

The Impact of Behavioral and Economic Drivers on Gig Economy Workers

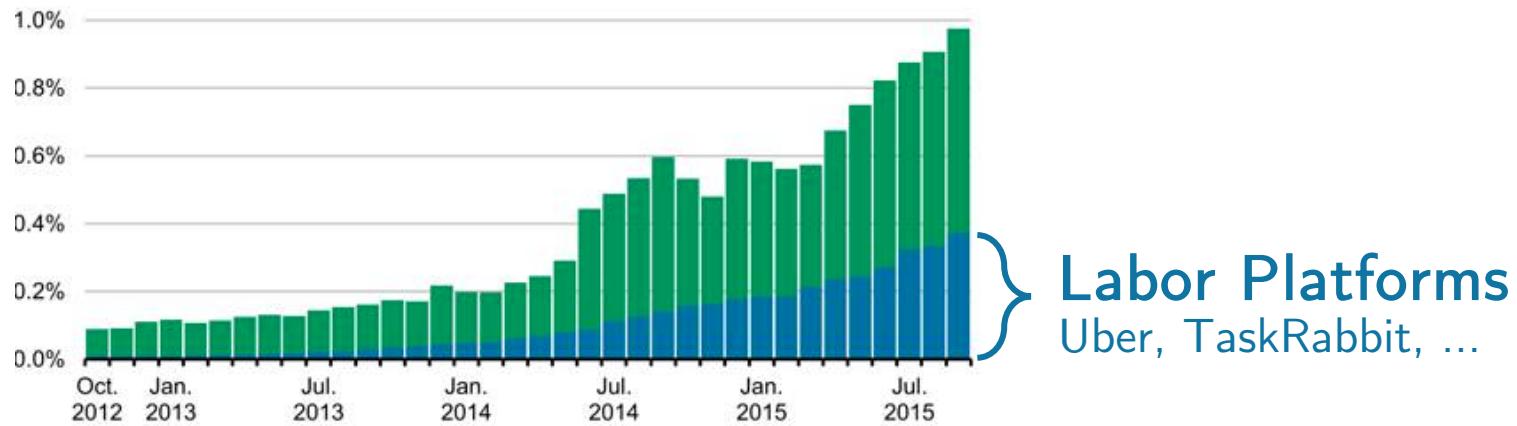
POMS 2019



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Gad Allon (Wharton), Maxime Cohen (NYU)

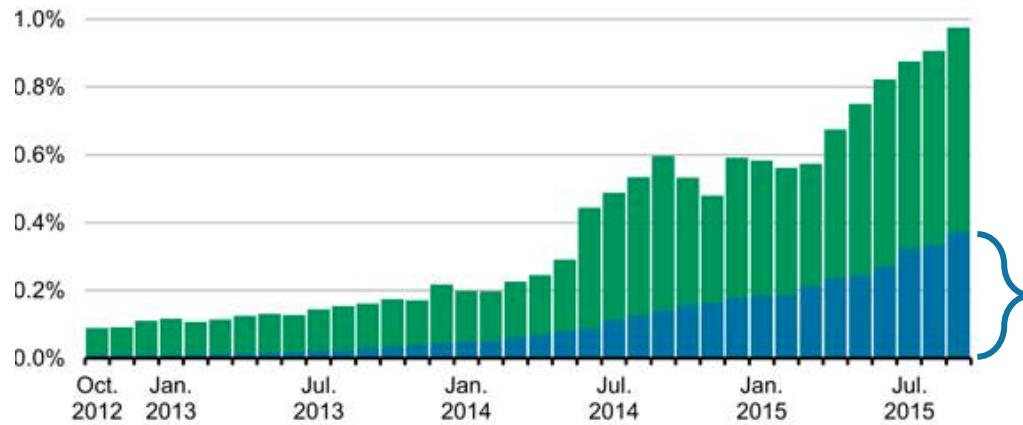
Gig Economy

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



Gig Economy

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

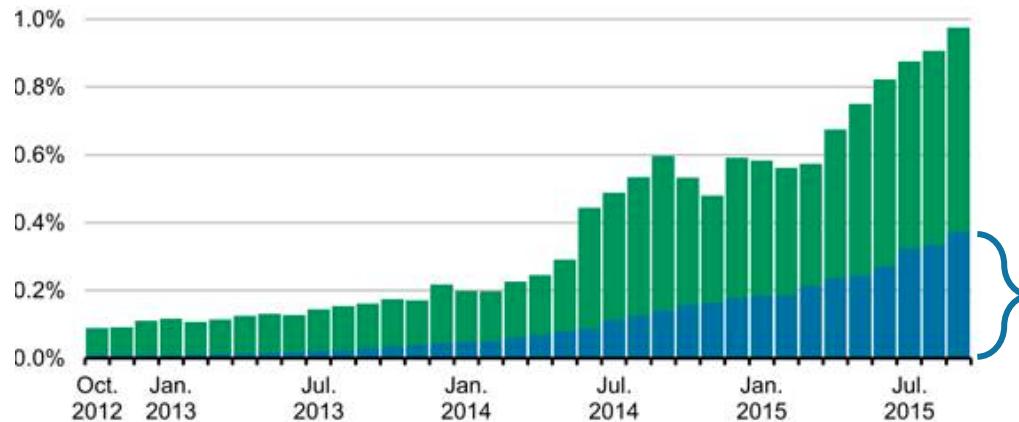


2015

44M people
in the US took on gig work (34%)

Gig Economy

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



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

Who are Gig Workers?

70% by choice

44% primary income

~50% millennials

Who are Gig Workers?

70% by choice



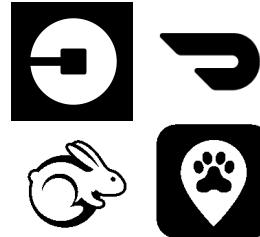
when to work?

44% primary income



how long?

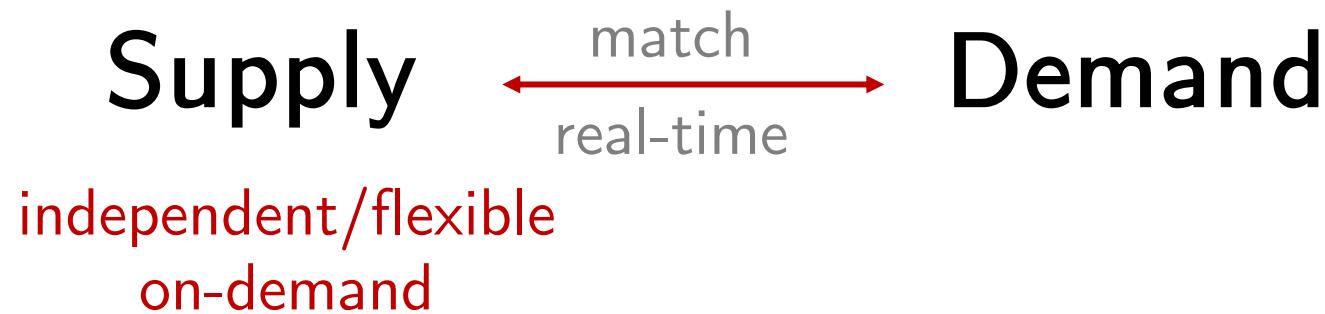
~50% millennials



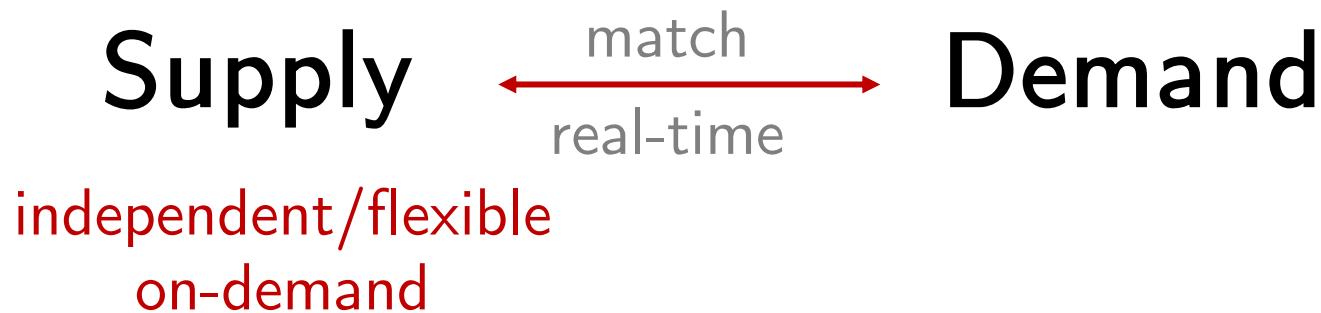
which platforms?

Workers decide work schedules

Gig Company



Gig Company



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

Experiment

Outline

- **What has been done**

- Practice / labor economics

- **Data and empirical strategy**

- Dealing with endogeneity and selection bias

- **Results**

- Impact of incentive and behavioral elements on labor decisions

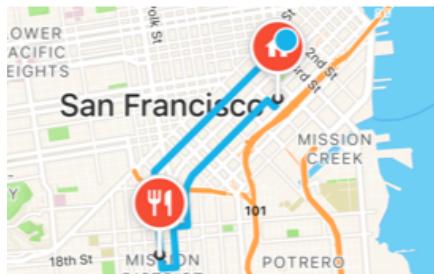
- **Implications**

- Simulation of optimal incentive re-allocation

In Practice

Real-time “surge pricing”

Deliver by 6:15pm Decline



Mission Chinese Food
\$22.78 subtotal (2 items)

BUSY PAY: +\$1.50

4.1 miles total

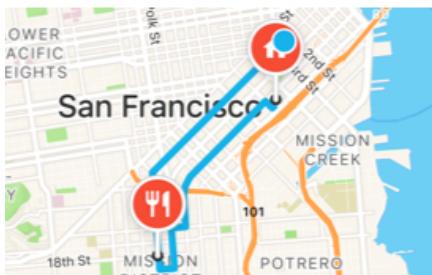
Accept Order



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)

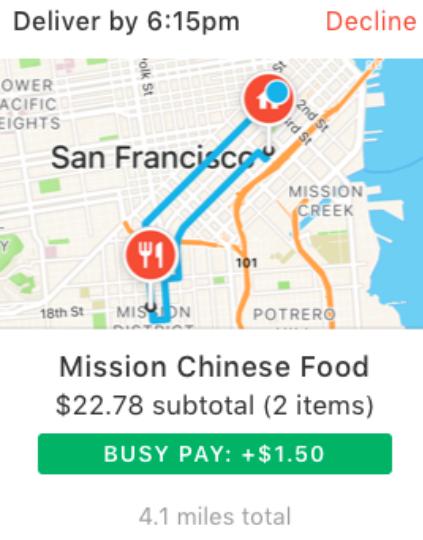
caviar

<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



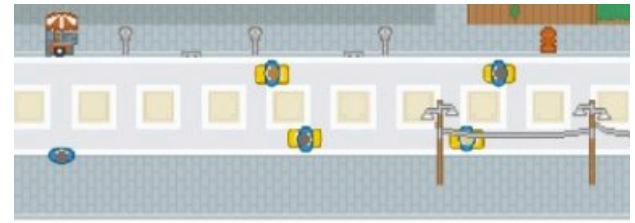
5:00 PM–6:00 PM
+10% (5:00pm - 5:30pm)
+30% (5:30pm - 6:00pm)



