The Impact of Behavioral and Economic Drivers on Gig Economy Workers

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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

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

Our Paper

1

How do gig economy workers make labor decisions?

Our Paper

1

How do gig economy workers make labor decisions?

$ Incentive

Behavioral Drivers

Labor Decisions

Work or not / How long to work

Our Paper

1

How do gig economy workers make labor decisions?

Observed for all registered drivers

$ Incentive

Behavioral Drivers

Labor Decisions

Work or not / How long to work

Today:

Ride-hailing

Data

Our Paper

1

How do gig economy workers make labor decisions?

Propose new types of instrument

$ Incentive

Behavioral Drivers

Modified two-stage Heckman selection model

Labor Decisions

Work or not / How long to work

Today:

Ride-hailing
Data

Endogeneity/Selection
Empirical Strategy

Our Paper

1

How do gig economy workers make labor decisions?

$ Incentive | Behavioral Drivers

↓

Within day
Across days

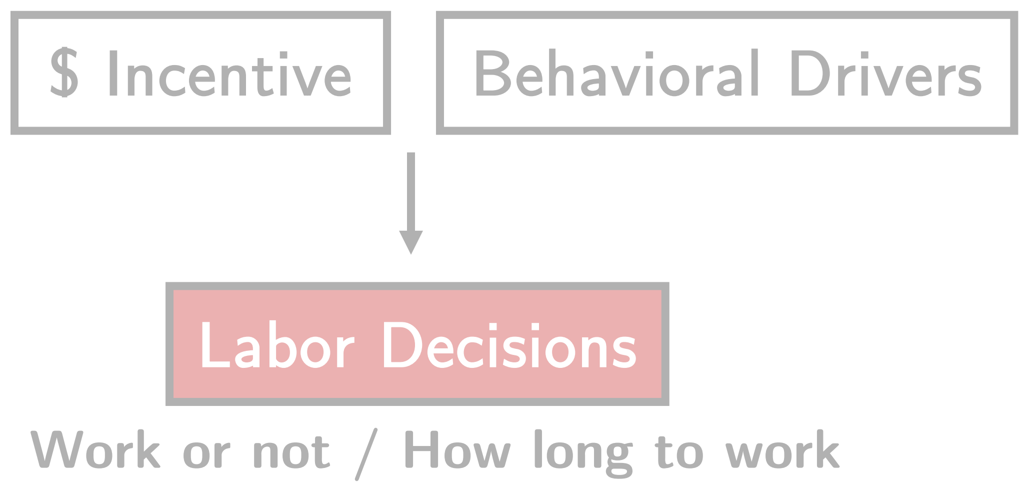
Labor Decisions

Work or not / How long to work

Today:

Ride-hailing	*Endogeneity/Selection*	*Direction* *Effect size*
Data	Empirical Strategy	Results

Our Paper



2

How can the platform influence workers' decisions?

Our Paper

Optimize targeted incentive

Counterfactual
simulation

$ Incentive

Behavioral Drivers

Labor Decisions

Work or not / How long to work

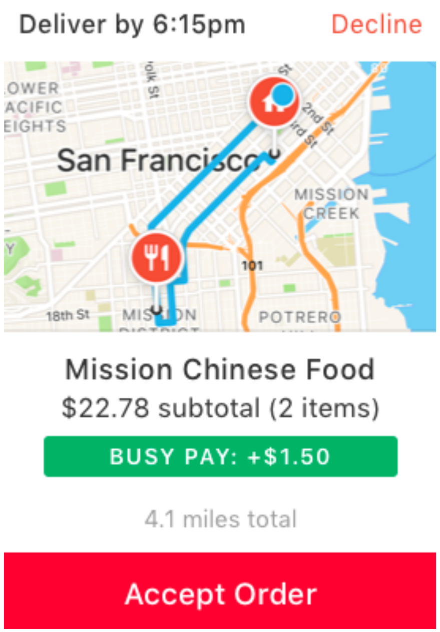
Today:

Ride-hailing	*Endogeneity/Selection*	*Direction* *Effect size*	
Data	Empirical Strategy	Results	Implications

What Has Been Done?

In Practice

Real-time "surge pricing"

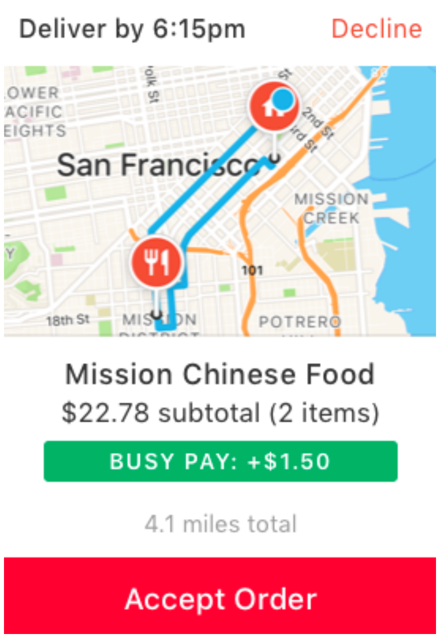


DOORDASH

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)

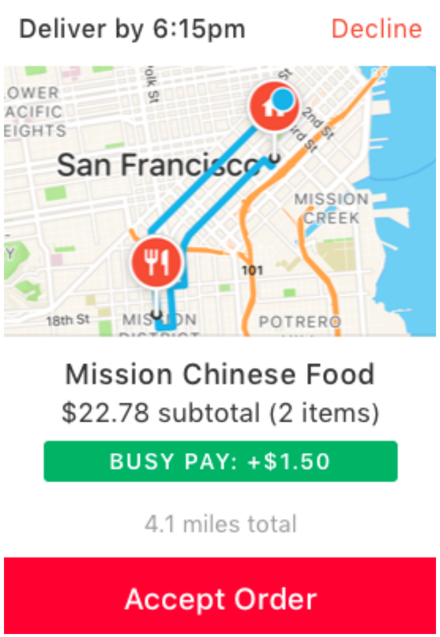
6:00 PM–7:00 PM
+30% (6:00pm - 6:30pm)
+40% (6:30pm - 7:00pm)

caviar

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

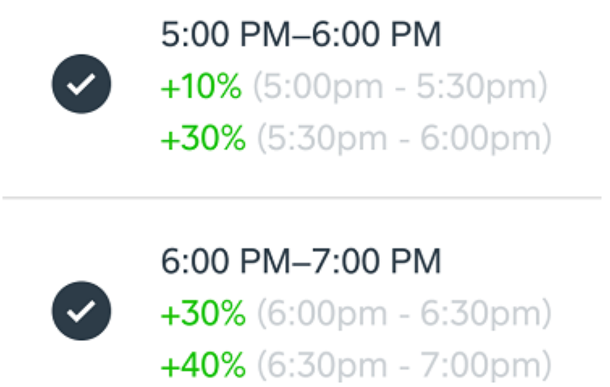
In Practice

Real-time "surge pricing"



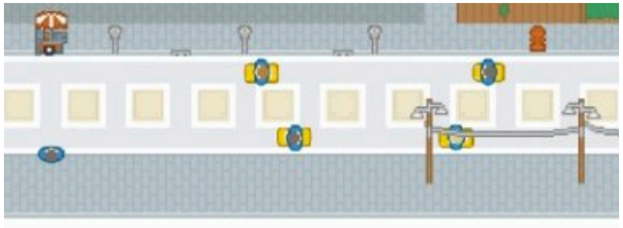
DOORDASH

Pre-announced bonus



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

Drivers of Work Decisions

We are interested in three effects

Hourly Wage

Income Target

Time Target

on two work decisions:

Work on 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 on not?	If so, how long?

Drivers of Work Decisions

We are interested in three effects

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

on two work decisions:

Work on not?

If so, how long?

Drivers of Work Decisions

We are interested in three effects

	"ISF"	"HSF"
Hourly Wage	Income So Far /Income Target	Hours So Far /Time Target
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 on not?

If so, how long?

Industry Partner

US Ride-Hailing Company

Industry Partner

US Ride-Hailing Company

Service

Pool passengers headed in similar direction
Corner to corner basis
"Dynamic bus"

Industry Partner

US Ride-Hailing Company

Service

Pool passengers headed
in similar direction
Corner to corner basis
"Dynamic bus"

Passengers

Regular commuters
Flat rate (no surge)

Industry Partner

US Ride-Hailing Company

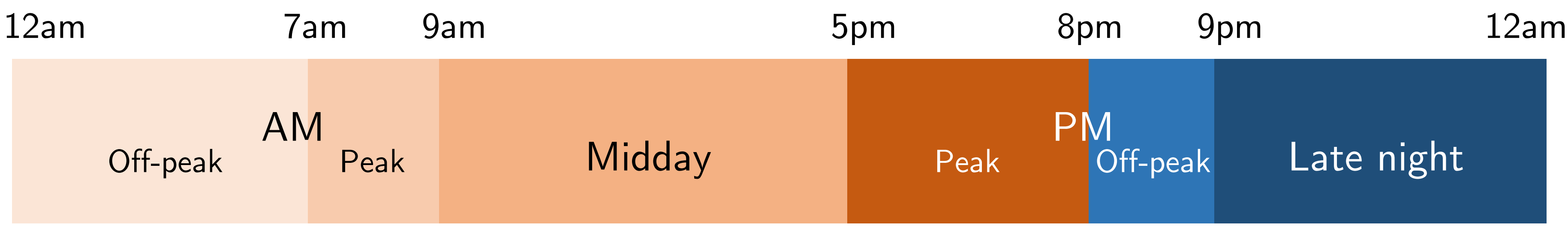
Service	Passengers	Pay
Pool passengers headed in similar direction Corner to corner basis "Dynamic bus"	Regular commuters Flat rate (no surge)	Drivers earn at a guaranteed hourly rate regardless of # pax

Data Ride-hailing drivers in NYC

Drivers earn at a guaranteed hourly $\underbrace{\boxed{\text{Base Rate}} + \boxed{\text{Promotions}}}_{\text{“Offer”}}$

