} x_{ij} \leq 1,$$

$$x_{ij} \in \{0,1\}.$$

linear assignment problem

- a fundamental combinatorial optimization problem
- small instances are easily solved by linear program
- other algorithms have been developed for large instances

- Mathematical formulation of batch matching
 - Set of riders: $I = \{1, ..., N\}$
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 - Matching indicator: $x_{ij} \in \{0,1\}, i \in I, j \in J$
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$$\min_{x} \quad \sum_{ij} t_{ij} x_{ij}$$
s.t.
$$\sum_{j} x_{ij} = 1,$$

$$\sum_{i} x_{ij} \leq 1,$$

$$x_{ij} \in \{0,1\}.$$

Extensions

- hold some riders for future match
- ride-pooling, i.e., match one driver to multiple riders
- ensure fairness among drivers in a long term
- * Research questions!

- Solving the matching problem is good, but ...
 - We need a model to capture the main trade-off in matching
 e.g., when # riders remains the same, increasing # drivers can reduce total
 pickup time



matching outputs

matching inputs

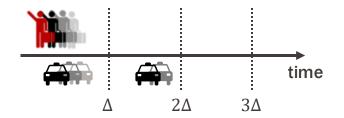
where

w: average waiting time (s)

 Π : density of waiting riders (#/m²)

 Λ : density of idle drivers(#/m²)

- Model I: Frictionless batch matching
 - Matching interval: Δ (s)
 - Rider arrival rate: λ (#/s/m²)
 - Idle driver arrival rate: μ (#/s/m²)



Matching probability: $p = \min(1, \mu/\lambda)$

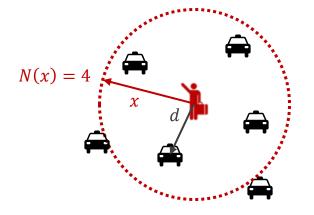
Expected num of matches: n = 1/p

Expected waiting time: $w = (n - 1/2)\Delta$

$$w = f(\Pi, \Lambda) = \left(\max\left(1, \frac{\Pi}{\Lambda}\right) - \frac{1}{2}\right)\Delta$$

Looks good, but ...

- Model II: Non-congested instant matching
 - Matching radius ∞ (m)
 - Vehicle speed v (m/s)



$$w = f(\Pi, \Lambda) = \frac{1}{2v\sqrt{\Lambda}}$$

Num of idle drivers within a distance x:

$$N(x) \sim \text{SpatialPP}(\Lambda)$$

Prob of at least one driver within a distance x:

$$1 - \Pr(N(x) = 0) = 1 - \exp(-\pi \Lambda x^2)$$

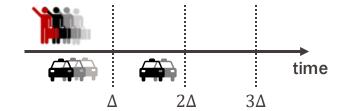
- equal to prob that the closest driver is within x
- equal to prob that the pickup distance $d \le x$

Expected waiting time:

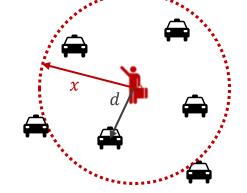
$$w = \frac{\mathbb{E}[d]}{v} = \frac{1}{2v\sqrt{\Lambda}}$$

Independent of rider demand because...

- Both make sense but look so different...
 - * because they each capture one part of total waiting time
 - Model I: $w \approx w_m = \left(\max\left(1, \frac{\Pi}{\Lambda}\right) \frac{1}{2}\right)\Delta$ * pickup time is missing



- Model II: $w \approx w_p = \frac{1}{2v\sqrt{\Lambda}}$
 - * matching time is missing



* The general model capturing both times is beyond the scope of this lecture

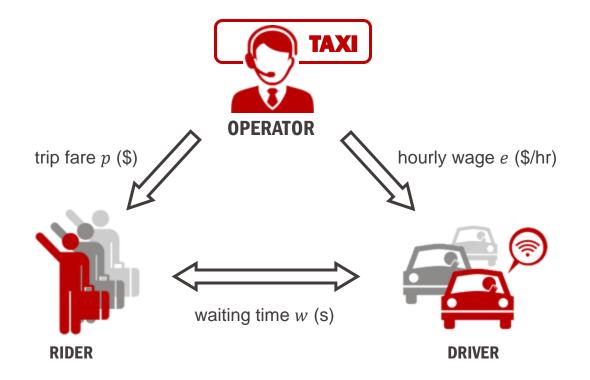


Questions?

