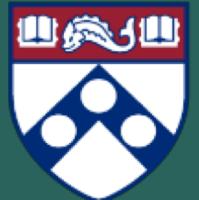




The Impact of Behavioral and Economic Drivers on Gig Economy Workers

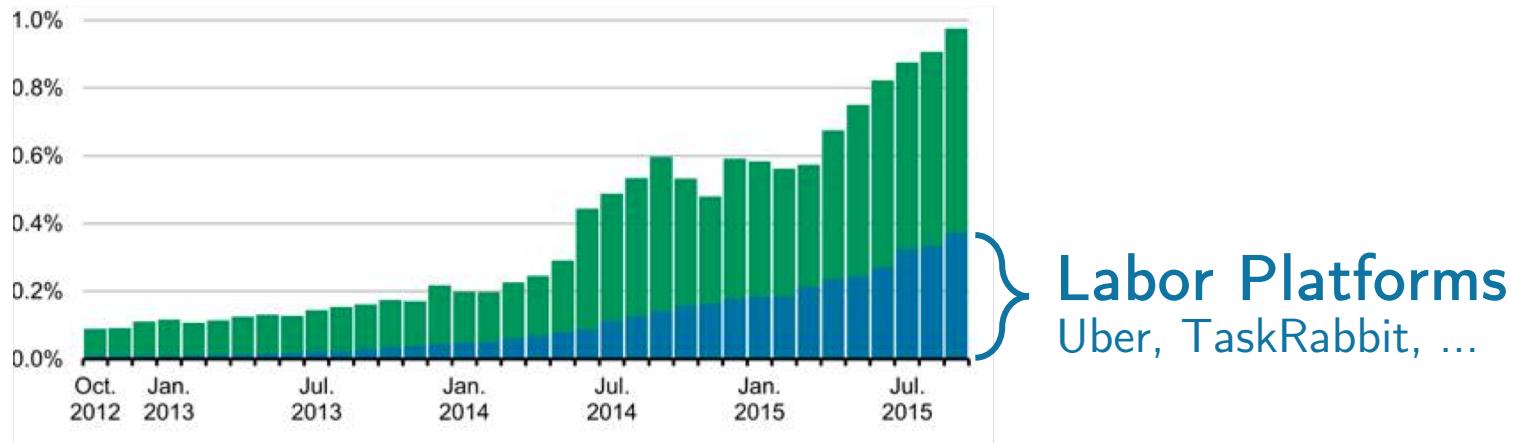
NYU Stern 3/28/2019



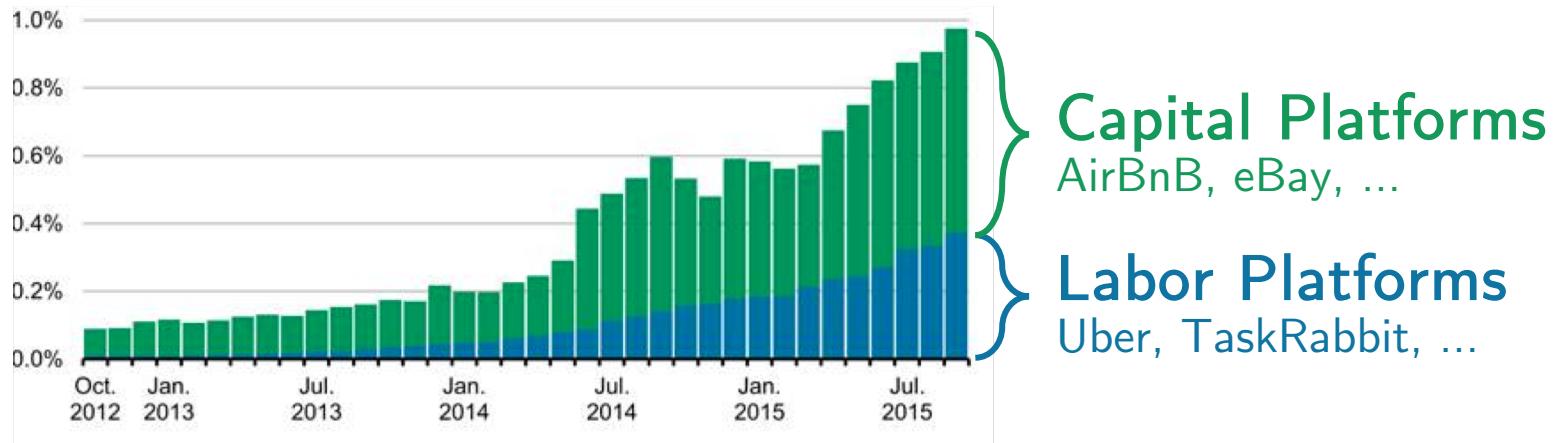
Park Sinchaisri (Wharton)
Gad Allon (Wharton), Maxime Cohen (NYU)

Gig Economy

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

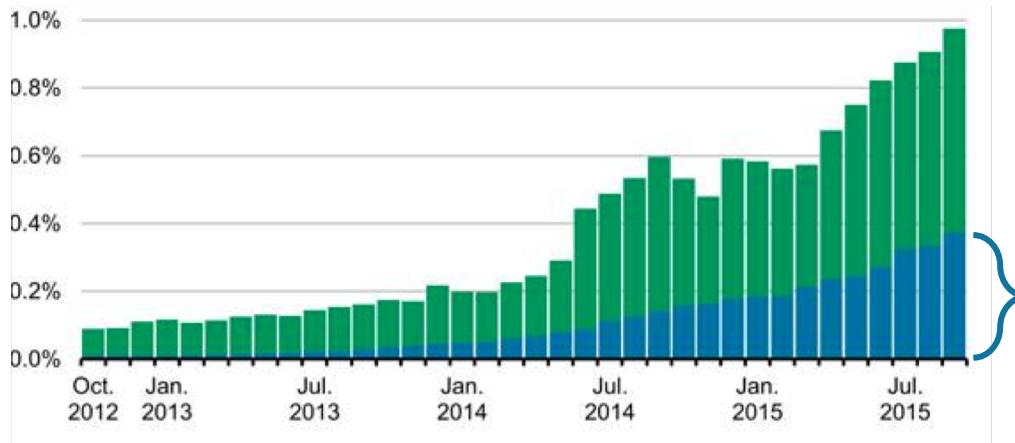


Share of US adults earning income in a given month via online platforms



Gig Economy

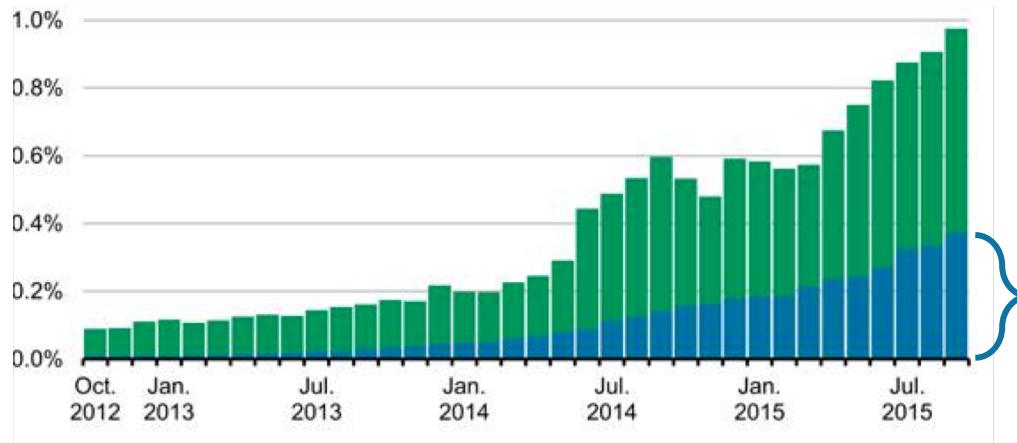
Share of US adults earning income in a given month via online platforms



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



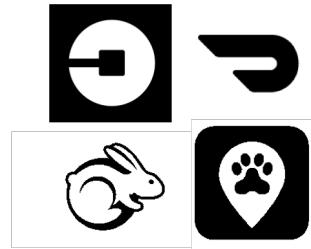
when to work?

44% primary income



how long?

~50% millennials



which platforms?

Who are Gig Workers?

70% by choice



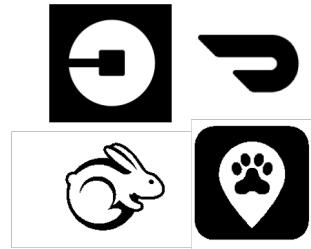
when to work?

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how long?

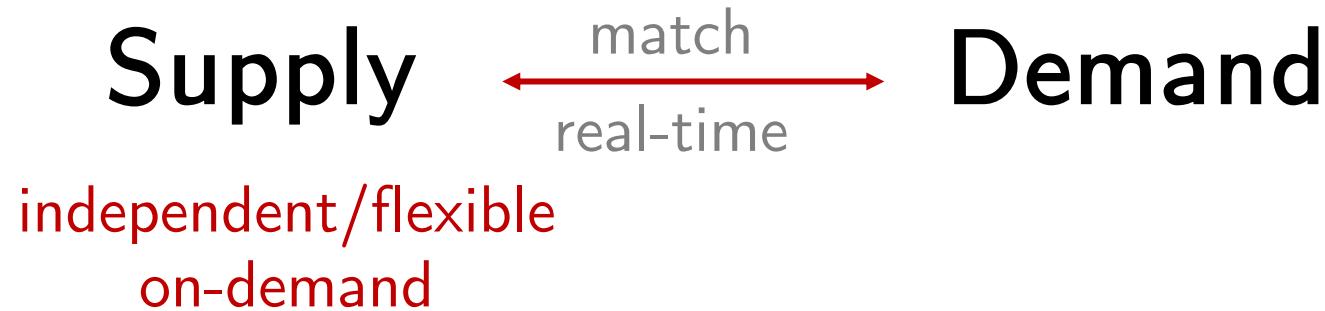
~50% millennials



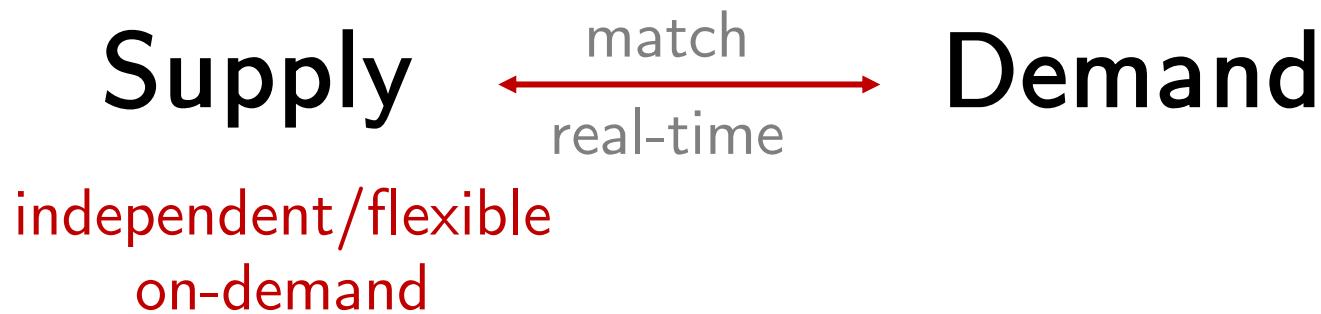
which platforms?

Workers decide work schedules

Gig Company



Gig Company



Workforce planning is challenging

Research Questions

How do gig economy workers
make labor decisions?

Research Questions

How do gig economy workers
make labor decisions?

How can the platform influence
their decisions?