Data Ride-hailing drivers in NYC

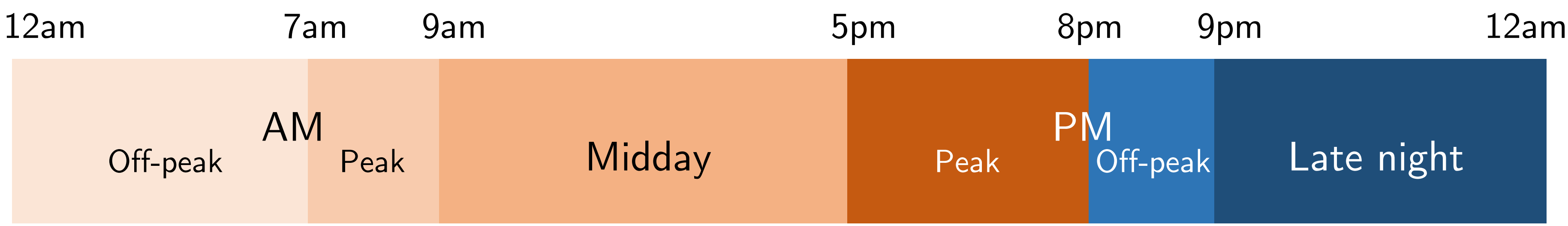
Drivers earn at a guaranteed hourly $\boxed{\text{Base Rate}} + \boxed{\text{Promotions}}$



