The Impact of Behavioral and Economic Drivers on Gig Economy Workers

SIG Service Operations 2019

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Gig Economy

Gig Economy

freelancing upwork fiverr

Gig Economy

freelancing Upwork fiverr

local tasks TaskRabbit handy

Gig Economy

freelancing Upwork fiverr

local tasks TaskRabbit handy

ride-hailing lyft Uber Grab

delivery instacart DOORDASH

Gig Economy

freelancing Upwork fiverr

local tasks TaskRabbit handy

retail (allwork) snag.work on-demand

ride-hailing lyft Uber Grab

delivery instacart DOORDASH

Gig Economy

2017

57.3 Million

= 36% of US workforce

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

Gig Economy

2017

57.3 Million

= 36% of US workforce

2027

60% of work

+ $2.7 trillion global GDP

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

Who are Gig Workers?

70% by choice

44% primary income

~50% millennials/gen z

2016 McKinsey Global Institute

Who are Gig Workers?

70% by choice

44% primary income

~50% millennials/gen z

when to work?

how long?

which platforms?

Workers decide work schedules

2016 McKinsey Global Institute

Gig Company

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

independent/flexible
on-demand

Gig Company

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

independent/flexible
on-demand

Workforce planning is challenging

Research Questions

How do gig economy workers make labor decisions?

How can the platform influence their decisions?

Research Questions

Econometrics

How do gig economy workers make labor decisions?

How can the platform influence their decisions?

Simulation

Structural

Experiment

Outline

- What has been done

  Practice / labor economics / OM

- Data and empirical strategy

  Dealing with endogeneity and selection bias

- Results

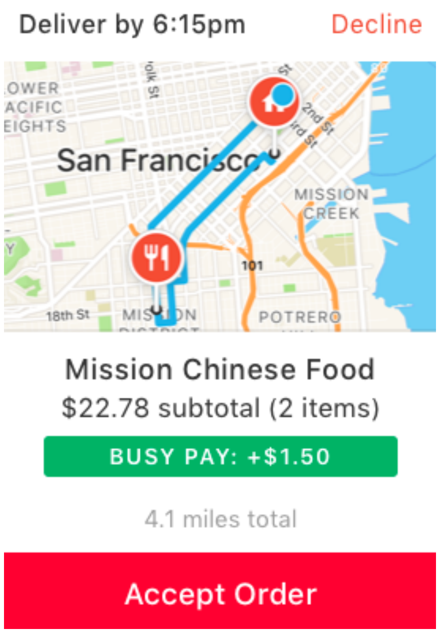
  Impact of incentive and behavioral elements on labor decisions

- Implications

  Simulation of optimal incentive re-allocation

In Practice

Real-time
“surge pricing”

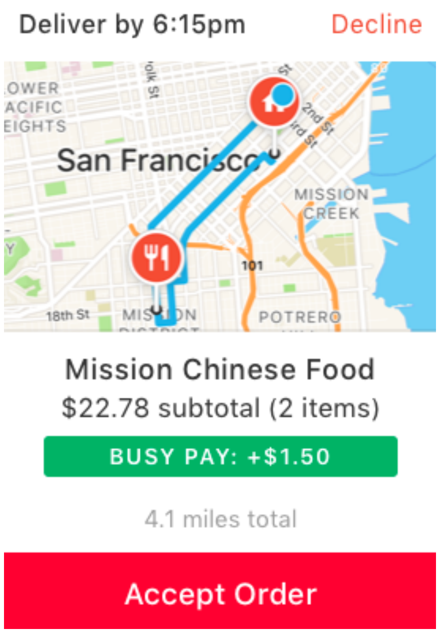


DOORDASH

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

In Practice

Real-time "surge pricing"



DOORDASH

Pre-announced bonus

5:00 PM–6:00 PM
+10% (5:00pm - 5:30pm)
+30% (5:30pm - 6:00pm)

6:00 PM–7:00 PM
+30% (6:00pm - 6:30pm)
+40% (6:30pm - 7:00pm)

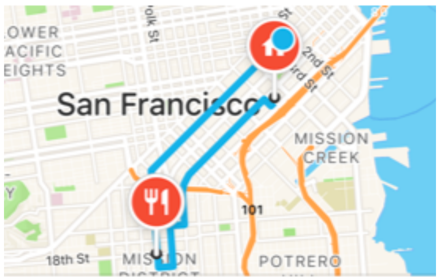
caviar

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

In Practice

Real-time “surge pricing”

Deliver by 6:15pm Decline



Mission Chinese Food
$22.78 subtotal (2 items)

BUSY PAY: +$1.50

4.1 miles total

Accept Order

DOORDASH

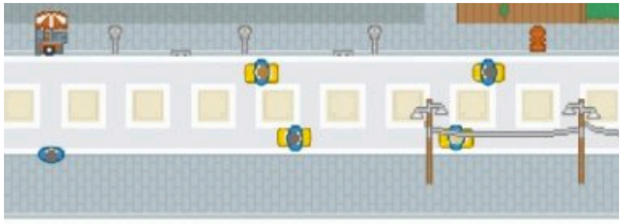
Pre-announced bonus

5:00 PM–6:00 PM
+10% (5:00pm - 5:30pm)
+30% (5:30pm - 6:00pm)

6:00 PM–7:00 PM
+30% (6:00pm - 6:30pm)
+40% (6:30pm - 7:00pm)

caviar

“You’re so close to your precious target”



How Uber Uses Psychological Tricks to Push Its Drivers’ Buttons

https://dasherhelp.doordash.com/busy-pay
https://courierhelp.trycaviar.com/customer/en/portal/articles/2821000-peak-hour-pay?b_id=9619/
https://nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html

Theories of Labor Supply

Theories of Labor Supply

Neoclassical

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

Wage $\uparrow$
Work more

Theories of Labor Supply

Neoclassical

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

Wage ↑
Work more

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

Recent Work in OM

Theoretical

Dong & Ibrahim (2018)
Taylor (2018)
Cachon, Daniels & Lobel (2017)
Hu & Zhou (2017)
Ibrahim (2017)
Bimpikis, Candogan & Saban (2017)
Gurvich, Lariviere & Moreno (2016)
Tang et al. (2016)
Banerjee, Riquelme & Johari (2016)
Benjaafar et al. (2015)
…

Empirical

Sun, Wang & Wan (2019)
Kabra, Belavina & Girotra (2018)
Karacaoglu, Moreno & Ozkan (2018)
Chen, Chevalier, Rossi & Oehlsen (2017)
Cui, Li & Zhang (2017)
Li, Moreno & Zhang (2016)
…

Our Paper

- Behavioral drivers of decisions
- Rich data with complete description of the supply side
- Connect to system-wide decisions

Drivers of Work Decisions

We are interested in three effects

Hourly Wage

Income Target

Time Target

on two work decisions:

Work or not?

If so, how long?

Drivers of Work Decisions

We are interested in three effects

Hourly Wage

Income Target

Time Target

H1: Positive

Carrington (1996), Oettinger (1999), Stafford (2015)

on two work decisions:

Work or not?

If so, how long?

Drivers of Work Decisions

We are interested in three effects

Hourly Wage	Income Target/ Income So Far	Time Target
H1: Positive	**H2:** Negative Farber (2008), Thakral & To (2017)	

on two work decisions:

Work or not?	If so, how long?

Drivers of Work Decisions

We are interested in three effects

Hourly Wage	Income Target/ Income So Far	Time Target/ Hours So Far
H1: Positive	**H2:** Negative	**H3:** Negative

Crawford & Meng (2011), Farber (2015), Agarwal et al (2015), Brachet et al (2012), Collewet & Sauermann (2017)

on two work decisions:

Work or not?

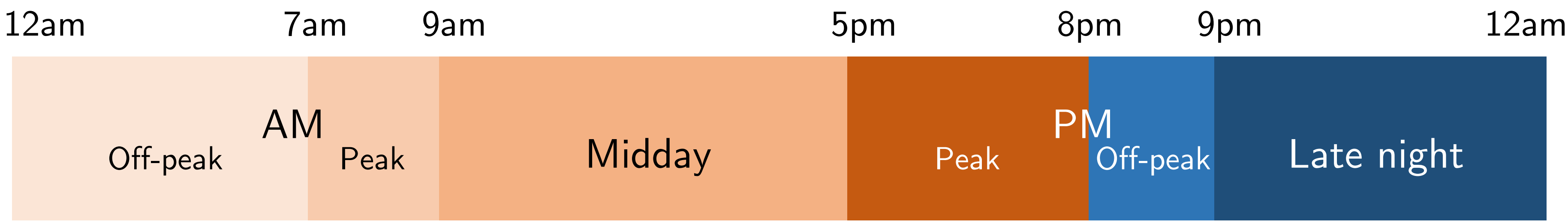
If so, how long?

