



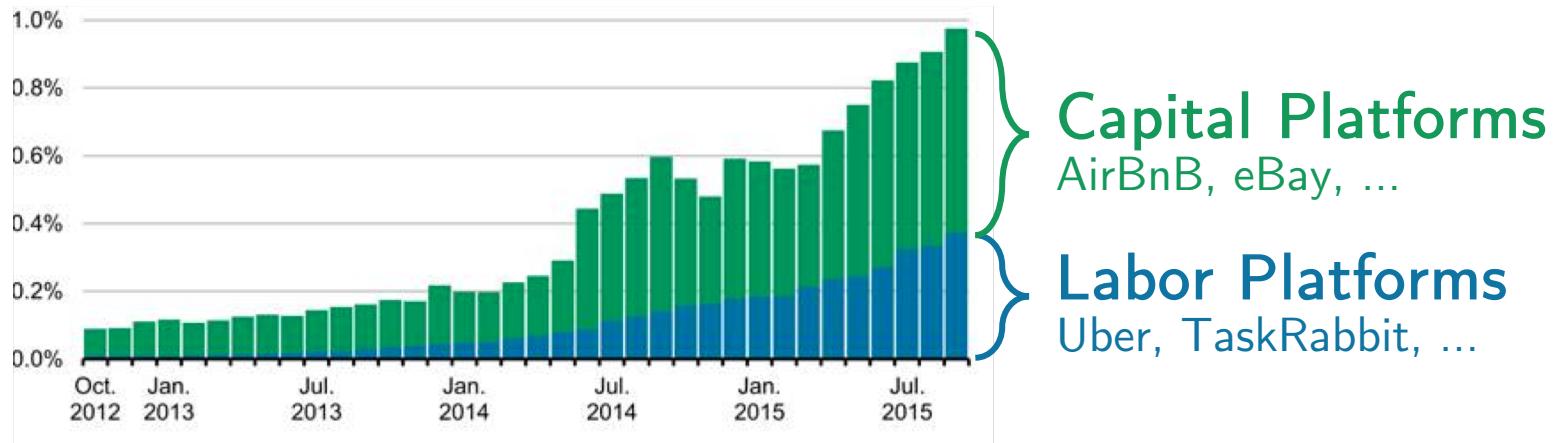
# The Impact of Behavioral and Economic Drivers on Gig Economy Workers

INFORMS 2018



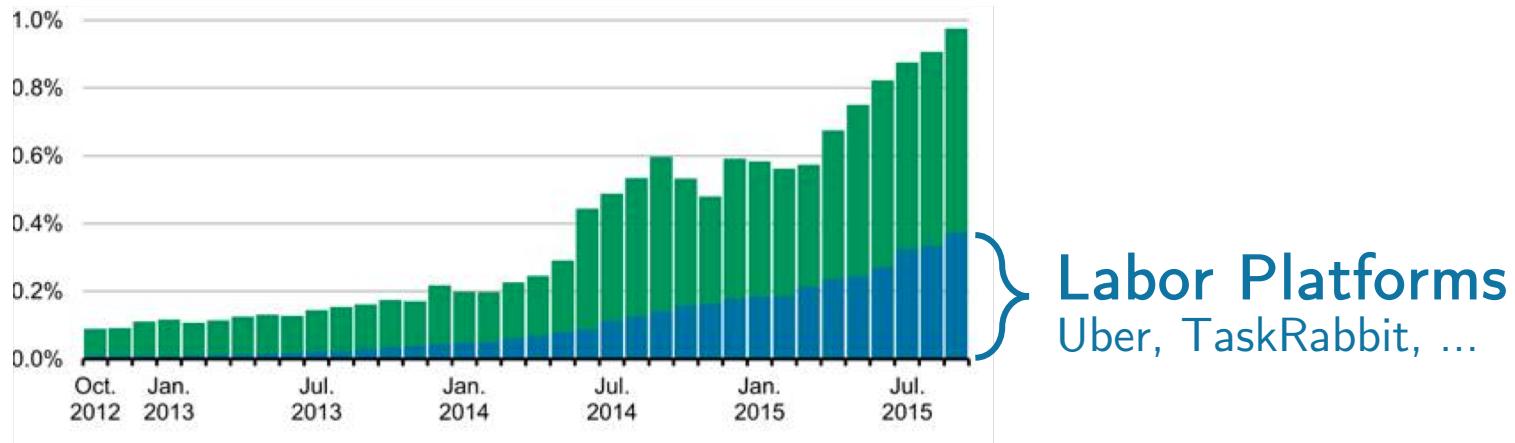
Park Sinchaisri (Wharton)  
Gad Allon (Wharton), Maxime Cohen (NYU)