Shift-level offer and driving activity *for all*

Data Ride-hailing drivers in NYC

Drivers earn at a guaranteed hourly Base Rate + Promotions



Shift-level offer and driving activity *for all*

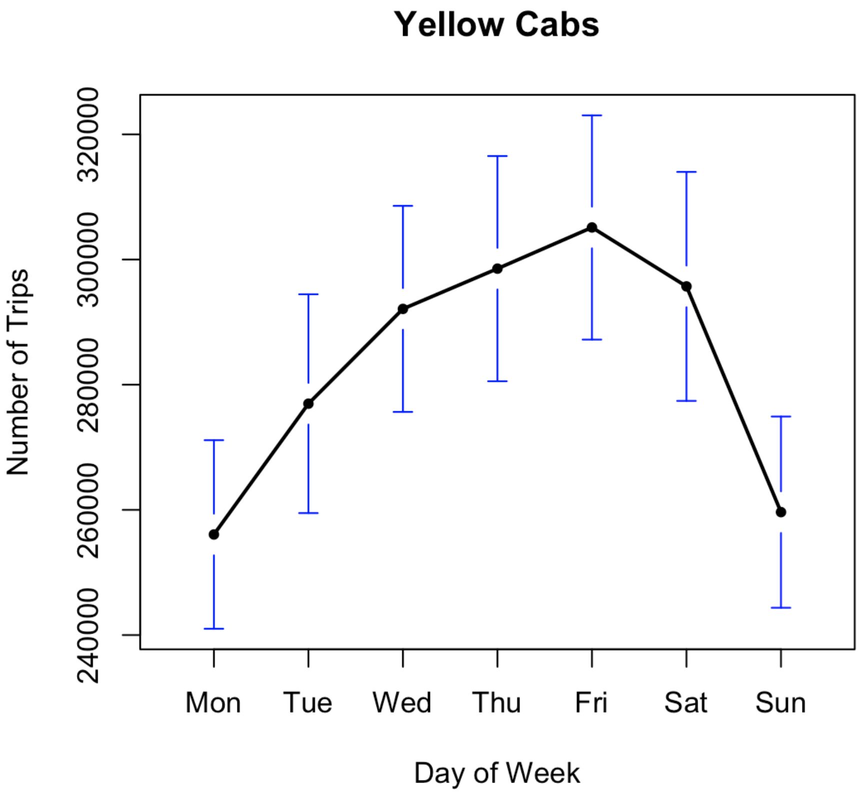
5.5M
Observations

358
Days
Oct 2016 – Sep 2017

7,826
Unique drivers
SUV/Sedan/Van

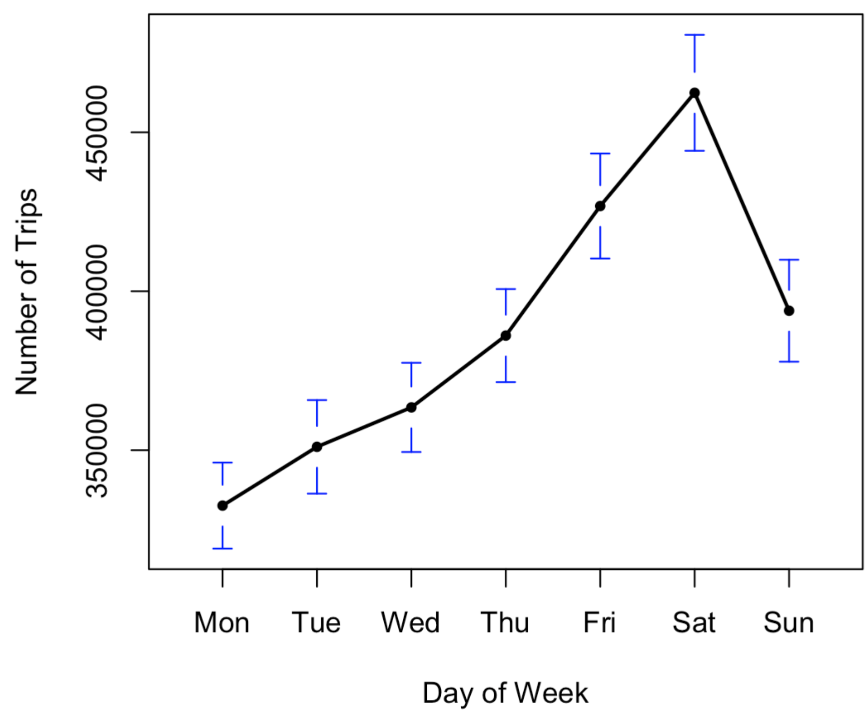
+ TLC Data

Trip records collected by Taxi & Limousine Commission



101M yellow cab trips

Uber lyft via JUNO

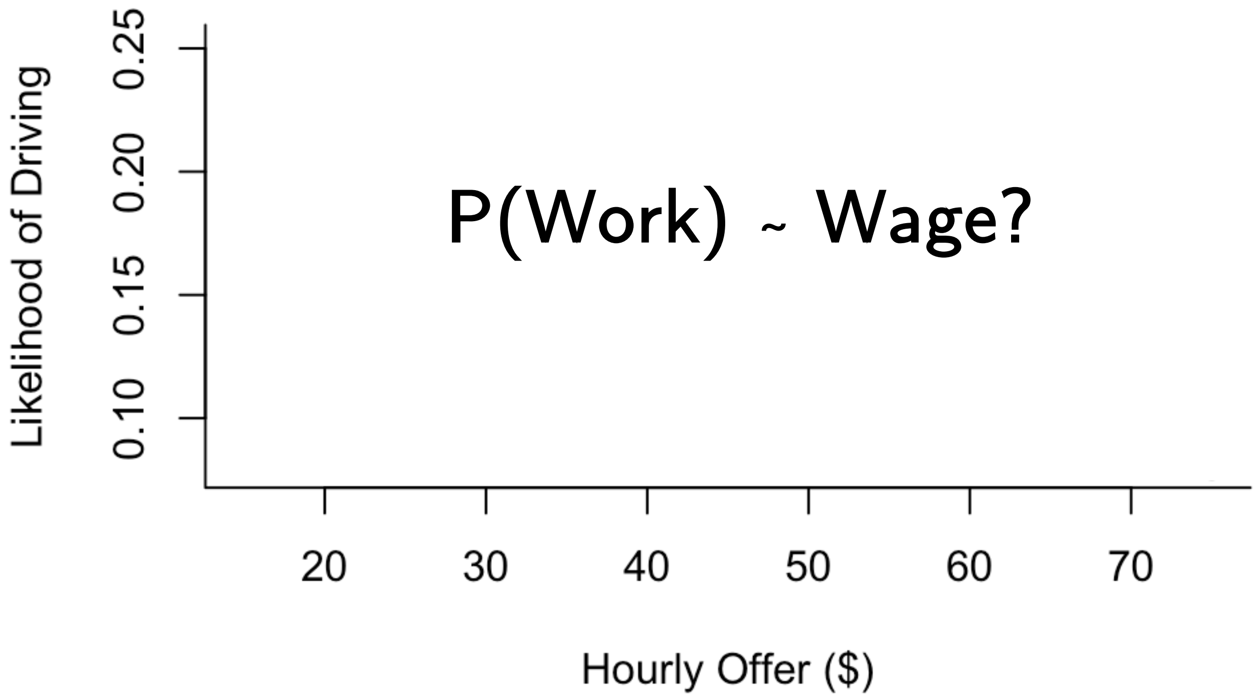


139M ride-hailing trips

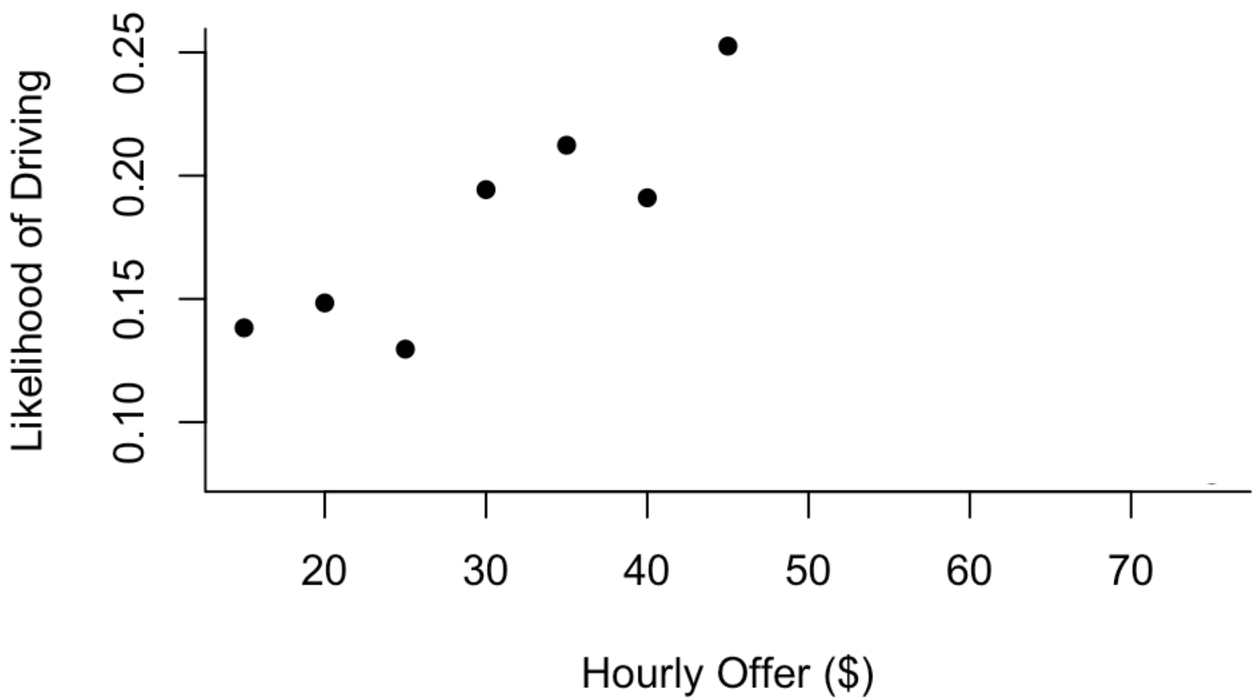
Empirical Strategy

Instrumental Variables + Selection Model

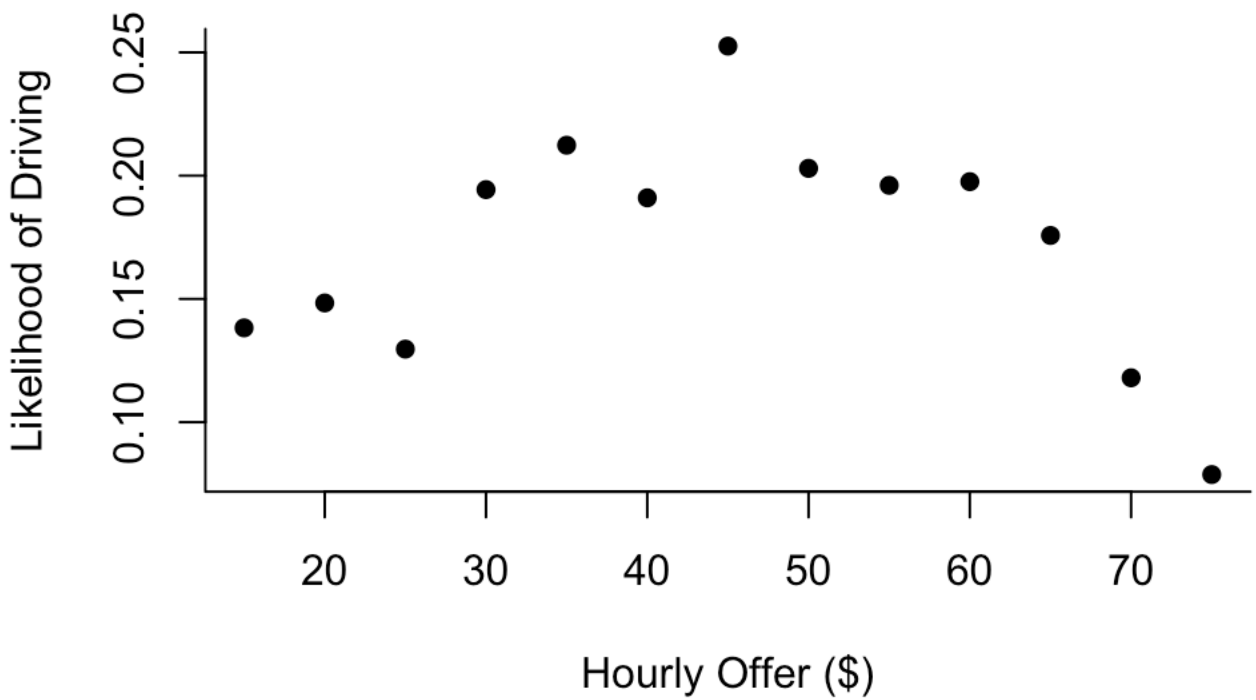
Empirical Strategy Challenges



Empirical Strategy Challenges



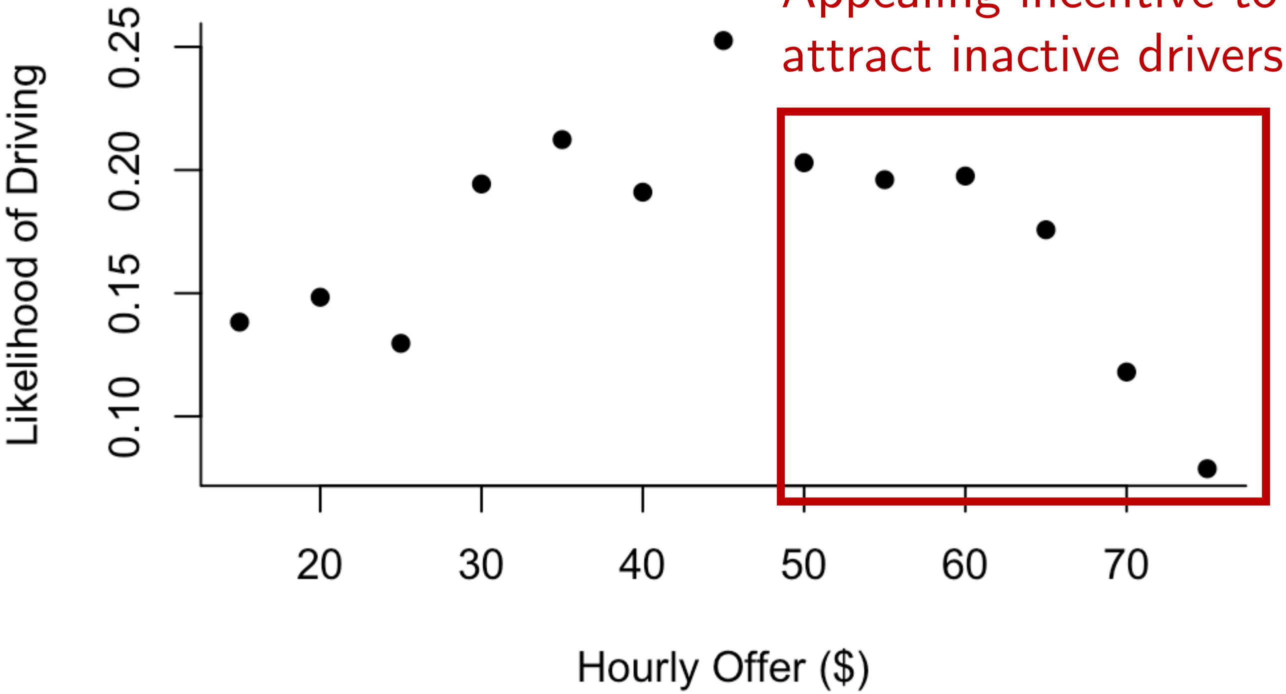
Empirical Strategy Challenges



Empirical Strategy Challenges

Higher wage, less likely to drive?

Appealing incentive to attract inactive drivers?

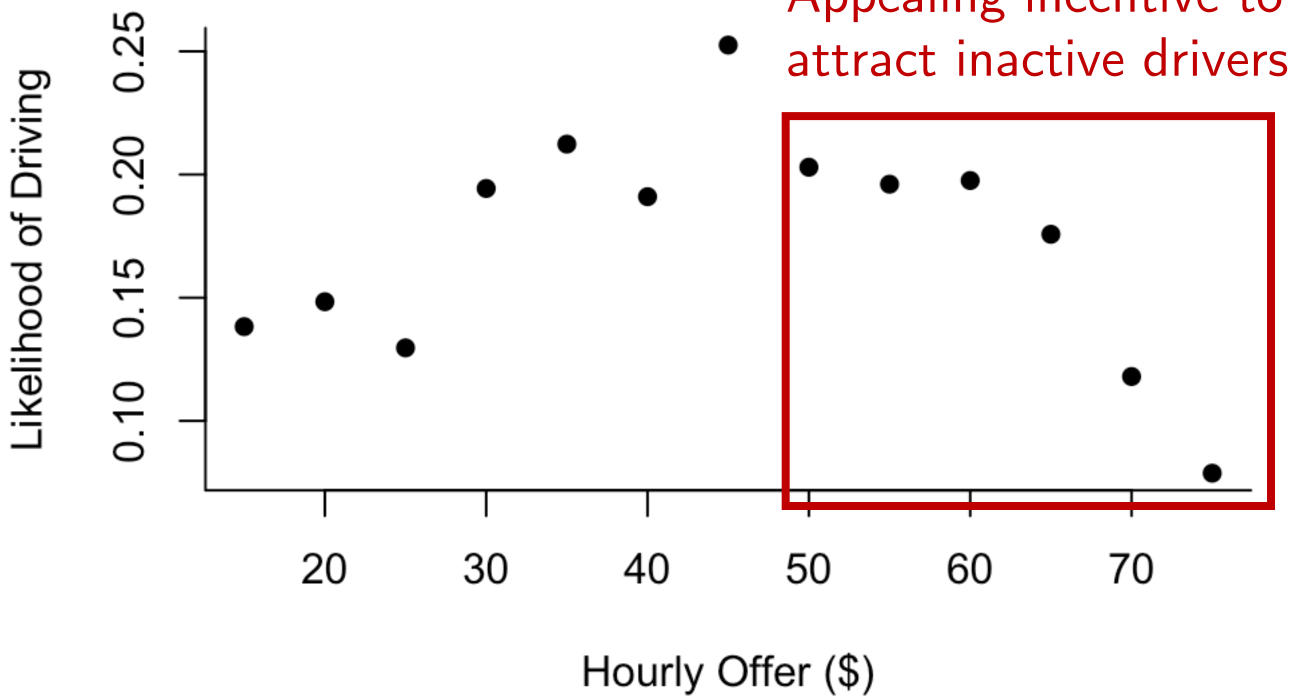


Empirical Strategy Challenges

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
Hourly offer	Average offers of "co-workers"

= currently available
+ made similar decisions
+ different vehicle type

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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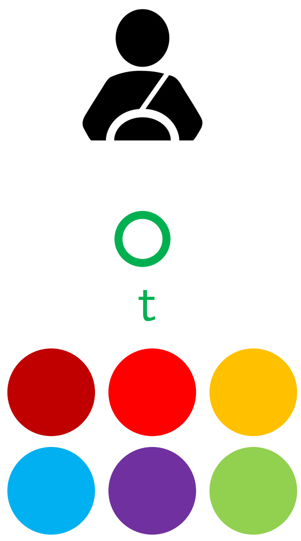


sedan

non-sedan

Empirical Strategy Challenges

Simultaneity

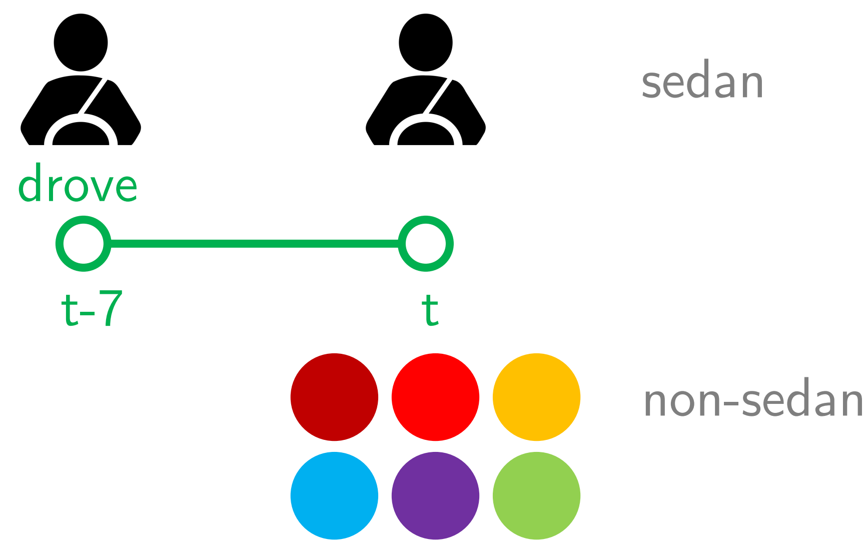
Solution: Instrumental Variables

Endogenous Variable

Hourly offer

Instrument

Average offers of “co-workers”