Data US ride-hailing firm

Drivers are guaranteed an hourly $\underbrace{\text{Base Rate} + \text{Promotions}}_{\text{“Offer”}}$

Data US ride-hailing firm

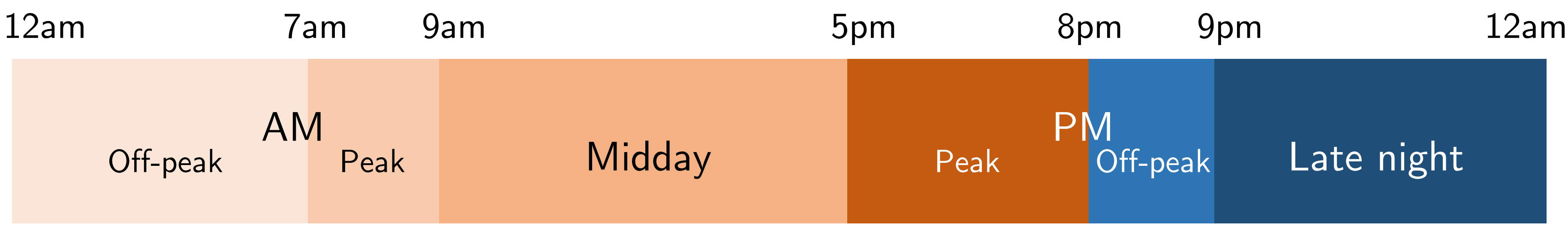
Drivers are guaranteed an hourly Base Rate + Promotions



Shift-level financial incentives and driving activity *for all*

Data US ride-hailing firm

Drivers are guaranteed an hourly **Base Rate** + **Promotions**



Shift-level financial incentives and driving activity *for all*

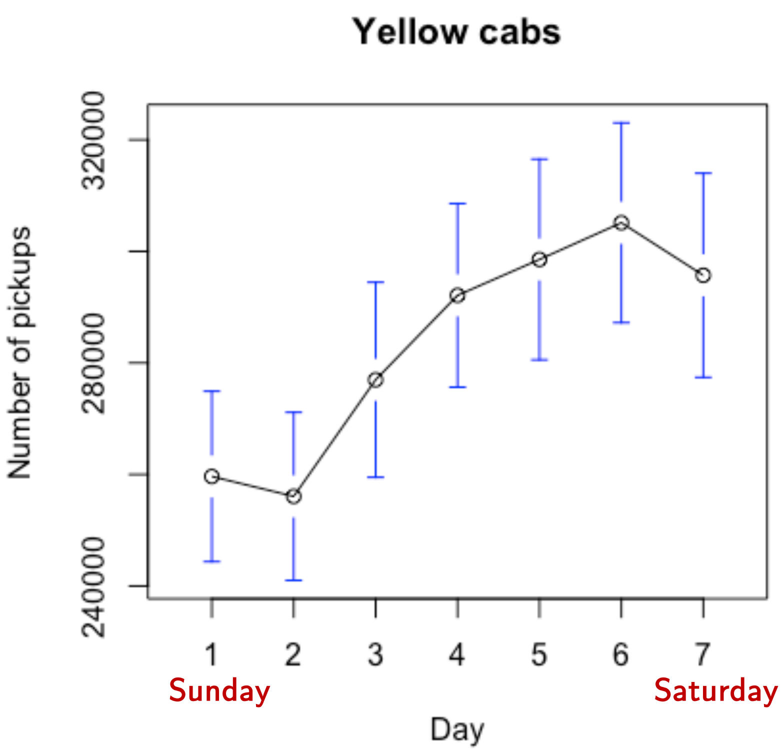
5.5M
Observations

358
Days
Oct 2016 – Sep 2017

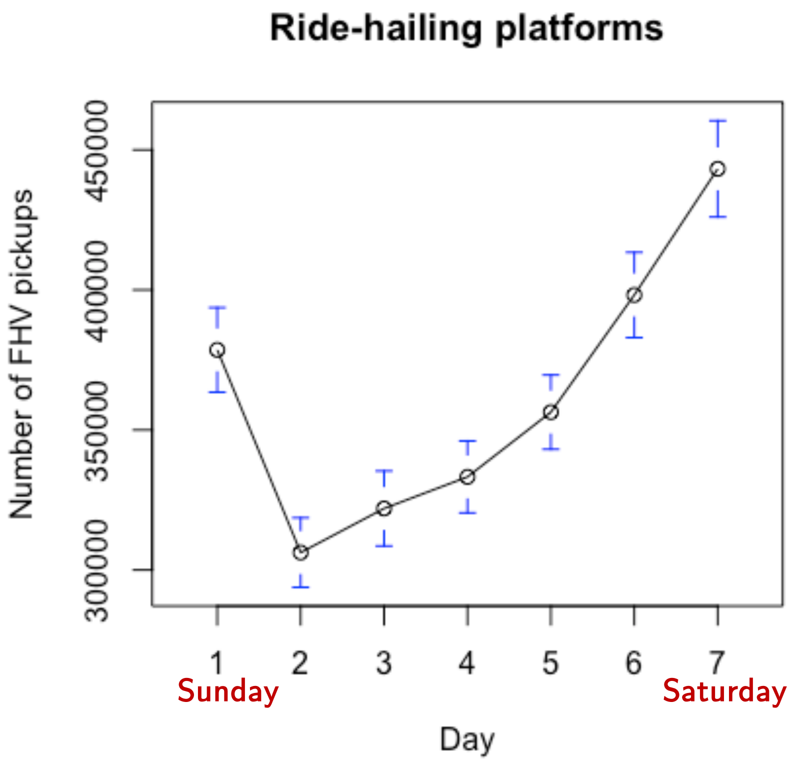
7,826
Unique drivers
SUV/Sedan/Van

TLC Data

Trip records collected by NYC Taxi & Limousine Commission from Oct 2016 to Sep 2017



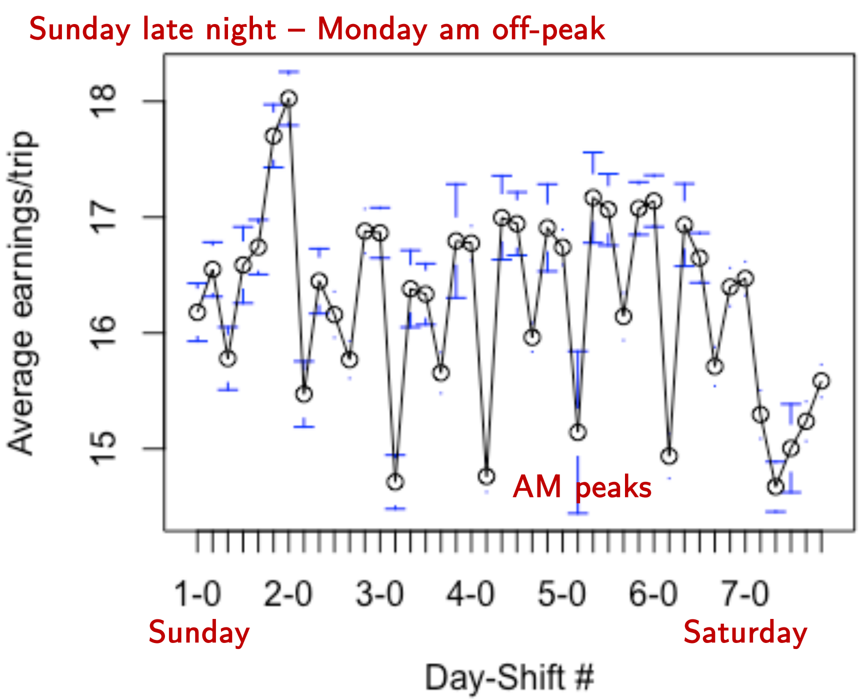
101M yellow cab trips

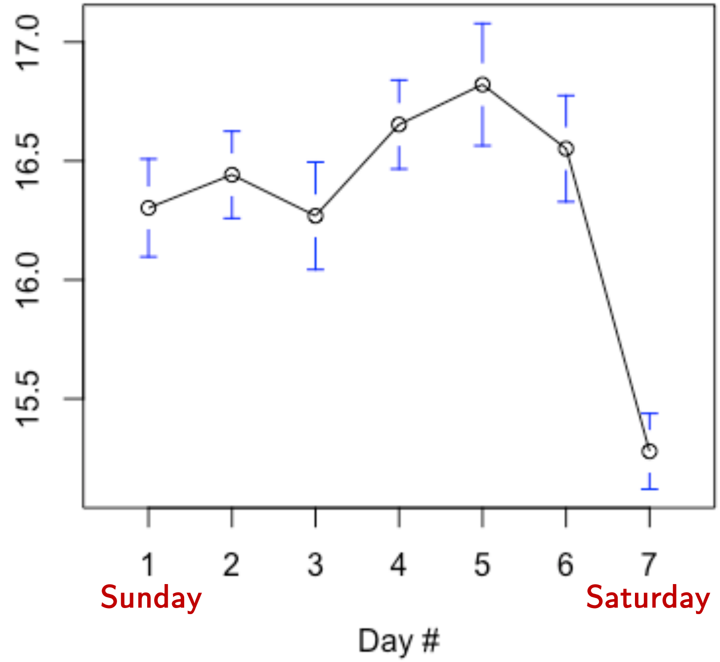


130M ride-hailing trips

TLC Data

Fares/earnings for all yellow cab trips





101M yellow cab trips

Empirical Strategy Challenges

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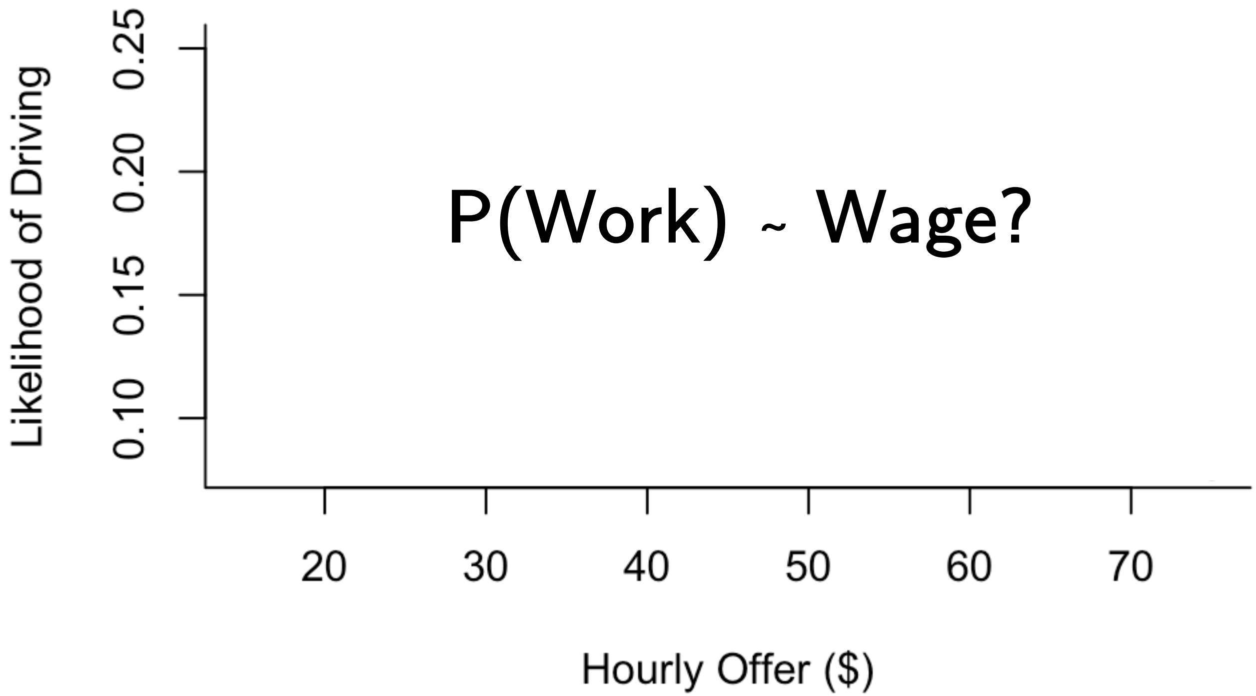