Next topic: Operations

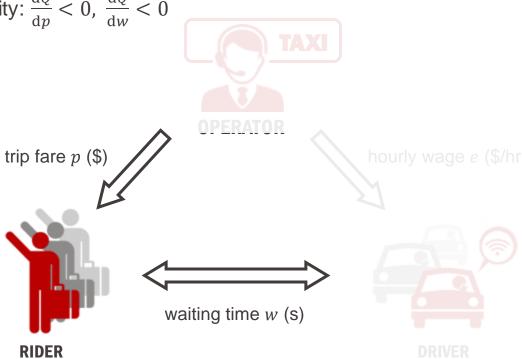
Monopoly market

A single dominating operator



Monopoly market

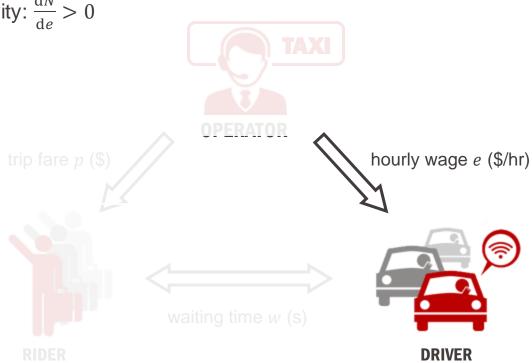
- Rider demand Q = D(p, w)
 - Sensitivity: $\frac{dQ}{dp} < 0$, $\frac{dQ}{dw} < 0$



Monopoly market

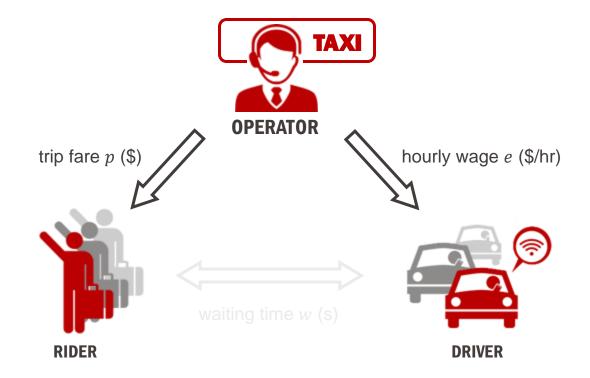
• Driver supply N = S(e)

• Sensitivity: $\frac{\mathrm{d}N}{\mathrm{d}e} > 0$



Monopoly market

• Operator profit R(p,e) = pQ - eN



- Pricing in a monopoly market
 - Assume trips are uniformly distributed with average in-vehicle time τ (s)
 - Decide trip fare p (\$) and hourly wage e (\$/hr) to max profit

max
$$P(p,e) = pQ - eN$$

 $P(p,e) = pQ - eN$
 $P(p,e) = pQ$
 $P(p,e) = pQ$

Demand function

Supply function

Matching model

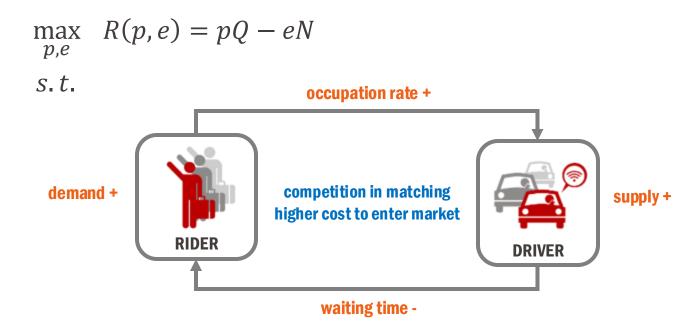
Fleet conservation

Unmatched riders

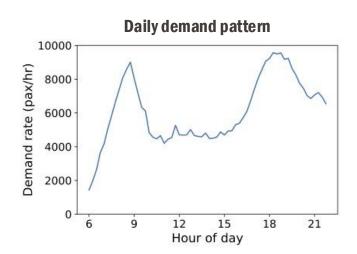
market equilibrium

- How to solve the optimal pricing strategy?
 - Option I: throw the entire problem into solver
 - * infeasible when model is highly nonlinear and complicated