Outline

- **What has been done**

- Practice / labor economics / OM

- **Data and empirical strategy**

- Dealing with endogeneity and selection bias

- **Results**

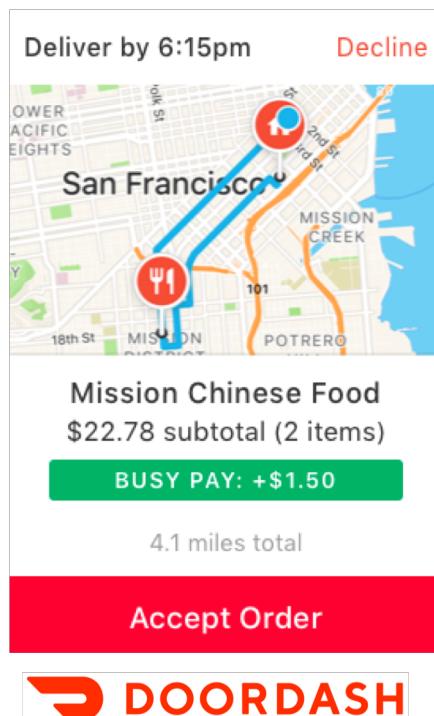
- Impact of incentive and behavioral elements on labor decisions

- **Implications**

- Simulation of optimal incentive re-allocation

In Practice

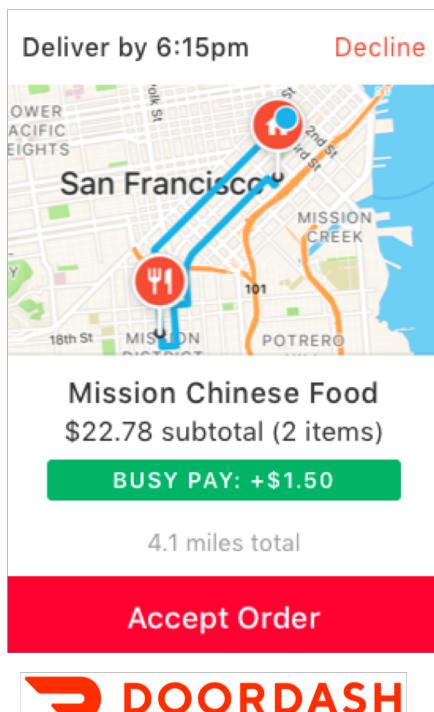
Real-time
“surge pricing”



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

In Practice

Real-time “surge pricing”



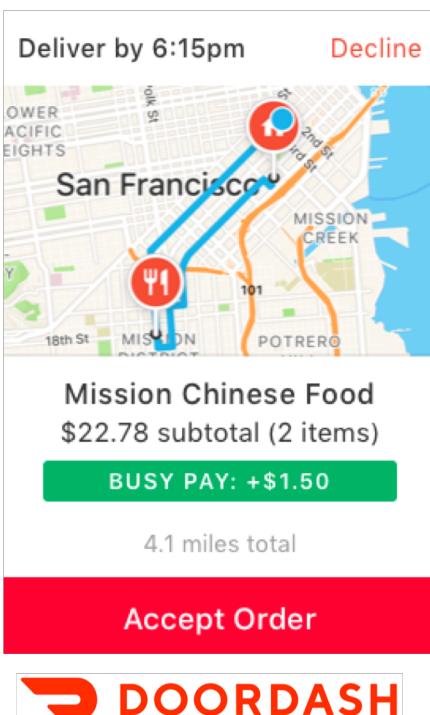
Pre-announced bonus

<input checked="" type="checkbox"/>	5:00 PM–6:00 PM	+10% (5:00pm - 5:30pm)
		+30% (5:30pm - 6:00pm)
<input checked="" type="checkbox"/>	6:00 PM–7:00 PM	+30% (6:00pm - 6:30pm)
		+40% (6:30pm - 7:00pm)

caviar

In Practice

Real-time “surge pricing”



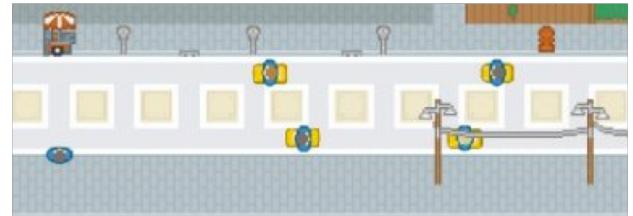
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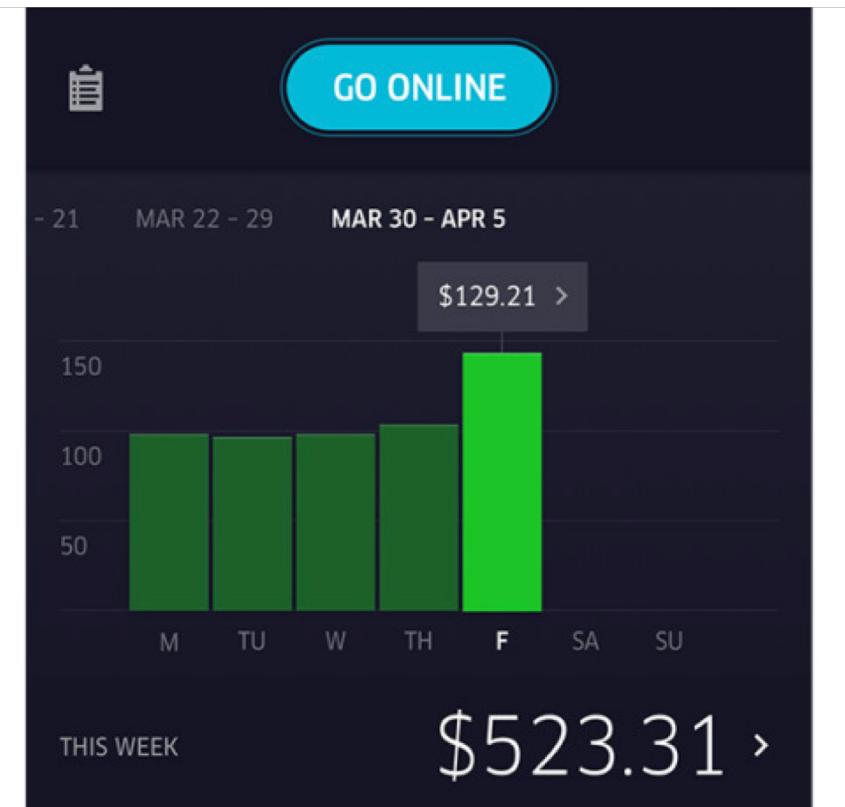
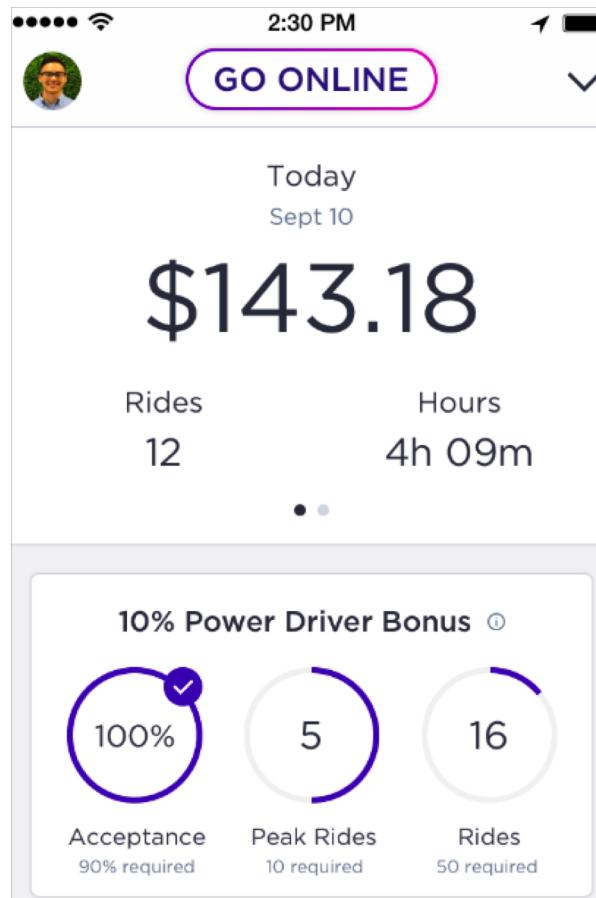
caviar

“You’re so close to your precious target”



How Uber Uses
Psychological Tricks to
Push Its Drivers’ Buttons

Driver's View



Theories of Labor Supply

Neoclassical

- Maximize lifetime utility

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

Carrington (1996) 

Oettinger (1999) 

Wage ↑
Work more

Stafford (2013) 

Chen/Sheldon (2016)
Sheldon (2016) 

Theories of Labor Supply

Neoclassical

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

Carrington (1996) ○

Oettinger (1999) ○

Wage ↑
Work more

Stafford (2013) ○

Chen/Sheldon (2016)
Sheldon (2016) ○○

Behavioral

- Reference-dependence, targets

Theories of Labor Supply

Neoclassical

- Maximize lifetime utility
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Carrington (1996)

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Wage ↑
Work more

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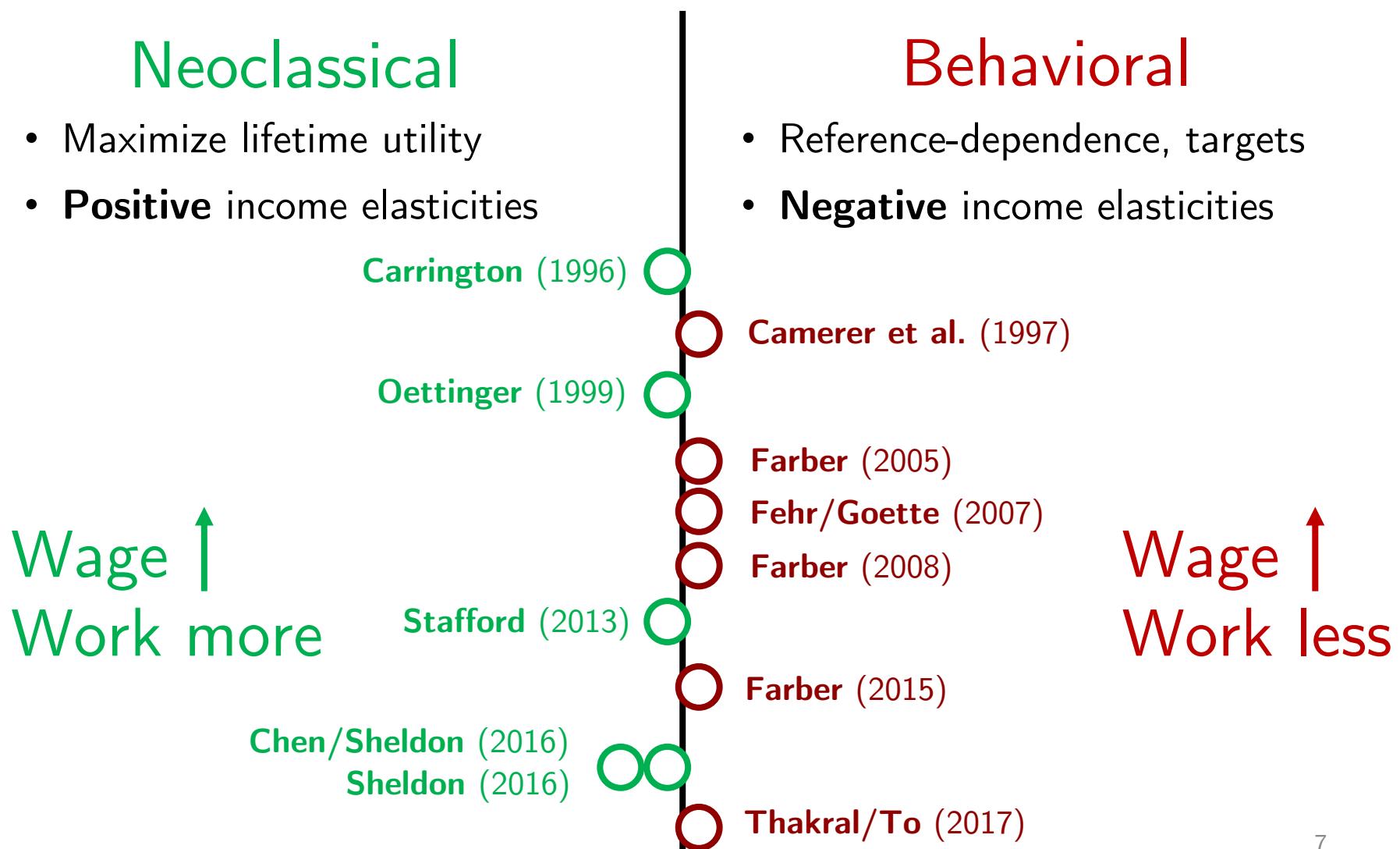
Chen/Sheldon (2016)
Sheldon (2016)

Behavioral

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

Wage ↑
Work less

Theories of Labor Supply



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

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/
Time 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