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



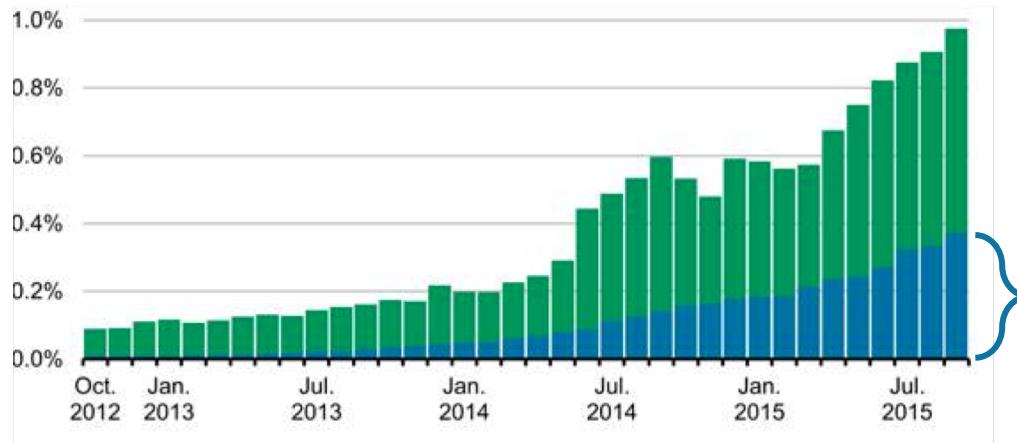
# Gig Economy

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



# Gig Economy

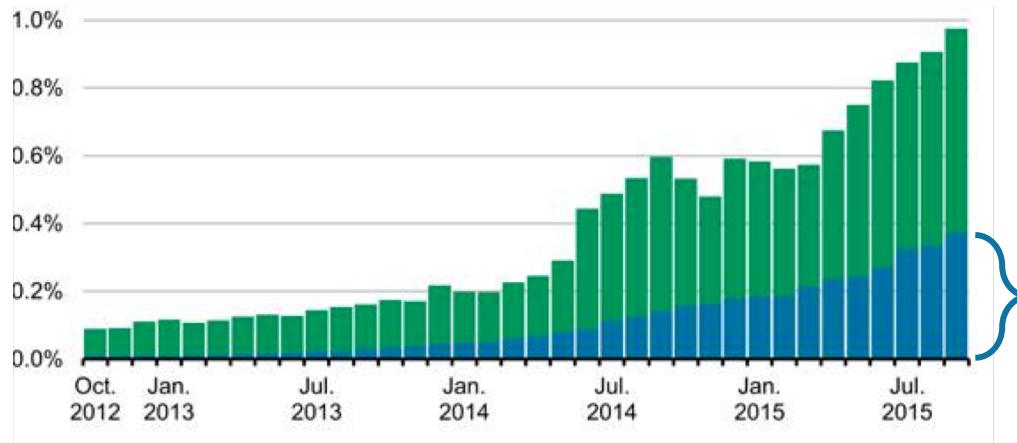
Share of US adults earning income in a given month via online platforms



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?