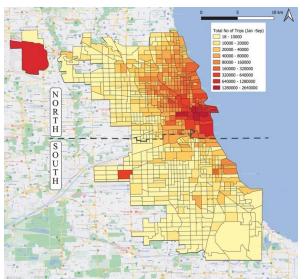
- How to solve the optimal pricing strategy?
 - Option I: throw the entire problem into solver
 - Option II: solve the equilibrium at each feasible price



- So far, we consider a uniform market
 - Demand and supply are evenly distributed over time and space
 - Clearly not the case in reality
 - e.g., Chicago ride-hailing trips

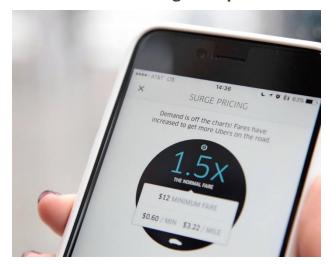


Trip origin distribution

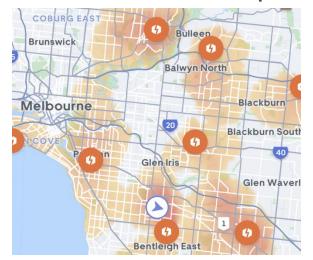


- Common solutions to address demand-supply imbalance
 - Surge pricing
 - Vehicle relocation

Rider side: surge multiplier



Driver side: demand heat map



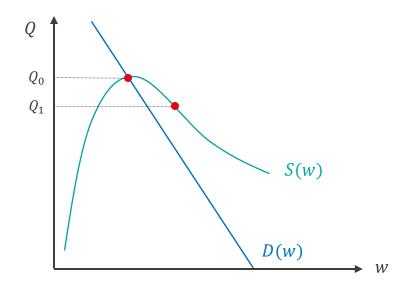
The rational of surge pricing

• Demand curve: $D(w) = D_0 - p - w$

• Supply curve: $S(w) = \frac{N - \Lambda(w)}{w + \tau}$

Notations:

- D_0 : potential demand
- p: trip fare
- w: waiting time
- N: fleet size
- Λ: idle driver density
- τ : trip duration
- Q: trip throughput



During a demand peak,

- D_0 increase while N remain the same
- Market moves to an inefficient state $Q_0 \rightarrow Q_1$

EPFL Monopoly market

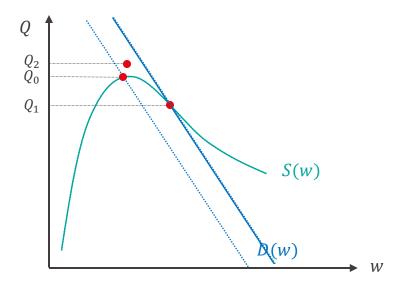
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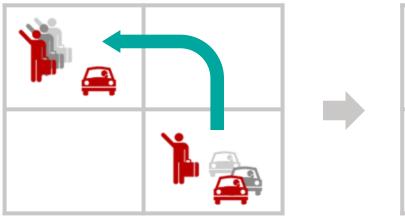
- D_0 : potential demand
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During a demand peak,

- D_0 increase while N remain the same
- Market moves to an inefficient state $Q_0 \rightarrow Q_1$
- A surge price pushes demand curve back and induce a larger supply
 Q₁ → Q₂

- Motivations of vehicle relocation
 - Trips are not evenly distributed over space
 - Drivers' spontaneous search may not be efficient
 - lack of real-time information
 - selfish decisions do not ensure system optimum
 - Some centralized control and intervention are beneficial to all





A static model of vehicle relocation

Notations:

• p_{ij} : trip fare

• μ_i : driver arrival rate

• c_{ij} : relocation cost

• c_{ij} : OD distribution

• c_{ij} : trip flow

• c_{ij} : trip duration

• c_{ij} : relocation flow

• c_{ij} : relocation flow

• c_{ij} : trip duration

$$\max_{x,x^{0}} \sum_{ij} p_{ij} x_{ij} - c_{ij} x_{ij}^{0}
s.t.
 x_{ij} = \alpha_{ij} g(\lambda_{i}, \mu_{i}),
 \mu_{i} = \sum_{k} (x_{ki} + x_{ki}^{0}),
 \sum_{k} (x_{ki} + x_{ki}^{0}) = \sum_{j} (x_{ij} + x_{ij}^{0}),
 \sum_{ij} (x_{ij} + x_{ij}^{0}) \tau_{ij} = N,
 x_{ij}, x_{ij}^{0} \ge 0.$$