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

Theories of Labor Supply



Theories of Labor Supply

Neoclassical

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

Wage ↑
Work more

Theories of Labor Supply

Neoclassical

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

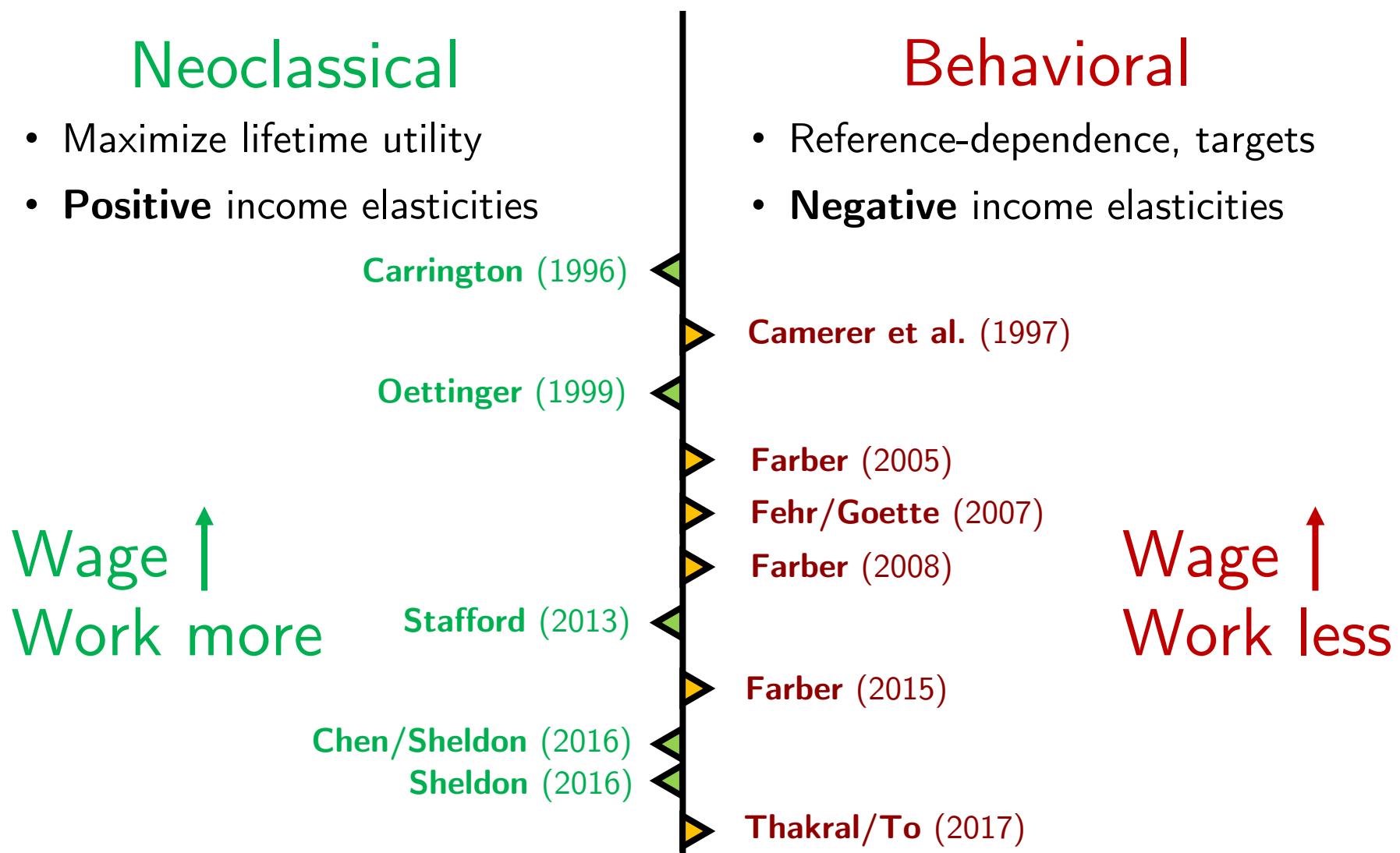
Wage ↑
Work more

Behavioral

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

Wage ↑
Work less

Theories of Labor Supply



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

Base Rate

+

Promotions

“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

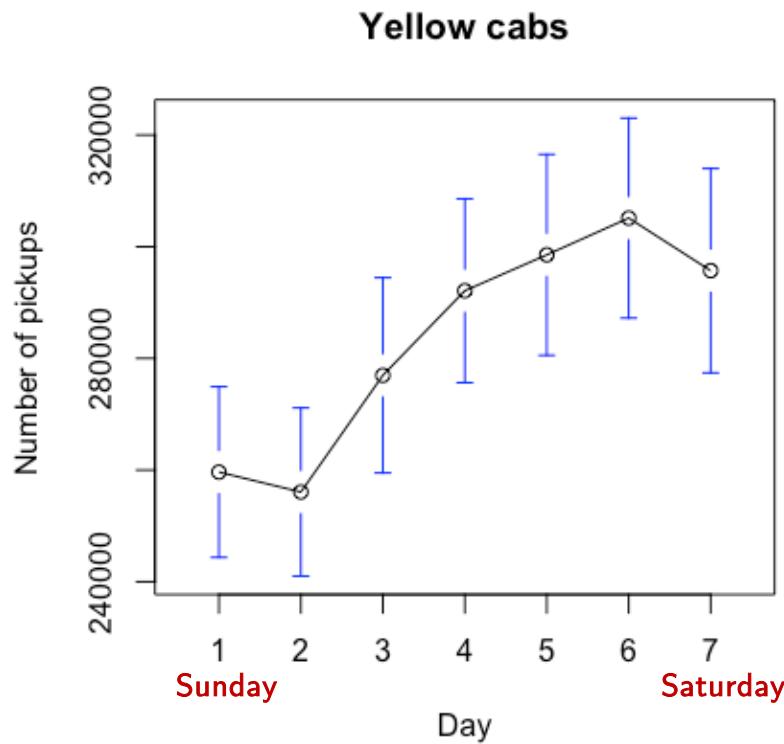
7,826

Unique drivers

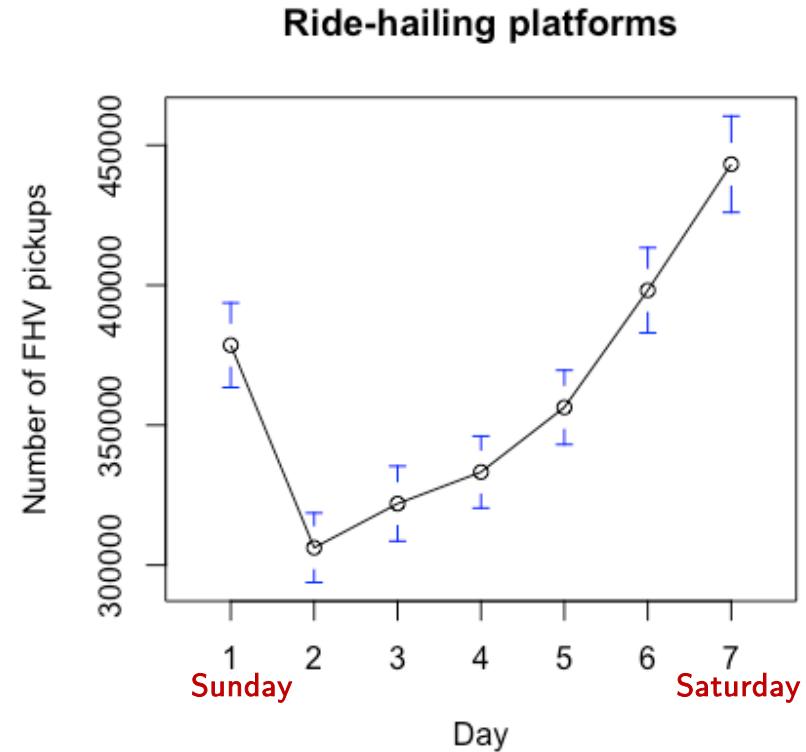
SUV/Sedan/Van

TLC Data

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



101M yellow cab trips

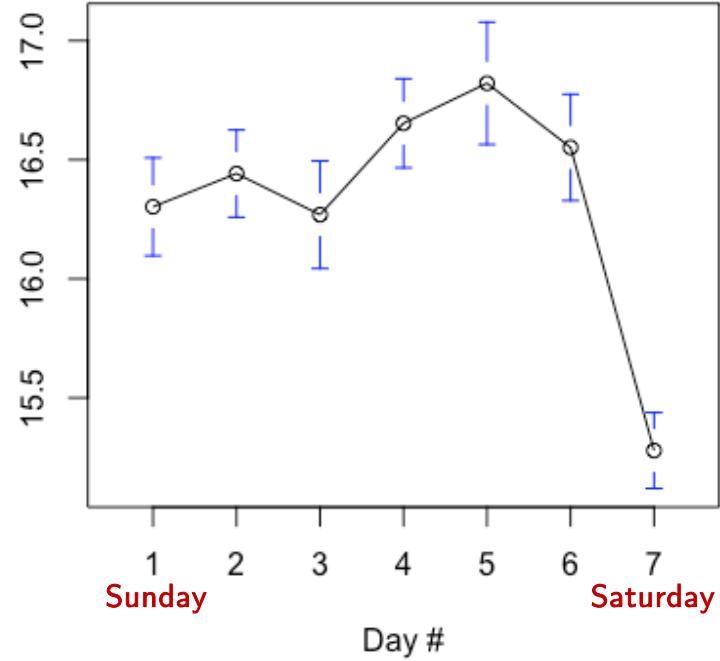
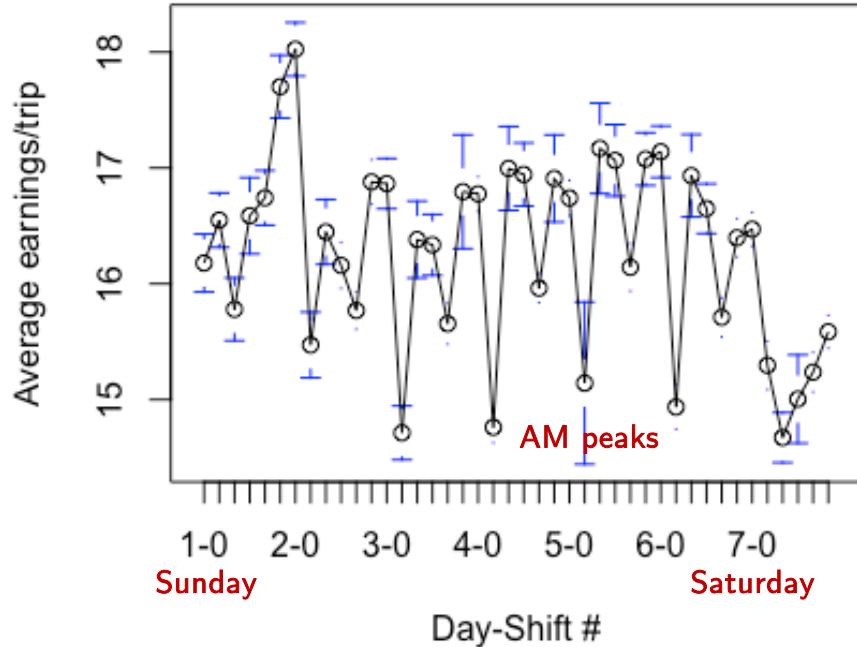