Empirical Strategy Challenges

Simultaneity

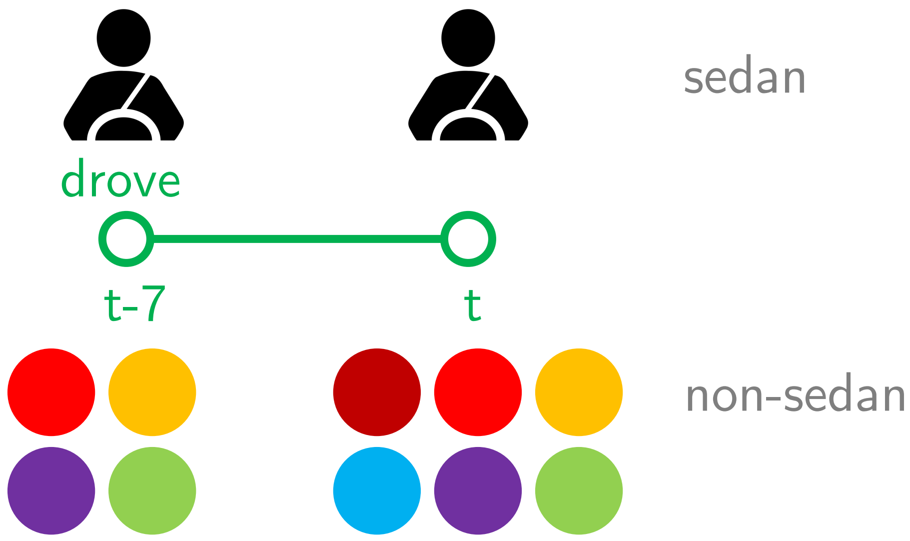
Solution: Instrumental Variables

Endogenous Variable

Hourly offer

Instrument

Average offers of "co-workers"



Empirical Strategy Challenges

Simultaneity

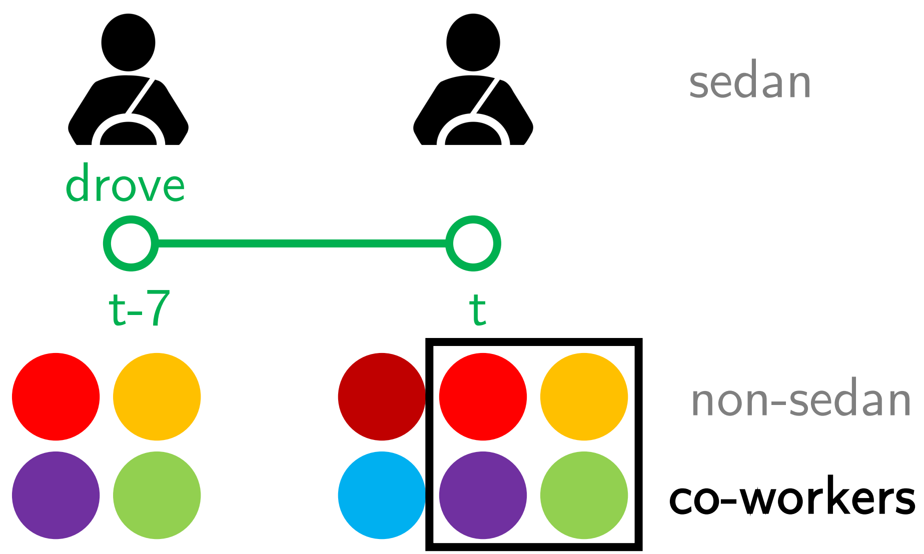
Solution: Instrumental Variables

Endogenous Variable

Hourly offer

Instrument

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"

= currently available
+ been similarly inactive
+ different vehicle type

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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Empirical Strategy Challenges

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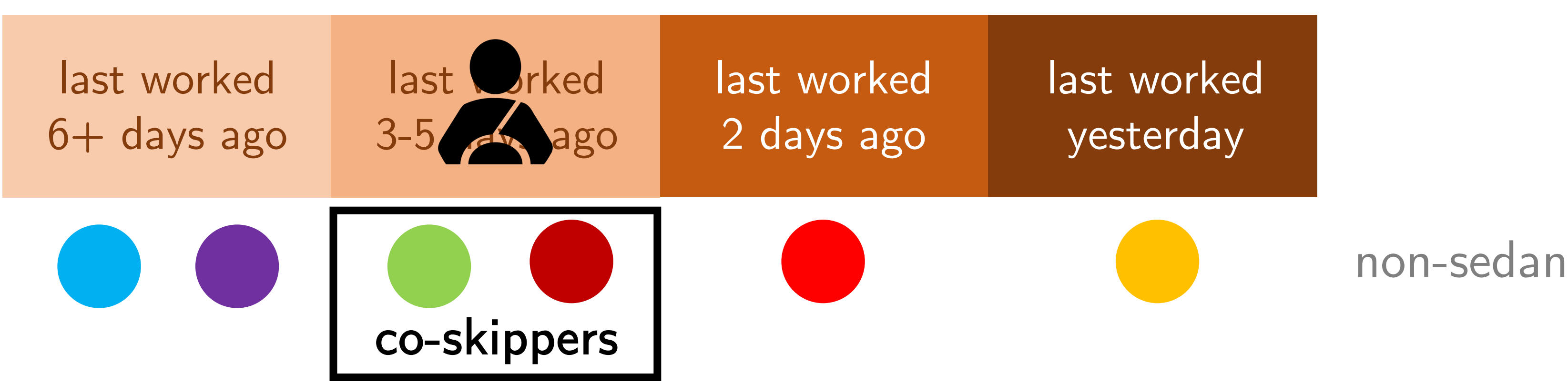
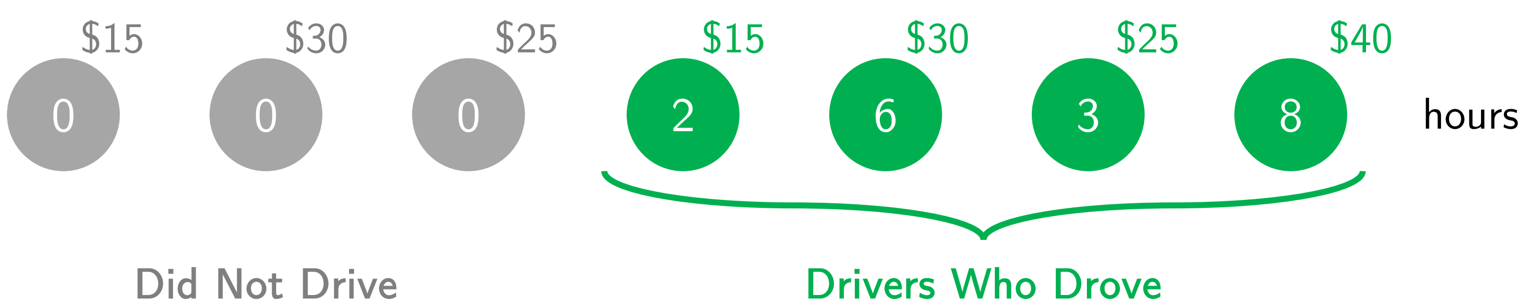


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Hours ~ Wage?



Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**

Hours ~ Wage?

$15	$30	$25	$15	$30	$25	$40	
0	0	0	2	6	3	8	hours

Did Not Drive

Drivers Who Drove

Empirical Strategy Challenges

Simultaneity

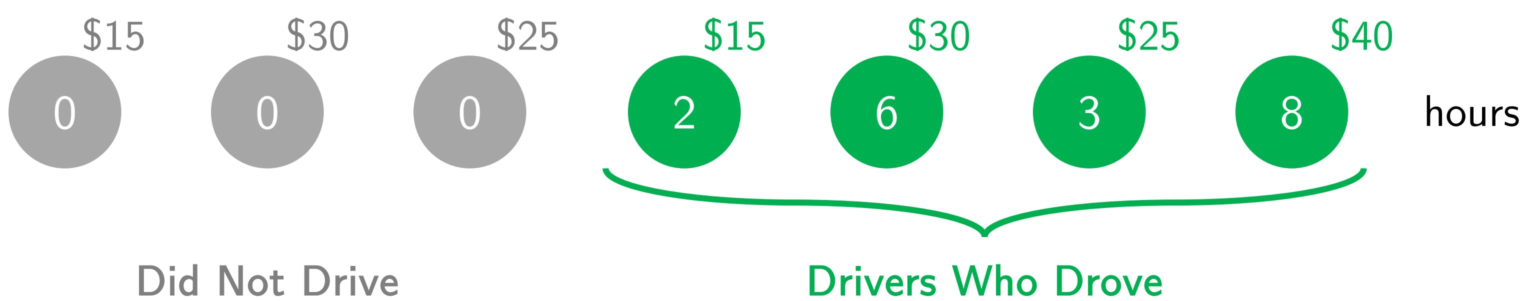
Solution: Instrumental Variables

Selection Bias

Solution: Modified 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***

*Bias corrected with panel jackknife (Hahn & Newey 2004)

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Income So Far

= cumulative income 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

Hours So Far
= cumulative active hours
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   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?

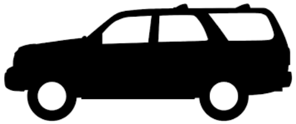
IV: Estimate **hourly earning** from IVs

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



"Offer"	"ISF"	"HSF"
$ Incentive	Income So Far	Hours So Far

Labor Decisions — 1 Work or not / 2 How long to work

Results

“Offer” — $ Incentive

“ISF” — Income So Far

“HSF” — Hours So Far

↓

Labor Decisions

1 **Work or not** / 2 **How long to work**

Within-Day Midday → Late Night (daily targets)

Across-Days Tuesday → Sunday (weekly targets)

Results

"Offer"	"ISF"	"HSF"
$ Incentive	Income So Far	Hours So Far

Labor Decisions

1 **Work or not** / 2 **How long to work**

Within-Day Midday → Late Night (daily targets)

Across-Days Tuesday → Sunday (weekly targets)

+	-
Positive	**Negative**

Results Within Day

1

Work or not?

