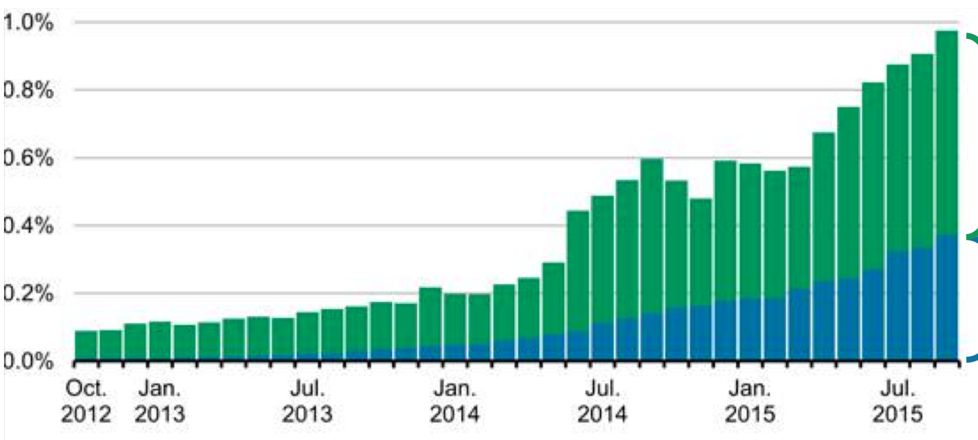
Dynamic Discrete Choice of Gig Economy Workers

HCMG 902 Fall 2018

Park Sinchaisri (OIDD, Wharton)

Share of US adults earning income in a given month via online platforms



Capital Platforms
AirBnB, eBay, ...

Labor Platforms
Uber, TaskRabbit, ...

Gig Economy

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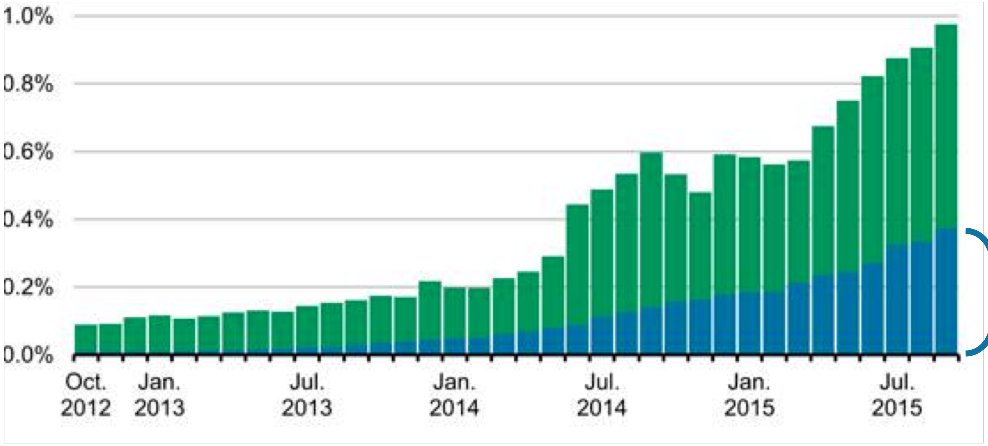

Labor Platforms
Uber, TaskRabbit, ...

JP Morgan Chase Institute / WSJ / Staffing Industry Analysts / McKinsey & Company

Gig Economy

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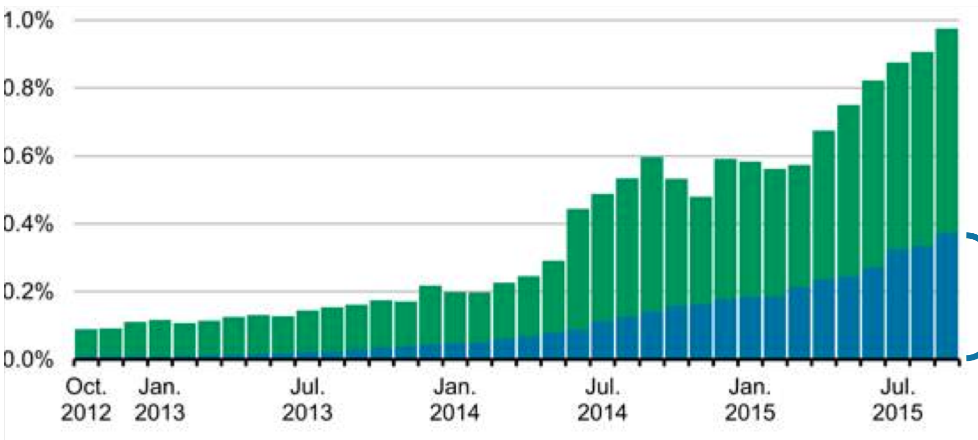

2015

44M people

in the US took on gig work (34%)