130M ride-hailing trips

TLC Data

Fares/earnings for all yellow cab trips

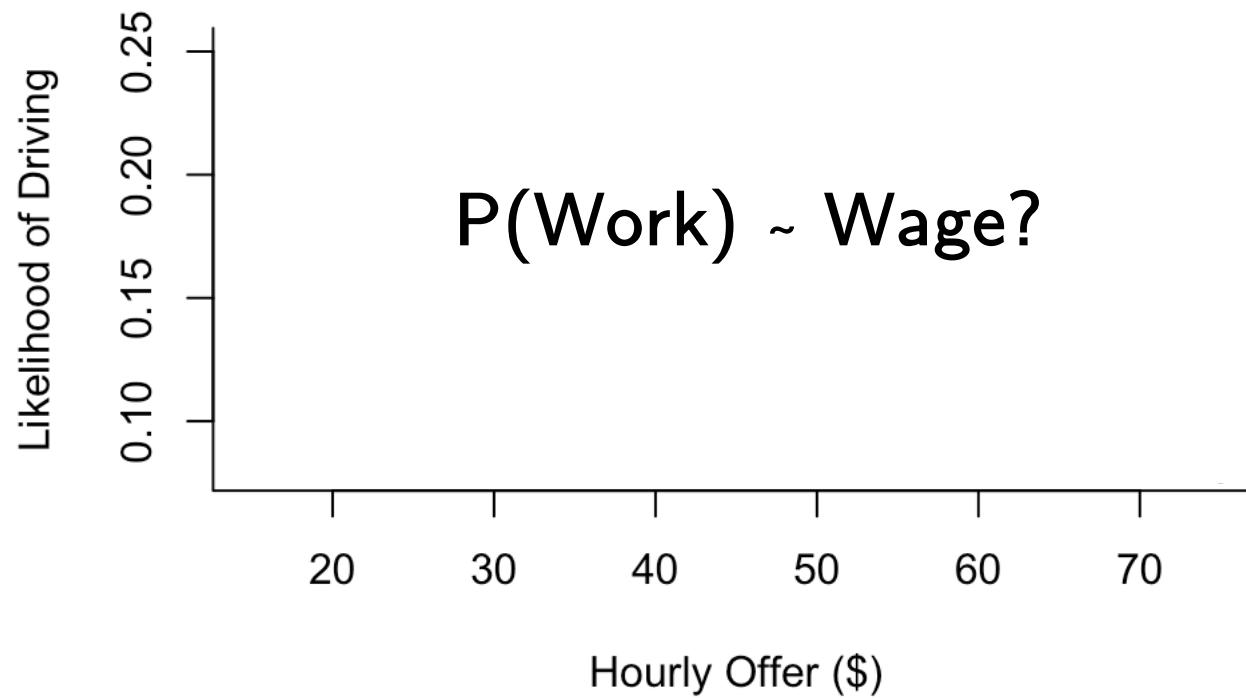
Sunday late night – Monday am off-peak



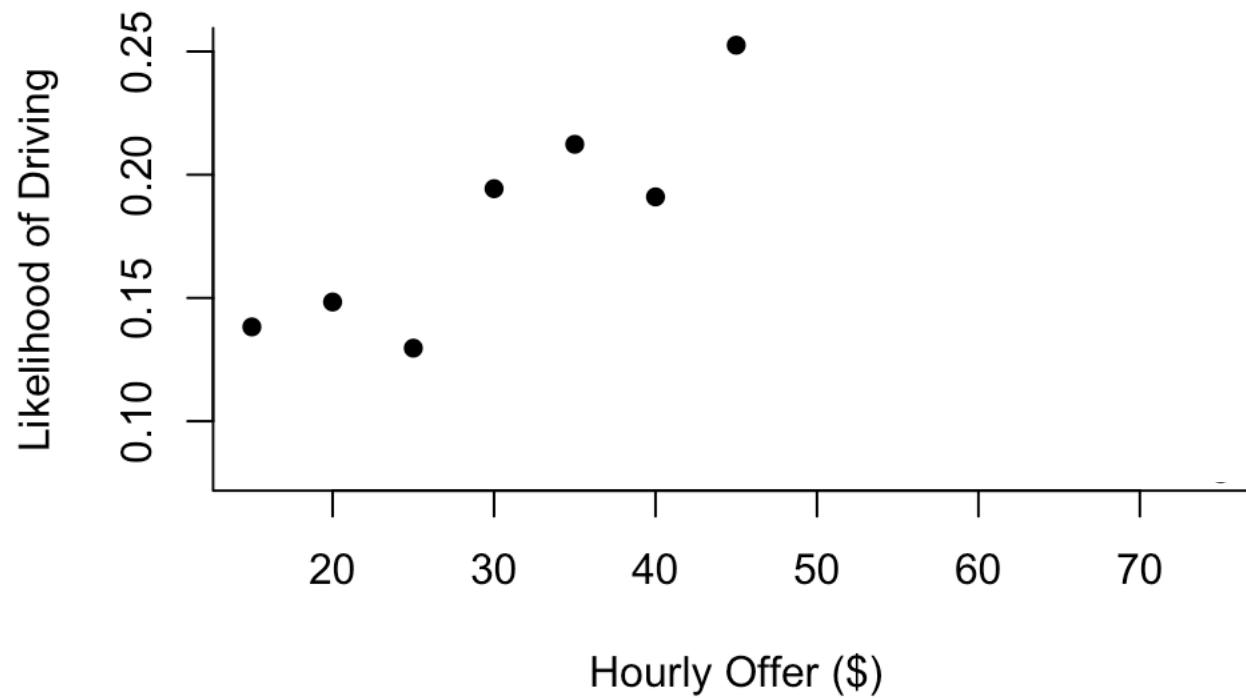
101M yellow cab trips

Empirical Strategy Challenges

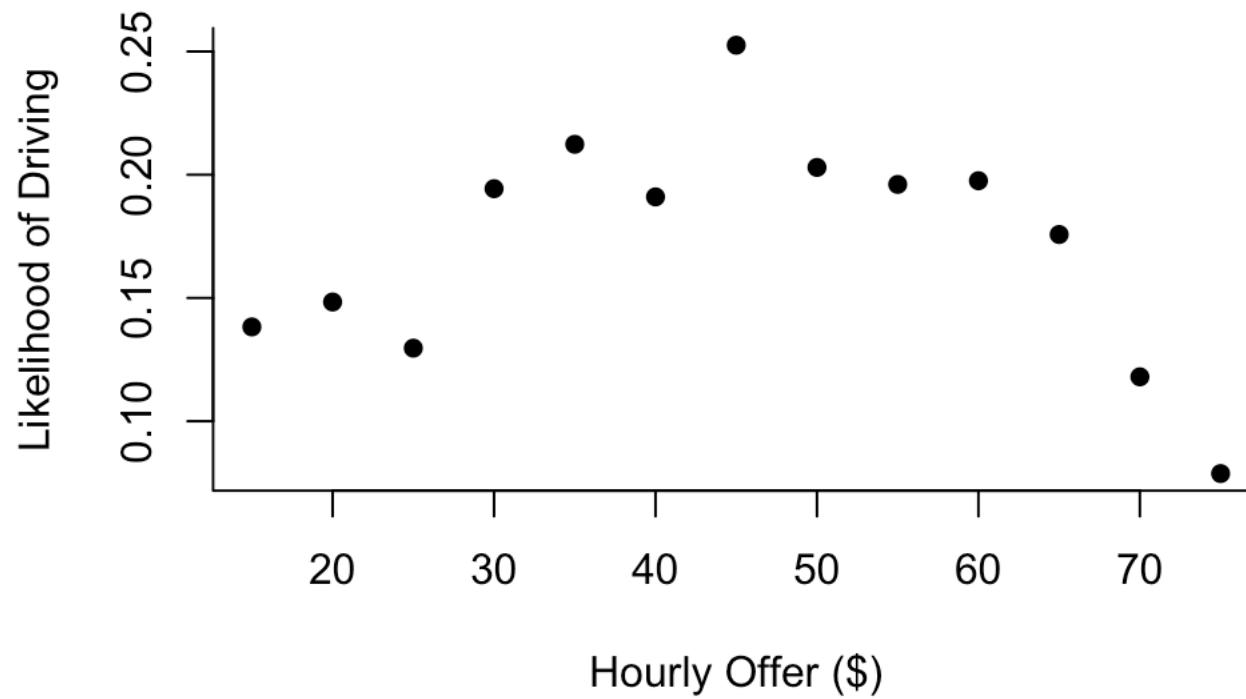
Empirical Strategy Challenges



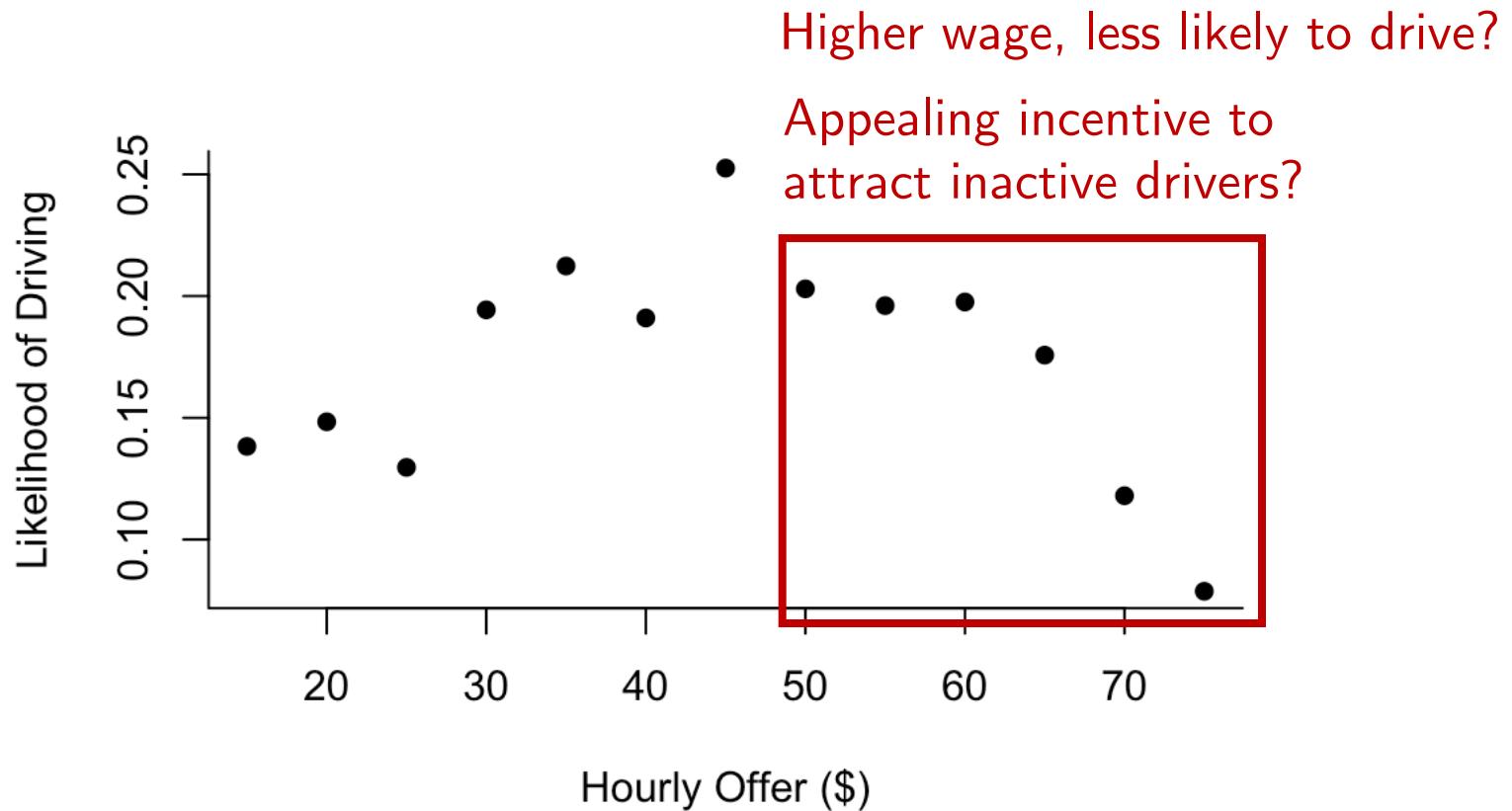
Empirical Strategy Challenges



Empirical Strategy Challenges

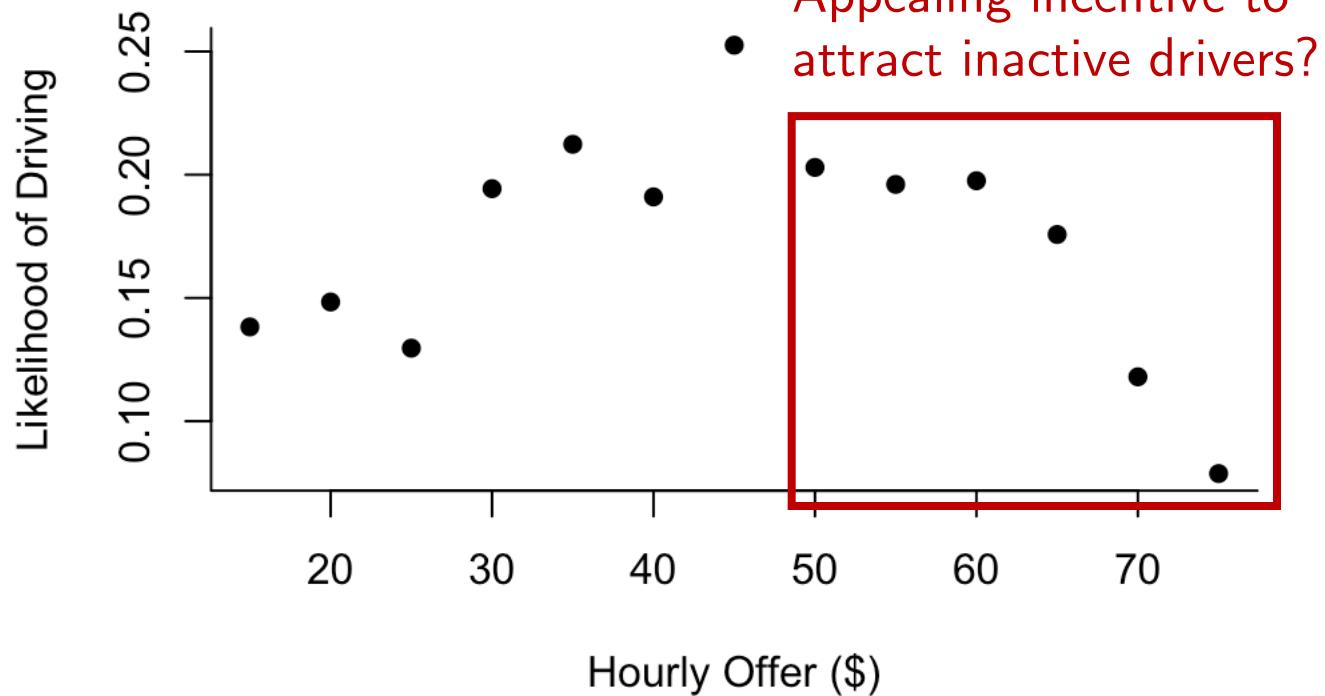


Empirical Strategy Challenges



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”



sedan



Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Endogenous Variable

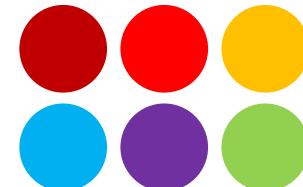
Instrument

Hourly offer

Average offers of “co-workers”



sedan



non-sedan

Empirical Strategy Challenges

Simultaneity

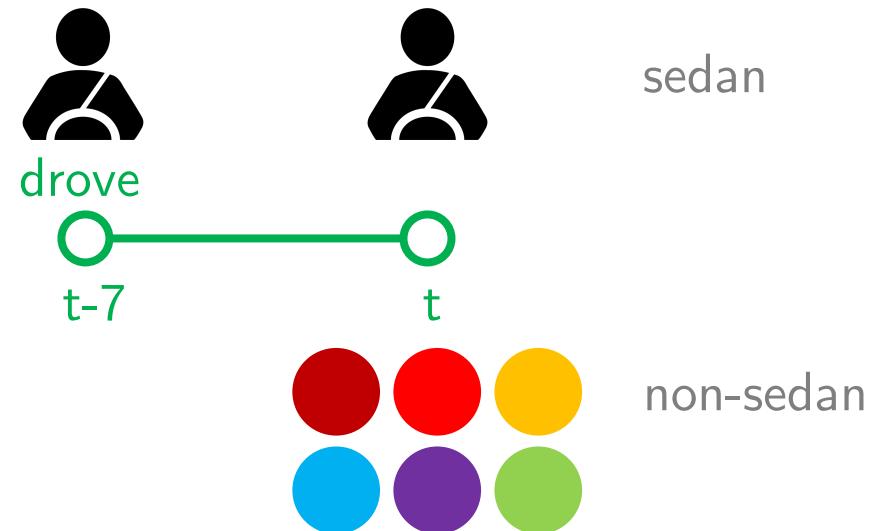
Solution: Instrumental Variables

Endogenous Variable

Hourly offer

Instrument

Average offers of “co-workers”



Empirical Strategy Challenges

Simultaneity

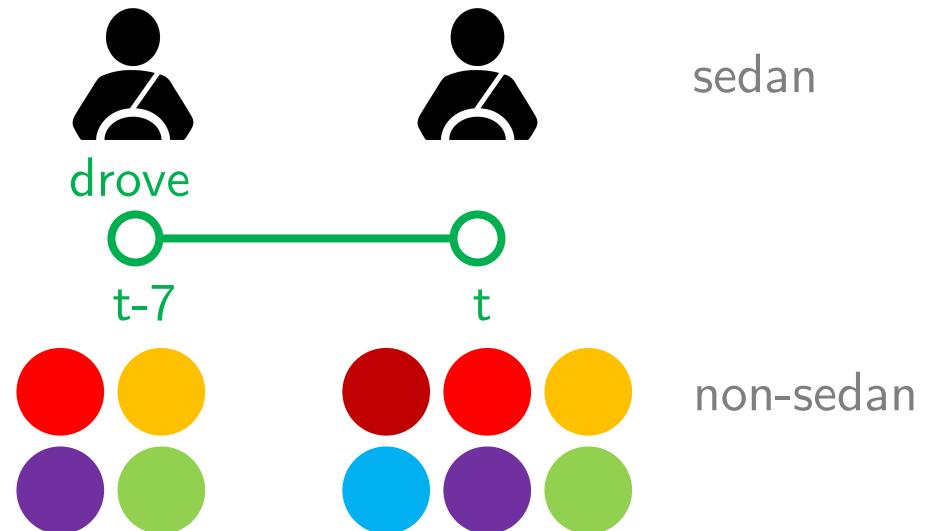
Solution: Instrumental Variables

Endogenous Variable

Instrument

Hourly offer

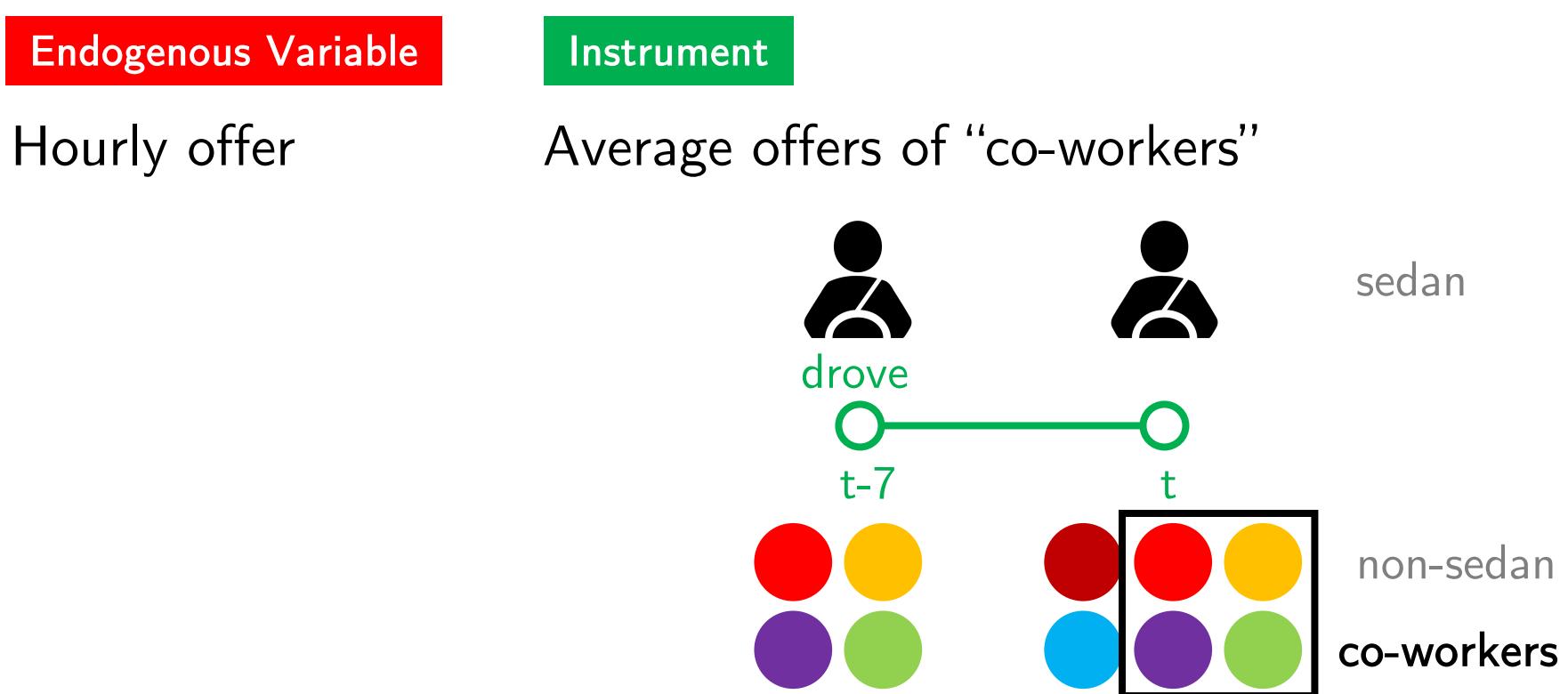
Average offers of “co-workers”