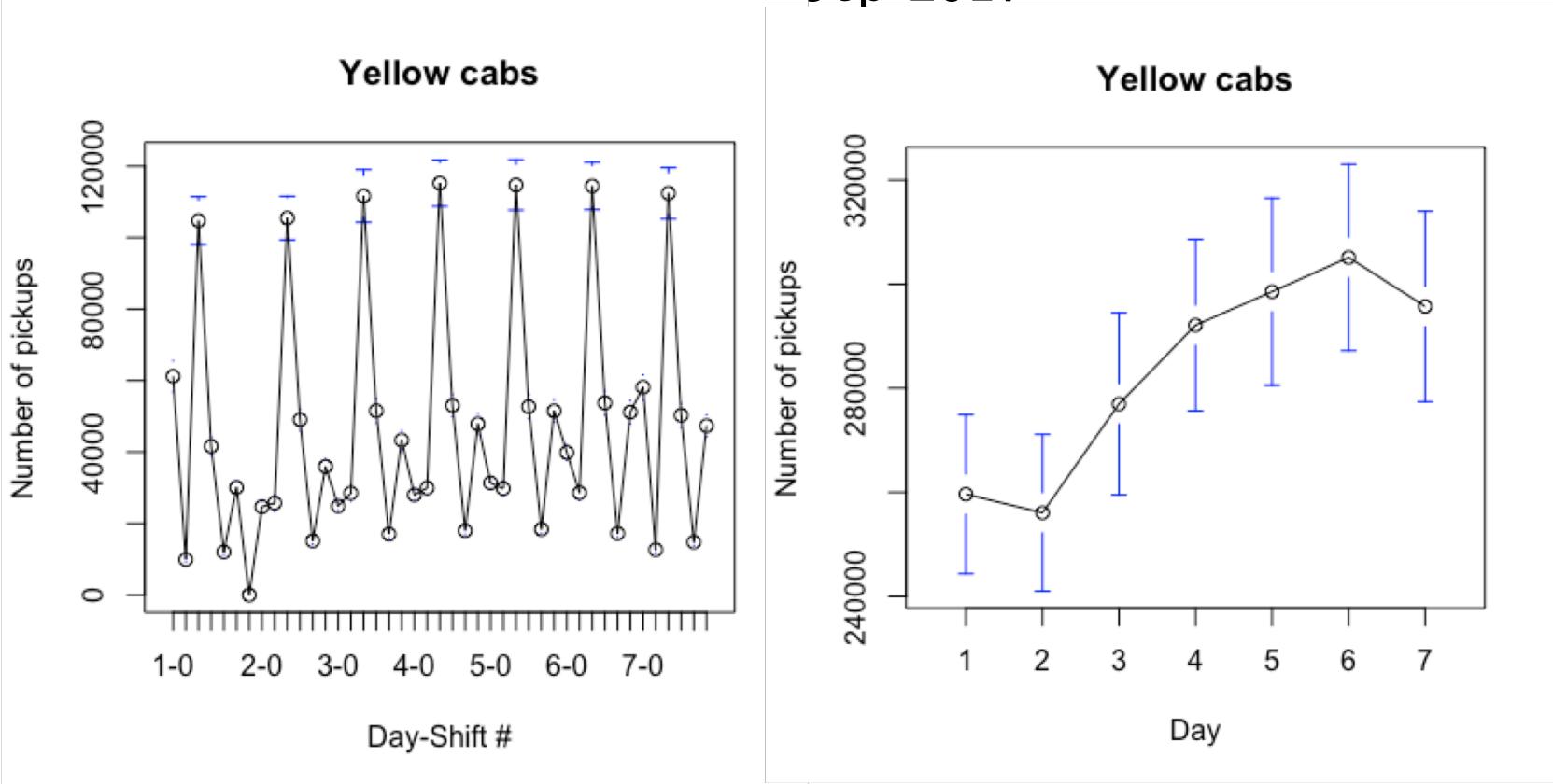
7,826

Unique drivers

SUV/Sedan/Van

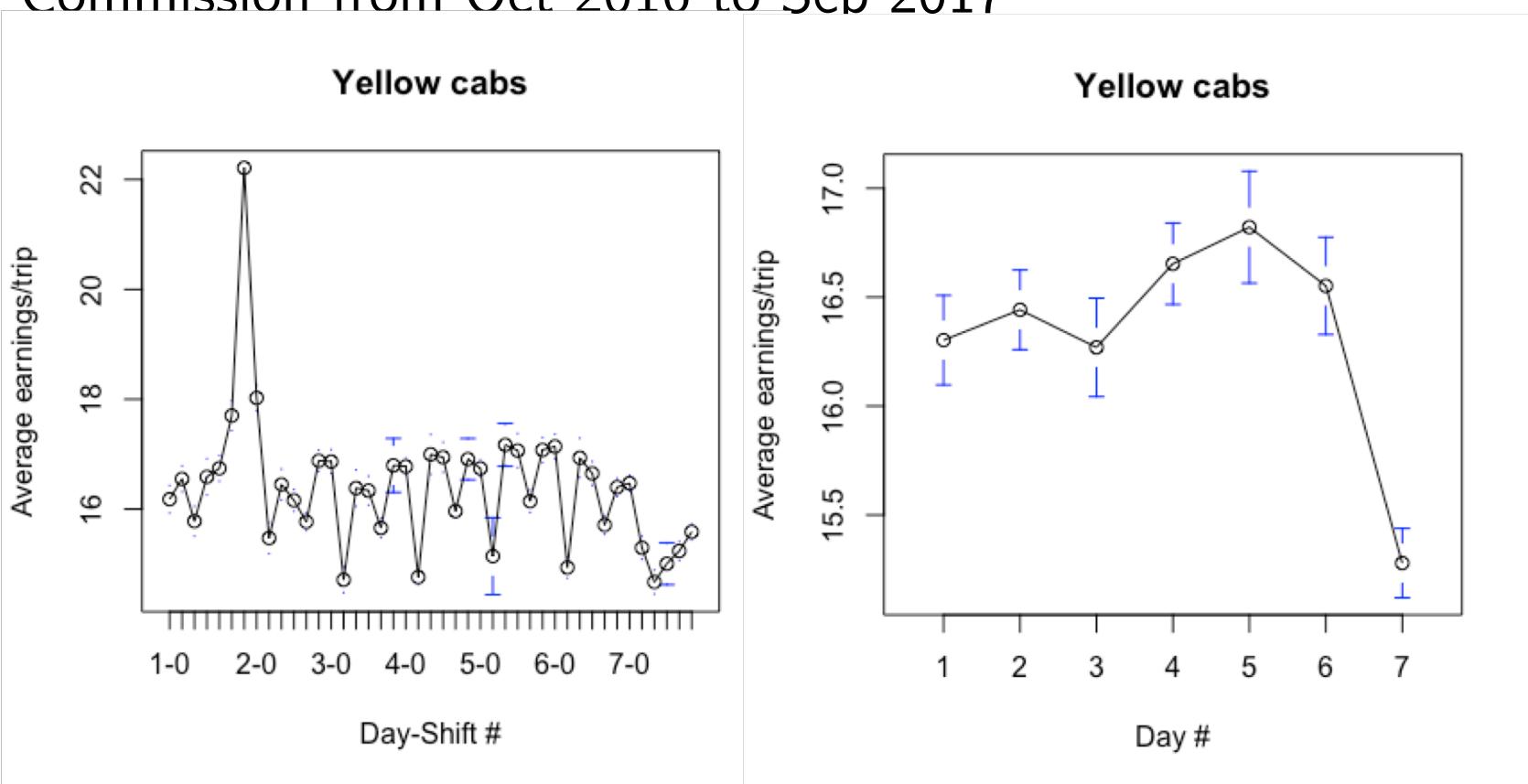
TLC Data

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



TLC Data

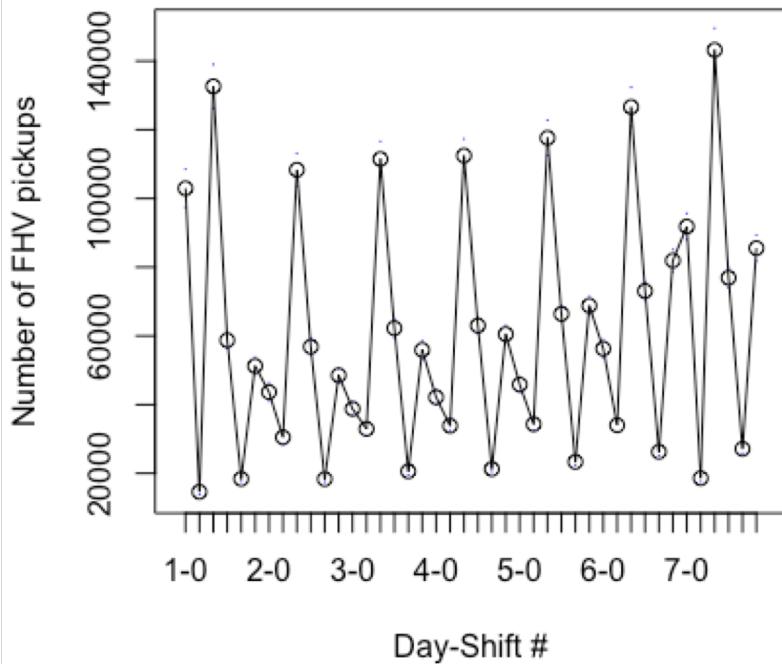
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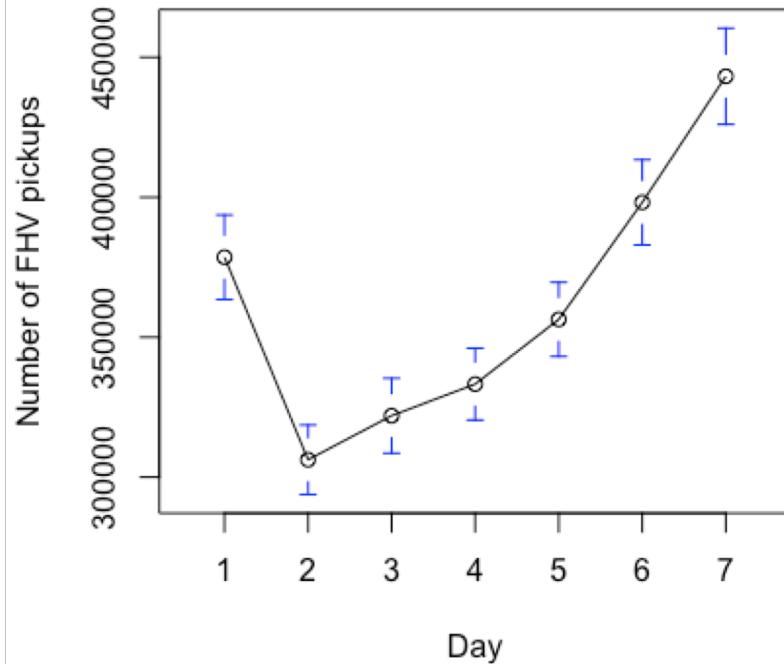
TLC Data