Gig Economy

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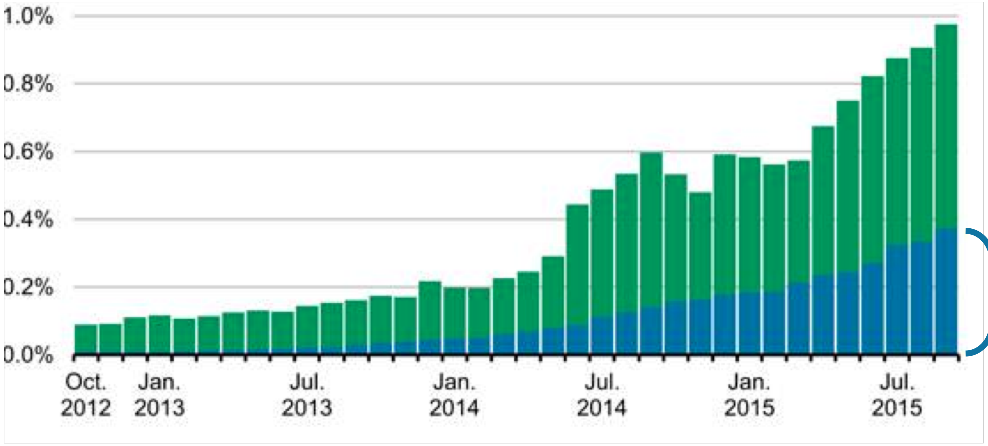

2015

44M people

in the US took on gig work (34%)

2027

Boost global GDP by $2.7 trillion

Gig work will become workforce majority

JP Morgan Chase Institute / WSJ / Staffing Industry Analysts / McKinsey & Company

Who are Gig Workers?

70% by choice

44% primary income

~50% millennials

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when to work?

how long?

which platforms?

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when to work?

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which platforms?

Workers decide work schedules

Gig Company

Supply $\xleftrightarrow[\text{real-time}]{\text{match}}$ Demand

independent/flexible
on-demand

Gig Company

Supply ⟷ Demand

match

real-time

independent/flexible

on-demand

Workforce planning is challenging

Research Questions

How do gig economy workers make labor decisions?

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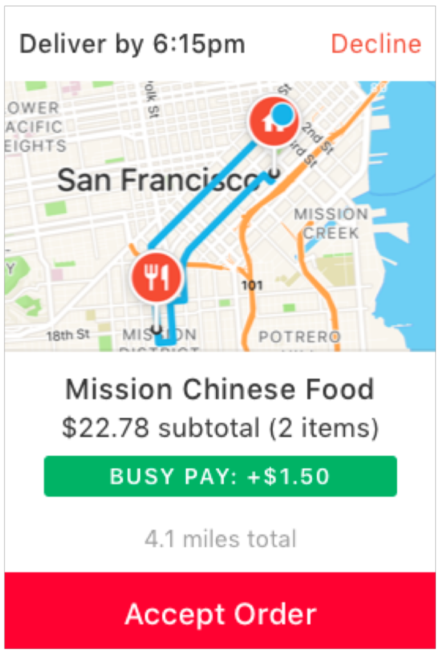
How do gig economy workers make labor decisions?

How can the platform influence their decisions?

In Practice

Real-time
“surge pricing”

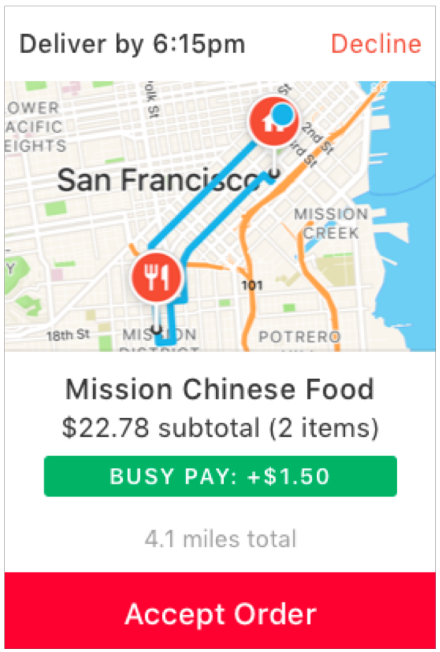


DOORDASH

https://dasherhelp.doordash.com/busy-pay

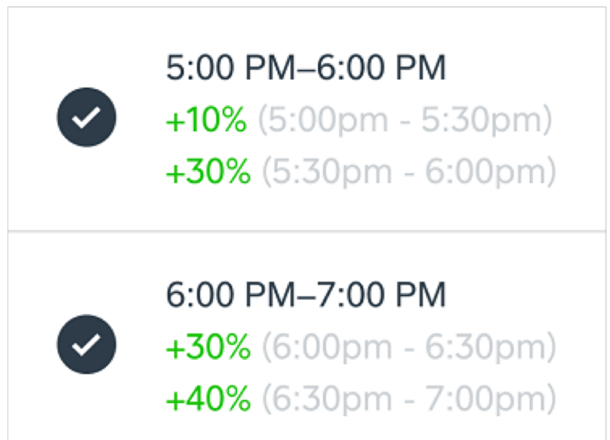
In Practice

Real-time “surge pricing”



DOORDASH

Pre-announced bonus



caviar

https://dasherhelp.doordash.com/busy-pay
https://courierhelp.trycaviar.com/customer/en/portal/articles/2821000-peak-hour-pay?b_id=9619/