Empirical Strategy Challenges

Simultaneity

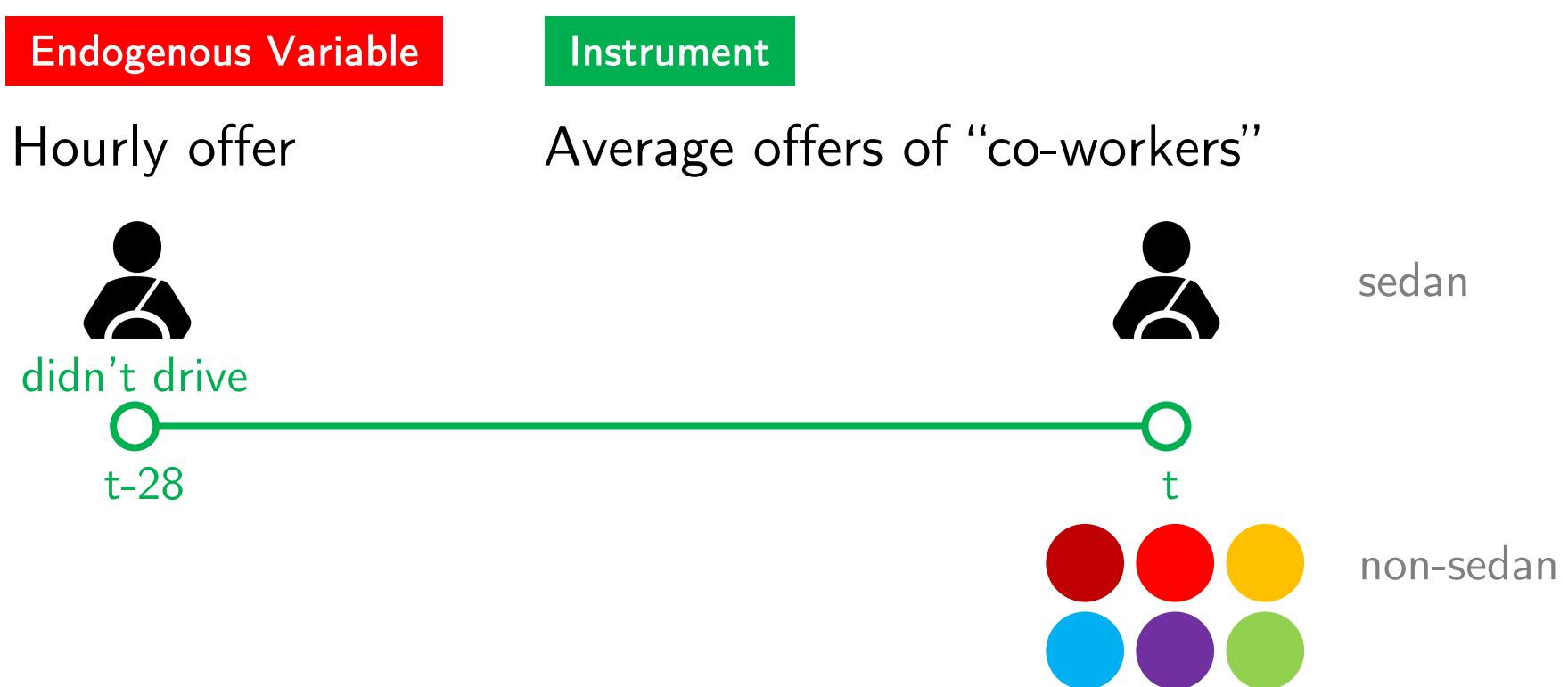
Solution: Instrumental Variables



Empirical Strategy Challenges

Simultaneity

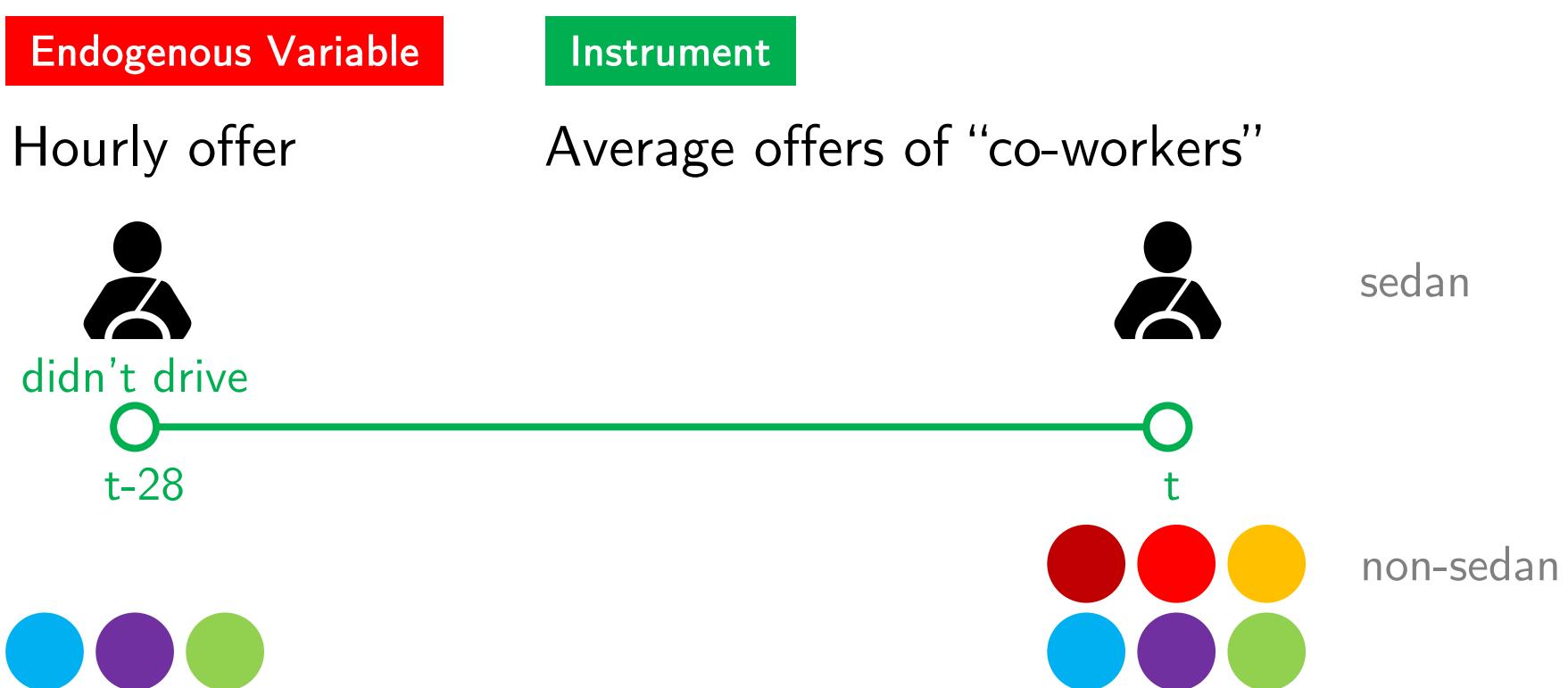
Solution: Instrumental Variables



Empirical Strategy Challenges

Simultaneity

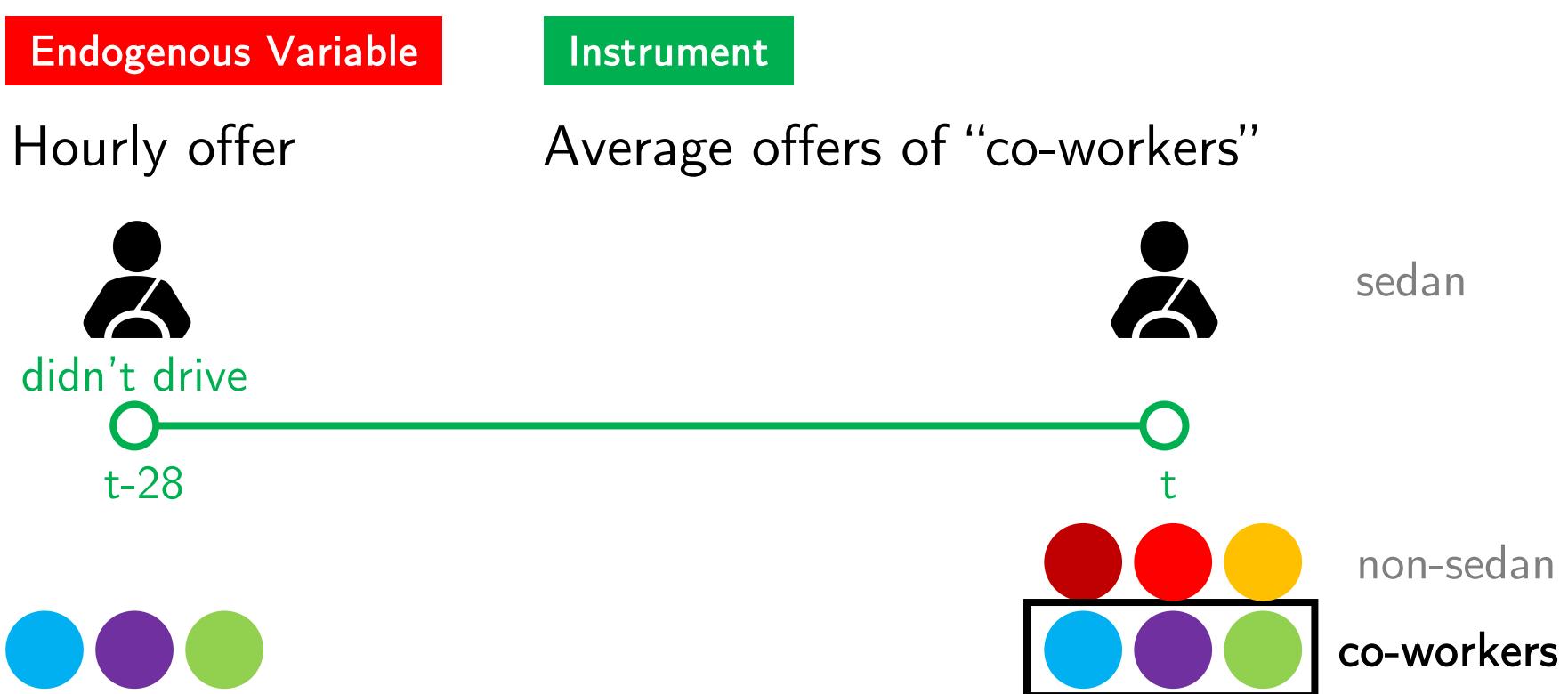
Solution: Instrumental Variables



Empirical Strategy Challenges

Simultaneity

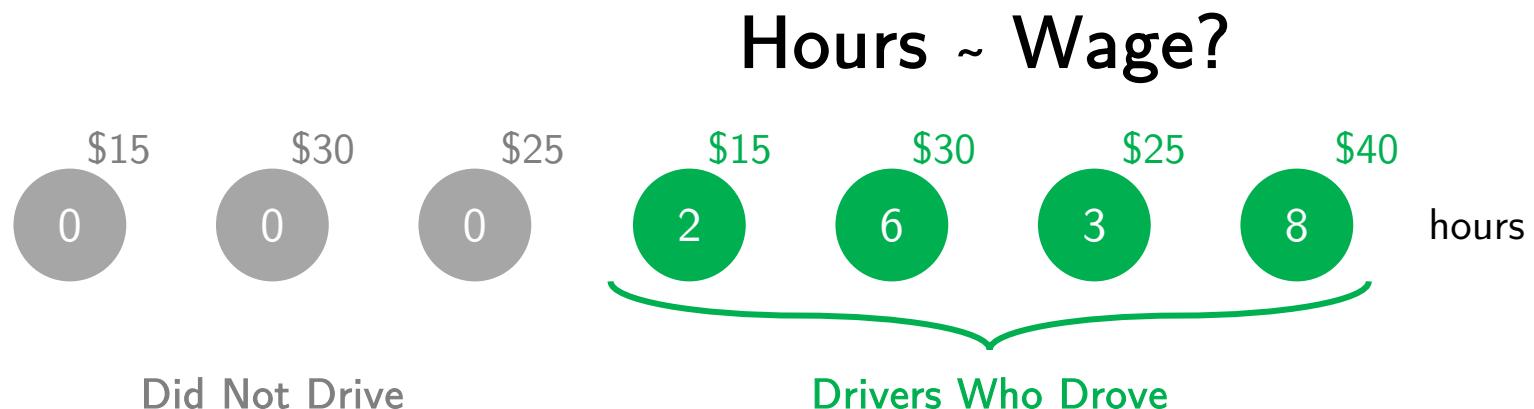
Solution: Instrumental Variables



Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

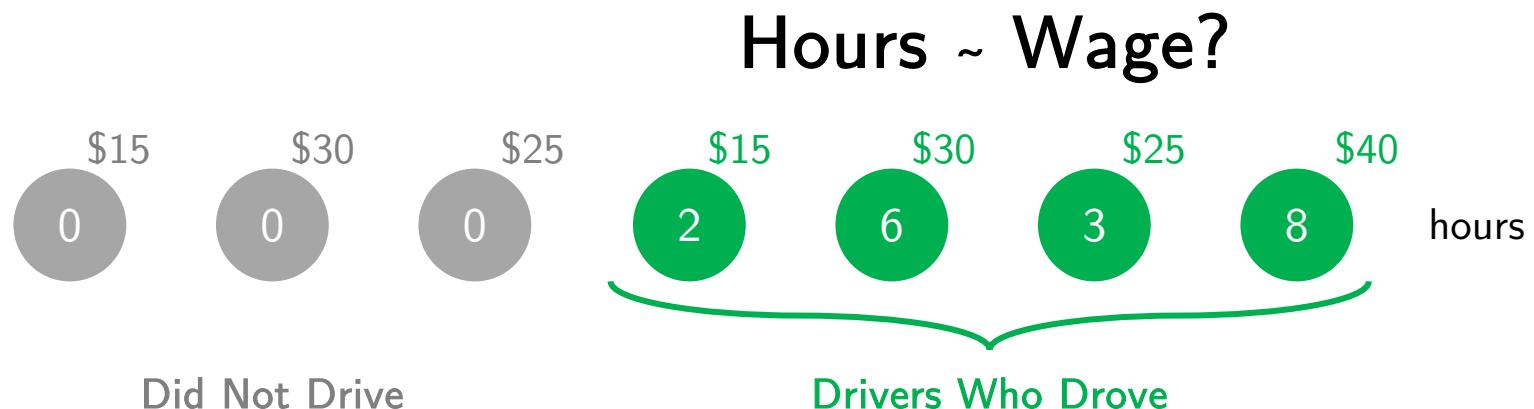


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**



Empirical Strategy Challenges

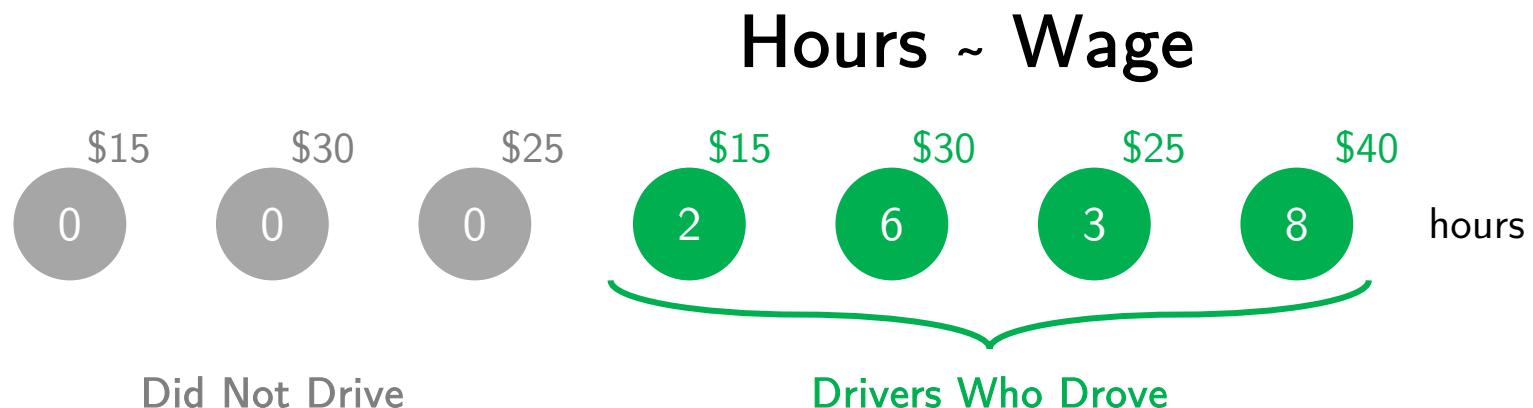
Simultaneity

Solution: Instrumental Variables

Selection Bias

Solution: Heckman Two-Stage Method

("Heckit" - Heckman 1979)



Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

$P(\text{drive})$ on *Offer*

Empirical Strategy

Heckman + IV

1) Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \textit{Offer}$

+ Controls_1



Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \textit{Offer} + \text{ISF}$ + Controls_1

Income So Far

= accumulated income since beginning of day

Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \textit{Offer} + \text{ISF}$ + Controls_1

|
Income So Far
= intensity of work

Empirical Strategy

Heckman + IV

1) Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \textit{Offer} + \textit{ISF} + \textit{HSF} + \text{Controls}_1$

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:

$P(\text{drive}) \text{ on } \textit{Offer} + \textit{ISF} + \textit{HSF} + \text{Controls}_1$

Income So Far
= intensity of work

Hours So Far
= amount of active time

Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \text{Offer} + \text{ISF} + \text{HSF} + \text{Controls}_1$

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:

$P(\text{drive}) \text{ on } \textit{Offer} + \text{ISF} + \text{HSF} + \text{Controls}_1$

Income So Far Hours So Far

Conditional
on working

2 How long to work?

2SLS with Fixed Effects

Hours on $\textit{Earning}$ + ISF + HSF + + Controls₂

Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \text{Offer} + \text{ISF} + \text{HSF} + \text{Controls}_1$

Income So Far Hours So Far

Conditional
on working

2 How long to work?

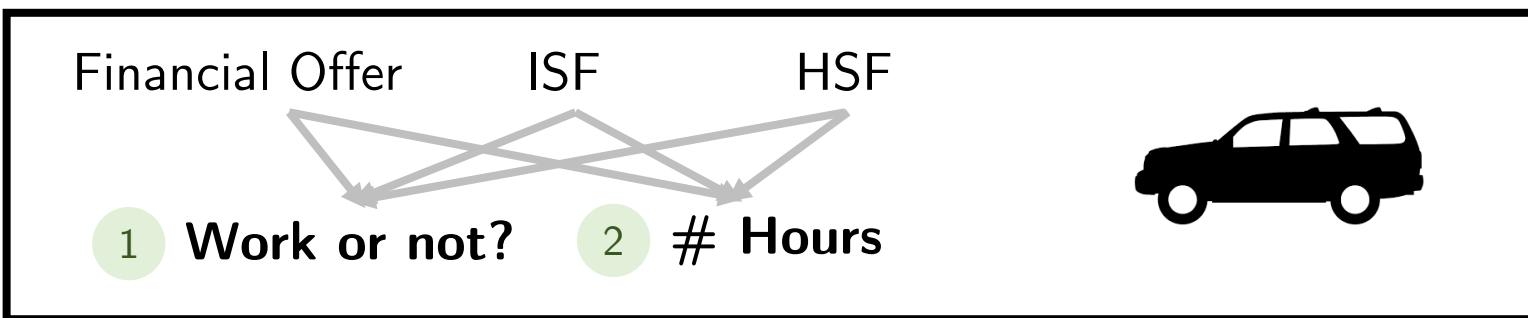
2SLS with Fixed Effects

Hours on $\text{Earning} + \text{ISF} + \text{HSF} + \text{IMR} + \text{Controls}_2$

Inverse Mills Ratio
= correct for selection bias

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

Results



Within-Day

Midday



Late Night

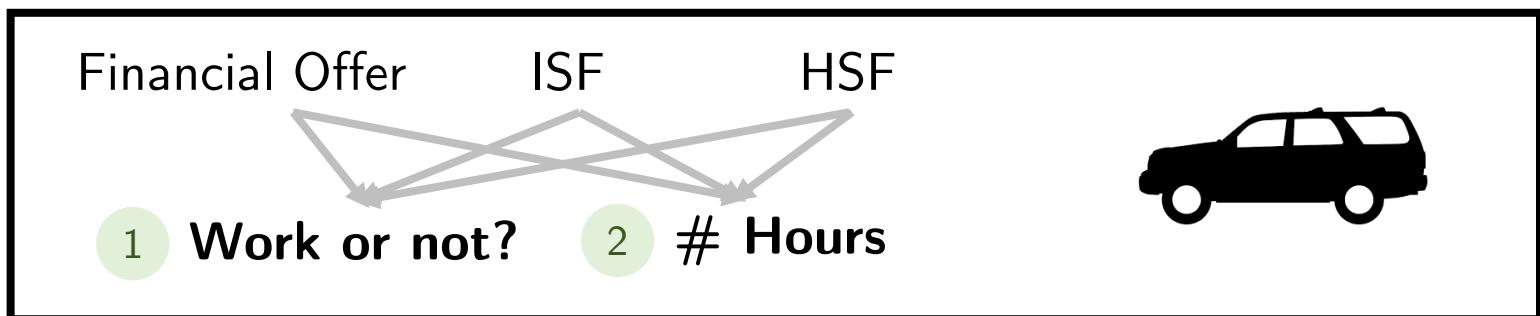
Across-Days

Tuesday



Sunday

Results



Within-Day

Midday



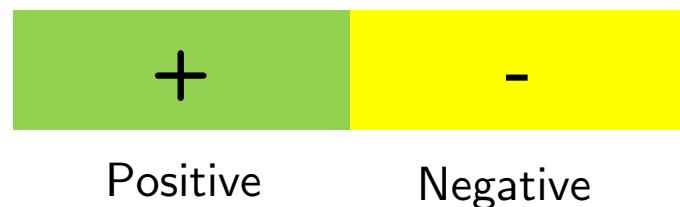
Late Night

Across-Days

Tuesday



Sunday



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

SUV	Mean	IV-F	Work or not?			# Hours
			Offer	ISF	HSF	
Midday	0.345	384.9	+	+	+	3.252
PM-Peak	0.277	359.4	-	-	+	1.334
PM-OPeak	0.179	326.6	+	-	+	0.458
Late Night	0.114	386.7	+	-	+	1.338

Income Inertia
Target

1 2

Results Within Day

SUV	Mean	IV-F	Work or not?			# Hours			R ²
			Offer	ISF	HSF	Mean	IV-F	Earning	
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 Inertia
Target Target

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

Work or not?

SUV	Mean	IV-F	Offer	ISF	HSF
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						2					
Work or not?						# 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.