SUV	Mean	IV-F	N
Midday	0.343	372.9	124,769
PM-Peak	0.277	345.1	131,910
PM-OPeak	0.182	320.6	130,651
Late Night	0.117	379.0	125,382

Results Within Day

1

Work or not?

SUV	Mean	IV-F	Offer	N
Midday	0.343	372.9	+	124,769
PM-Peak	0.277	345.1	-	131,910
PM-OPeak	0.182	320.6	+	130,651
Late Night	0.117	379.0	+	125,382

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

Results Within Day

1

Work or not?

SUV	Mean	IV-F	Offer	ISF	N
Midday	0.343	372.9	+	-	124,769
PM-Peak	0.277	345.1	-	-	131,910
PM-OPeak	0.182	320.6	+	-	130,651
Late Night	0.117	379.0	+	-	125,382

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

Income targeting has a **consistently negative** impact.

Results Within Day

1

Work or not?

SUV	Mean	IV-F	Offer	ISF	HSF	N
Midday	0.343	372.9	+	-	+	124,769
PM-Peak	0.277	345.1	-	-	+	131,910
PM-OPeak	0.182	320.6	+	-	+	130,651
Late Night	0.117	379.0	+	-	+	125,382

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					2		
			Work or not?					# Hours		
SUV	Mean	IV-F	Offer	ISF	HSF	N	Mean	IV-F		N
Midday	0.343	372.9	+	-	+	124,769	4.987	180.2		45,329
PM-Peak	0.277	345.1	-	-	+	131,910	2.421	58.5		39,592
PM-OPeak	0.182	320.6	+	-	+	130,651	0.731	50.5		26,699
Late Night	0.117	379.0	+	-	+	125,382	1.996	39.91		17,137

Results Within Day

	1						2						
	Work or not?						# Hours						
SUV	Mean	IV-F	Offer	ISF	HSF	N	Mean	IV-F	Earn	ISF	HSF	R^2	N
Midday	0.343	372.9	+	-	+	124,769	4.987	180.2	+	-	+	0.552	45,329
PM-Peak	0.277	345.1	-	-	+	131,910	2.421	58.5	+	-	+	0.244	39,592
PM-OPeak	0.182	320.6	+	-	+	130,651	0.731	50.5	+	-	+	0.281	26,699
Late Night	0.117	379.0	+	-	+	125,382	1.996	39.91	+	-	+	0.296	17,137

The three effects are consistent in both stages

Results Within Day/Effect Size

1

% Change in P(Work)

+$10 Offer	+$10 ISF	+1h HSF

2

Change in Minutes Worked

+$10 Earn	+$10 ISF	+1h HSF

Results Within Day/Effect Size

1

% Change in P(Work)

SUV	+$10 Offer	+$10 ISF	+1h HSF
Midday	**0.82**	**-5.73**	**57.21**
PM-Peak	**-4.39**	**-0.57**	**15.27**
PM-OPeak	**0.27**	**-0.36**	**6.43**
Late Night	**0.34**	**-0.22**	**3.32**

2

Change in Minutes Worked

SUV	+$10 Earn	+$10 ISF	+1h HSF
Midday	0.51	**-4.87**	**109.53**
PM-Peak	**13.64**	**-0.24**	**18.96**
PM-OPeak	**1.72**	**-0.08**	**1.18**
Late Night	**14.87**	-0.11	**1.35**

Results Within Day/Effect Size

1 — % Change in P(Work)

SUV	+$10 Offer	+$10 ISF	+1h HSF
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2 — Change in Minutes Worked

SUV	+$10 Earn	+$10 ISF	+1h HSF
Midday	0.51	**-4.87**	**109.53**
PM-Peak	**13.64**	**-0.24**	**18.96**
PM-OPeak	**1.72**	**-0.08**	**1.18**
Late Night	**14.87**	-0.11	**1.35**

For an average SUV driver,

+$10 hourly wage: P(work) increases by **0.5%** / works **10m** longer
+$10 ISF: P(work) drops **2%** / works **1.3m** shorter
+1 HSF: P(work) increases by **21%** / works **33m** longer

Results Across Days

Results Across Days

1. Work or not?

SUV	Mean	IV-F	N
Tuesday	0.409	43.6	28,883
Wednesday	0.418	55.9	21,965
Thursday	0.426	73.4	29,233
Friday	0.412	74.0	20,294
Saturday	0.203	98.1	15,788
Sunday	0.162	82.2	13,025

Results Across Days

1 Work or not?

SUV	Mean	IV-F	Offer	ISF	HSF	N
Tuesday	0.409	43.6	+	+	+	28,883
Wednesday	0.418	55.9	+	+	+	21,965
Thursday	0.426	73.4	+	+	+	29,233
Friday	0.412	74.0	+	+	+	20,294
Saturday	0.203	98.1	-	-	+	15,788
Sunday	0.162	82.2	-	-	+	13,025

<u>Inertia</u> has consistent positive effects.

<u>Financial incentive</u> and <u>cumulative income</u> switch from positive to negative later on.
--> Positive outlook early on in the week

Results Across Days

1 Work or not?

SUV	Mean	IV-F	Offer	ISF	HSF	N
Tuesday	0.409	43.6	+	+	+	28,883
Wednesday	0.418	55.9	+	+	+	21,965
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Friday	0.412	74.0	+	+	+	20,294
Saturday	0.203	98.1	-	-	+	15,788
Sunday	0.162	82.2	-	-	+	13,025

2 # Hours

	IV-F	Earn	ISF	HSF	R^2	N
Tuesday	18.3	-	-	+	0.422	9,482
Wednesday	26.2	-	-	+	0.422	10,120
Thursday	34.6	-	-	+	0.412	9,894
Friday	33.7	+	-	+	0.436	9,283
Saturday	19.1	-	+	-	0.398	4,372
Sunday	15.1	+	+	-	0.390	3,240

Hours not decided at the day level

Results Summary

As day proceeds...

Neoclassical
Financial Incentive — encourages working

Results Summary

As day proceeds...

Neoclassical Financial Incentive	encourages working
Behavioral Income Target	discourages working

Results Summary

	As day proceeds...
Neoclassical Financial Incentive	encourages working
Behavioral Income Target	discourages working
New Inertia	encourages working

Results Summary

	As day proceeds…	As week proceeds…
Neoclassical Financial Incentive	encourages working	discourages later on
Behavioral Income Target	discourages working	discourages later on
New Inertia	encourages working	encourages working

Results Summary

	As day proceeds…	As week proceeds…
Neoclassical Financial Incentive	encourages working	discourages later on
Behavioral Income Target	discourages working	discourages later on
New Inertia	encourages working	encourages working

Platform Loyalty

Robustness Tests

- Isolating ISF and HSF effect
  - Positive HSF (inertia) effect dominates ISF (targeting) effect.
- Nonlinearity in ISF and HSF
- Instrumenting for ISF and HSF
- Controlling on types of 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

✓ Insights remain qualitatively consistent.

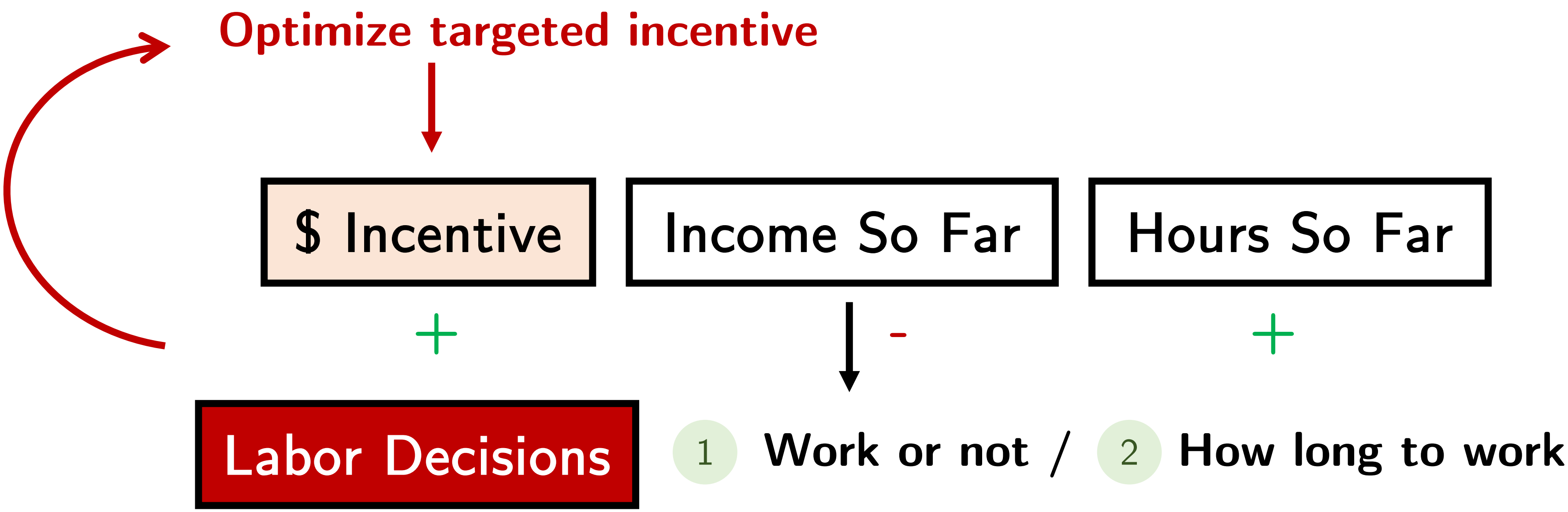
$ Incentive | Income So Far | Hours So Far