Objective: max total revenue

Trip flow between every two zones

Driver supply in each zone

Inflow equals outflow for each zone

Fleet conservation

Beyond monopoly market

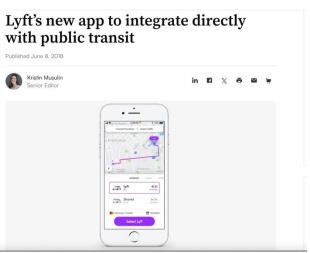
- Cities are rarely dominated by a single operator
 - Competition and cooperation often co-exist
 - Uber vs Lyft
 - Uber + taxis
 - Lyft + Metro/Citi Bike

Uber Partners With Yellow Taxi Companies in N.Y.C.

The ride-hailing giant is teaming up with two taxi technology companies in an unlikely alliance.



Source: Smart Cities Dive Source: New York Times



Uber Rewards







Source: Uber

Citi Bike: Now available in the Lyft app

Update your Lyft app to get riding!



Source: Citi Bike



Questions?

Next topic: Regulations

Why regulation is needed

Incompatible objectives



- Operator:
 - max profit, market share, ...



- Regulator:
 - max social welfare
 - = travel utility of riders
 - + profit of operator
 - + earning of drivers
 - + ...
 - min congestion and emission
 - ensure mobility accessiblity



Ride-hailing vehicles cause more congestion in San Francisco Erhardt et al. (2019)



Oversupply of shared bikes in China

Regulations in practice

Supply side

- min wage rate
- fleet cap
- contractor vs employee
-

Demand side

- congestion charge
- mobility credits
-

Operations

- dedicated service region
- data sharing
-

Uber, Lyft must continue to limit size of fleets in New York City

To fight congestion, the city council votes to indefinitely extend a cap on the number of ride-hailing vehicles on New York streets.



Chicago congestion tax on rideshare trips takes effect





California sued over gig economy law. What Uber and Postmates say about AB 5

BY DALE KASLER
UPDATED DECEMBER 30, 2019 5:40 PM



Waymo expands into metro Phoenix, downtown Mesa, Talking Stick

By Lauren Kobley Published: Jun. 6.

Published: Jun. 6, 2024 at 1:08 AM CEST | Updated: Jun. 6, 2024 at 3:39 AM CEST

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PHOENIX (AZFamily) — Waymo, the autonomous rideshare program, is expanding its reach in the Valley to include parts of north



How to analyze a policy

- Additional constraints in the operator's problem
 - e.g., max fleet size \overline{N} and min wage rage e

$$\max_{p,e} R(p,e) = pQ - eN$$

$$N = S(e)$$
,

s.t.
$$Q = D(p, w),$$
$$N = S(e),$$
$$w = f(\Pi, \Lambda),$$

$$N = \Lambda + Q(w + \tau),$$

$$\Pi = Qw$$
.

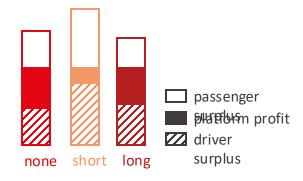
$$N \leq \overline{N}, e \geq \underline{e},$$

market equilibrium

regulatory constraints

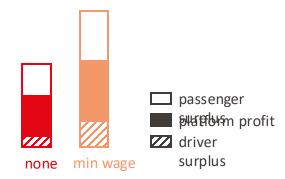
How to analyze a policy

- Be careful of potential "pitfalls"
 - Short-term vs long-term



- min wage helps improve social welfare in short-term by sacrificing platform profit
- in a long run, it could even be harmful to social welfare

Market structure



 min wage does benefit a duopoly market with multi-homing by maintaining a sufficient supply Ken an Zhang

Summary

- What we've discussed today
 - Matching in a solo ride-hailing trip
 - Pricing strategy of a monopoly operator
 - Surge pricing and vehicle relocation
 - Overview of regulations
- What are other interesting topics
 - Matching in micromobility and pooling trips
 - Competition and cooperation among operators
 - Introduction of autonomous vehicles
 - Integration of mobility-on-demand into transit system
 - Issue of equity and fairness
 - •