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

Ride-hailing platforms

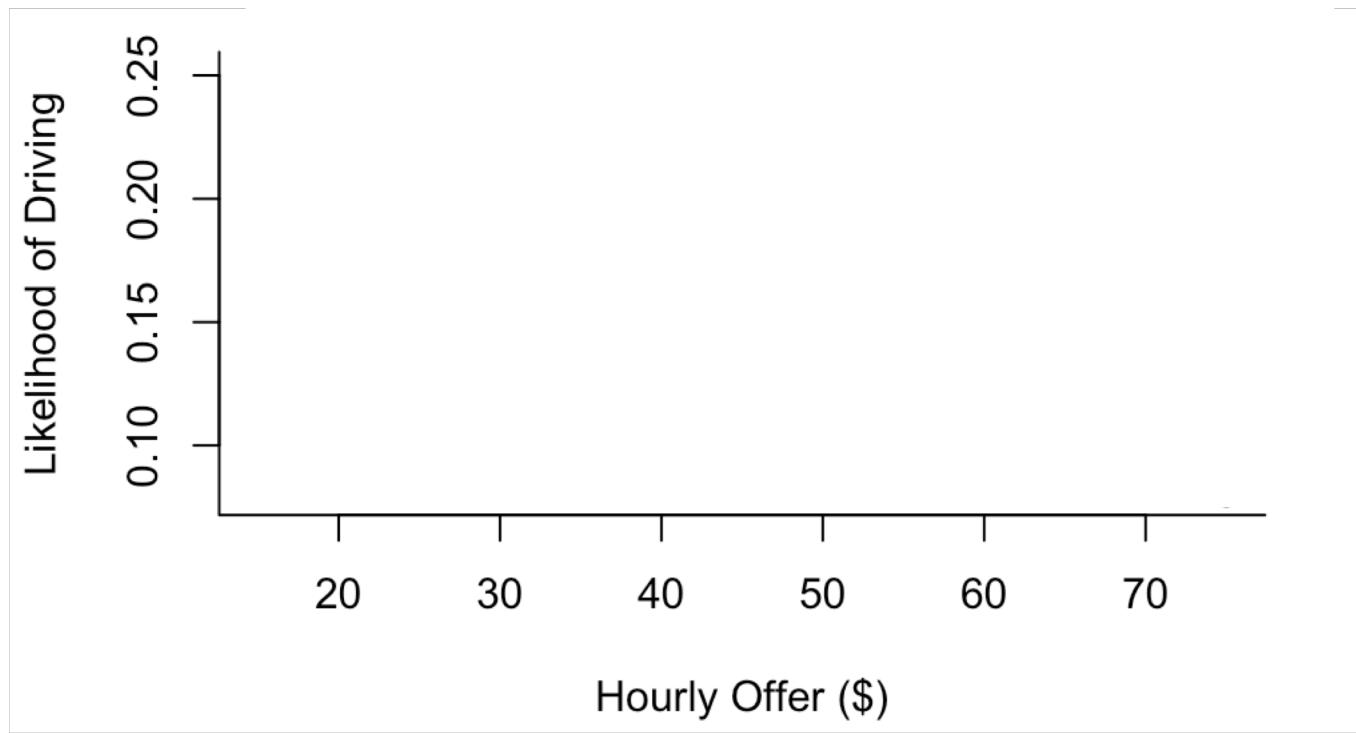


Ride-hailing platforms

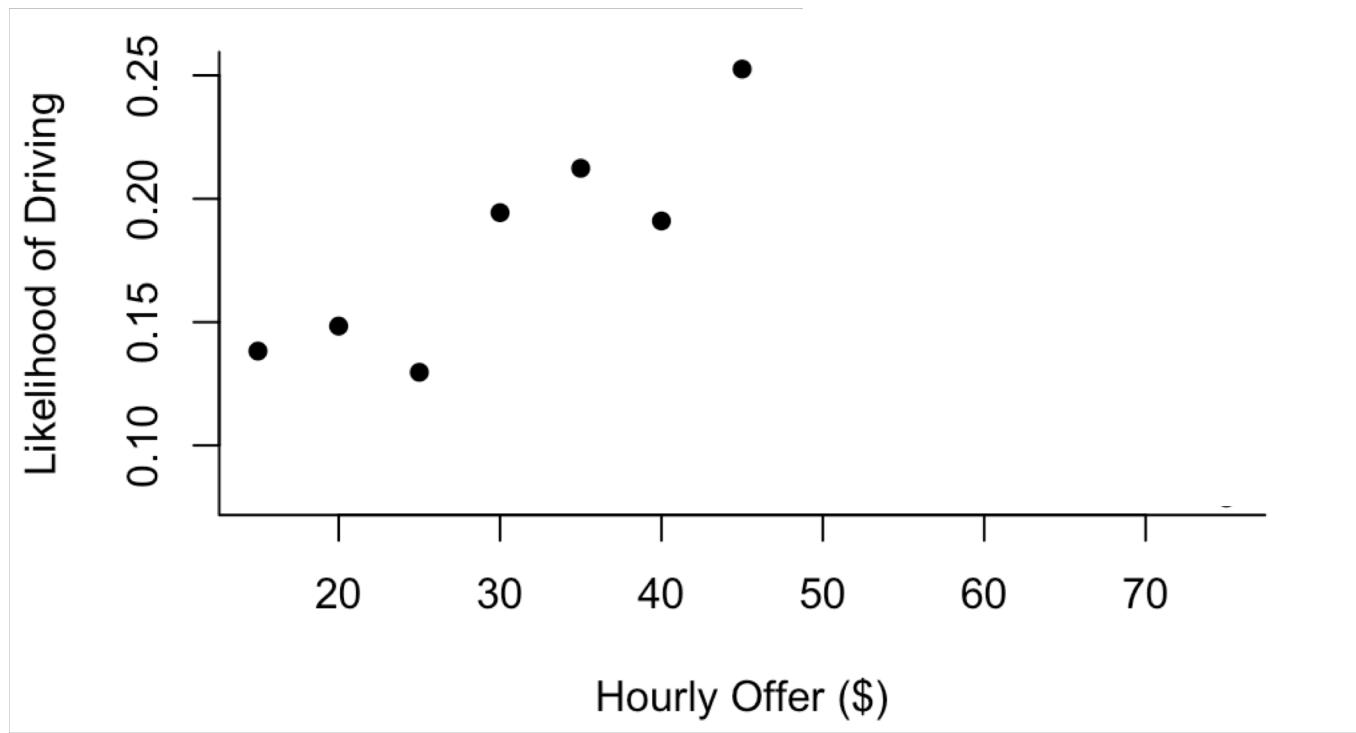


Empirical Strategy Challenges

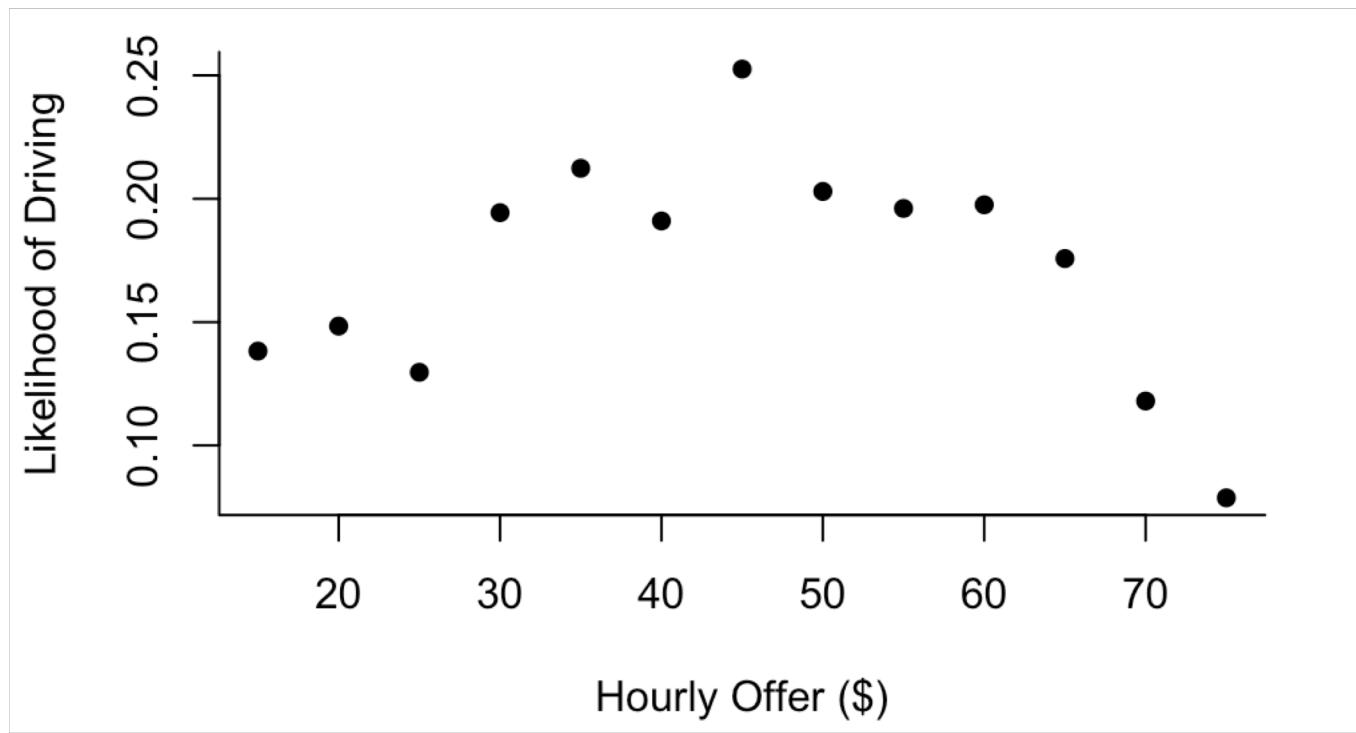
Empirical Strategy Challenges



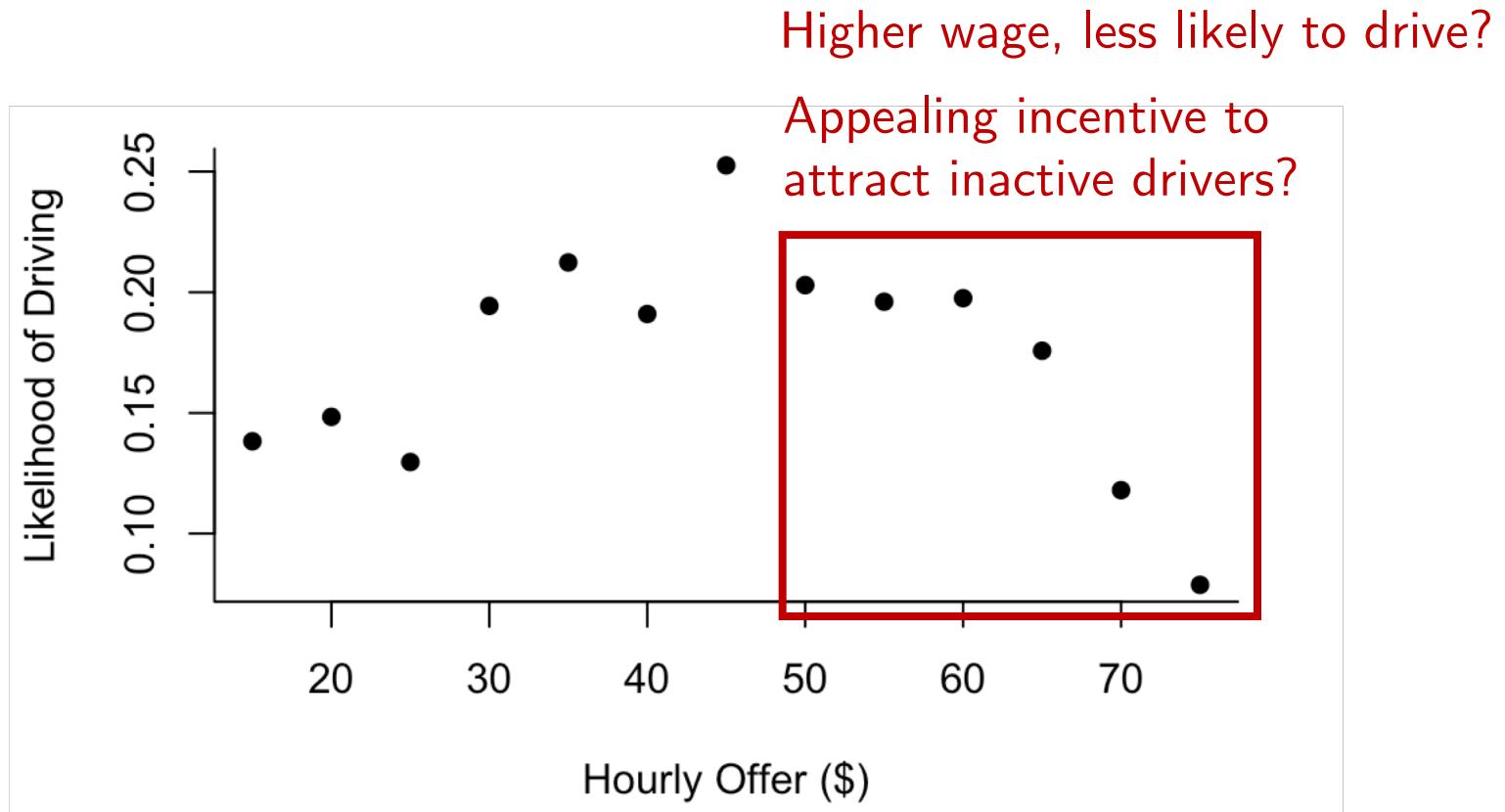
Empirical Strategy Challenges



Empirical Strategy Challenges



Empirical Strategy Challenges

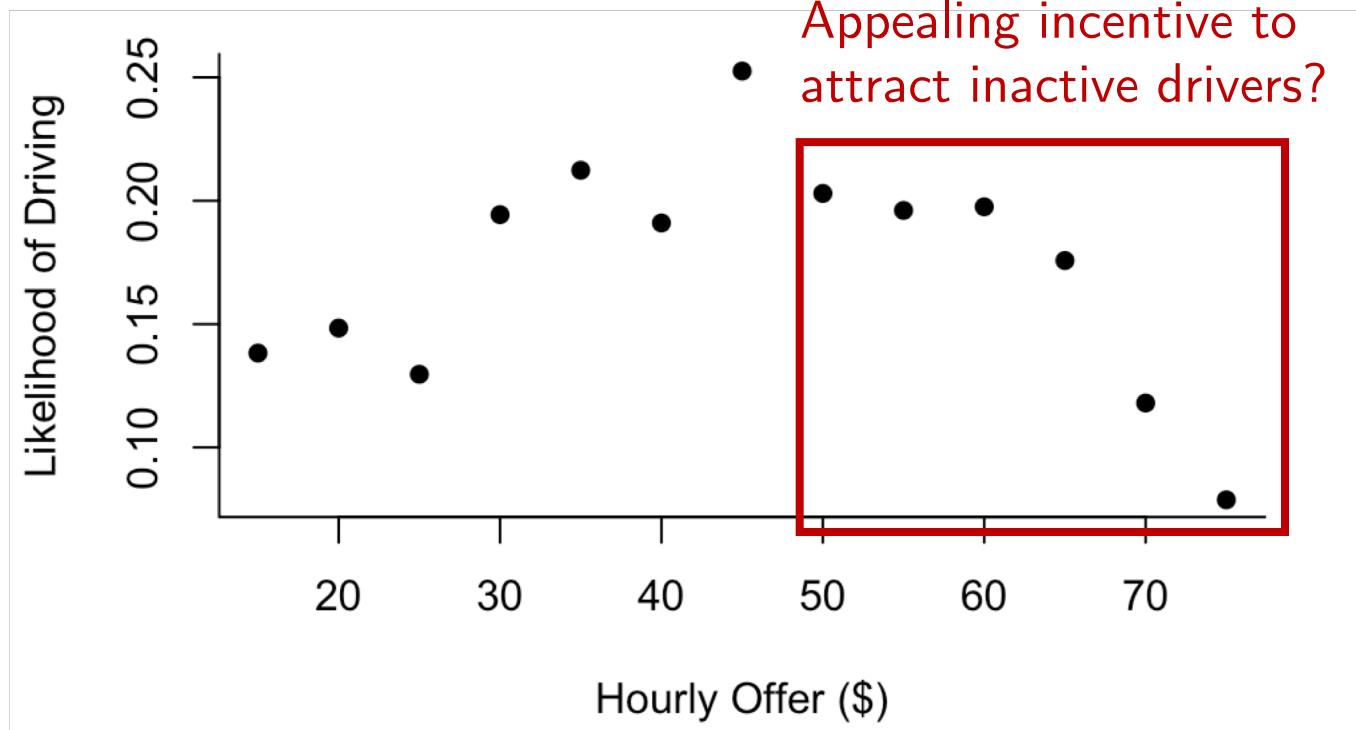


Empirical Strategy Challenges

Simultaneity

Higher wage, less likely to drive?

Appealing incentive to attract inactive drivers?



Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Offer:

- Average of other drivers' offers (Hausman 1996, Sheldon 2016, Xu et al 2017)

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Offer:

- Average of other drivers' offers (Hausman 1996, Sheldon 2016, Xu et al 2017)
 - Mutual offer/earning rate in NYC at particular time
 - Promotions decided ahead of time
 - Controlling for weather and market condition
 - This IV won't work for other ride-hailing platforms