In Practice

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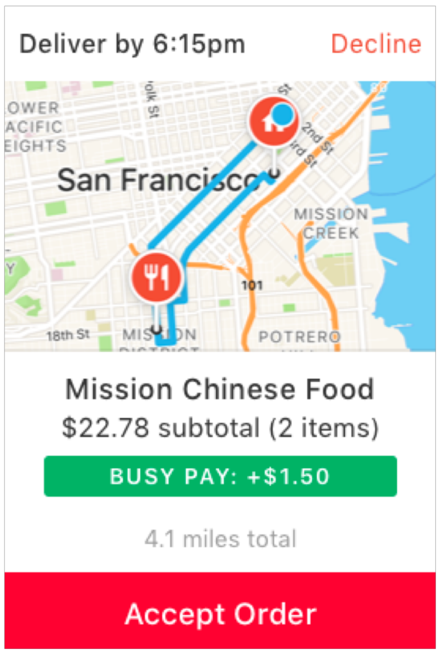

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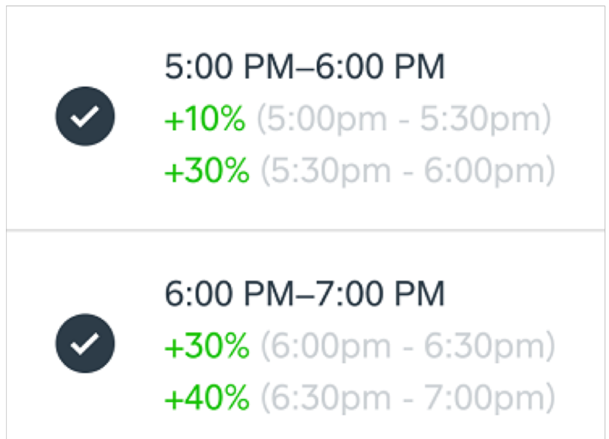
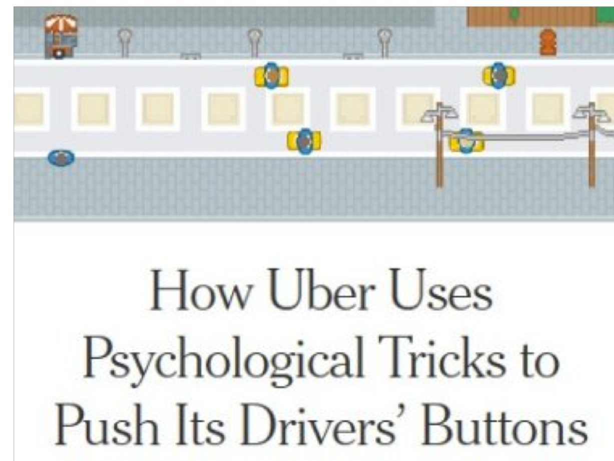


caviar

“You’re so close to your precious target”



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https://nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html

Theories of Labor Supply

Neoclassical

- Maximize lifetime utility

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- **Positive** income elasticities

Wage $\uparrow$

Work more

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Carrington (1996)

Oettinger (1999)

Wage ↑

Work more

Stafford (2013)

Chen/Sheldon (2016)

Sheldon (2016)

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Behavioral

- Reference-dependence, targets

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Wage ↑
Work more

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Behavioral

- Reference-dependence, targets
- **Negative** income elasticities

Wage ↑
Work less

Theories of Labor Supply

Neoclassical

- Maximize lifetime utility
- **Positive** income elasticities

Behavioral

- Reference-dependence, targets
- **Negative** income elasticities

Carrington (1996)

Camerer et al. (1997)

Oettinger (1999)

Farber (2005)

Fehr/Goette (2007)

Farber (2008)

Stafford (2013)

Farber (2015)

Chen/Sheldon (2016)

Sheldon (2016)

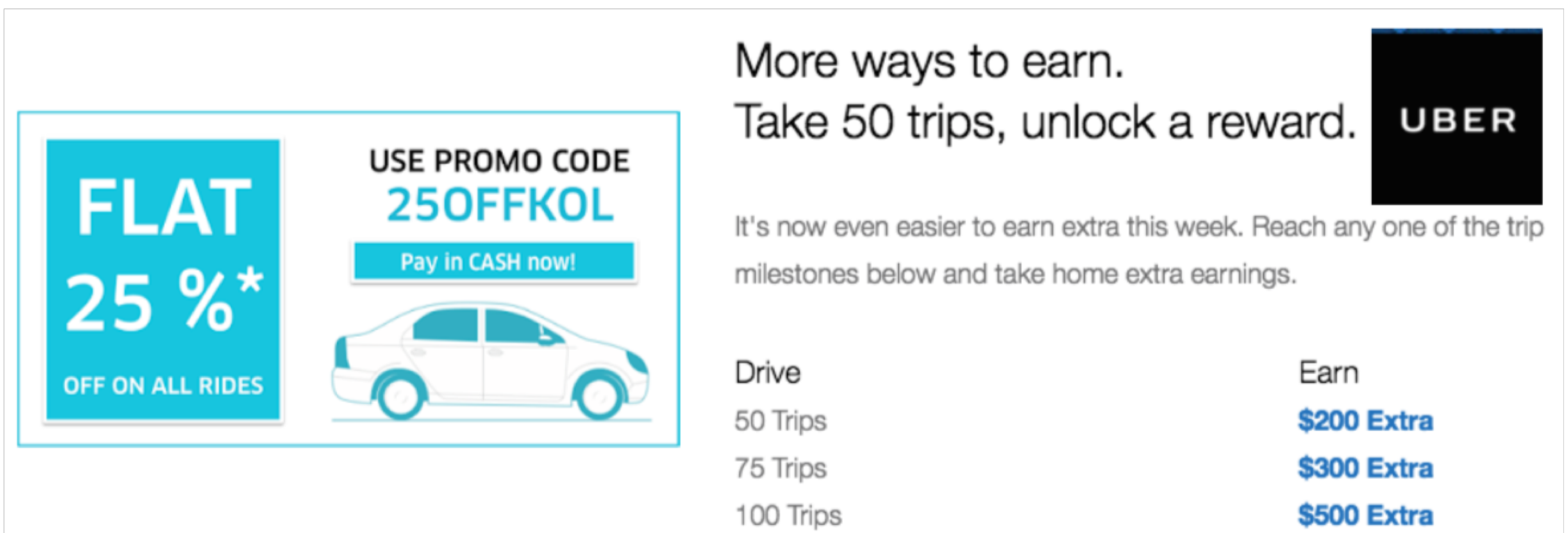
Thakral/To (2017)