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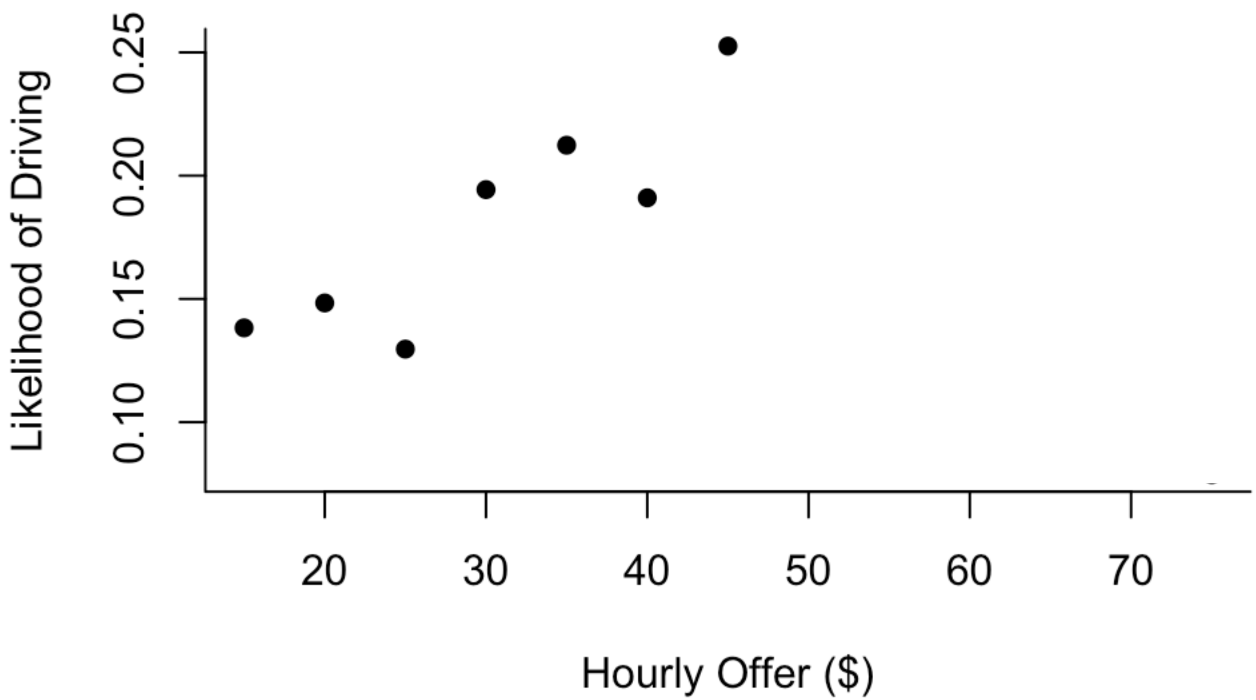
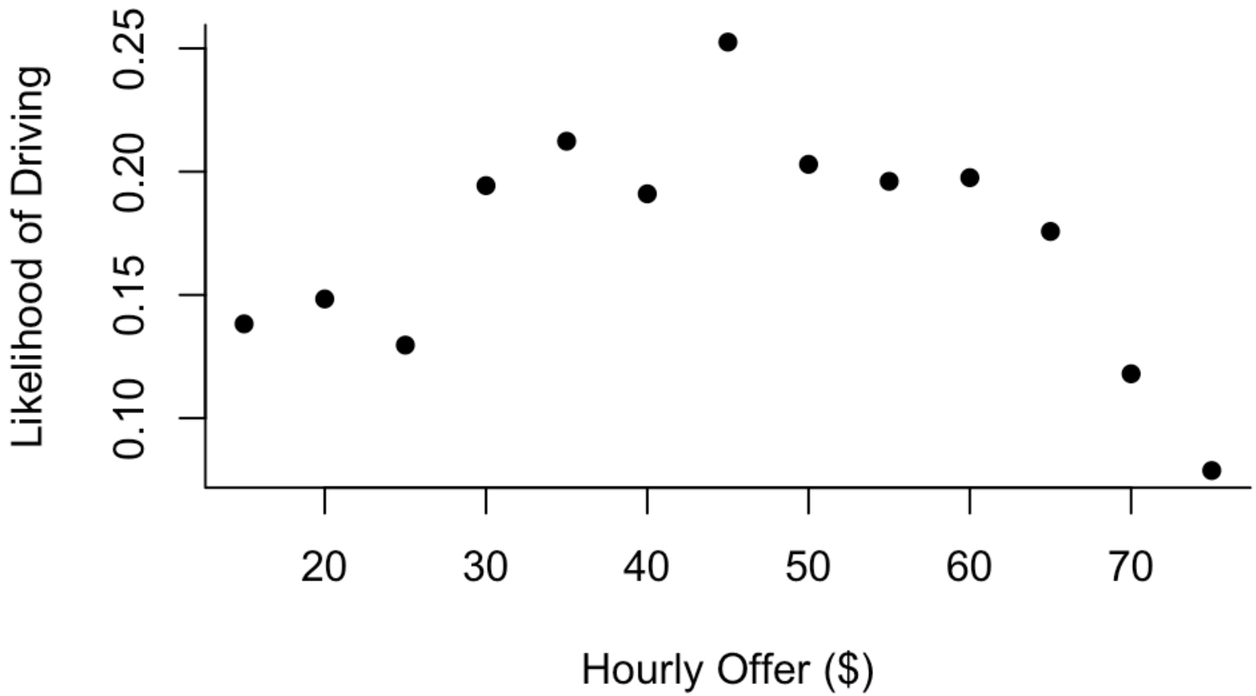