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



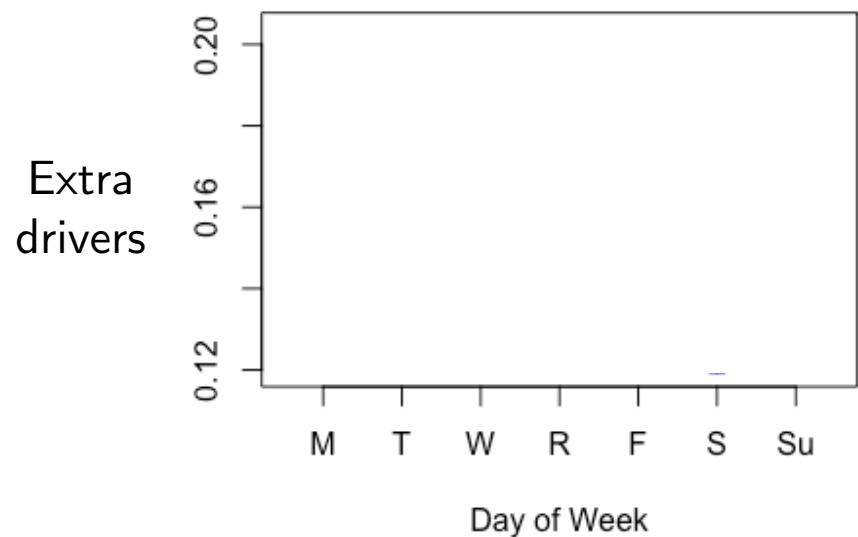
Reallocating Incentives

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

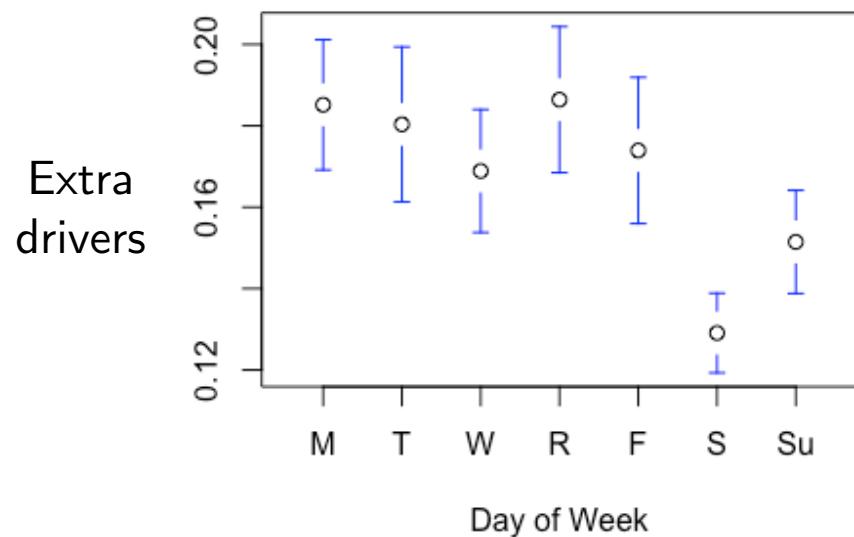
Given the same budget



Reallocating Incentives

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

Given the same budget



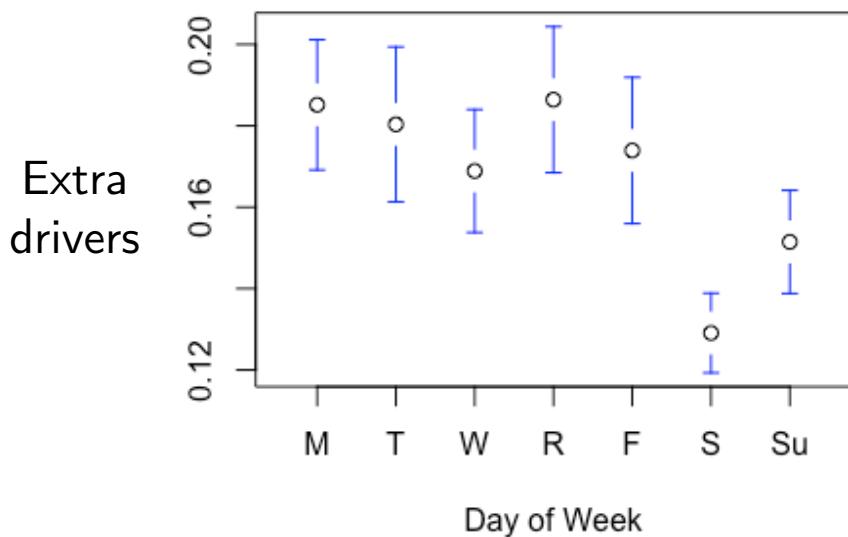
Can recruit **17% more drivers**

Average promo: 1.61x

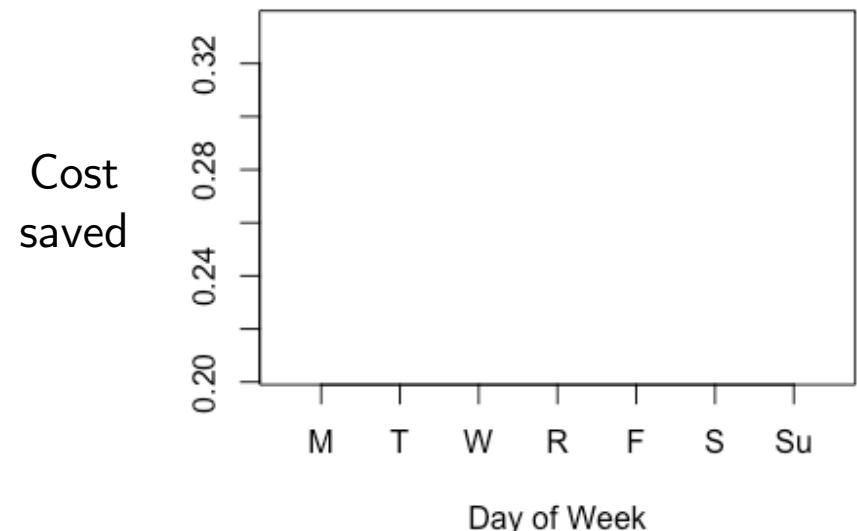
Reallocating Incentives

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

Given the same budget



Given the same capacity



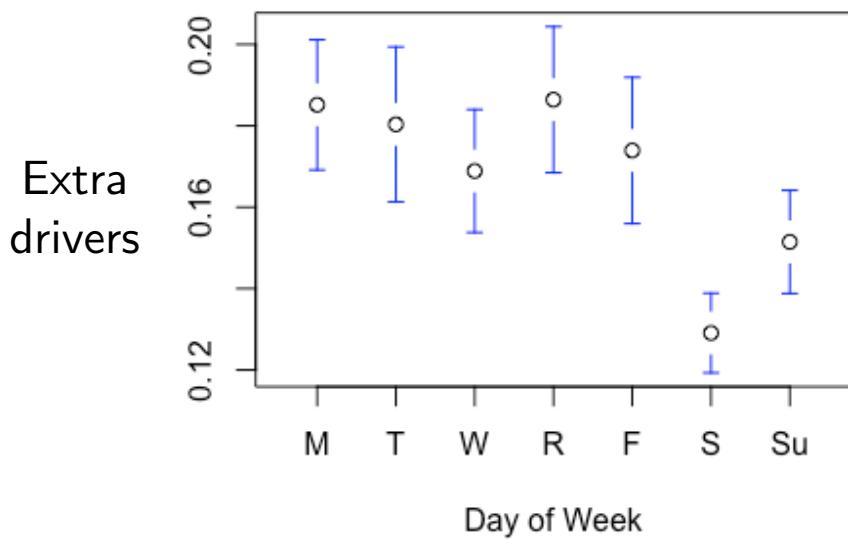
Can recruit **17% more drivers**

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Reallocating Incentives

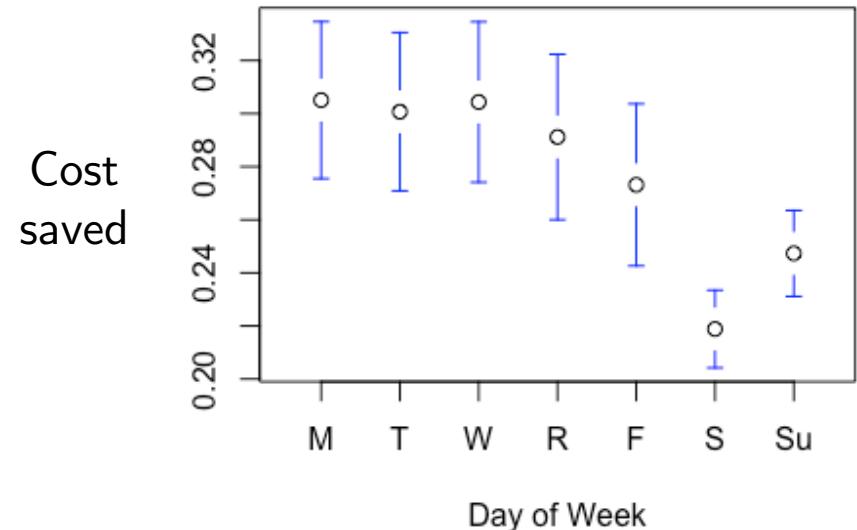
Compared to current practice from Jan to Sep 2017 out-of-sample

Given the same budget



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

Given the same capacity



Costs 28% less to maintain capacity

Results Recap

As day/week proceeds...

Neoclassical
Financial Incentive

encourages working

Behavioral
Income Target

discourages working later on

New
Inertia

encourages working

Results Recap

As day/week proceeds...

Neoclassical
Financial Incentive

encourages working

Behavioral
Income Target

discourages working later on

New
Inertia

encourages working

The longer I've been active,
the more likely I'll continue to work

Drivers Work Long Hours

- In NYC, ride-sharing drivers need a specific commercial license.

Drivers Work Long Hours

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- Some just enjoy driving...

Posted by u/

1 year ago



I actually love driving uber.



r/uberdrivers

Sure it started out for financial reasons but at this point I just Love f :ing driving.

I'm still doing things to make most money possible but its not a bad gig as long as your car costs 2k.

Experiment

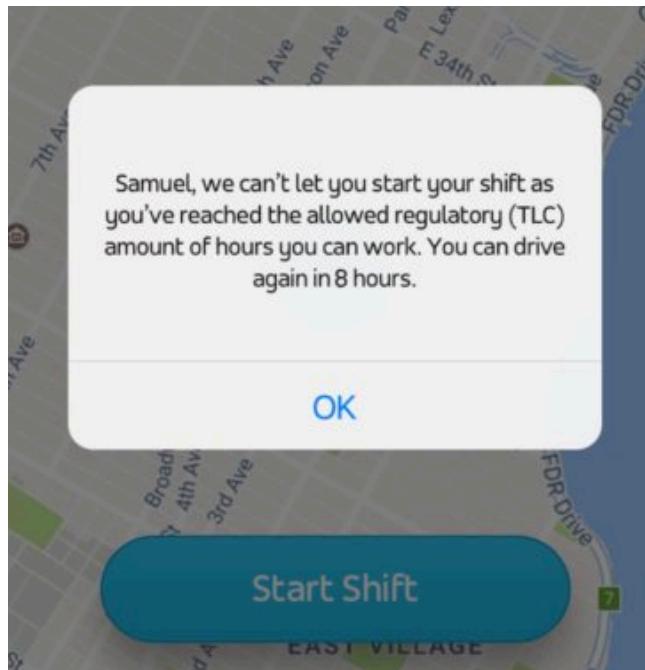
How to Nudge Workers to Quit?

Experiment

How to Nudge Workers to Quit?

Why would company want to do that?

- Fatigue / overwork



TRANSPORTATION \ UBER \ RIDE-SHARING

Uber will require drivers in the US to take six-hour breaks between long shifts

The app will use GPS and telematics to track driving time

By Andrew J. Hawkins | @andyjayhawk | Feb 12, 2018, 1:32pm EST

Experiment

How to Nudge Workers to Quit?

Why would company want to do that?

- Fatigue / overwork
- Match supply with demand

Experiment

How to Nudge Workers to Quit?

Why would company want to do that?

- Fatigue / overwork
- Match supply with demand

Intervention randomly assigned based of ISF/HSF

- Monetary: bonus now / higher future rate
- “You’ve reached goals!”
- Utilization forecast

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

Appendix

Robustness Tests

- Isolating ISF and HSF effect
 - Positive HSF (inertia) effect dominates ISF effect.
- Controlling on types of promotions
 - Same insights for 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.

Recent Work in OM

Theoretical

Dong & Ibrahim (2018)
Taylor (2017)
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)
...

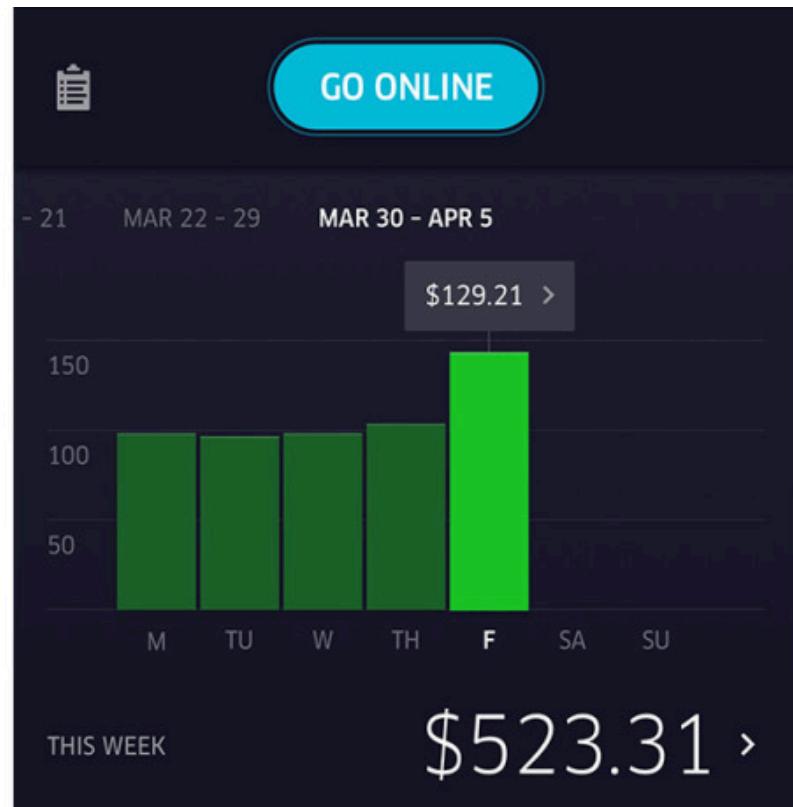
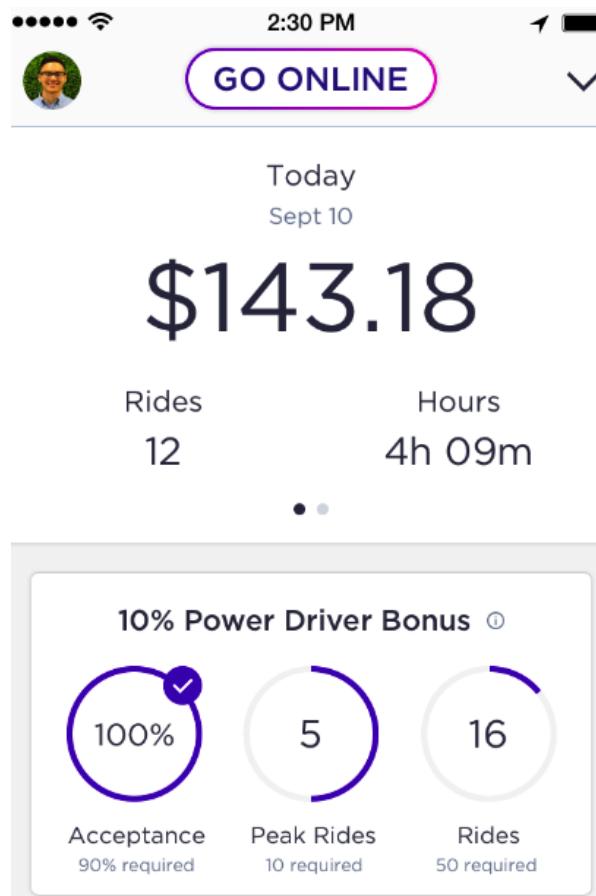
Empirical