Wage ↑
Work more

Wage ↑
Work less

Ride-Hailing Space

- Drivers are matched to passengers by the platform
  - Less search friction compared to taxi industry
- Destination and fare only known when accepting the ride
- Generally no restrictions on working hours

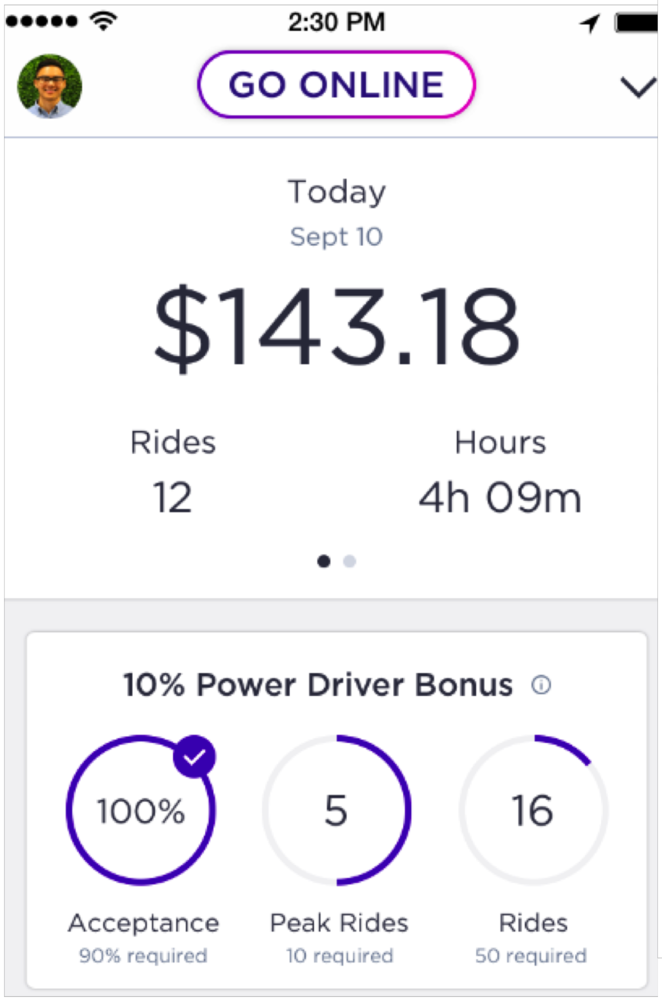


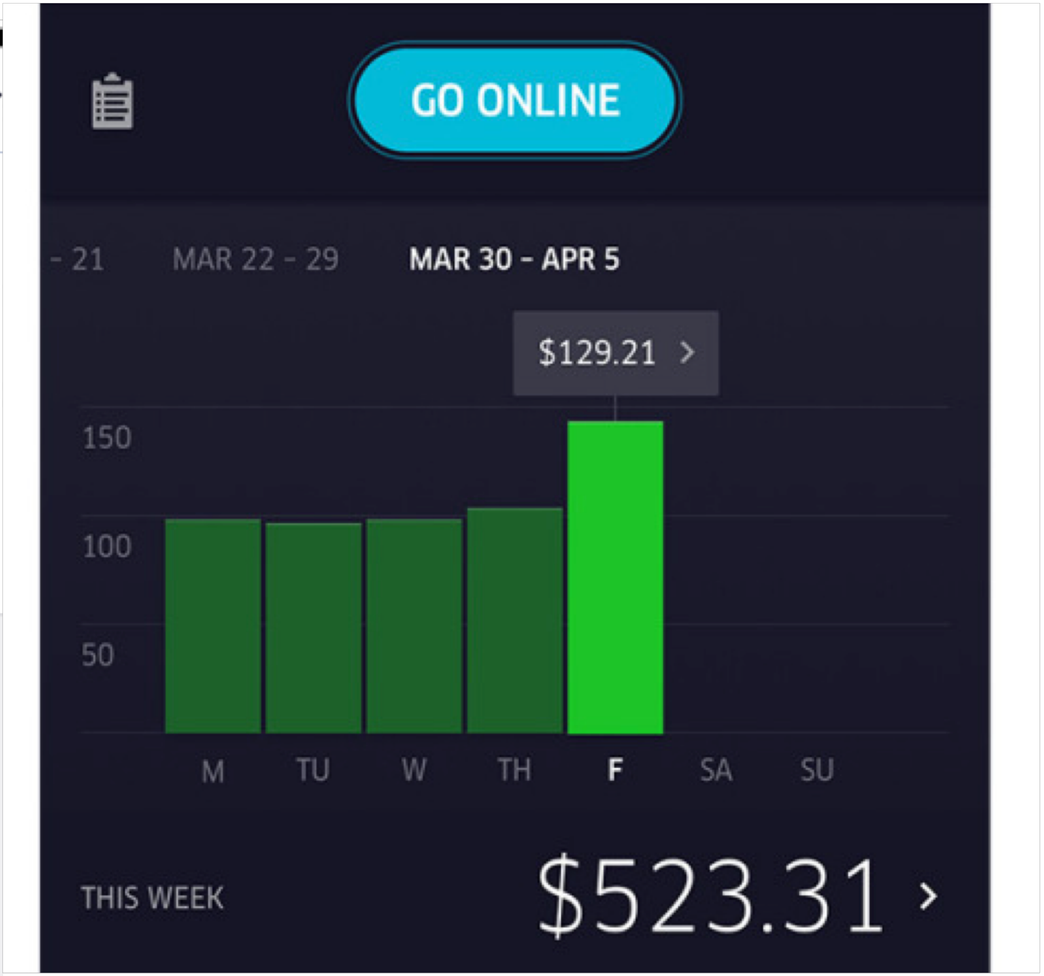
Single-Agent Dynamics

What information (state variables) observed by the drivers?

- Current earning rate
- Current destination
- Weather
- Traffic
- Demand

Single-Agent Dynamics





Single-Agent Dynamics

What information (state variables) observed by the drivers?

- Current earning rate
- Current destination
- Weather
- Traffic
- Demand
- Income earned so far today
- Time spent working so far today

Single-Agent Dynamics

After each session t, each driver

- observes state variables X_t which include accumulated earnings (s_{it}), hours worked so far (h_{it})
- experiences random utility shocks ε_t
- and chooses a decision $Y_t = (continue, quit)$
- to maximize current and future expected payoffs

Future ambitious goal: Y_t to include work for another platform

Optimal Stopping Problem

- Infinite horizon
- With $X_t = (s_t, h_t)$, driver maximizes the expected and discounted sum of the per-session utilities:

Discount factor

Random shock, known to driver

$$\max_{\{y_t, y_{t+1}, \ldots\}} \mathbb{E}\left\{\sum_{s=t}^{\infty} \beta^{s-t} u_s(y_s, X_s, \epsilon_s) | X_t, \epsilon_t\right\}$$

Single-period payoff function

State variables

subject to $f_{X_{t+1}, \epsilon_{t+1} | X_t, \epsilon_t, Y_t}$ which is the Markov transition for the state variables (X, e).

Utility Functions

For simplicity, assume that

Enjoy the earnings