\+ | - | +

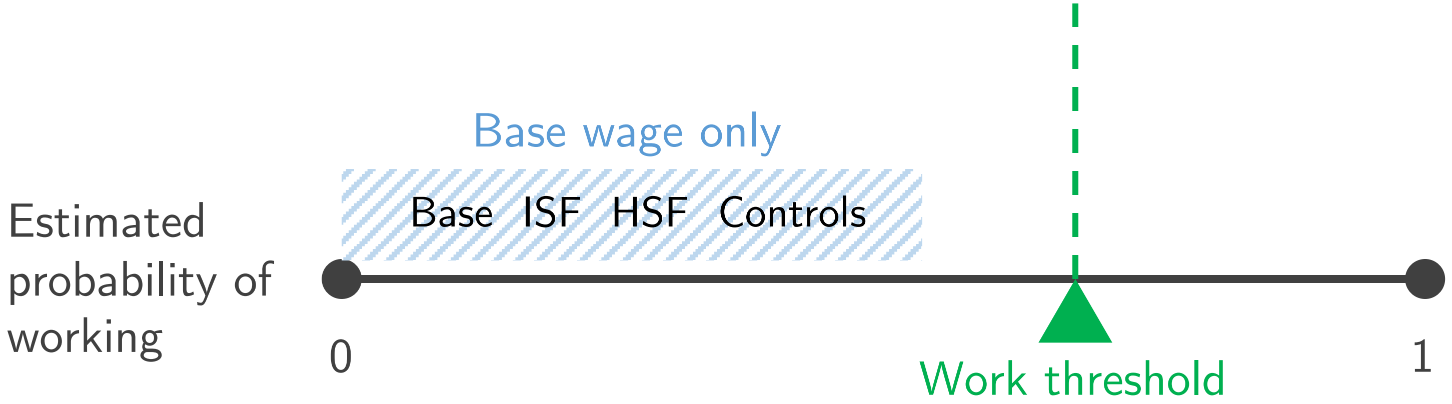
Labor Decisions

1 Work or not / 2 How long to work

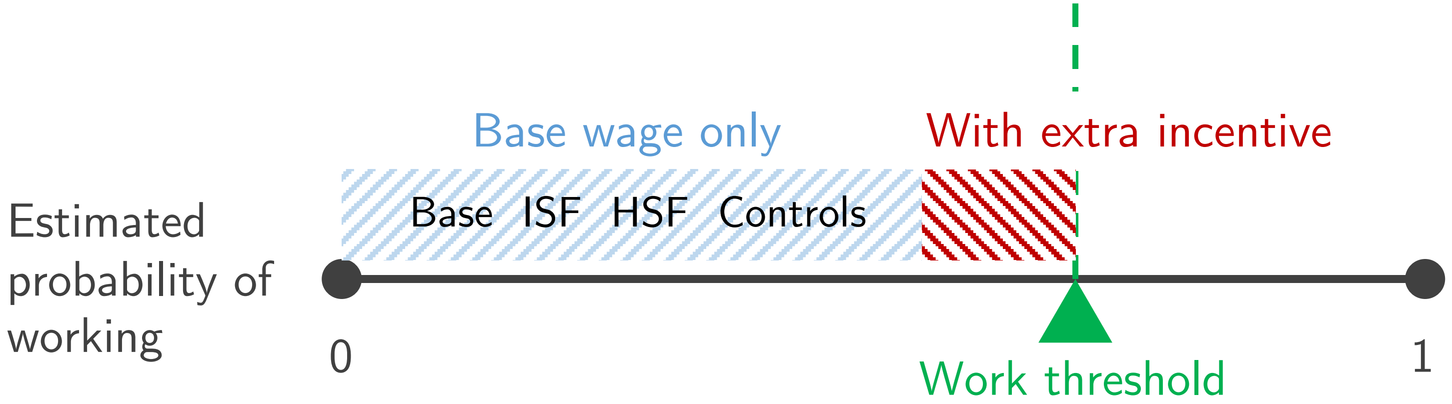
Implications



Optimal Targeted Incentive

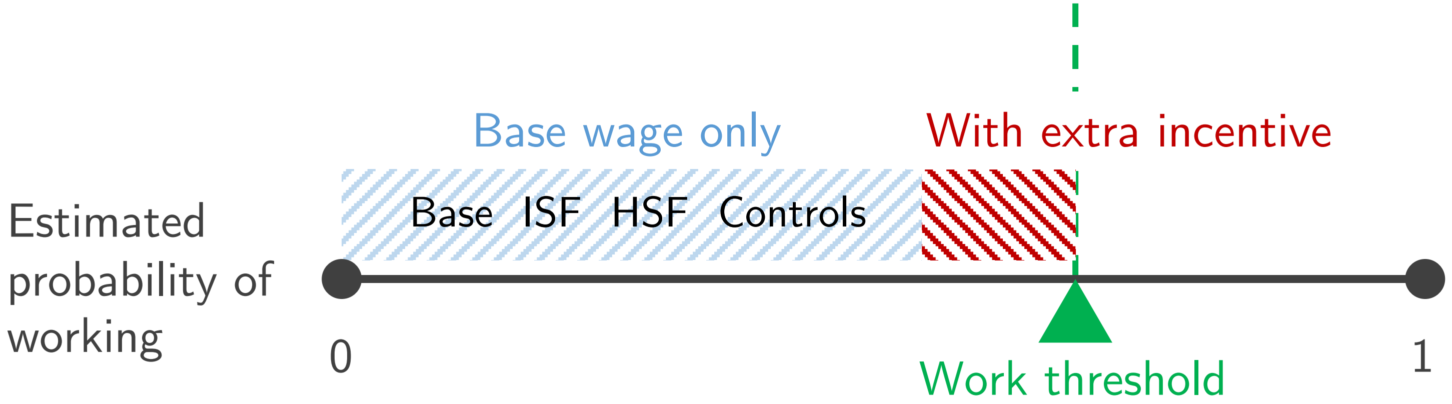


Optimal Targeted Incentive



Optimal Targeted Incentive

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



Reallocating Incentives

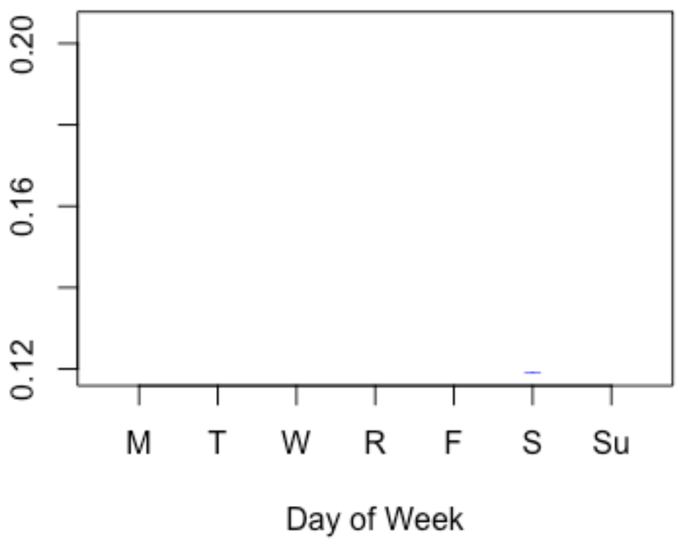
Compared to current practice from Jan to Sep 2017 out-of-sample
(Using data from Oct 2016 to right before the focal date as training)

Reallocating Incentives

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

Given the same budget

Extra drivers



Reallocating Incentives

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

Given the same budget

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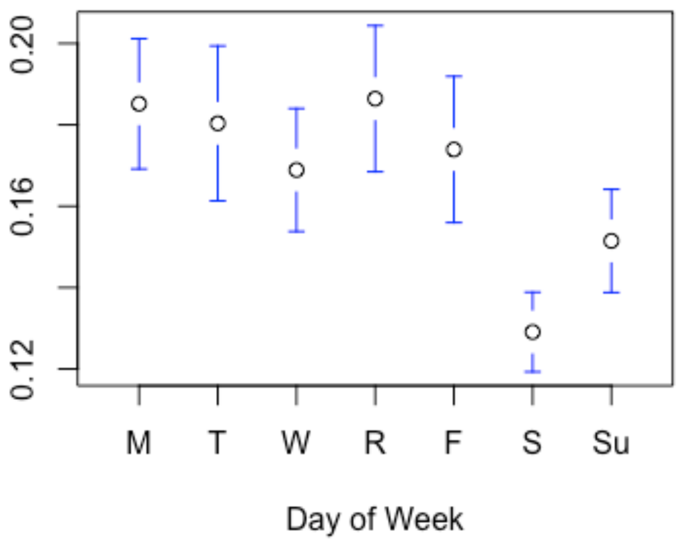

Can recruit **17% more drivers**

Average promo: 1.61x

Reallocating Incentives

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

Given the same budget

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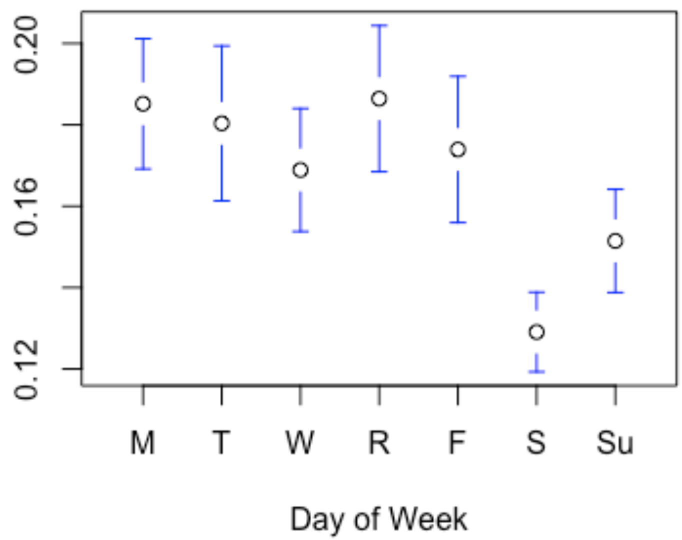
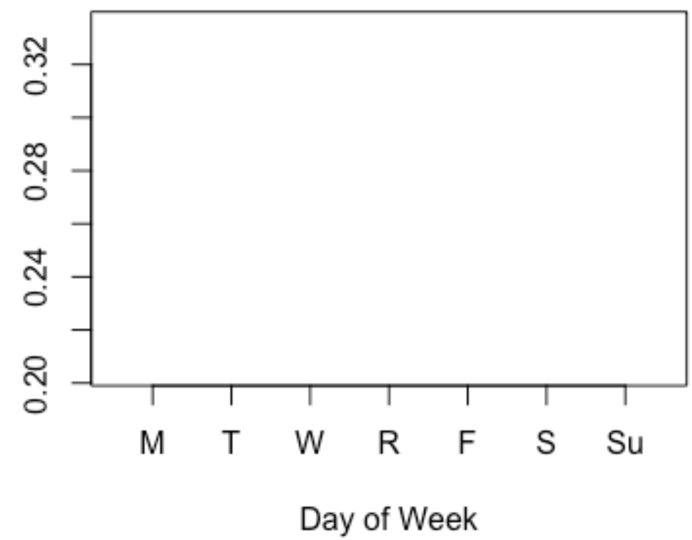