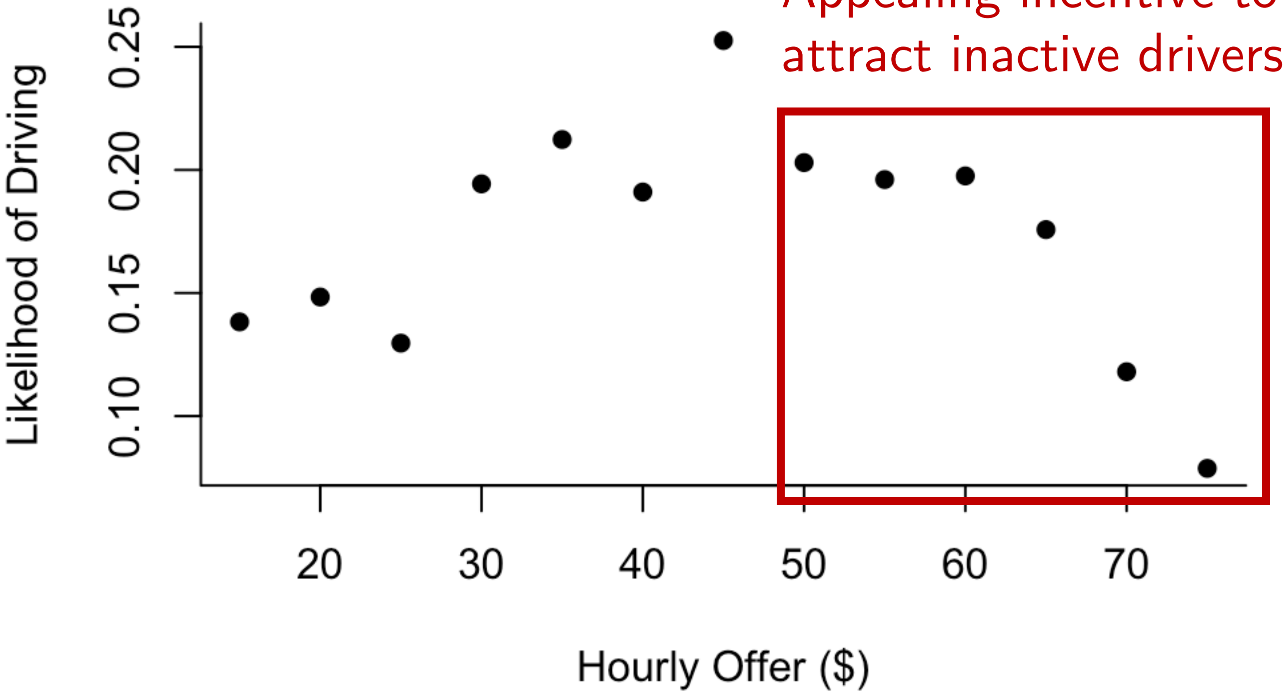
Empirical Strategy Challenges



Empirical Strategy Challenges

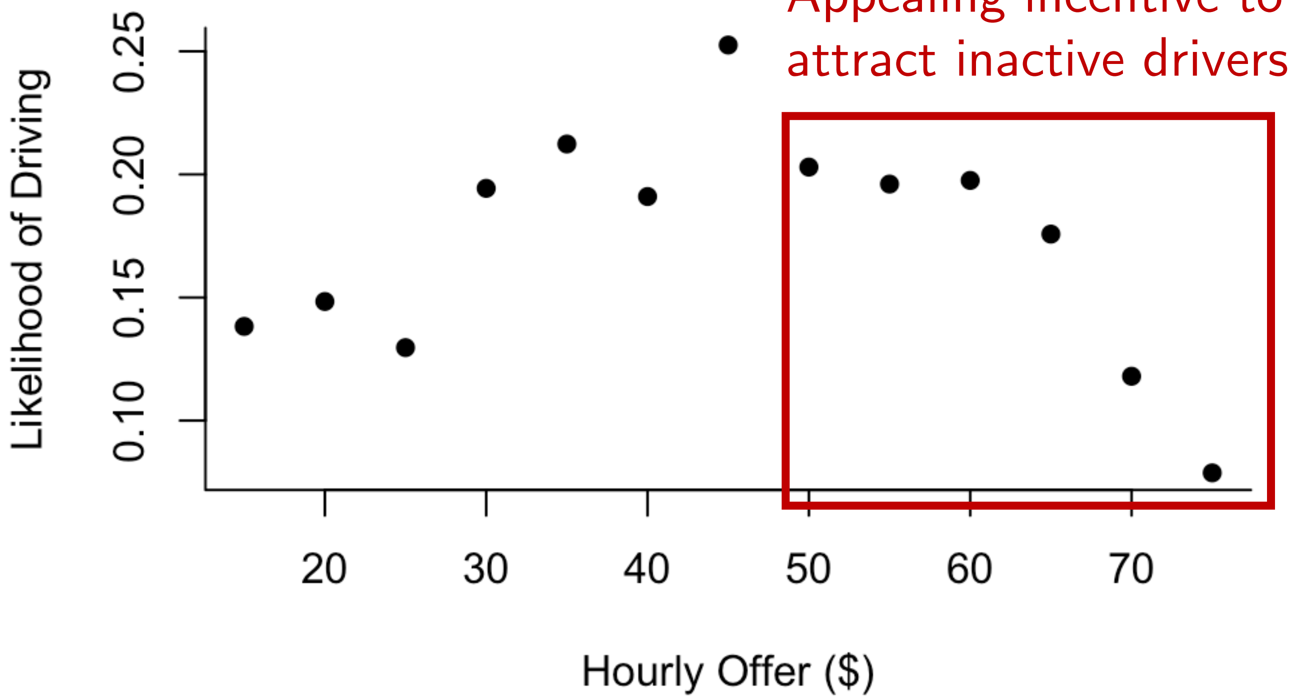
Higher wage, less likely to drive?

Appealing incentive to attract inactive drivers?



Empirical Strategy Challenges

Simultaneity



Higher wage, less likely to drive?

Appealing incentive to attract inactive drivers?

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable

Hourly offer

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable	Instrument
Hourly offer	Average offers of "co-workers"

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable	Instrument
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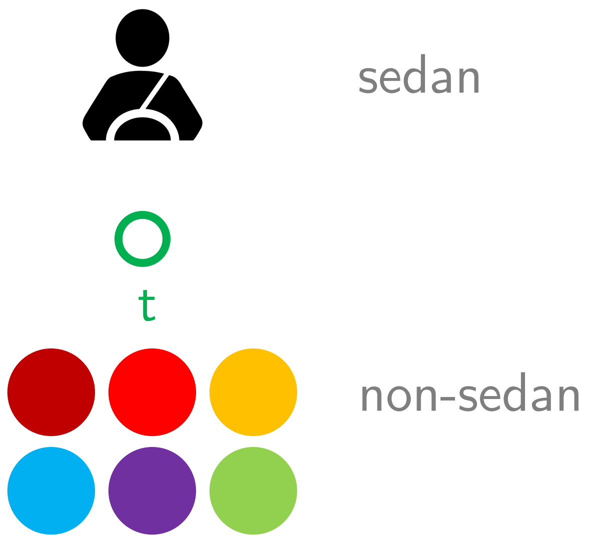
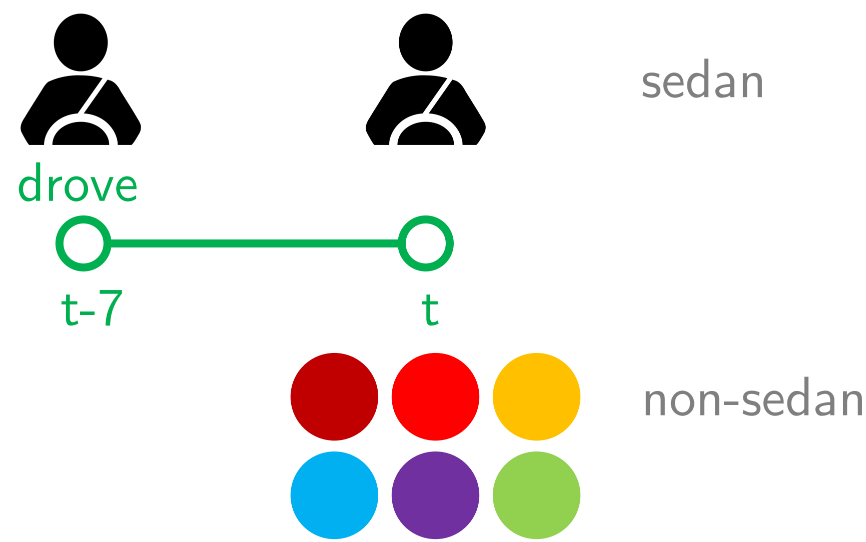


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable	Instrument
Hourly offer	Average offers of “co-workers”



Empirical Strategy Challenges

Simultaneity

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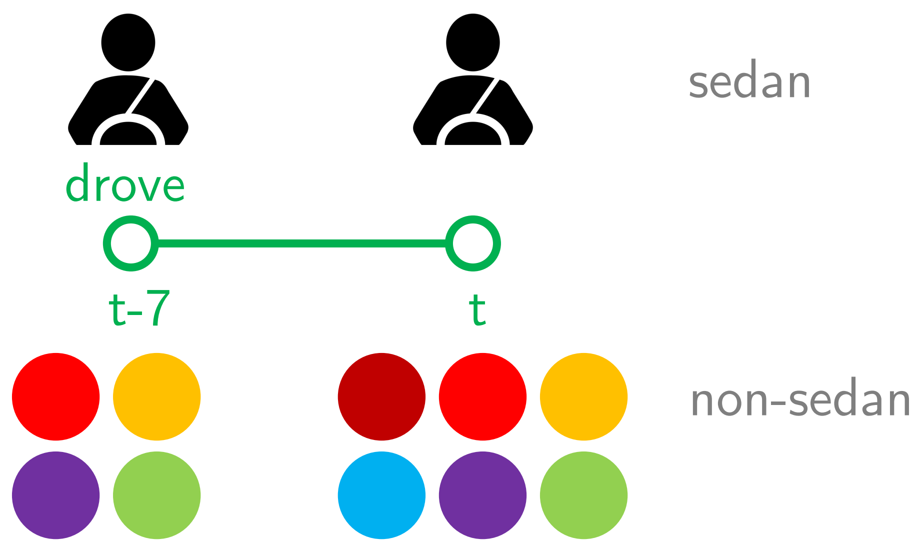

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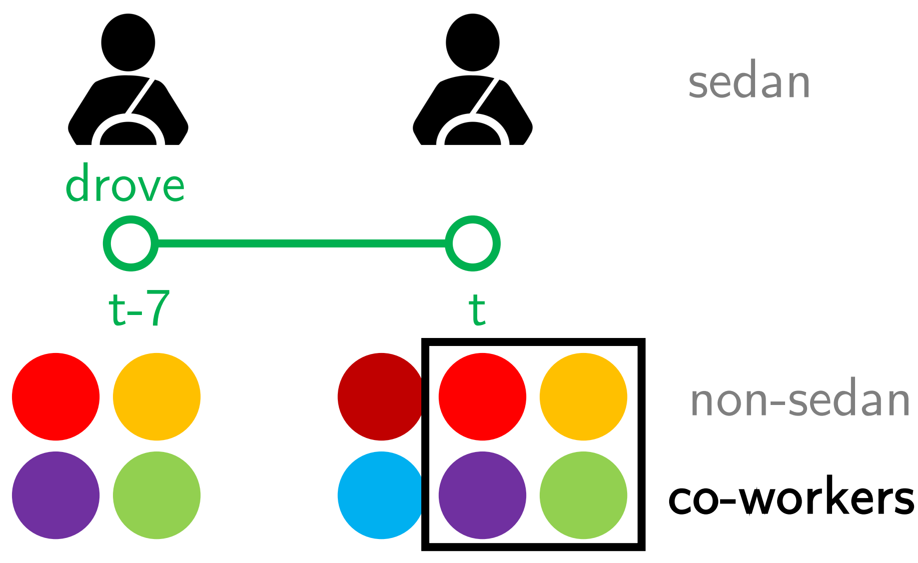

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Hourly offer	Average offers of “co-workers”

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable	Instrument
Hourly offer	Average offers of “co-skippers”

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable	Instrument
Hourly offer	Average offers of "co-skippers"

Level of inactivity for drivers eligible to work today

last worked 6+ days ago	last worked 3-5 days ago	last worked 2 days ago	last worked yesterday

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable	Instrument
Hourly offer	Average offers of "co-skippers"

Level of inactivity for drivers eligible to work today

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

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Hourly offer	Average offers of “co-skippers”

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Empirical Strategy Challenges