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Offer:

- Average of other drivers' offers (Hausman 1996, Sheldon 2016, Xu et al 2017)
- Average offers of drivers of other vehicle types who made the same work decisions as me previous week/previous month

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Offer:

- Average of other drivers' offers (Hausman 1996, Sheldon 2016, Xu et al 2017)
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sedan



non-sedan

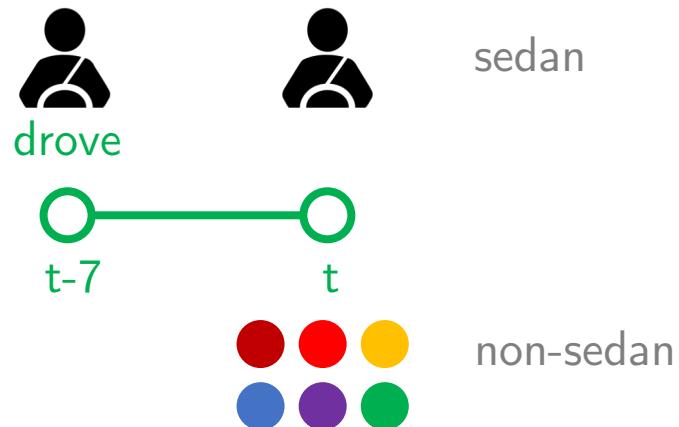
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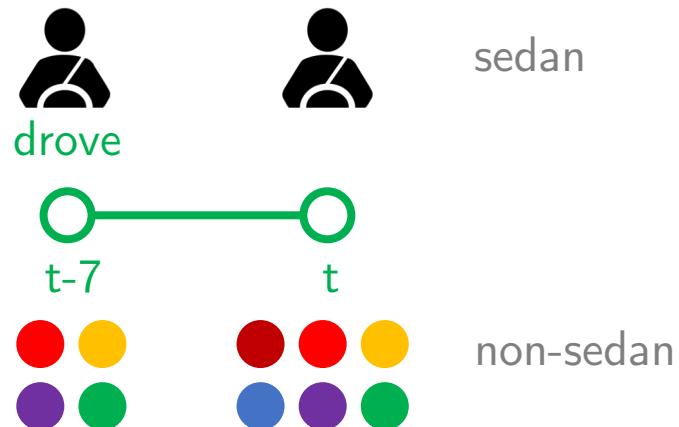
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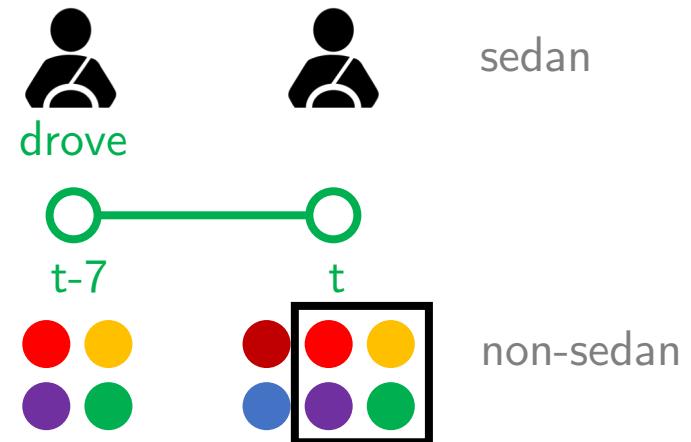
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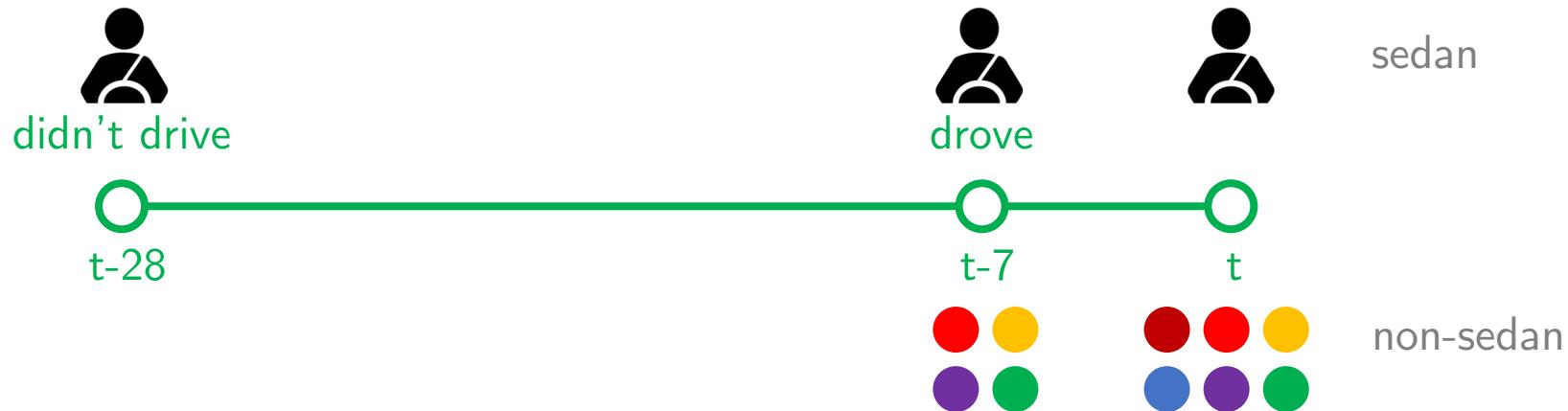
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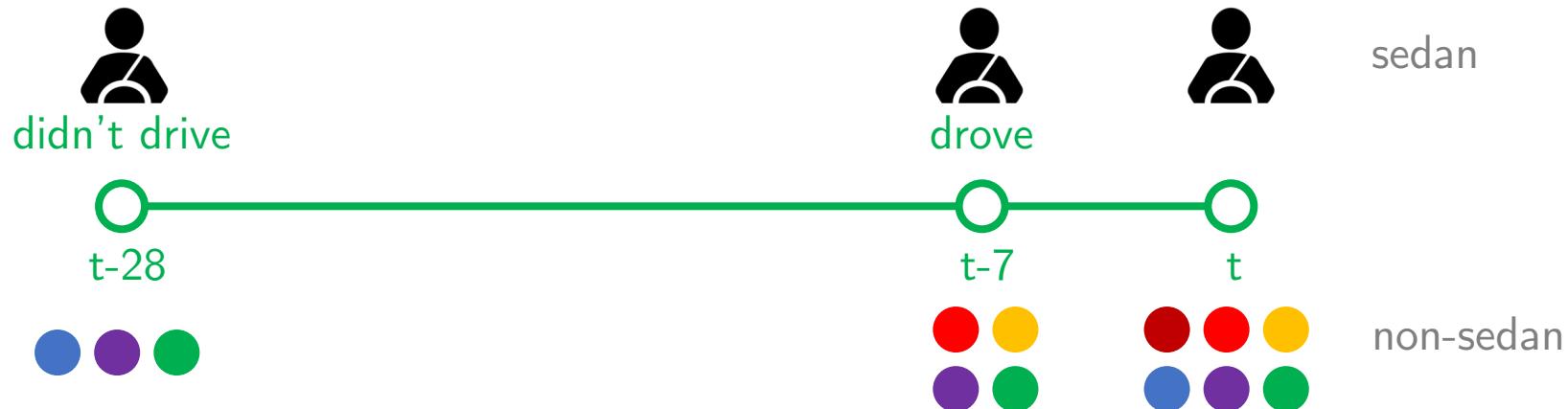
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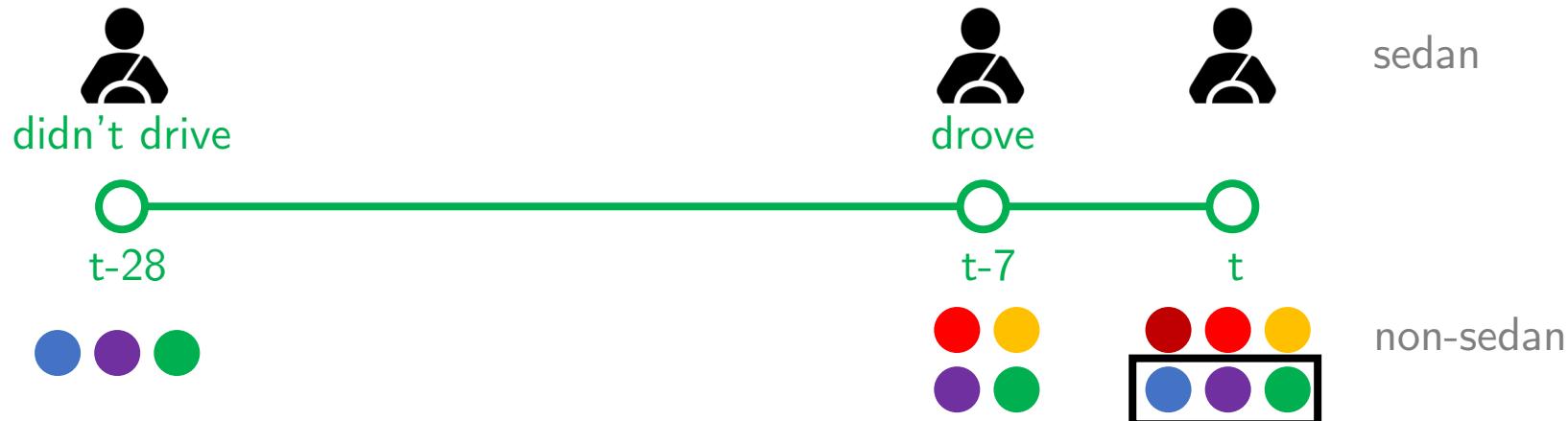
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Simultaneity