Can recruit **17% more drivers**

Average promo: 1.61x

Given the same capacity

Cost saved

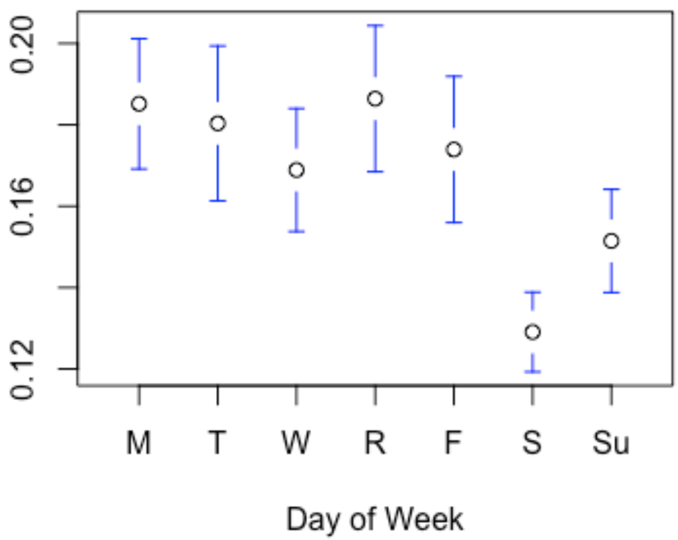


Reallocating Incentives

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

Given the same budget

Extra drivers



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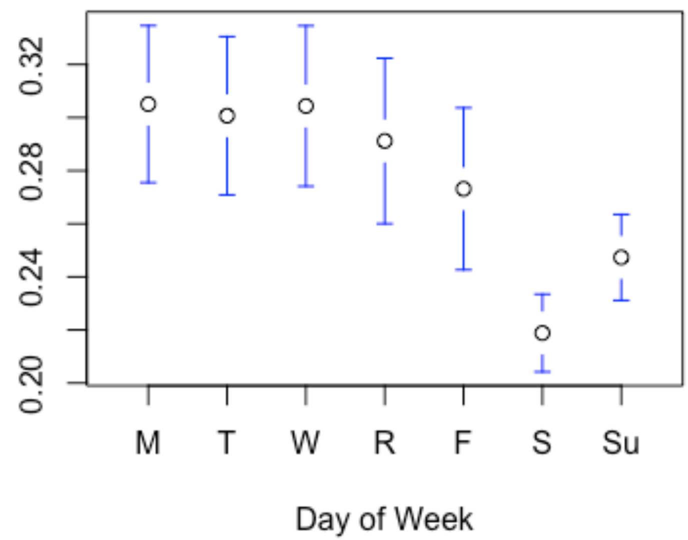
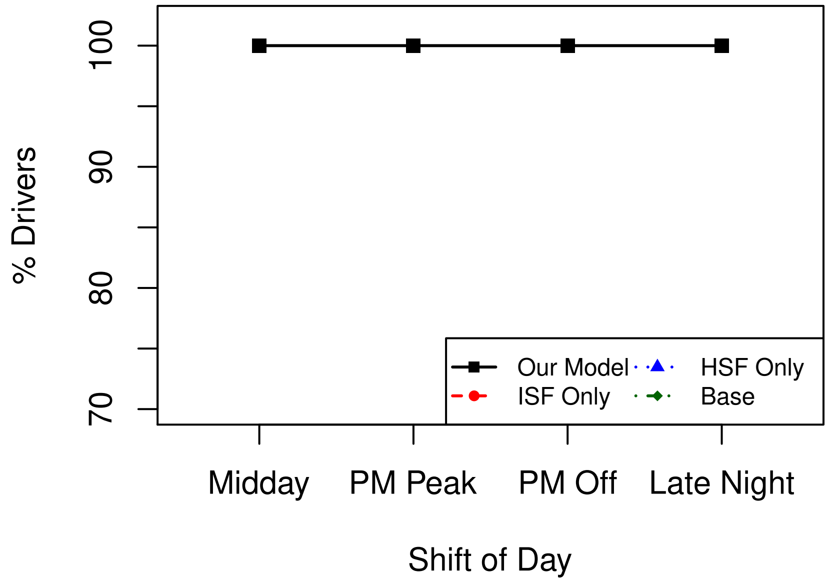
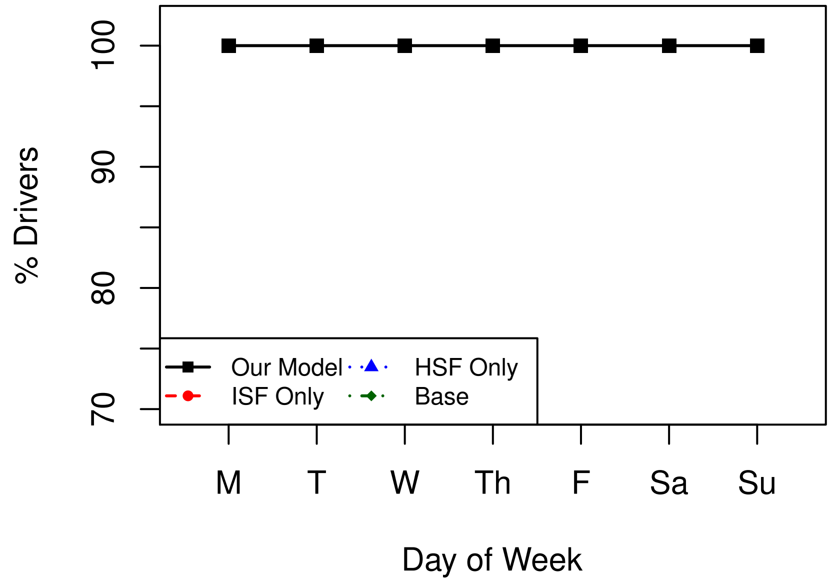


Costs 28% less to maintain capacity

Ignoring Behavioral Factors

Assuming our model is correct, how many workers the firm would fail to attract if it did not incorporate income targeting and inertia?





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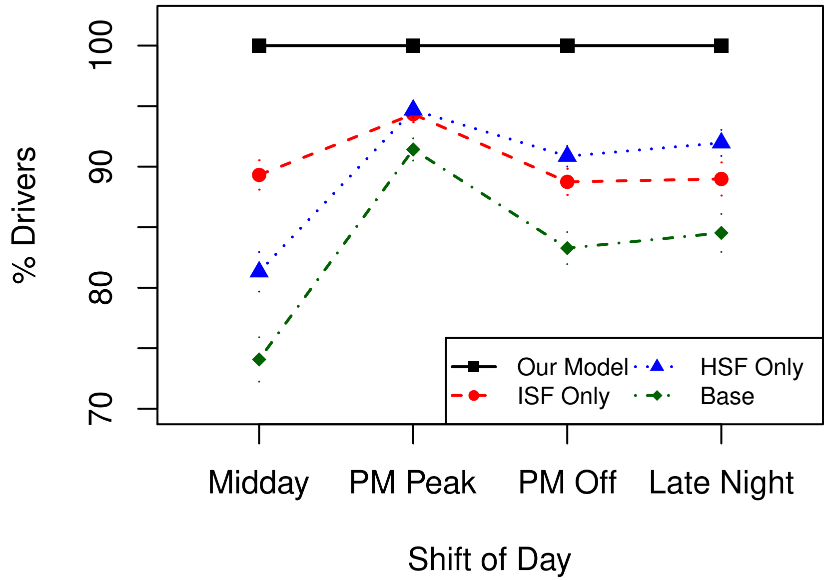
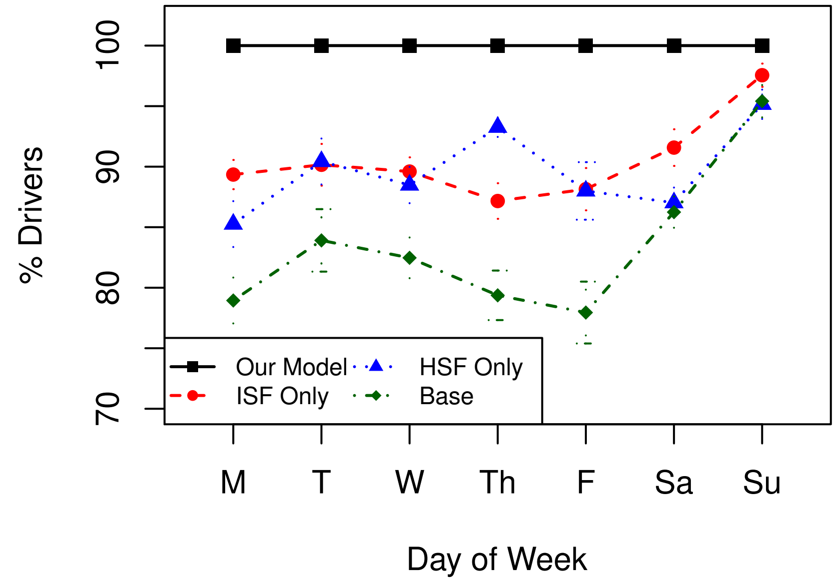




Average loss in capacity:

Ignoring: Income targeting 10.32% / Inertia 9.63% / Both 16.70%

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 proceeds...