$$u_i(s_{it}, h_{it}, y_{it}; \theta, X_t) = \begin{cases} u_{i1}(s_{it}) + \varepsilon_i(1) & \text{if } y_{it} = 1 \\ u_{i0}(h_{it}) + \varepsilon_i(0) & \text{if } y_{it} = 0 \end{cases}$$

Quit

Not Quit

Suffer from disutility of working

Known transformations

$$u_t(Y_t, X_t, \epsilon_t) = \begin{cases} W_1(X_t)^\intercal \theta_1 + \epsilon_{1t}, & \text{if } Y_t = 1; \\ W_0(X_t)^\intercal \theta_0 + \epsilon_{0t}, & \text{if } Y_t = 0. \end{cases}$$

(The other way is have $X_t = X_{t\text{-}1} + g(Z_t)$ where Z_t is trip's characteristics)

Value Functions

- Let *V(X, ε)* be the value function given *X* and *ε*
- Assume stationarity, drop *t* and ‘ = next period
- The Bellman equation is

$$V(X,\epsilon) = \max_{y\in\{0,1\}} \left\{[u(y,X,\epsilon) + \beta\mathbb{E}[V(X',\epsilon')|X,\epsilon,Y=y]\right\}$$

- Assume the transitions *W* are bounded and the shocks are independent of *X* = conditional independence

$$V(X,\epsilon) = \max\Big\{W_1^\intercal\theta_1 + \epsilon_1 + \beta\mathbb{E}[V(X',\epsilon')|X,Y=1],$$
$$W_0^\intercal\theta_0 + \epsilon_0 + \beta\mathbb{E}[V(X',\epsilon')|X,Y=0]\Big\}$$

Value Functions

- Let $\eta = \epsilon_0 - \epsilon_1$
- Then the decision will be a cut-off $Y = \mathbb{1}\{\eta \leq \eta^*(X)\}$

$$\eta^*(X) \equiv W_1^\intercal \theta_1 - W_0^\intercal \theta_0 + \beta \left\{ \mathbb{E}[V(X', \epsilon')|X, Y=1] - \mathbb{E}[V(X', \epsilon')|X, Y=0] \right\}$$

- Let $V^e(X) \equiv \mathbb{E}[V(X, \epsilon)|X]$ and $u^e(X) \equiv \mathbb{E}[u(y, X, \epsilon)|X]$

$$= \mathbb{E}(\epsilon_0) + W_1^\intercal \theta_1 \cdot F_\eta\big(\eta^*(X)\big)$$

$$+ W_0^\intercal \theta_0 \cdot [1 - F_\eta\big(\eta^*(X)\big)] - \mathbb{E}\big\{\eta \cdot \mathbb{1}[\eta \leq \eta^*(X)]\big\}$$