Solution: Instrumental Variables

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Empirical Strategy Challenges

Simultaneity

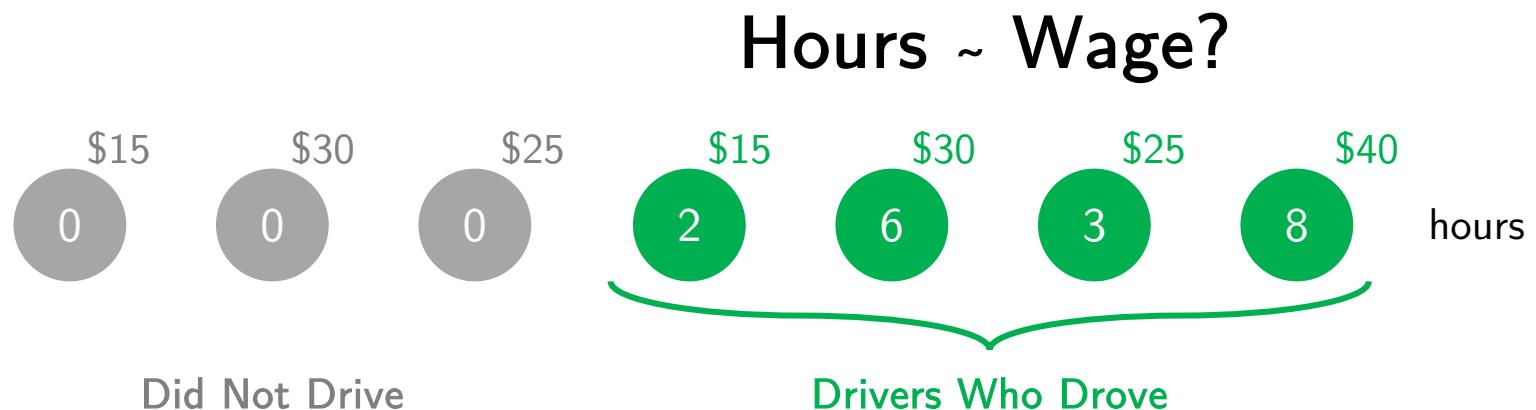
Solution: Instrumental Variables



Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

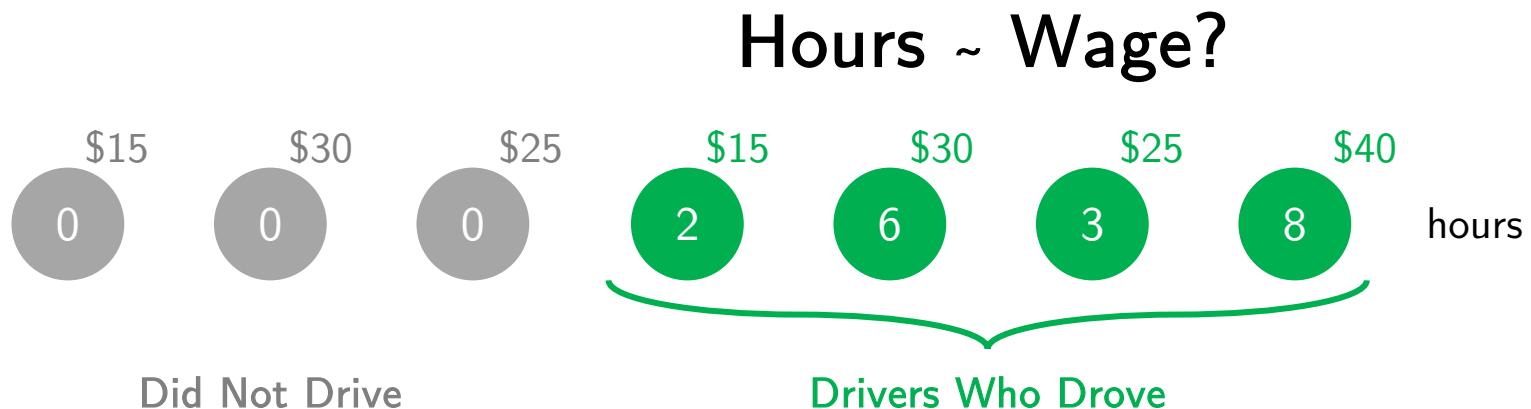


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**

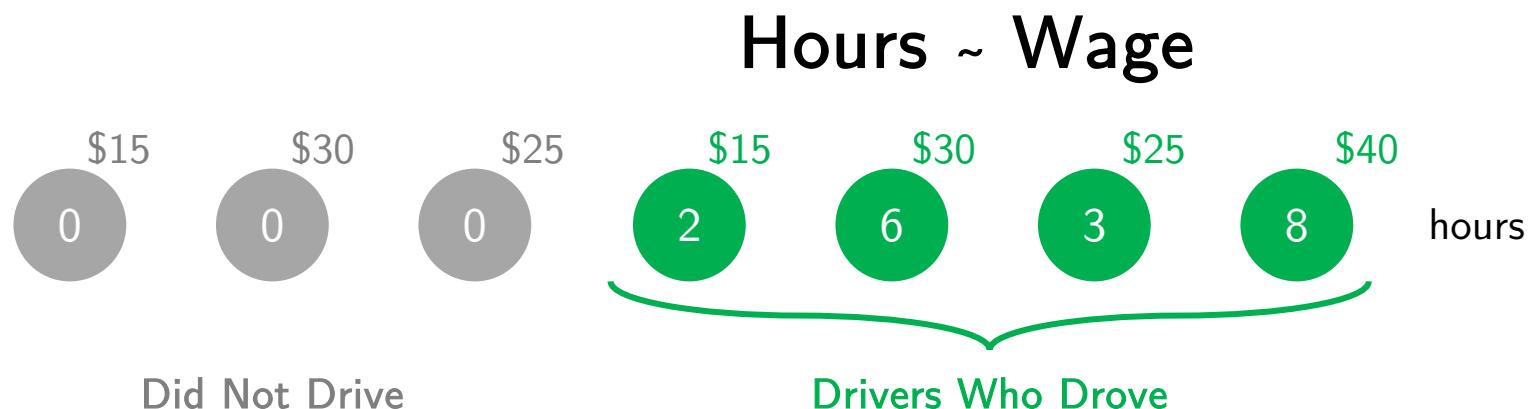


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Selection Bias



Empirical Strategy Challenges

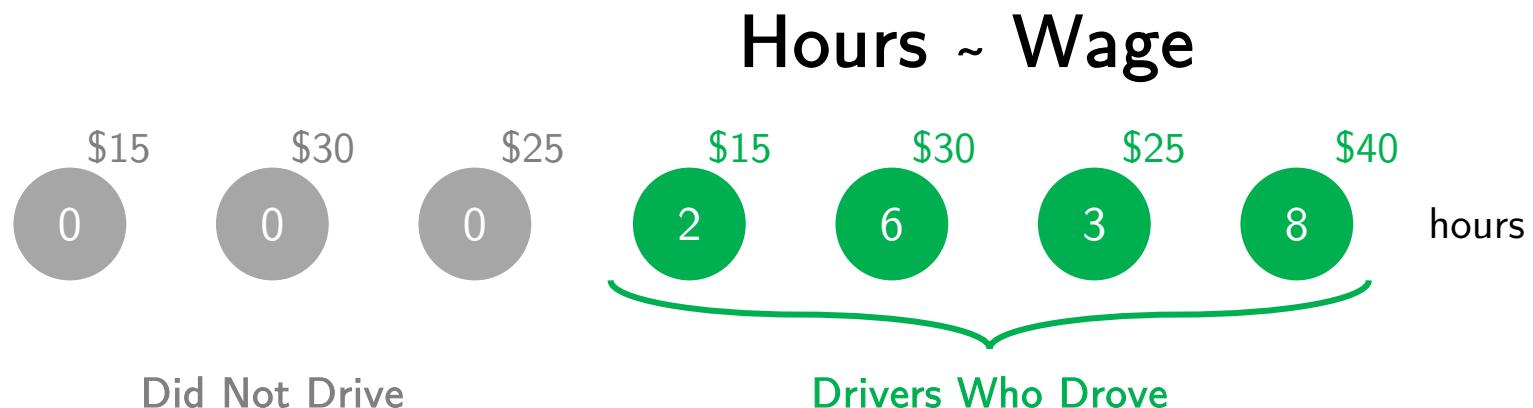
Simultaneity

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

Demand {
Short-term Habits {
Long-term Habits {

Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

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

+ Controls₁



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:

$P(\text{drive}) \text{ on } \textit{Offer} + \text{ISF}$ + Controls₁

|
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:

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

|
Income So Far
= intensity of work

|
Hours So Far
= amount of active time

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

Empirical Strategy

Heckman + IV

1 Work or not?

Control Function Probit:

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

Income So Far
= intensity of work

Hours So Far
= amount of active time

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:

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

Income So Far
= intensity of work

Hours So Far
= amount of active time

Conditional
on working

2 How long to work?

2SLS with Fixed Effects

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

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 $P(\text{drive})$

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

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?

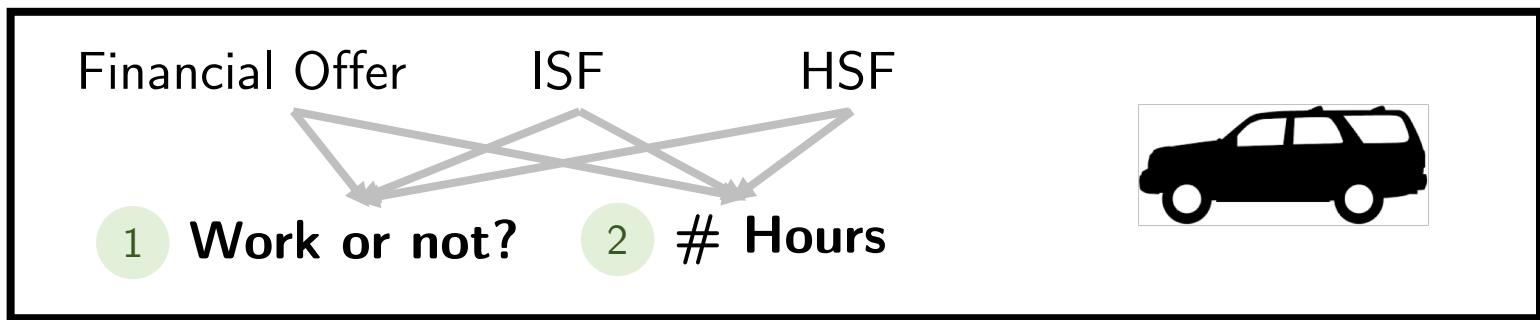
IV: Estimate hourly earning from IVs

OLS: Estimate hours

$$f(\text{Hour}_{i,t}) = \beta_{0,i} + \beta_w w_{i,t} + \boldsymbol{\beta} \mathbf{Z}_{i,t} + \theta \lambda_{i,t} + u_{i,t}$$

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

Results



Within-Day

Midday



Late Night

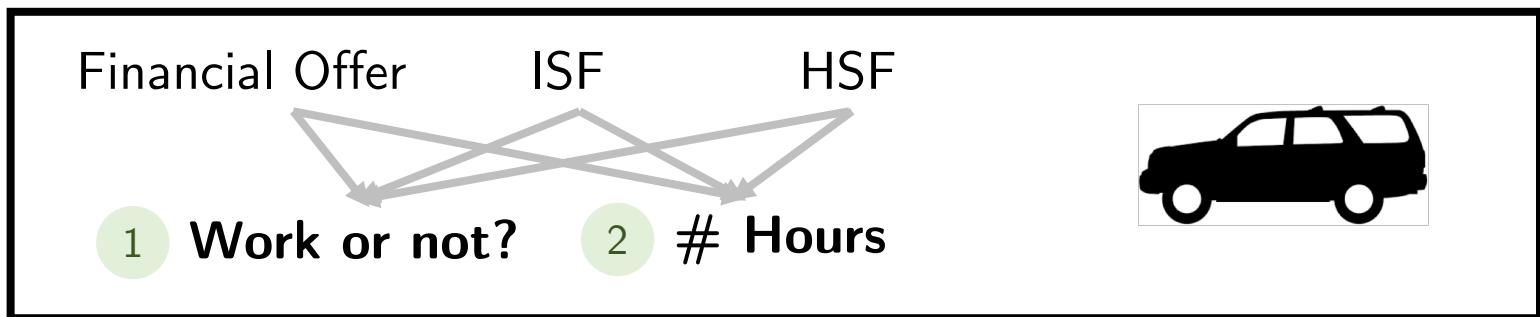
Across-Days

Tuesday



Sunday

Results



Within-Day

Midday



Late Night

Across-Days

Tuesday



Sunday

+ -

Positive Negative

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

N = 166,766

The more you've earned,
the less likely you're going to
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		
AIC	95,856.010	72,887.620

N = 166,766

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.