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

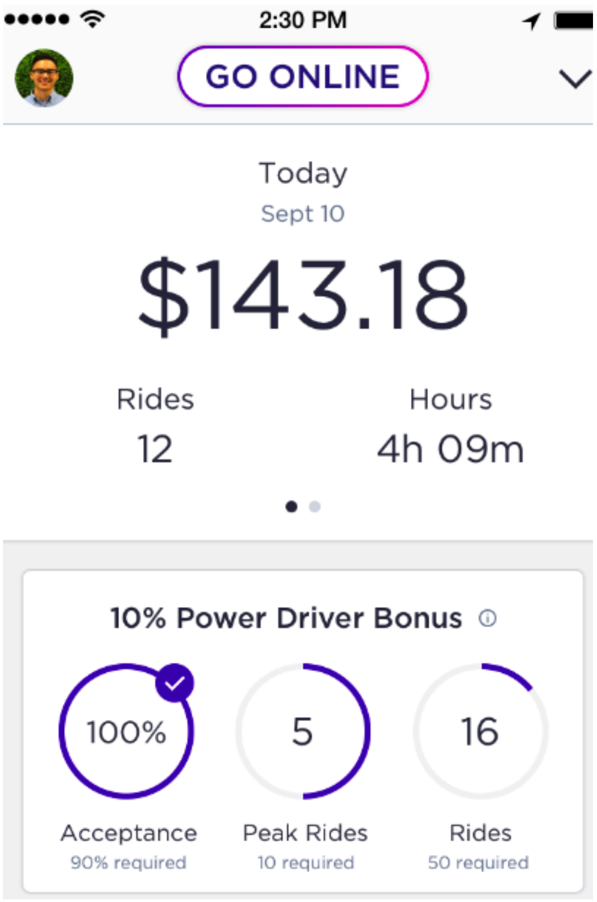
Implications

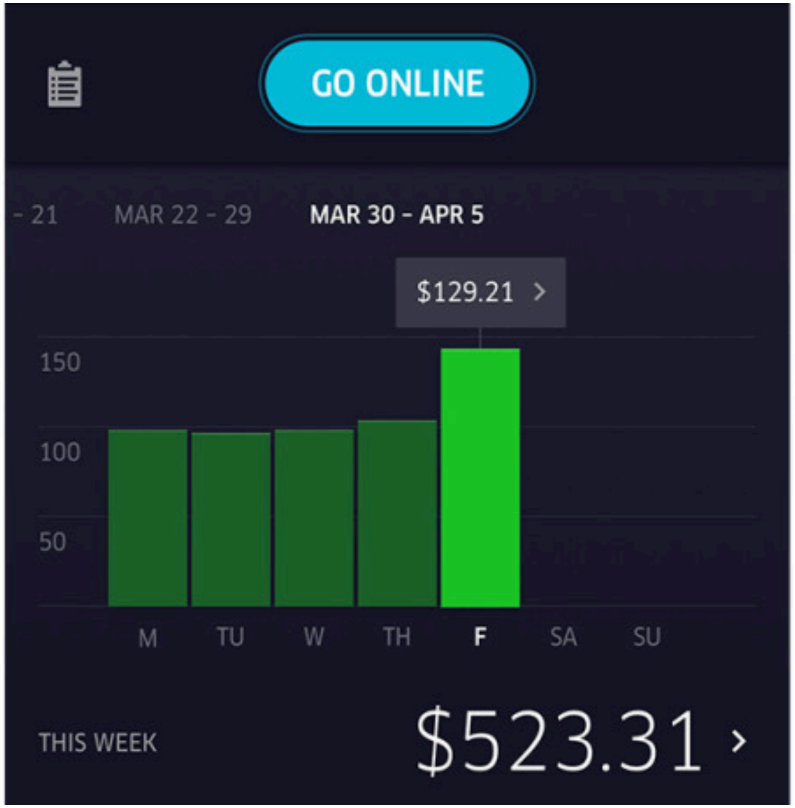
- Compared to current practice, our approach can improve service capacity without incurring extra cost or maintain the same capacity at a lower cost

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

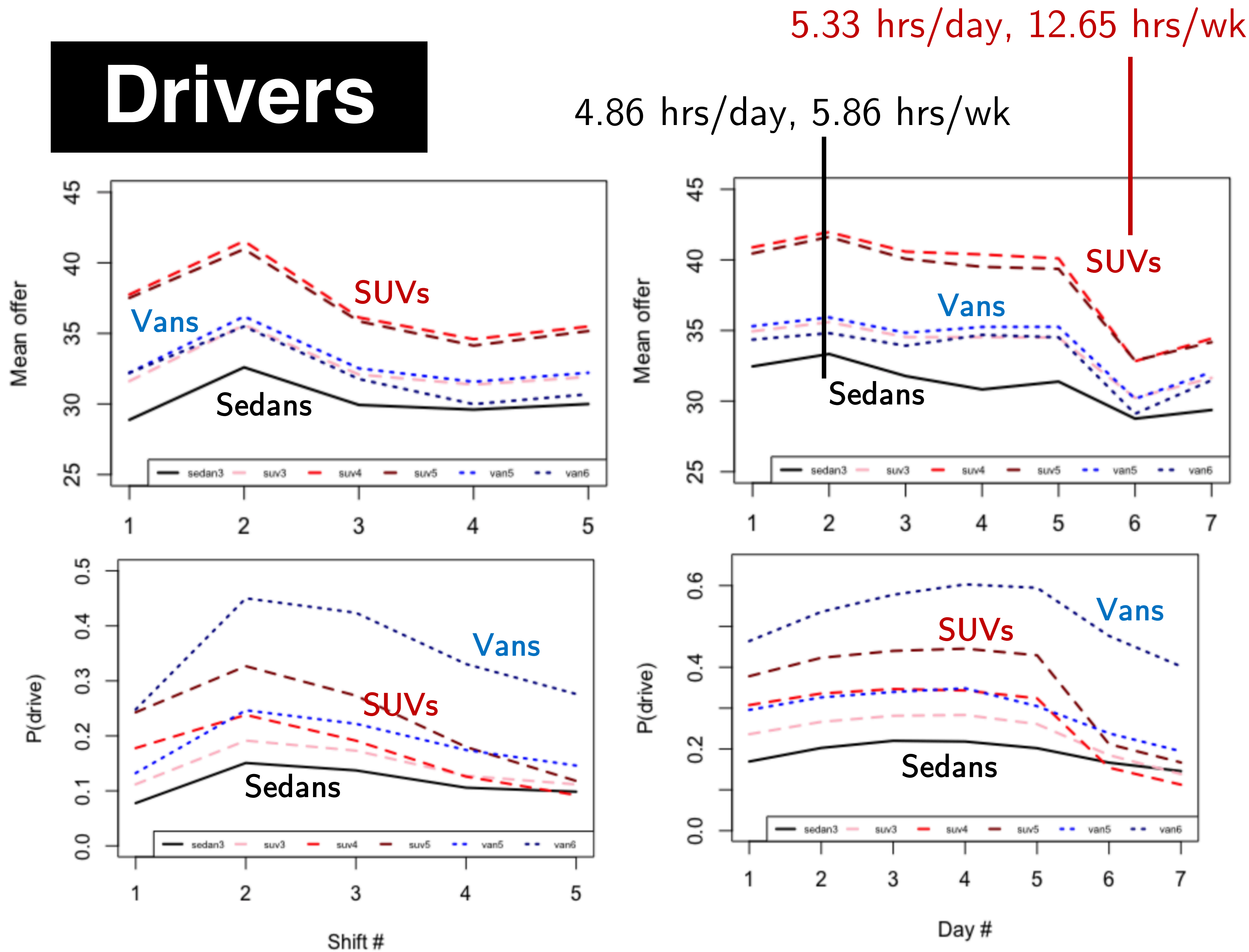
Appendix

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.

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

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

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

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Empirical Strategy Challenges

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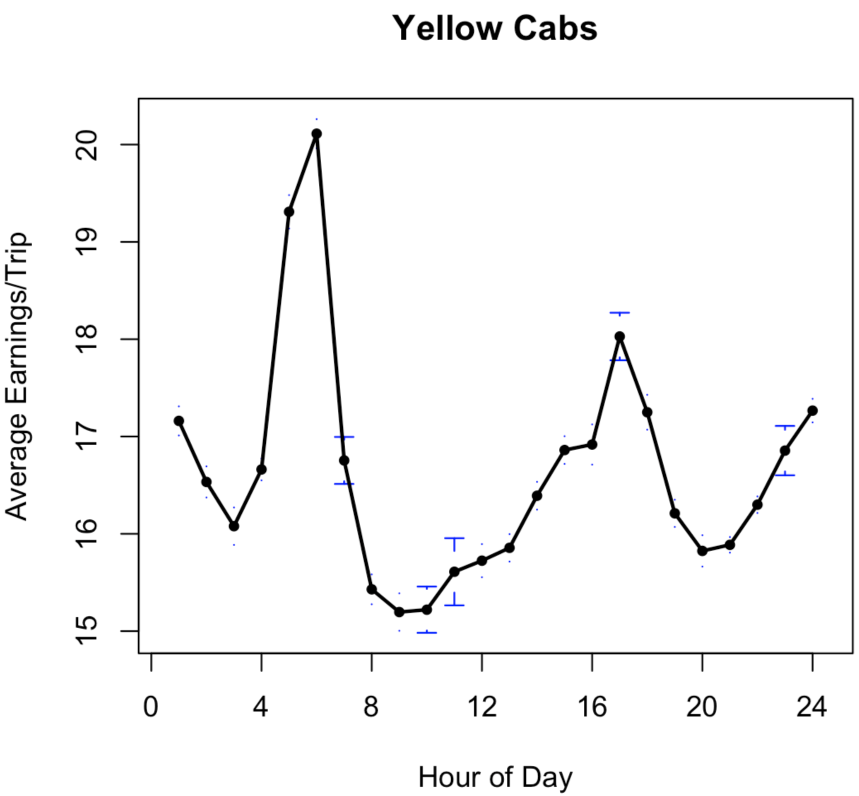
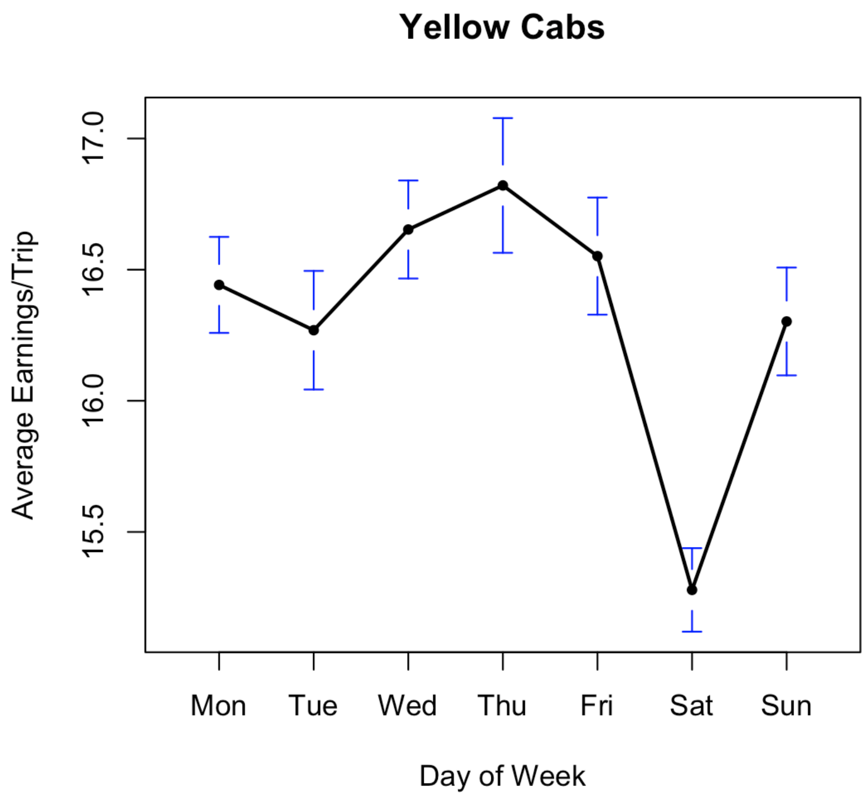
TLC Data

Fares/earnings for all yellow cab trips





101M yellow cab trips