Need to specify F_n

- Taking expectation of *V(X,e)* over *e*:

$$V^e(X) = u^e(X) + \beta \cdot \mathbb{E}[V^e(X')|X]$$

Estimation

- We can then use Rust's nested-fixed point approach iterating over

$$V^e(X) = u^e(X) + \beta \cdot \mathbb{E}[V^e(X')|X]$$

- Srisuma & Linton (2012) suggests $V^e(X)$ is equivalent to a discounted sum of current and future expected utilities

$$V^e(x) = u^e(X) + \sum_{s=1}^{\infty} \beta^s \cdot \mathbb{E}[u^e(X^{[s]})|X]$$

then use two-step CCP approach of Hotz & Miller (1993)

Data Needed

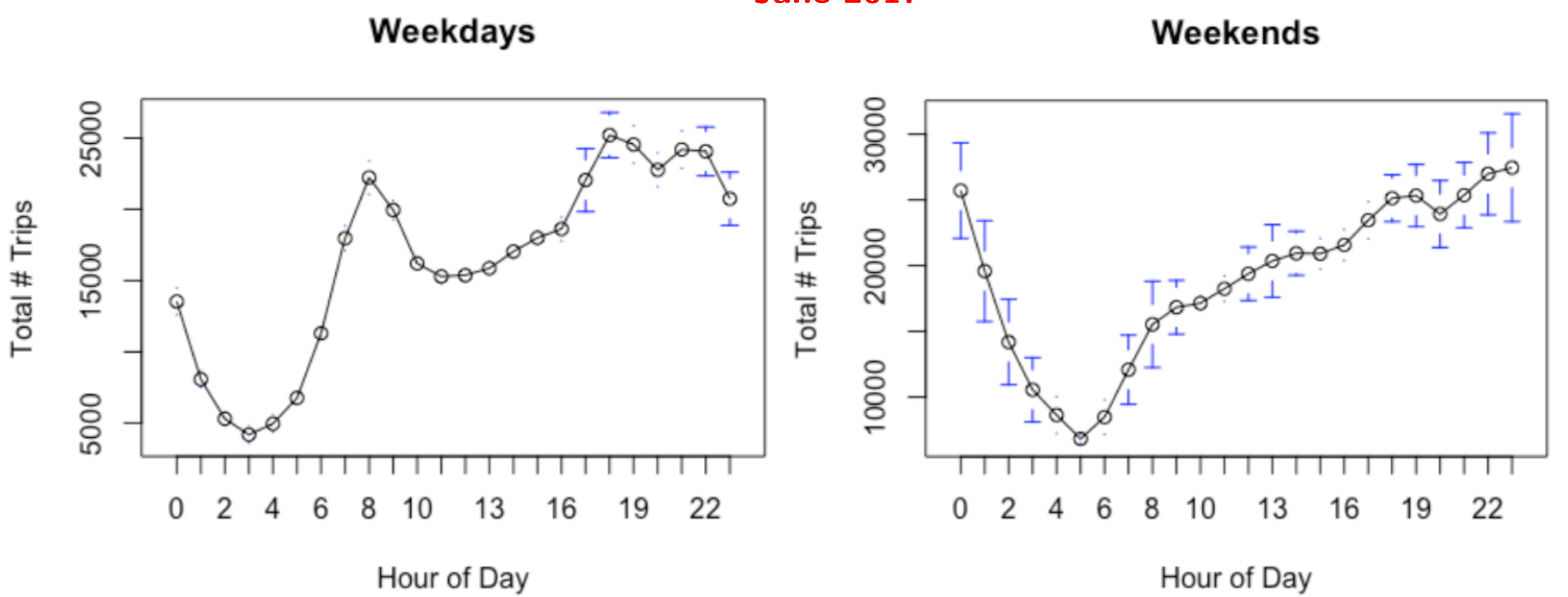
Trip-, session-, or shift-level data on the drivers

- When and how long
- Resulting earnings
- Location/distance traveled
- Number of passengers requesting service
- Number of drivers with and without passengers

TLC Data for NYC

- Information about all trips completed by all the ride-hailing platforms (12.6M trips/month) ~ censored demand