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**44%** primary income

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when to work?



how long?



which platforms?

# Who are Gig Workers?

**70%** by choice



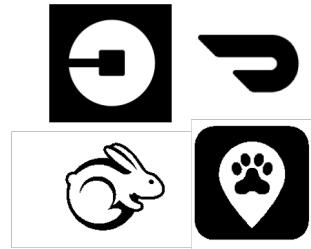
when to work?

**44%** primary income



how long?

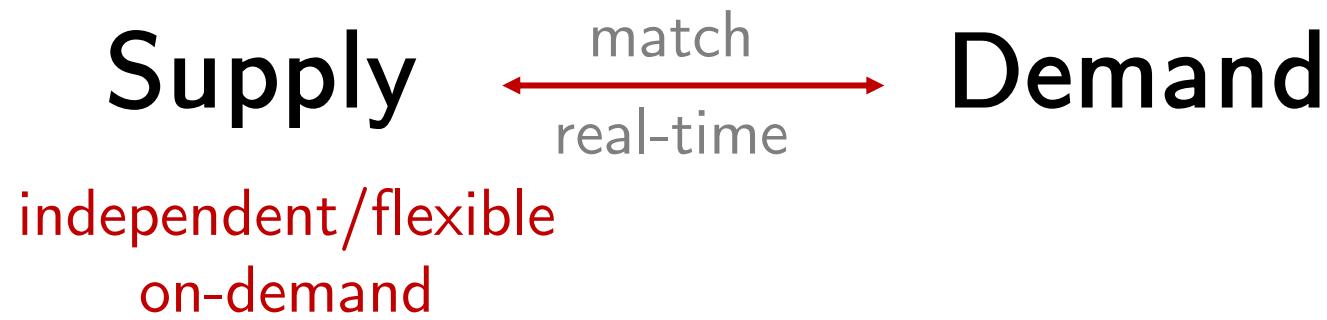
**~50%** millennials



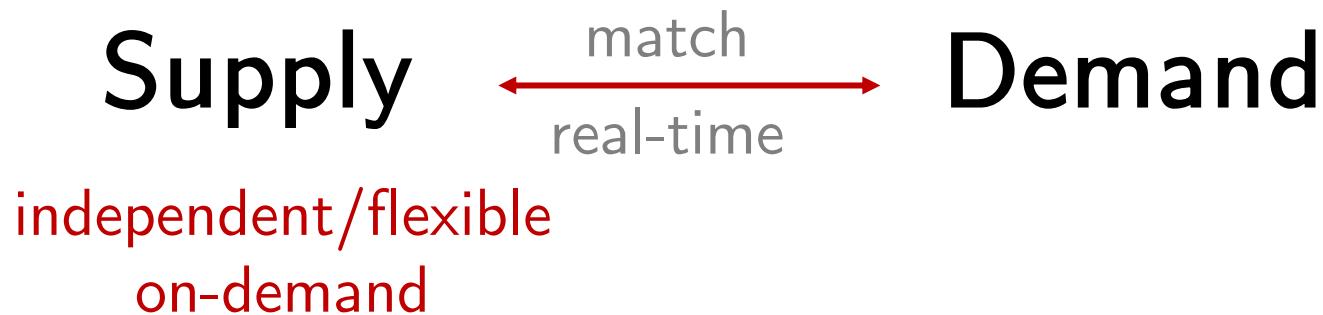
which platforms?

## Workers decide work schedules

# Gig Company



# Gig Company



## Workforce planning is challenging

# Research Questions

How do gig economy workers  
make labor decisions?

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make labor decisions?