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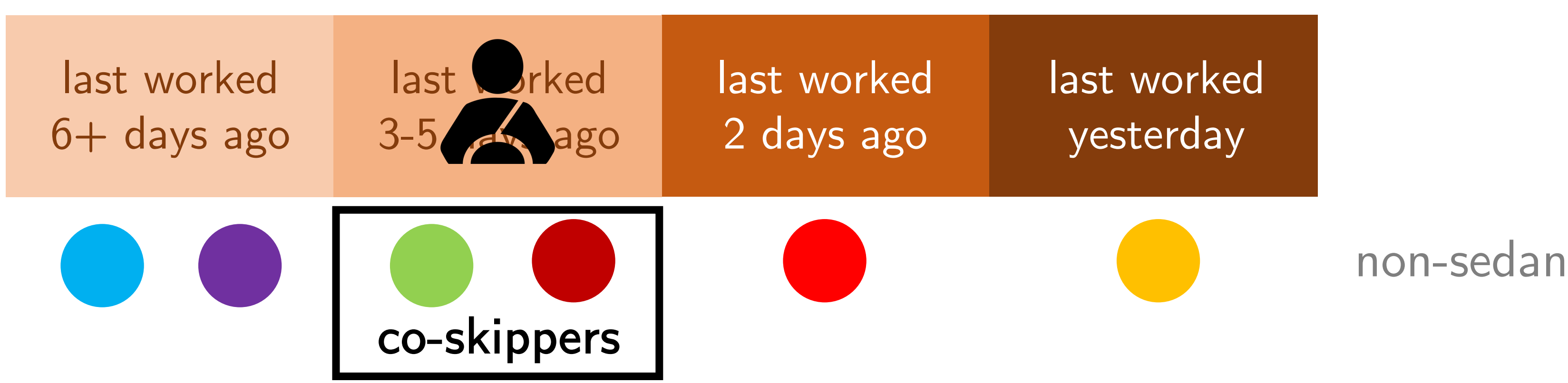
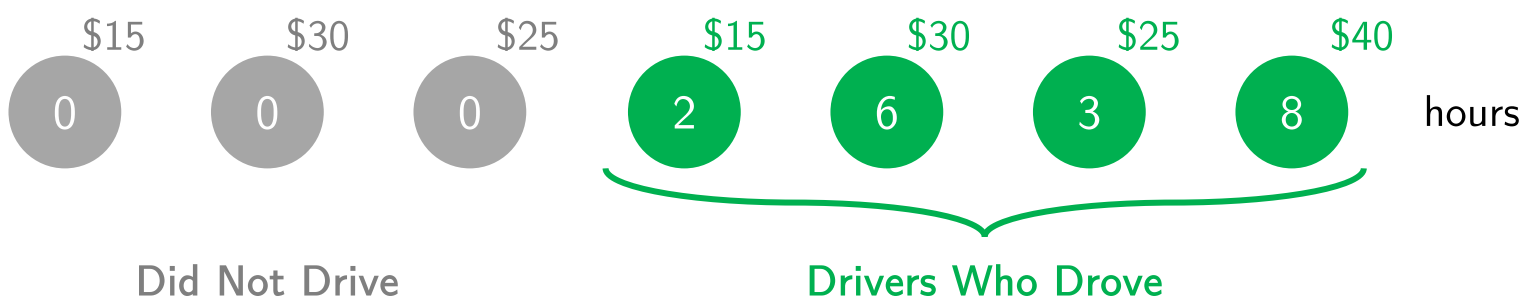


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Hours ~ Wage?



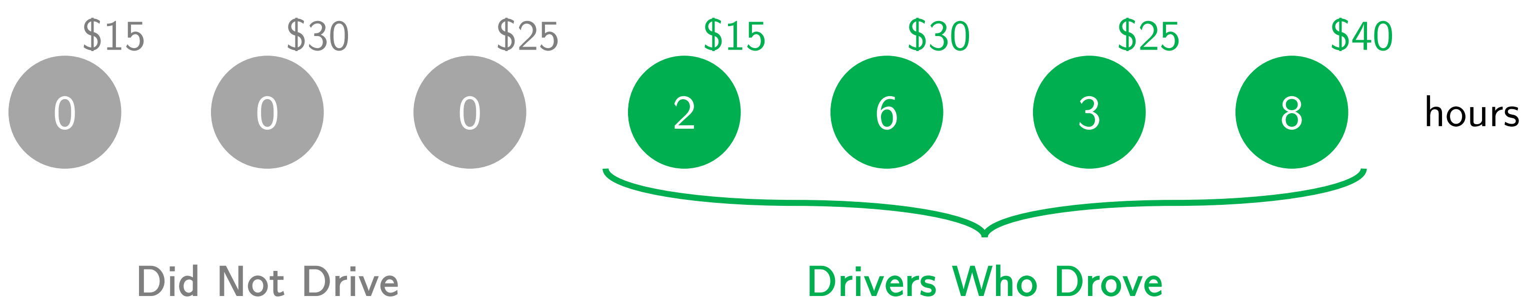
Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**

Hours ~ Wage?



Empirical Strategy Challenges

Simultaneity

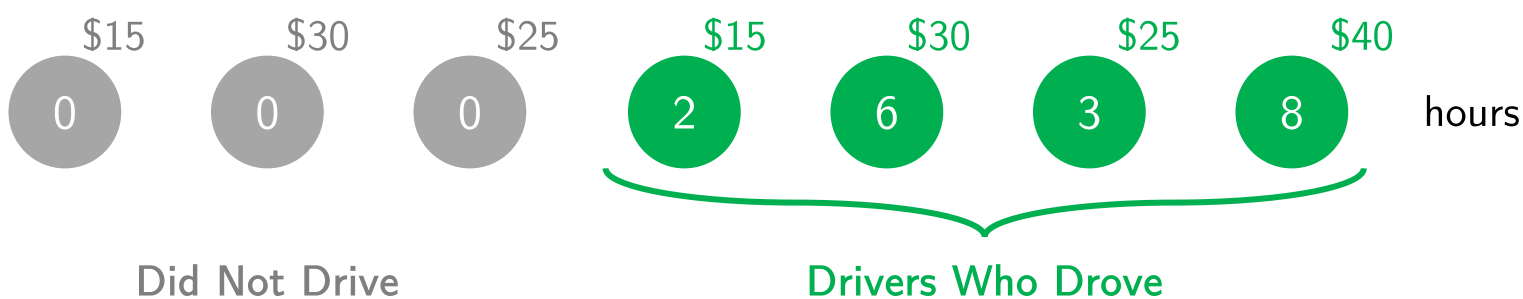
Solution: Instrumental Variables

Selection Bias

Solution: Heckman Two-Stage Method

("Heckit" - Heckman 1979)

Hours ~ Wage



Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

P(drive) on ***Offer***

Empirical Strategy Heckman + IV

1 Work or not?

Control Function Probit:

P(drive) on ***Offer*** + Controls_1

Demand

Short-term Habits

Long-term Habits

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + Controls_1

Demand
- **# Ride-Hailing Pickups** right before
- **Hourly Weather** Humidity, Temp, PrecipProb
- **Holiday, Day of Week**
- **Month-Year FE**

Short-term Habits
- **Past Work Habits**
  Hours worked last week, income last week

Long-term Habits
- **Driver's Experience** New?
- **Driver's FE**

Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + ISF + Controls$_1$

Income So Far

= accumulated income since beginning of day

Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + **ISF** + **Controls**$_1$

Income So Far
= intensity of work

Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + **ISF** + **HSF** + **Controls**$_1$

Income So Far
= intensity of work

Hours So Far
= accumulated time
logged in since beginning of day

Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + **ISF** + **HSF** + **Controls**$_1$

Income So Far
= intensity of work

Hours So Far
= amount of active time

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + ISF + HSF + **Controls**$_1$

Income So Far
= intensity of work

Hours So Far
= amount of active time

Bias corrected with panel jackknife
(Hahn & Newey 2004)

Also include ISF^2 and HSF^2 to capture nonlinearity

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

P(drive) on ***Offer*** + **ISF** + **HSF** + **Controls**$_1$

Income So Far **Hours So Far**

Conditional on working

2 **How long to work?**

2SLS with Fixed Effects

 # Hours on ***Earning*** + **ISF** + **HSF** + + **Controls**$_2$

Empirical Strategy Heckman + IV

1 Work or not?

Control Function Probit:

P(drive) on ***Offer*** + ISF + HSF + Controls_1

Income So Far

Hours So Far

Conditional on working

2 How long to work?

2SLS with Fixed Effects

Hours on ***Earning*** + ISF + HSF + IMR + Controls_2

Inverse Mills Ratio

= correct for selection bias

Empirical Strategy Heckman + IV

1 Work or not?

CF: Regress **hourly offer** on IVs. Keep **residuals**

Probit: Estimate **P(drive)**

$$P(Drive_{i,t}=1|\boldsymbol{X_{i,t}})=\Phi(\alpha_{0,t}+\alpha_w w_{i,t}+\boldsymbol{\alpha X_{i,t}}+\alpha_e \hat{e}_{i,t})$$

Bias corrected with panel jackknife (Hahn & Newey 2004)

Inverse Mills Ratio (IMR)

$$\lambda(c_z)=\frac{\phi(c_z)}{1-\Phi(c_z)}$$

Conditional on working

2 How long to work?

IV: Estimate **hourly earning** from IVs

OLS: Estimate **hours**

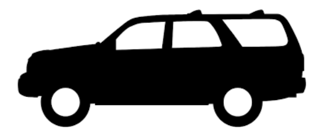
$$f(Hour_{i,t})=\beta_{0,i}+\beta_\omega \omega_{i,t}+\boldsymbol{\beta Z_{i,t}}+\theta\lambda_{i,t}+u_{i,t}$$

Adjust standard errors to account for the fact that IMR is an estimate (and hence random) covariate in the above model.

Results

Financial Offer ISF HSF

1 **Work or not?** 2 **# Hours**



Within-Day

Midday

↓

Late Night

Across-Days

Tuesday

↓

Sunday

Results

Financial Offer ISF HSF

1 **Work or not?** 2 **# Hours**

Within-Day

Midday

↓

Late Night

Across-Days

Tuesday

↓

Sunday

+	-
Positive	Negative

Results Within Day

1

Work or not?

SUV	Mean	IV-F
Midday	0.345	384.9
PM-Peak	0.277	359.4
PM-OPeak	0.179	326.6
Late Night	0.114	386.7

Results Within Day

1

Work or not?

SUV	Mean	IV-F	Offer
Midday	0.345	384.9	+
PM-Peak	0.277	359.4	-
PM-OPeak	0.179	326.6	+
Late Night	0.114	386.7	+

Financial incentives have a generally **positive** impact.

Results Within Day

1

Work or not?

SUV	Mean	IV-F	Offer	ISF
Midday	0.345	384.9	+	+
PM-Peak	0.277	359.4	-	-
PM-OPeak	0.179	326.6	+	-
Late Night	0.114	386.7	+	-

Income Target

Income Target:
The more you earned, the less likely you'll work a new shift.

The negative impact of **income target kicks in later in the day**.

Results Within Day

1

Work or not?

SUV	Mean	IV-F	Offer	ISF	HSF
Midday	0.345	384.9	+	+	+
PM-Peak	0.277	359.4	-	-	+
PM-OPeak	0.179	326.6	+	-	+
Late Night	0.114	386.7	+	-	+

Income Target — Inertia

Inertia: The longer you've been active, the more likely you'll work another shift.

Inertia has a **consistently positive** impact.