June 2017



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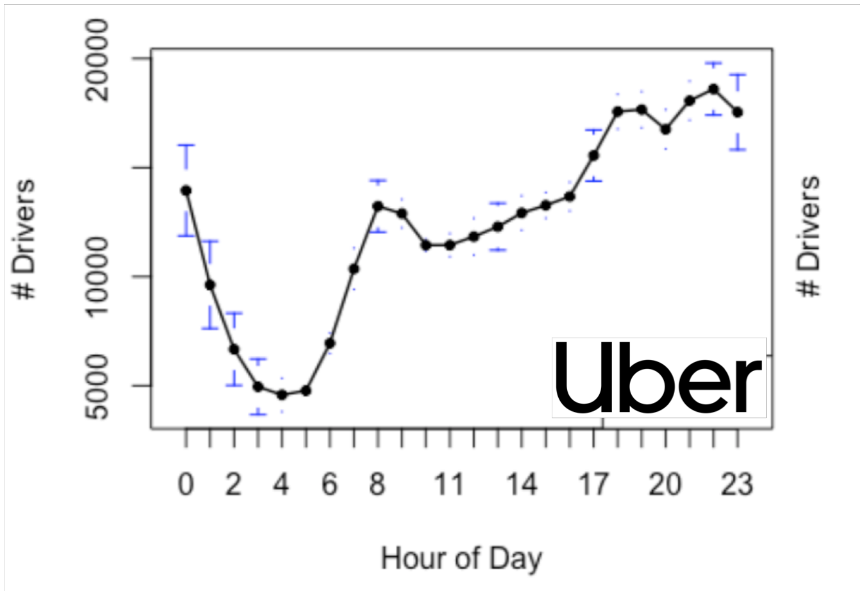
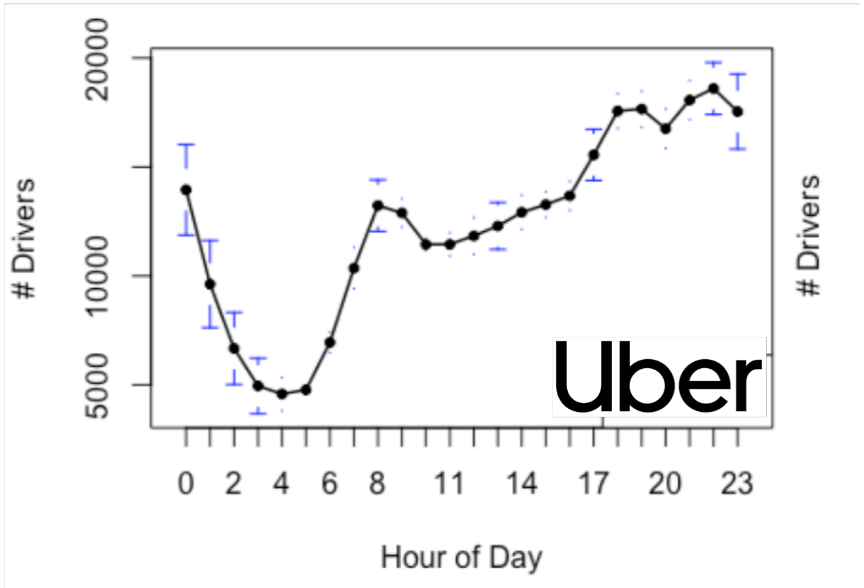


First assume that the driver sticks with one platform.

We know time and location of each pickup and each drop-off.

- Infer the driver ID by comparing times and locations
- Given distance and time of day, we can use estimated fares as a proxy for earnings.

TLC Data for NYC



Distribution of each trip

Median 18.6 minutes, Mean 20.8 minutes

99.1% trip $<$ 1 hour. 82.5% $<$ 30 min. 15% $<$ 10 min

Matching Model

If we know the information about # passengers

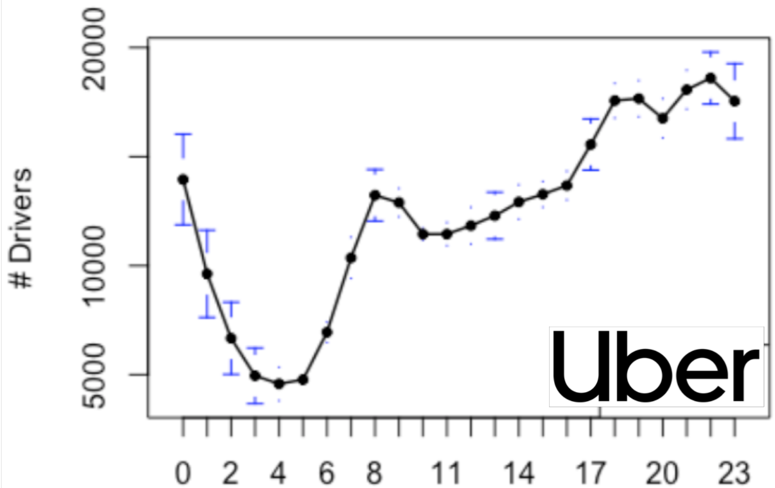
- Model passenger requests in a shift/day/week
- Model number of passengers who are still active users of the platform
- Model number of trips = match between requests and driver supply
- Model service levels