Kabra, Belavina & Girotra (2017)
Karacaoglu, Moreno & Ozkan (2017)
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

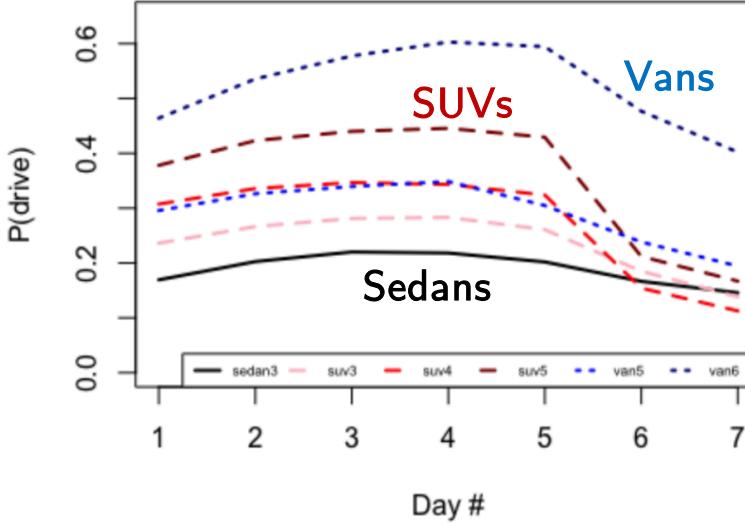
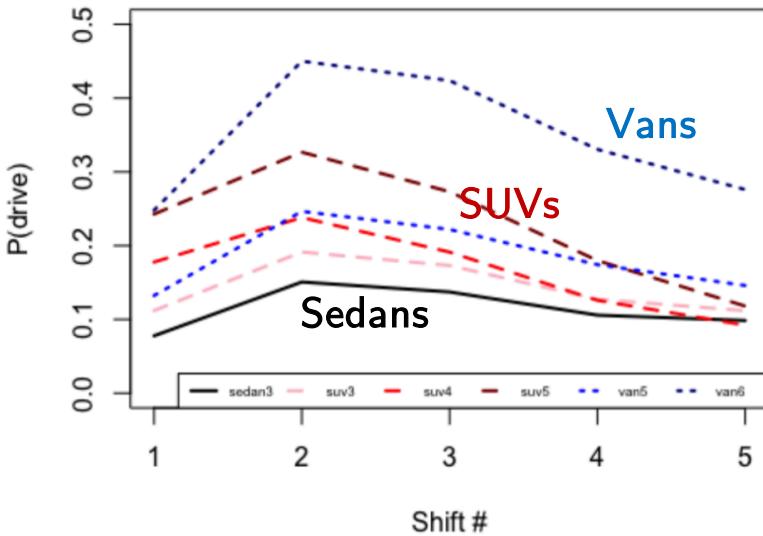
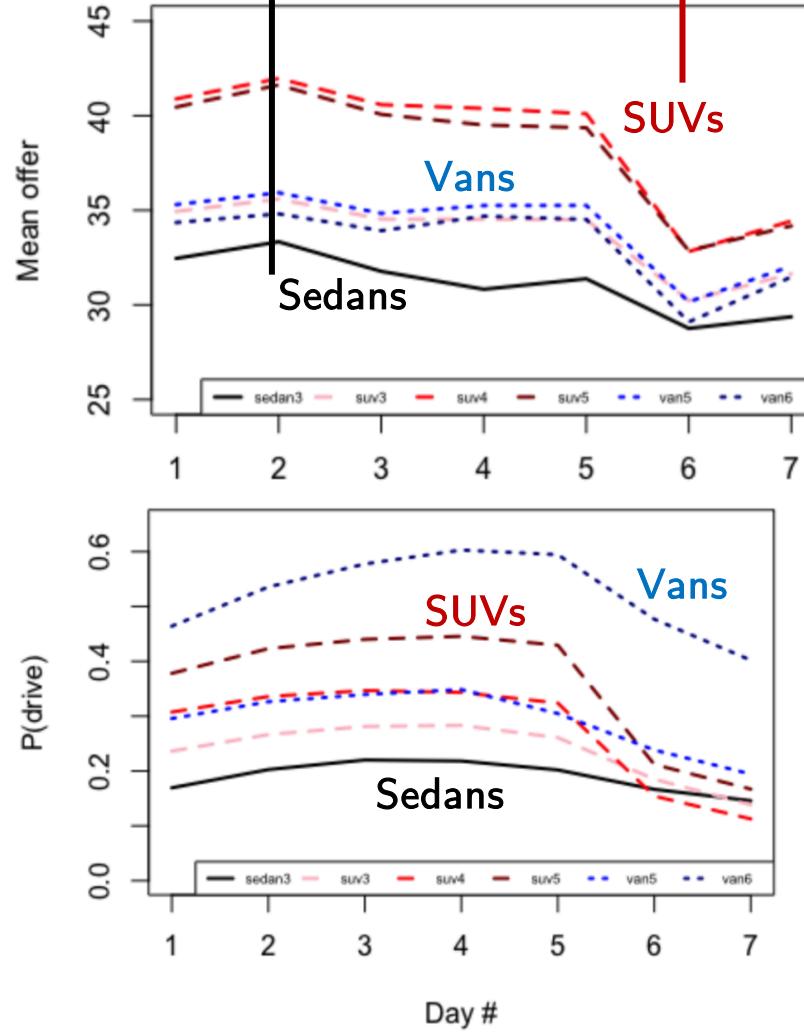
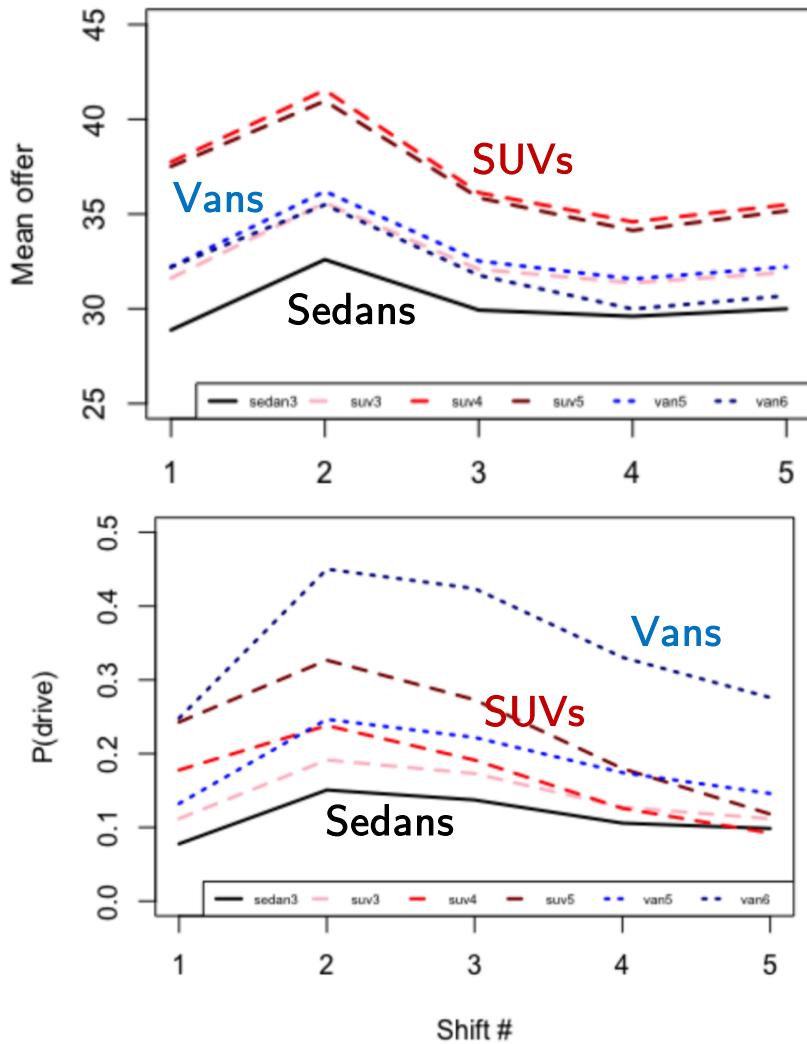
Driver's View



Drivers

5.33 hrs/day, 12.65 hrs/wk

4.86 hrs/day, 5.86 hrs/wk



Gig Economy x Retail



- **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



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 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.

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings		
Income so far		
Hours so far		
AIC		

N = 166,766

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far		
Hours so far		
AIC	95,856.010	72,887.620

Financial incentives
encourage working

N = 166,766

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far		-0.002*** (0.0002)
Hours so far		
AIC	95,856.010	72,887.620

N = 166,766

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far		
AIC	95,856.010	72,887.620

The more you've earned,
the less likely you're going to
continue working.

N = 166,766

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far		
AIC	95,856.010	72,887.620

For average driver,
\$100 additional income so far,
 $P(\text{drive})$ decreases by 2.5%

The more you've earned,
the less likely you're going to
continue working.

N = 166,766

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far		0.361*** (0.007)
AIC	95,856.010	72,887.620

N = 166,766

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far	Inertia	0.361*** (0.007)
AIC	95,856.010	72,887.620

N = 166,766

The longer you've been active,
the more likely you'll continue
working

Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far	Inertia	0.361*** (0.007)
AIC	95,856.010	72,887.620

N = 166,766

For average driver,
1 additional hour so far,
 $P(\text{drive})$ increases by 4.1%

The longer you've been active,
the more likely you'll continue
working

Late Night

1

2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)			
Income so far	Income Target	-0.002*** (0.0002)			
Hours so far	Inertia	0.361*** (0.007)			
IMR					
AIC/R ²	95,856.010	72,887.620			

N = 166,766

Late Night

1

2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
Income so far	Income Target	-0.002*** (0.0002)			
Hours so far	Inertia	0.361*** (0.007)			
IMR				***	***
AIC/R ²	95,856.010	72,887.620	0.313	0.324	0.913

N = 166,766

N = 18,941

Late Night

1

2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
Income so far	Income Target	-0.002*** (0.0002)			-0.0002*** (0.00002)
Hours so far	Inertia	0.361*** (0.007)			0.187*** (0.001)
IMR				***	***
AIC/R ²	95,856.010	72,887.620	0.313	0.324	0.913

N = 166,766

N = 18,941

Late Night

1

2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	The more you've earned, you'll drive shorter hours.			
Income so far	Income Target	-0.002*** (0.0002)		Income Target	-0.0002*** (0.00002)
Hours so far	Inertia	0.361*** (0.007)		Inertia	0.187*** (0.001)
IMR	The longer you've been active, you'll drive longer hours.				
AIC/R ²	95,856.010	72,887.620	0.313	0.324	0.913

N = 166,766

N = 18,941

Late Night

1

2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
Income so far		-0.002*** (0.0002)			-0.0002*** (0.00002)
Hours so far		0.361*** (0.007)			0.187*** (0.001)
IMR				***	***
AIC/R ²	95,856.010	72,887.620	0.313	0.324	0.913

Late Night

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	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
Income so far		-0.002*** (0.0002)			-0.0002*** (0.00002)
Hours so far		0.361*** (0.007)			0.187*** (0.001)
IMR				***	***



Work or not?



Late Night

1

2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
Income so far		-0.002*** (0.0002)			-0.0002*** (0.00002)
Hours so far		0.361*** (0.007)			0.187*** (0.001)
IMR				***	***



Work or not?

Hours

Offer

ISF

HSF

Earning

ISF

HSF

Late night

+

-

+

+

-

+