Results Within Day

1 Work or not?

2 # Hours

SUV	Mean	IV-F	Offer	ISF	HSF	Mean	IV-F
Midday	0.345	384.9	+	+	+	3.252	187.6
PM-Peak	0.277	359.4	-	-	+	1.334	61.08
PM-OPeak	0.179	326.6	+	-	+	0.458	51.05
Late Night	0.114	386.7	+	-	+	1.338	39.14

Income Target Inertia

Results Within Day

SUV	1 Work or not? Mean	IV-F	Offer	ISF	HSF	2 # Hours Mean	IV-F	Earning	ISF	HSF	R^2
Midday	0.345	384.9	+	+	+	3.252	187.6	+	+	+	0.752
PM-Peak	0.277	359.4	-	-	+	1.334	61.08	+	-	+	0.930
PM-OPeak	0.179	326.6	+	-	+	0.458	51.05	+	-	+	0.929
Late Night	0.114	386.7	+	-	+	1.338	39.14	+	-	+	0.913
				Income Target	Inertia				Income Target	Inertia	

The three effects are consistent in both stages

Results Across Days

1

Work or not?

SUV	Mean
Tuesday	0.420
Wednesday	0.430
Thursday	0.446
Friday	0.428
Saturday	0.204
Sunday	0.160

Results Across Days

1

SUV	Mean	IV-F	Offer	ISF	HSF
			Work or not?		
Tuesday	0.420	43.58	+	+	+
Wednesday	0.430	54.78	+	+	+
Thursday	0.446	67.92	+	+	+
Friday	0.428	67.02	+	+	+
Saturday	0.204	90.07	+	+	+
Sunday	0.160	75.54	+	-	+

Financial incentives and inertia have consistent positive effects, but income targeting is weaker.

Results Across Days

		1 Work or not?					2 # Hours					
SUV	Mean	IV-F	Offer	ISF	HSF	Mean	IV-F	Earning	ISF	HSF	R^2
Tuesday	0.420	43.58	+	+	+	5.240	22.01	-	-	+	0.043
Wednesday	0.430	54.78	+	+	+	5.349	29.14	+	-	+	0.049
Thursday	0.446	67.92	+	+	+	4.444	40.51	-	-	+	0.057
Friday	0.428	67.02	+	+	+	5.537	37.79	-	-	+	0.044
Saturday	0.204	90.07	+	+	+	5.275	17.89	-	+	-	0.077
Sunday	0.160	75.54	+	-	+	4.750	15.06	-	+	-	0.083

Drivers made work duration decision on a shift basis.

Results Summary

As day/week proceeds...

Neoclassical Financial Incentive	encourages working

Results Summary

As day/week proceeds...

Neoclassical Financial Incentive	encourages working
Behavioral Income Target	discourages working later on

Results Summary

	As day/week proceeds... →
Neoclassical **Financial Incentive**	encourages working
Behavioral **Income Target**	discourages working later on
New **Inertia**	encourages working

Robustness Tests

- Isolating ISF and HSF effect
  - Positive HSF (inertia) effect dominates ISF (targeting) effect.
- Controlling on types of promotions
  - Same insights for only rate-based promotions
- Other approaches to sample selection
  - Two-part models: insights stay the same in both parts
  - Dahl's correction: using B-splines instead of IMR
- Looking at granular log-on/log-off data
  - Smaller sample of sedan and SUV drivers
  - The longer the previous active session is,
    the longer the current active session is.

Outline

- What has been done

  Practice / labor economics / OM

- Data and empirical strategy

  Dealing with endogeneity and selection bias

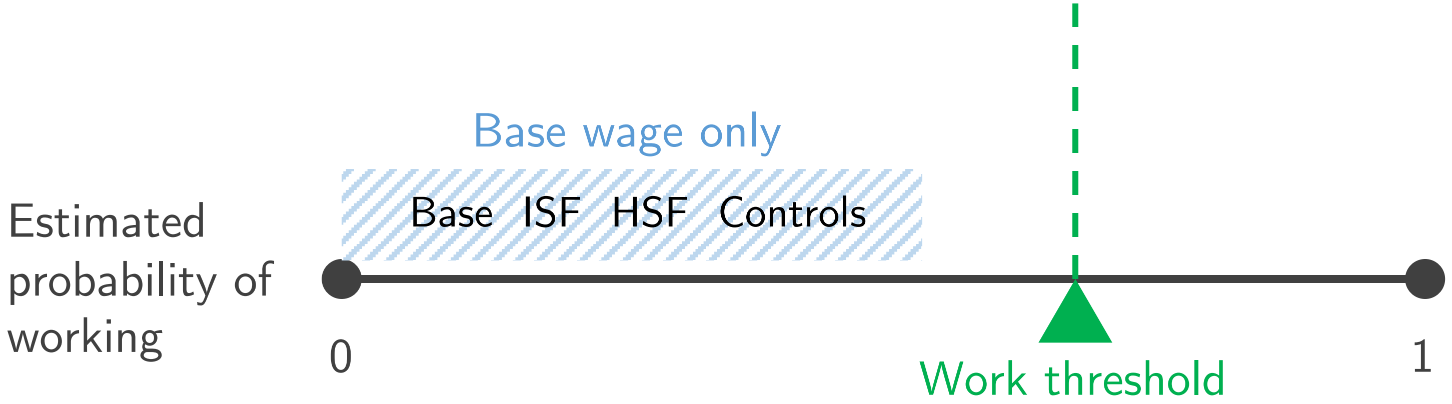
- Results

  Impact of incentive and behavioral elements on labor decisions

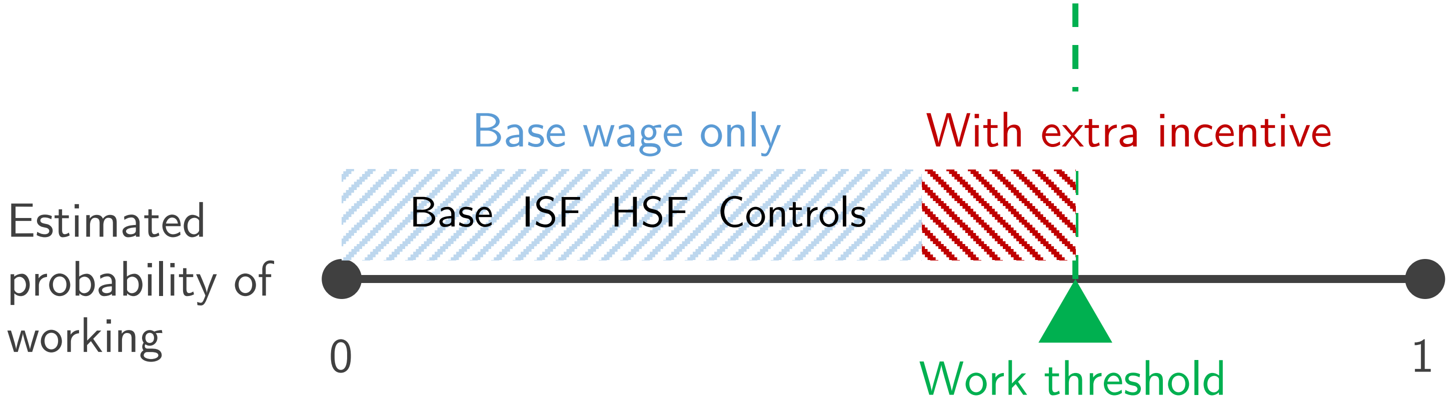
- Implications

  Simulation of optimal incentive re-allocation

Optimal Targeted Incentive

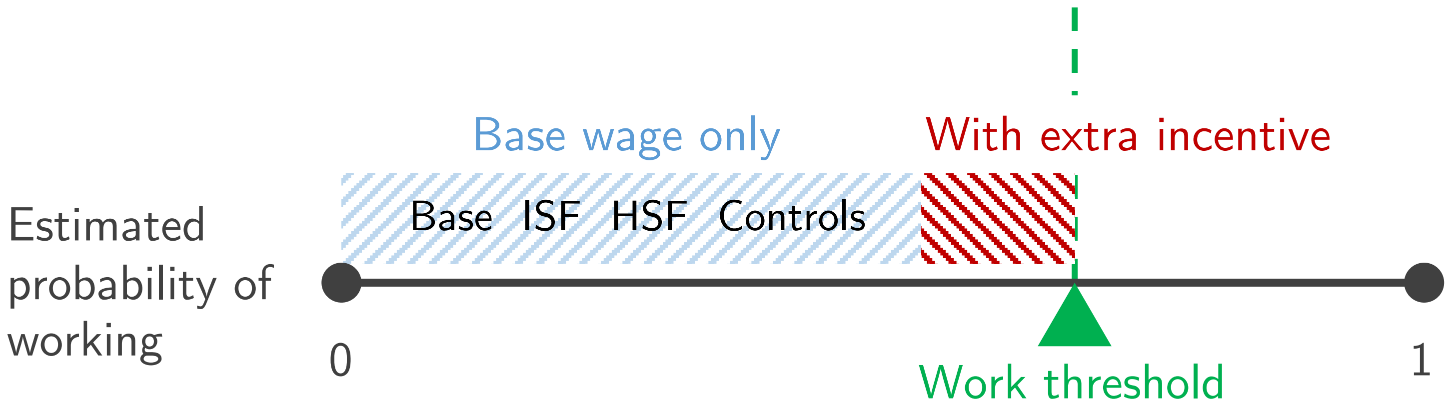


Optimal Targeted Incentive



Optimal Targeted Incentive

Ranking each driver by her
minimum work-inducing incentive
= how much to trigger working decision



Reallocating Incentives

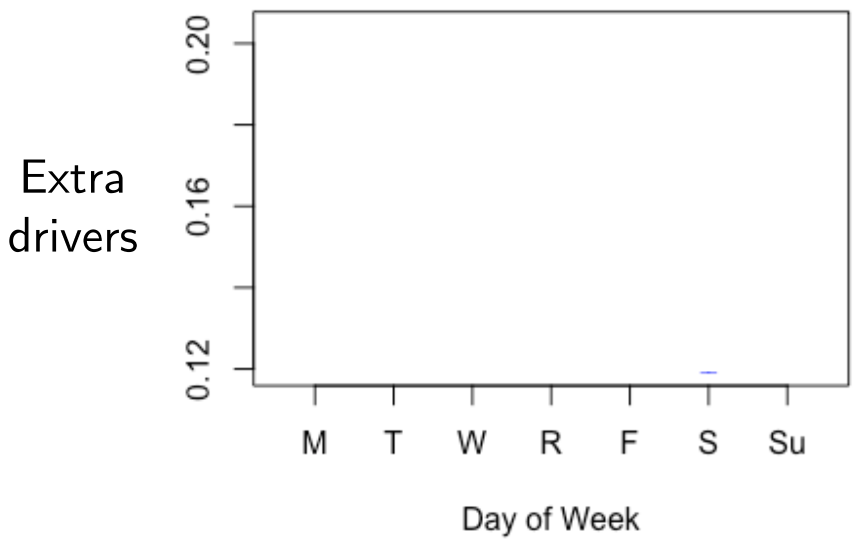
Compared to current practice from Jan to Sep 2017 out-of-sample