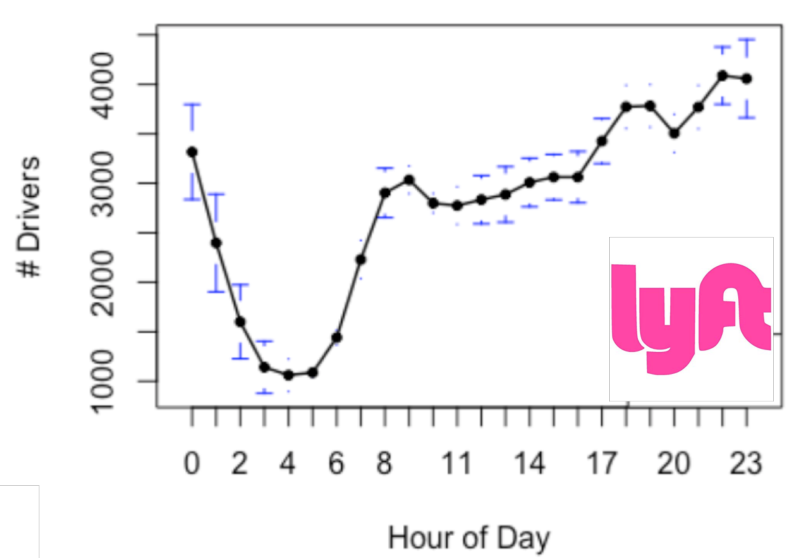
Multi-homing Behavior

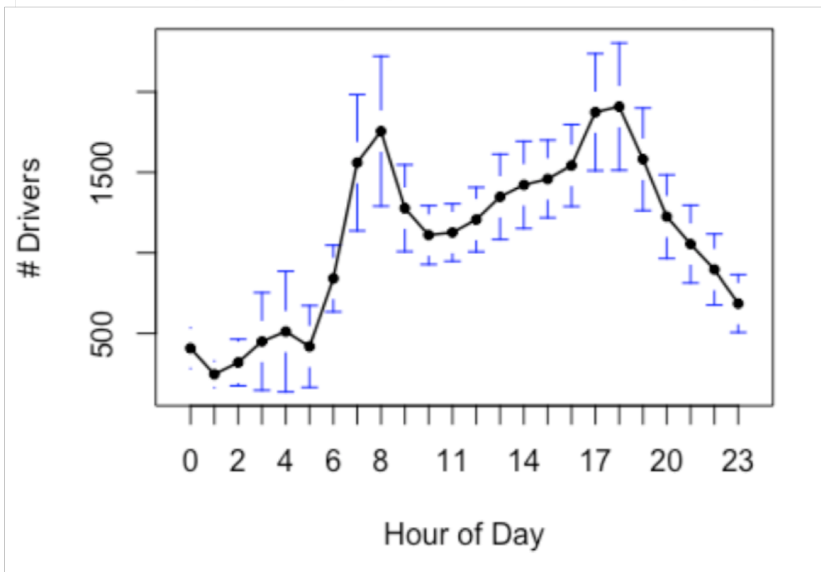
- Workers can actually switch over multiple platforms

TLC Data for NYC

Drivers paid by trip
Unknown rate
Uncertain route

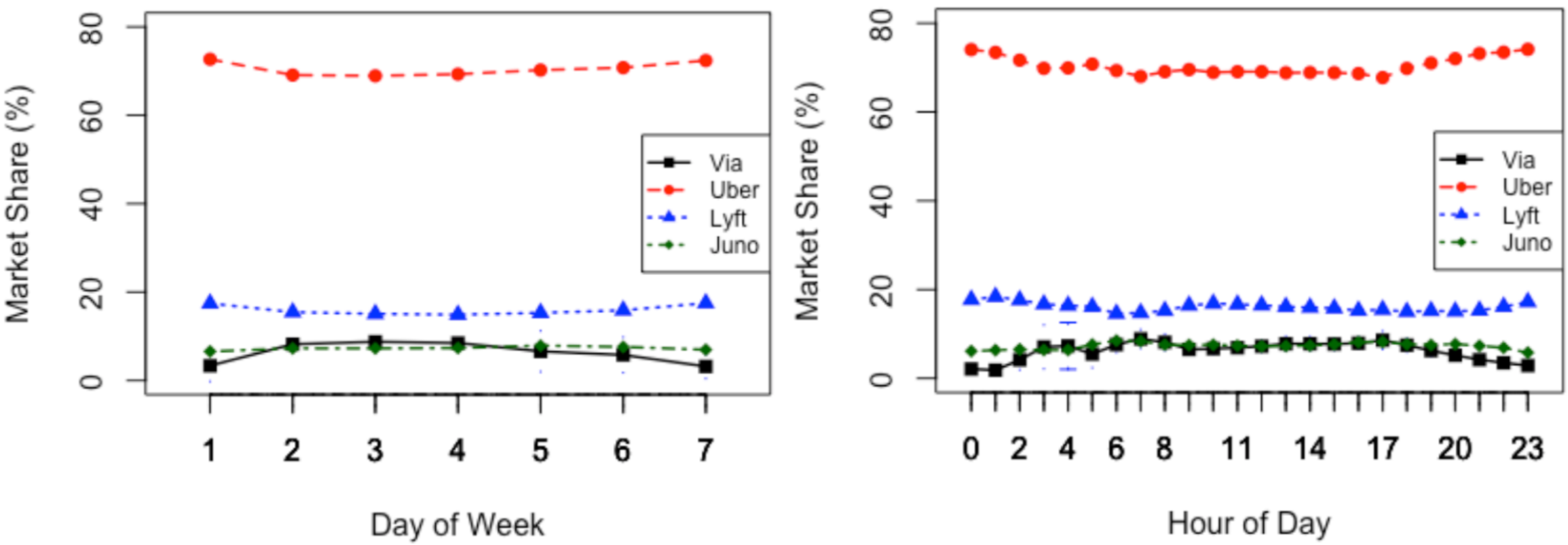






Drivers paid hourly with
known guaranteed rate
Relatively fixed route

TLC Data for NYC



More Complexed Choices

With $Xt = (st, ht)$, driver maximizes the expected and discounted sum of the per-session utilities:

- **Continue:** known wage, cost of driving fixed route
- **Switch to competitor**: uncertain wage, cost of driving uncertain route
- **Not work:** leisure time, no cost