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)
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

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?



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	+	-	+	+	-	+

Results Within Day

1

Work or not?

Offer

Midday	+
PM peak	+
PM off	+
Late night	+

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

Results Within Day

1

Work or not?

	Offer	ISF
Midday	+	+
PM peak	+	-
PM off	+	-
Late night	+	-

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?

	Offer	ISF	HSF
Midday	+	+	+
PM peak	+	-	+
PM off	+	-	+
Late night	+	-	+

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			2		
	Work or not?			# Hours		
	Offer	ISF	HSF	Earning	ISF	HSF
Midday	+	+	+	-	+	+
PM peak	+	-	+	+	-	+
PM off	+	-	+	+	-	+
Late night	+	-	+	+	-	+

Income Inertia Income Inertia

Target Target

The negative impact of income target kicks in later in the day for both stages.

Results Within Day

Mean	IV-F	Work or not?			# Hours			IV-F
		Offer	ISF	HSF	Earning	ISF	HSF	
0.345	384.9	+	+	+	-	+	+	187.6
0.277	359.4	+	-	+	+	-	+	61.08
0.179	326.6	+	-	+	+	-	+	51.05
0.114	386.7	+	-	+	+	-	+	39.14

Income Inertia Income Inertia

Target Target

1 2

Results Across Days

	1 Work or not?			2 # Hours		
	Offer	ISF	HSF	Earning	ISF	HSF
Tuesday	+	+	-	+	+	+
Wednesday	+	+	+	+	-	+
Thursday	+	-	+	-	+	+
Friday	+	+	+	+	-	+
Saturday	+	-	+	+	-	+
Sunday	+	-	+	+	-	+

Income Target Inertia Income Target Inertia

The results are consistent across days as well.

Results Across Days

1			2						
Work or not?			# Hours						
Mean	IV-F	Offer	ISF	HSF	Earning	ISF	HSF	Mean	IV-F
0.420	43.58	+	+	-	+	+	+	5.240	22.01
0.430	54.78	+	+	+	+	-	+	5.349	29.14
0.446	67.92	+	-	+	-	+	+	4.444	40.51
0.428	67.02	+	+	+	+	-	+	5.537	37.79
0.204	90.07	+	-	+	+	-	+	5.275	17.89
0.160	75.54	+	-	+	+	-	+	4.750	15.06

Income Target Inertia Income Target Inertia

The results are consistent across days as well.

Results Summary

Neoclassical
Financial Incentive

As day/week proceeds...

encourages working

Results Summary

Neoclassical
Financial Incentive

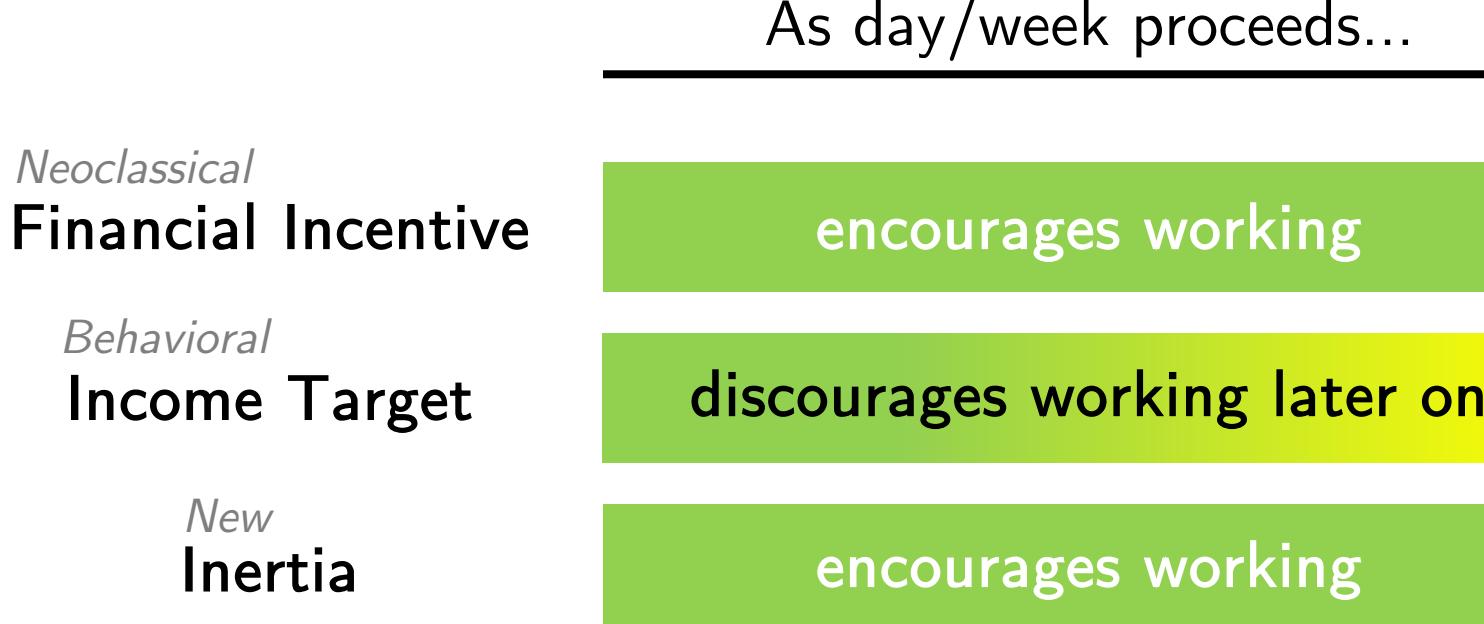
Behavioral
Income Target

As day/week proceeds...