(Using data from Oct 2016 to right before the focal date as training)

Reallocating Incentives

Compared to current practice from Jan to Sep 2017 out-of-sample

Given the same budget

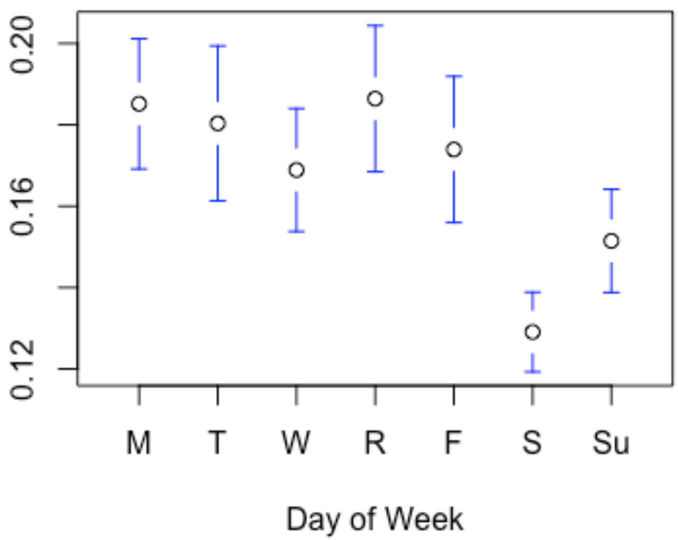


Reallocating Incentives

Compared to current practice from Jan to Sep 2017 out-of-sample

Given the same budget

Extra drivers



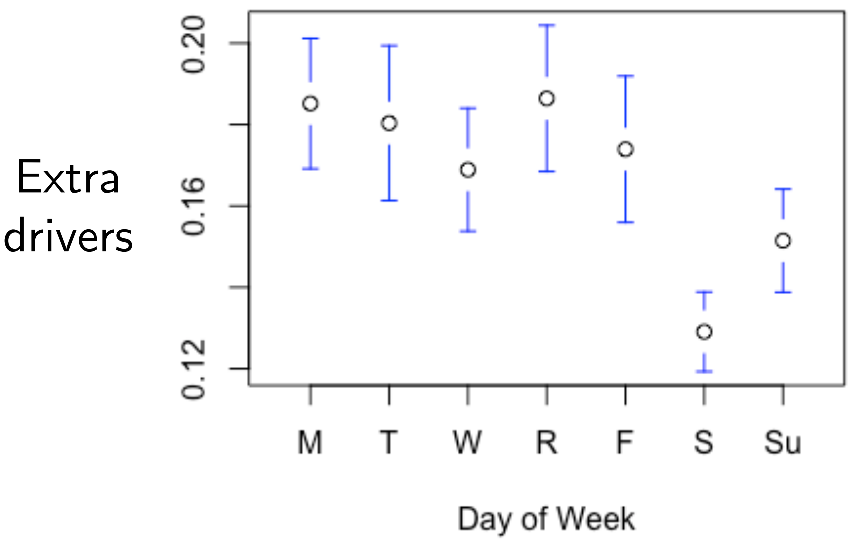
Can recruit **17% more drivers**

Average promo: 1.61x

Reallocating Incentives

Compared to current practice from Jan to Sep 2017 out-of-sample

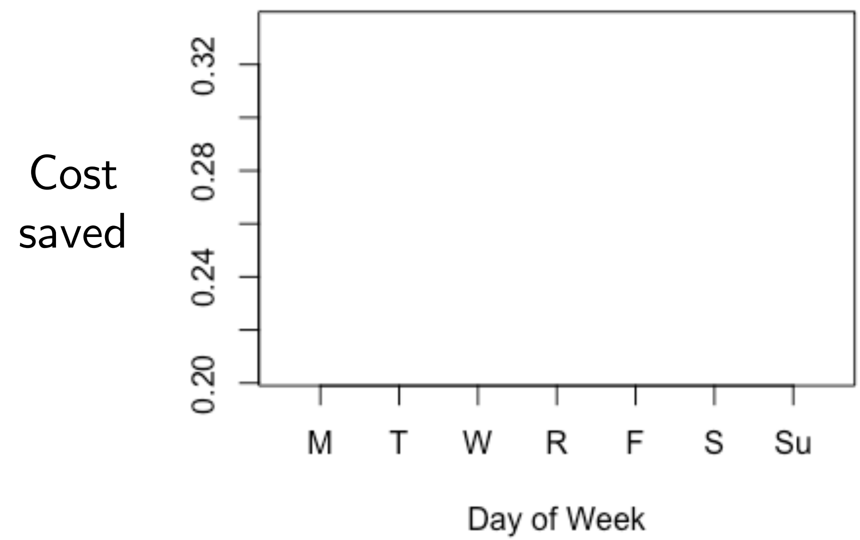
Given the same budget



Can recruit **17% more drivers**

Average promo: 1.61x

Given the same capacity

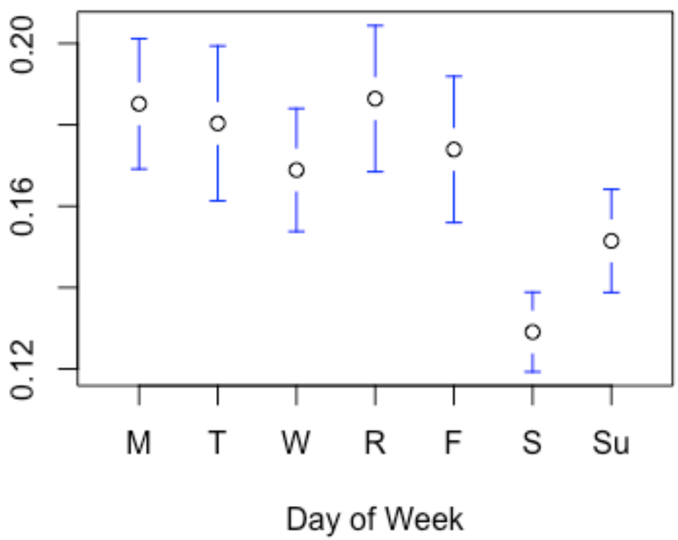


Reallocating Incentives

Compared to current practice from Jan to Sep 2017 out-of-sample

Given the same budget

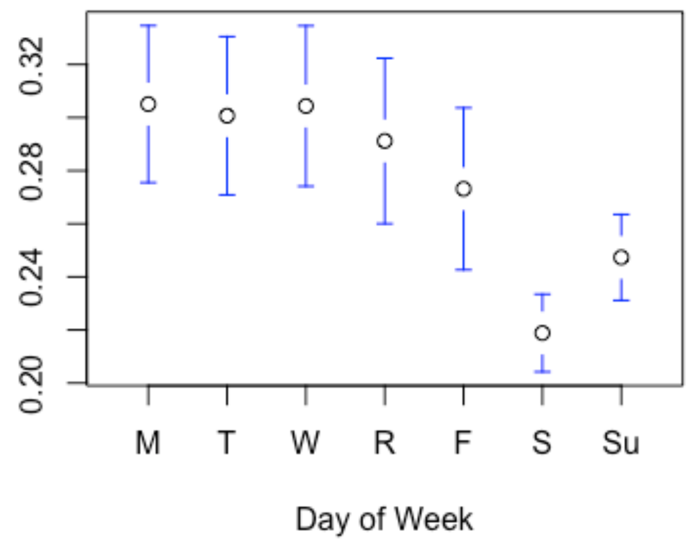
Extra drivers



Can recruit **17% more drivers**
Average promo: 1.61x

Given the same capacity

Cost saved



Costs 28% less to maintain capacity

Summary

How do gig economy workers make labor decisions?

Approach

- Shift-level data from ride-hailing company
- Modified Heckman estimation w/ IVs and fixed effects

Findings

As day/week proceeds...

Neoclassical	Financial Incentive	encourages working
Behavioral	Income Target	discourages working later on
New phenomenon	Inertia	encourages working