encourages working

discourages working later on

Results Summary



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



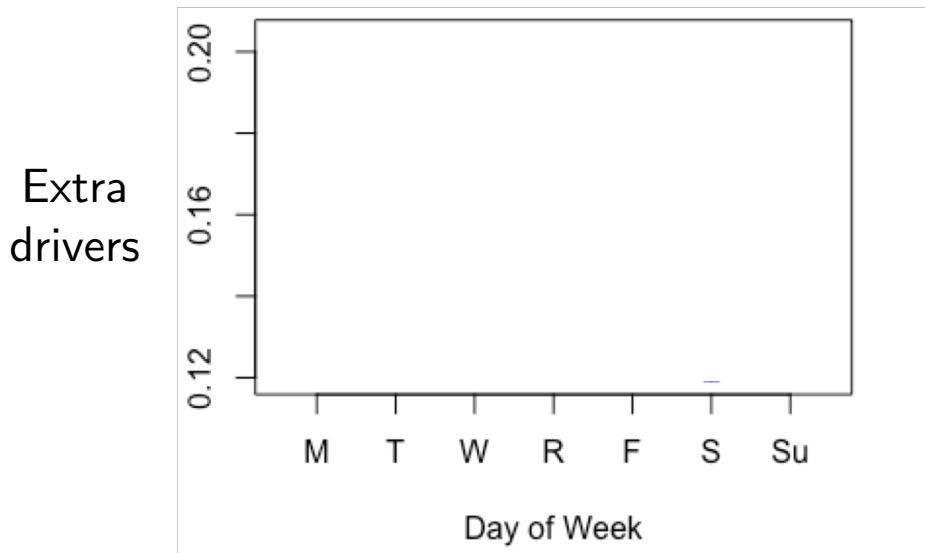
Reallocating Incentives

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

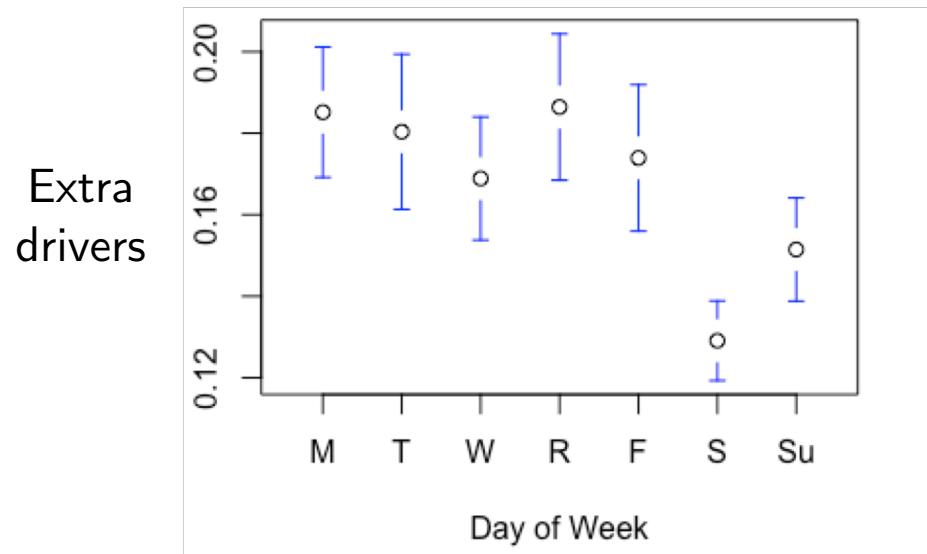
Given the same budget



Reallocating Incentives

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

Given the same budget



Can recruit **17% more drivers**

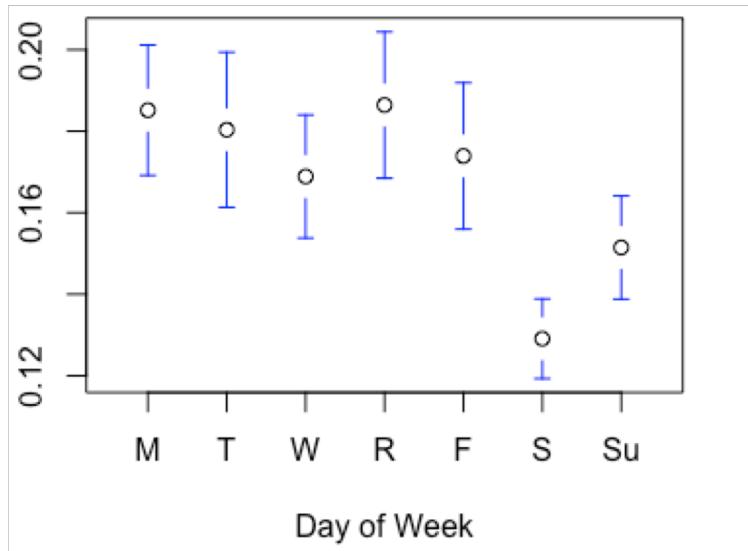
Average promo: 1.61x

Reallocating Incentives

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

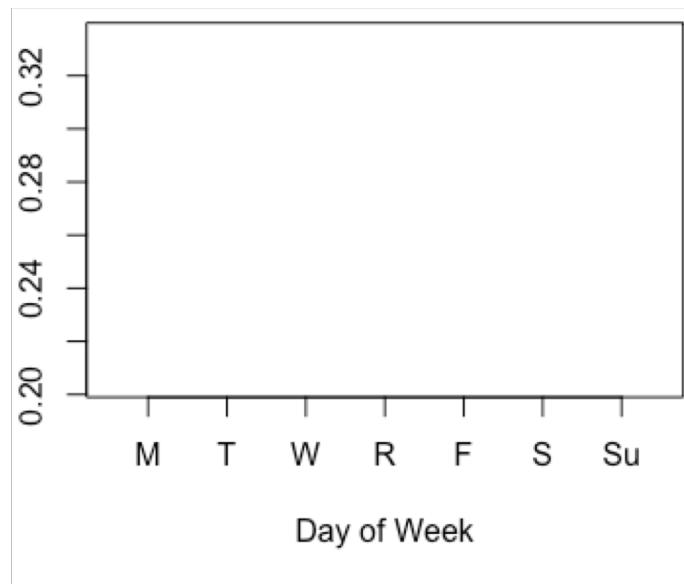
Given the same budget

Extra drivers



Given the same capacity

Cost saved



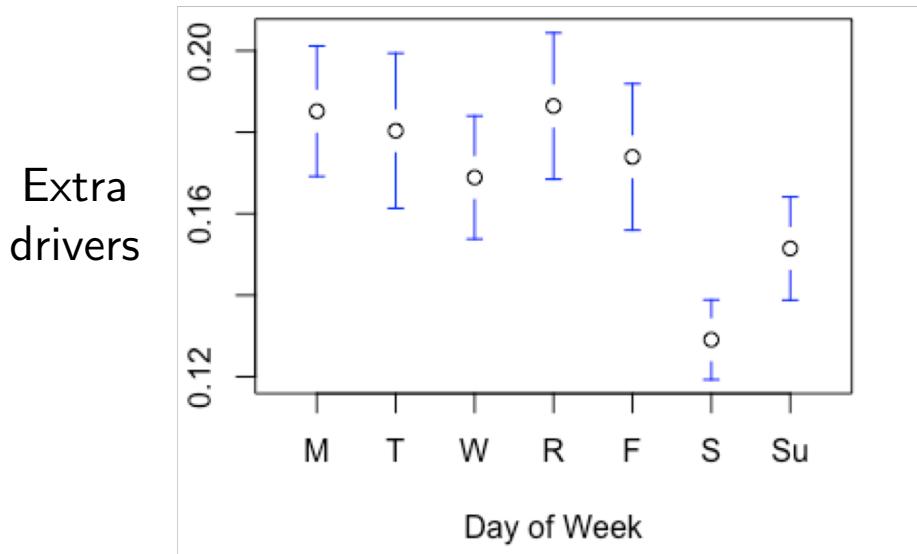
Can recruit **17% more drivers**

Average promo: 1.61x

Reallocating Incentives

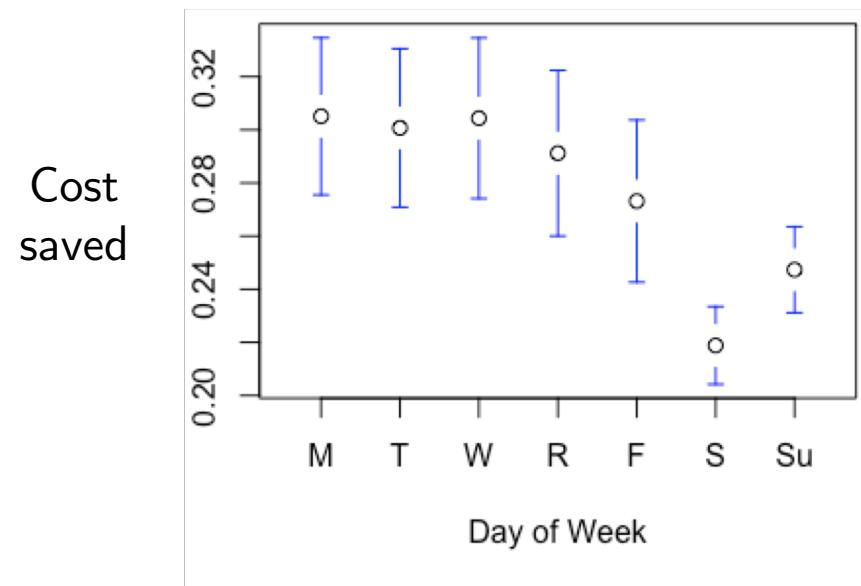
Compared to current practice from Jan to Sep 2017 out-of-sample

Given the same budget



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

Given the same capacity



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

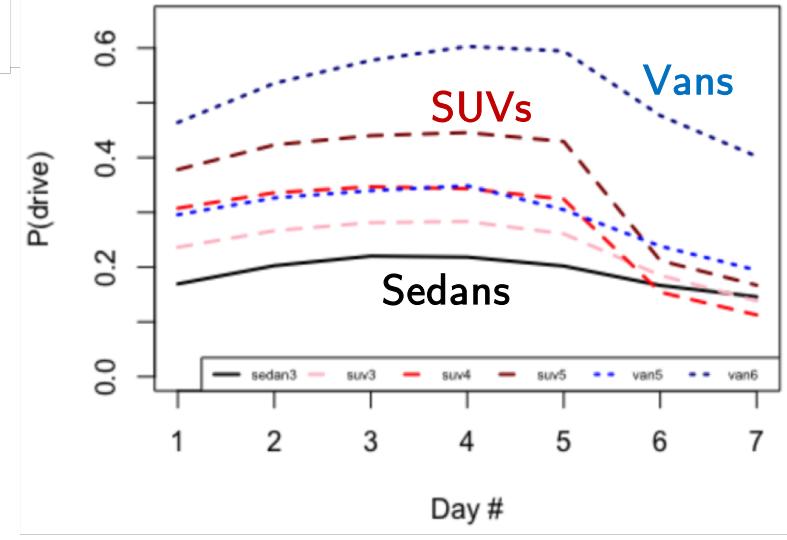
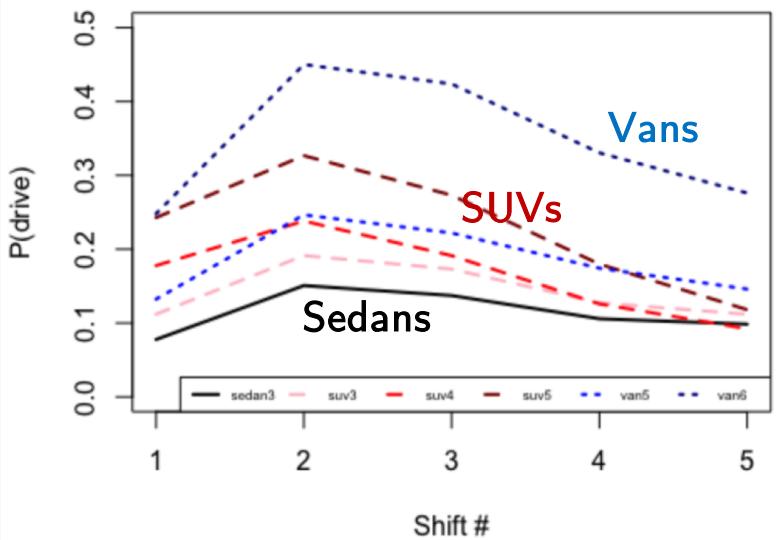
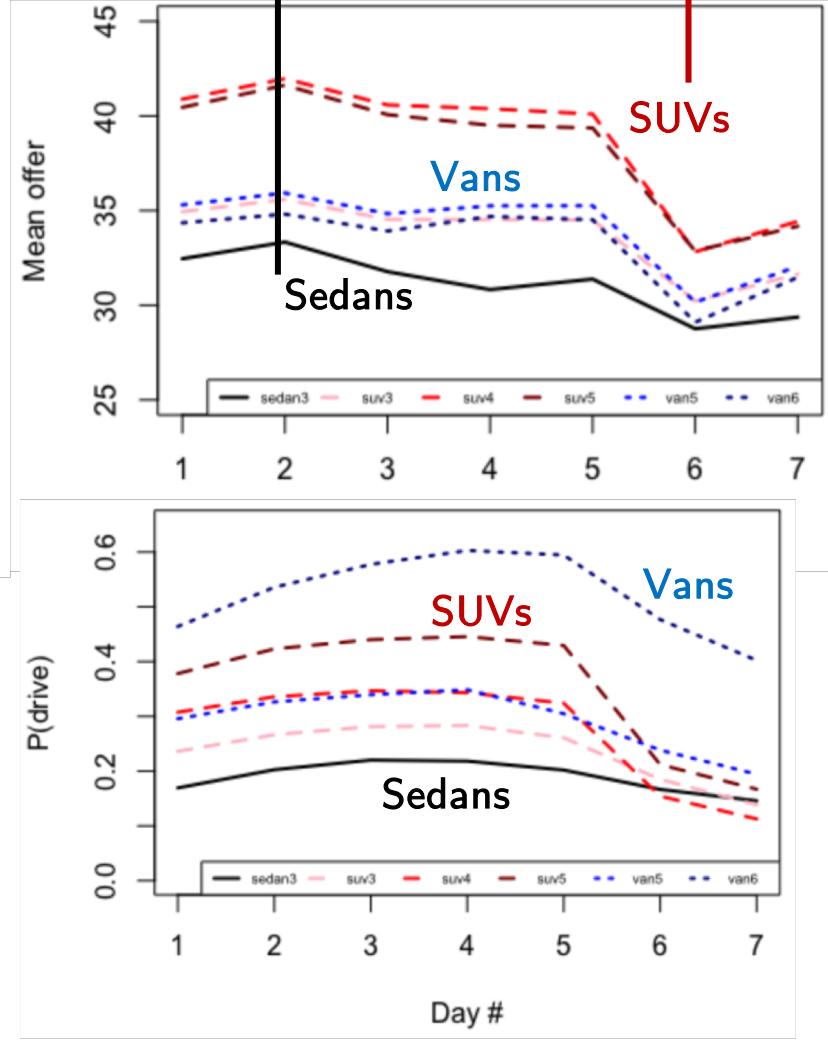
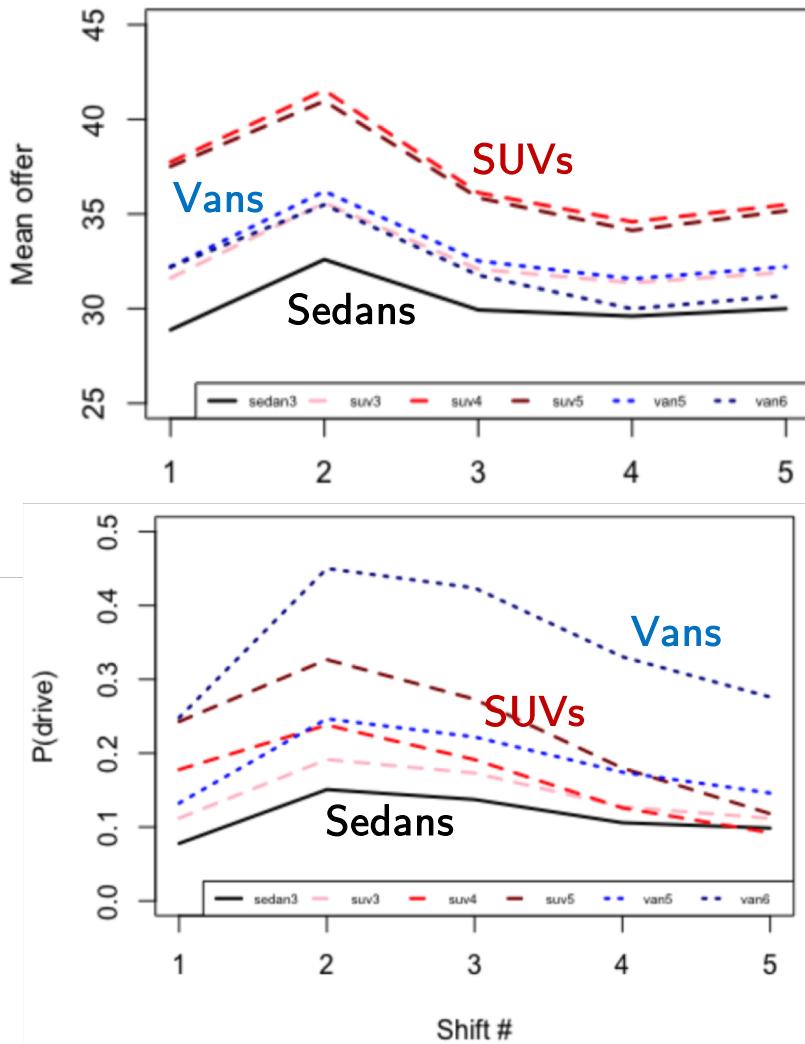
- Compared to current practice, our approach can improve service capacity without incurring extra cost or maintain the same capacity at a lower cost

Appendix

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



Concerns about Heckman

- Multicollinearity of IMR and regressors.
- $R^2 = 0.69$ on average
- Strategically choose two sets of regressors.
- Two part models
- Using FIML instead of Heckman to alleviate the problem with IMR.