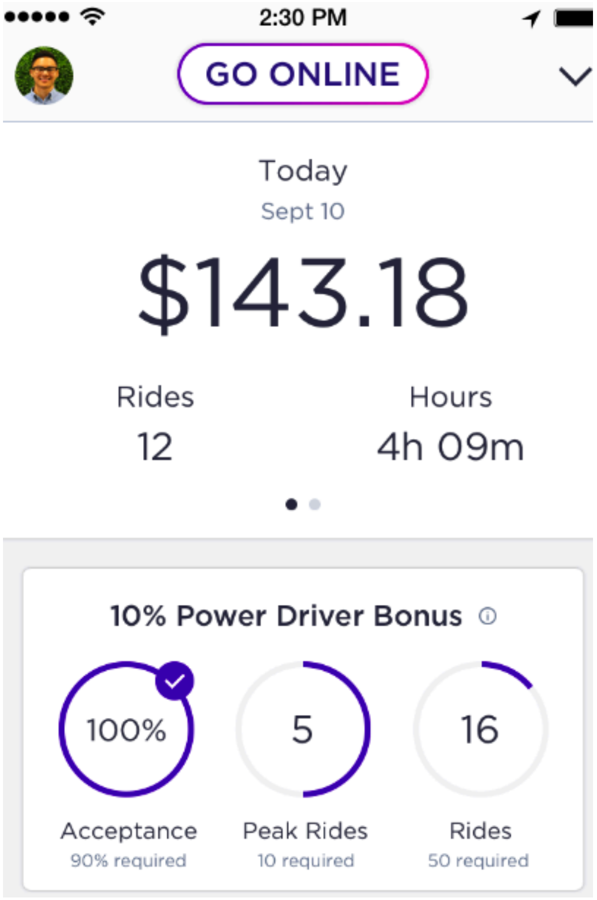
Implications

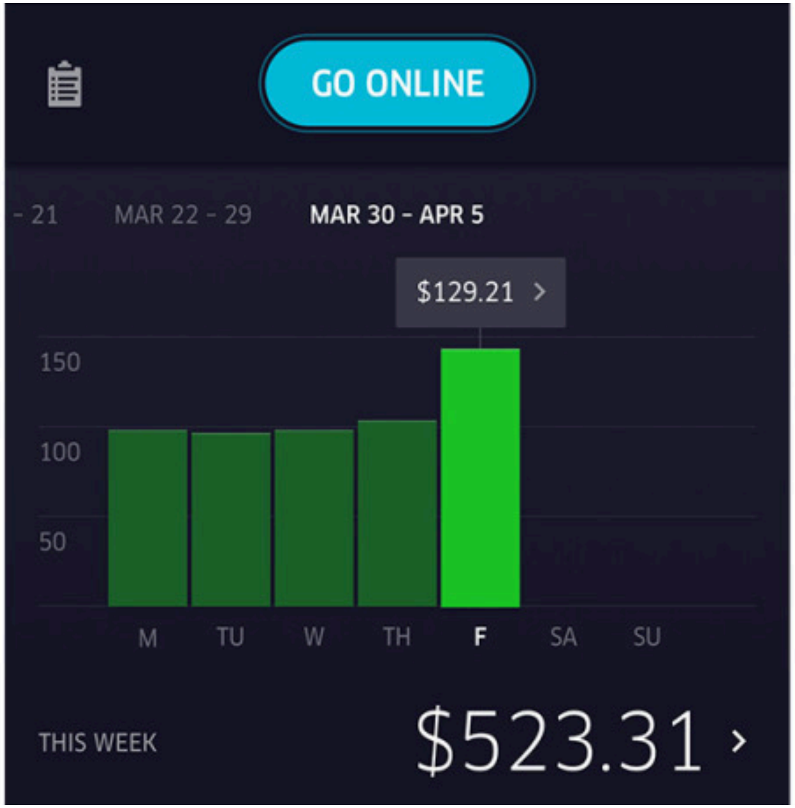
- Compared to current practice, our approach can improve service capacity without incurring extra cost or maintain the same capacity at a lower cost

Gad Allon, Maxime Cohen, **Park Sinchaisri** (swich@wharton.upenn.edu | @wichinpong)

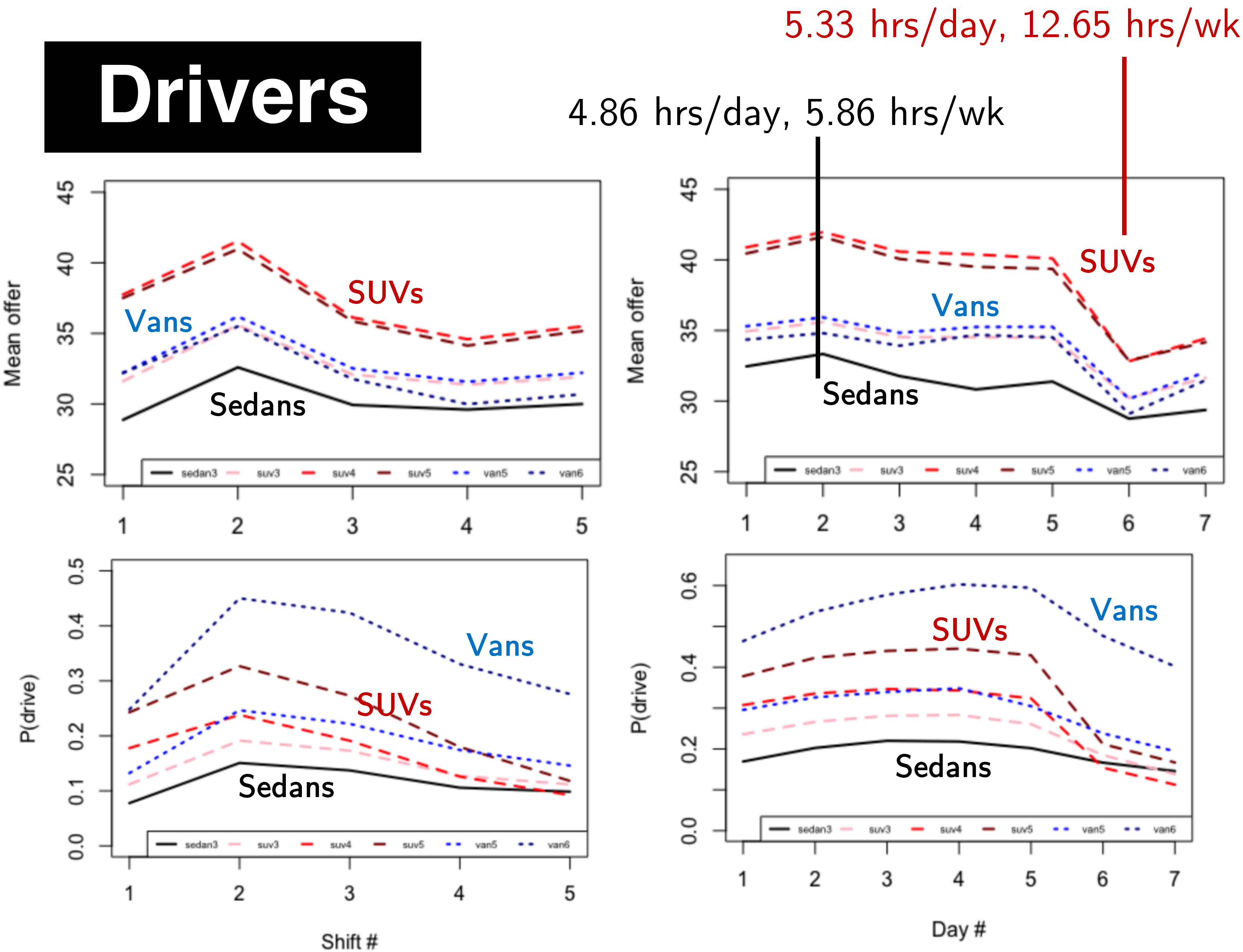
Appendix

Driver’s View





Drivers


5.33 hrs/day, 12.65 hrs/wk
4.86 hrs/day, 5.86 hrs/wk
Mean offer
SUVs
Vans
Sedans
sedan3
suv3
suv4
suv5
van5
van6
P(drive)
Shift #
Day #

Gig Economy x Retail

Baker Retailing Center

- **Retail candidates value flexible shift patterns** and shorter work weeks over compensation and benefits.

- Benefits of adopting flexible workforce: Seasonality, resolving high turnover, matching consumer trend, high quality/fresh perspective

- Many have already adopted/worked closely with gig companies
  - Delivery business: Walmart x Uber/Lyft, GM x Lyft, Apple x Didi
  - Flexible staffing: IKEA x TaskRabbit, Samsung x Upwork

snag.work on-demand

Wonolo

coople

(allwork)

Heckman Sample Selection

Suppose that the pattern of missingness (I'll refer to this as censored hereafter) is related to the latent (unobserved) process

$$\mathbf{z}^* = \mathbf{w}\gamma + \mathbf{u}$$

From this process, the researcher can observe

$$\begin{aligned} z_i =& 1 \text{ if } z_i^* > 0 \\ =& 0 \text{ if } z_i^* \leq 0 \end{aligned}$$

or $z_i = 1$ (y_i not censored) when

$$u_i \geq -\mathbf{w}_i\gamma$$

The probability of y_i not censored is

$$\begin{aligned} Pr(u_i \geq -\mathbf{w}_i\gamma) =& 1 - \Phi(-\mathbf{w}_i\gamma) \\ =& \Phi(\mathbf{w}_i\gamma) \end{aligned}$$

if we are willing to assume that $\mathbf{u} \sim N(\mathbf{0}, \mathbf{I})$. Note for identification purposes in the Heckman Model we restrict $Var(u_i) = 1$. Also note that $1 - \Phi(-\mathbf{w}_i\gamma) = \Phi(\mathbf{w}_i\gamma)$ by symmetry of the standard normal distribution.

Heckman Sample Selection

Having constructed a model a model for censoring, we can construct "amounts" equation as follows. Denoting $\mathbf{y}$ as the not censored (observed) dependent variable, the censoring model defines what is in the estimation sample as

$$y_i = y_i^* = \mathbf{x}_i\beta + \epsilon_i \text{ observed, if } z_i = 1$$

Finally, the joint distribution of the errors in the selection (u_i) and amounts equation (ϵ) is distributed iid as

$$\begin{bmatrix} u_i \\ \epsilon_i \end{bmatrix} \sim Normal\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & \sigma_\epsilon^2 \end{bmatrix}\right)$$

To see how the selection and amounts model are related, consider

$$\begin{aligned} E(y_i|y_i \text{ observed}) =& E(y_i|z^* > 0) \\ =& E(y_i|u_i > -\mathbf{w}_i\gamma) \\ =& \mathbf{x}_i\beta + E(\epsilon_i|u_i > -\mathbf{w}_i\gamma) \\ =& \mathbf{x}_i\beta + \rho\sigma_\epsilon \frac{\phi(\mathbf{w}_i\gamma)}{\Phi(\mathbf{w}_i\gamma)} \end{aligned}$$

What is immediately apparent is that the conditional mean ($E(y_i|y_i \text{ observed})$) differs from the unconditional mean ($\mathbf{x}_i\beta$) only if $\rho \neq 0$ since all the other elements in the far right hand term (i.e., the variance of the error in the amounts equation, σ_ϵ, and the Inverse Mills Ratio, $\frac{\phi(\mathbf{w}_i\gamma)}{\Phi(\mathbf{w}_i\gamma)}$) in the preceding equation are strictly positive. So if the errors in the amounts and selection equations are uncorrelated ($\rho = 0$) we can safely apply ordinary least squares to uncover unbiased estimates for β and can ignore endogenous selection effects and the selection equation portion of the model.