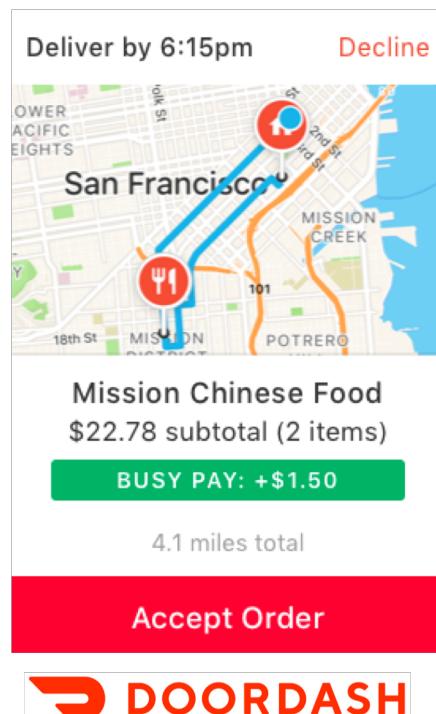
How can the platform influence  
their decisions?

# 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

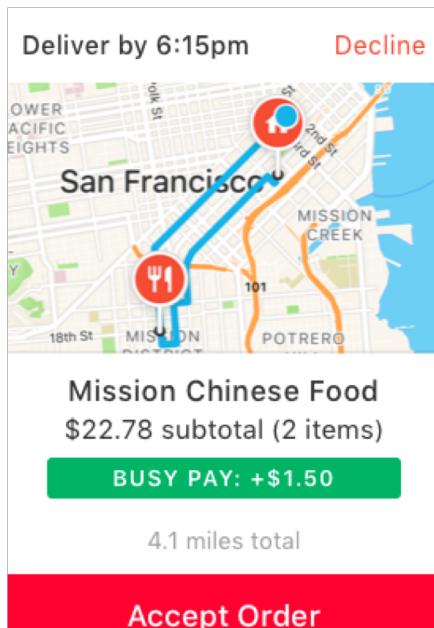
## Real-time “surge pricing”



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

# In Practice

## Real-time “surge pricing”



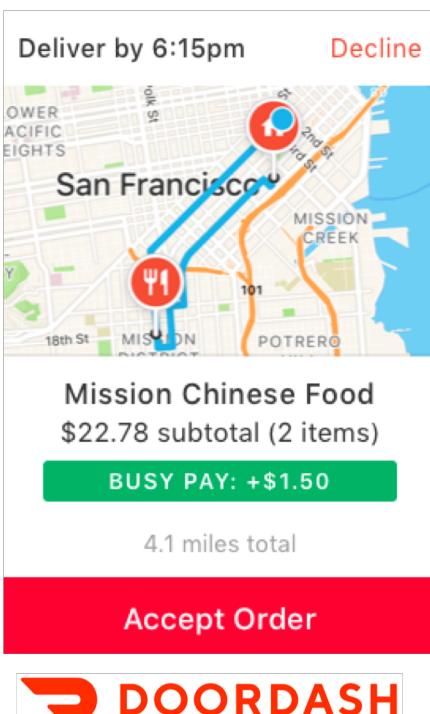
## Pre-announced bonus

	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

# In Practice

## Real-time “surge pricing”



## Pre-announced bonus



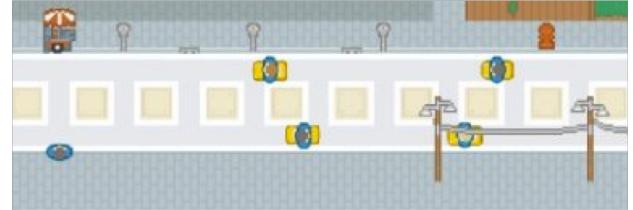
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caviar

## “You’re so close to your precious target”



How Uber Uses  
Psychological Tricks to  
Push Its Drivers' Buttons

# Theories of Labor Supply

## Neoclassical

- Maximize lifetime utility

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- **Positive** income elasticities

Wage ↑  
Work more

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- 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
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Carrington (1996) ○

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Wage ↑  
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Sheldon (2016) ○○

## Behavioral

- Reference-dependence, targets

# Theories of Labor Supply

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- **Positive** income elasticities

Carrington (1996)

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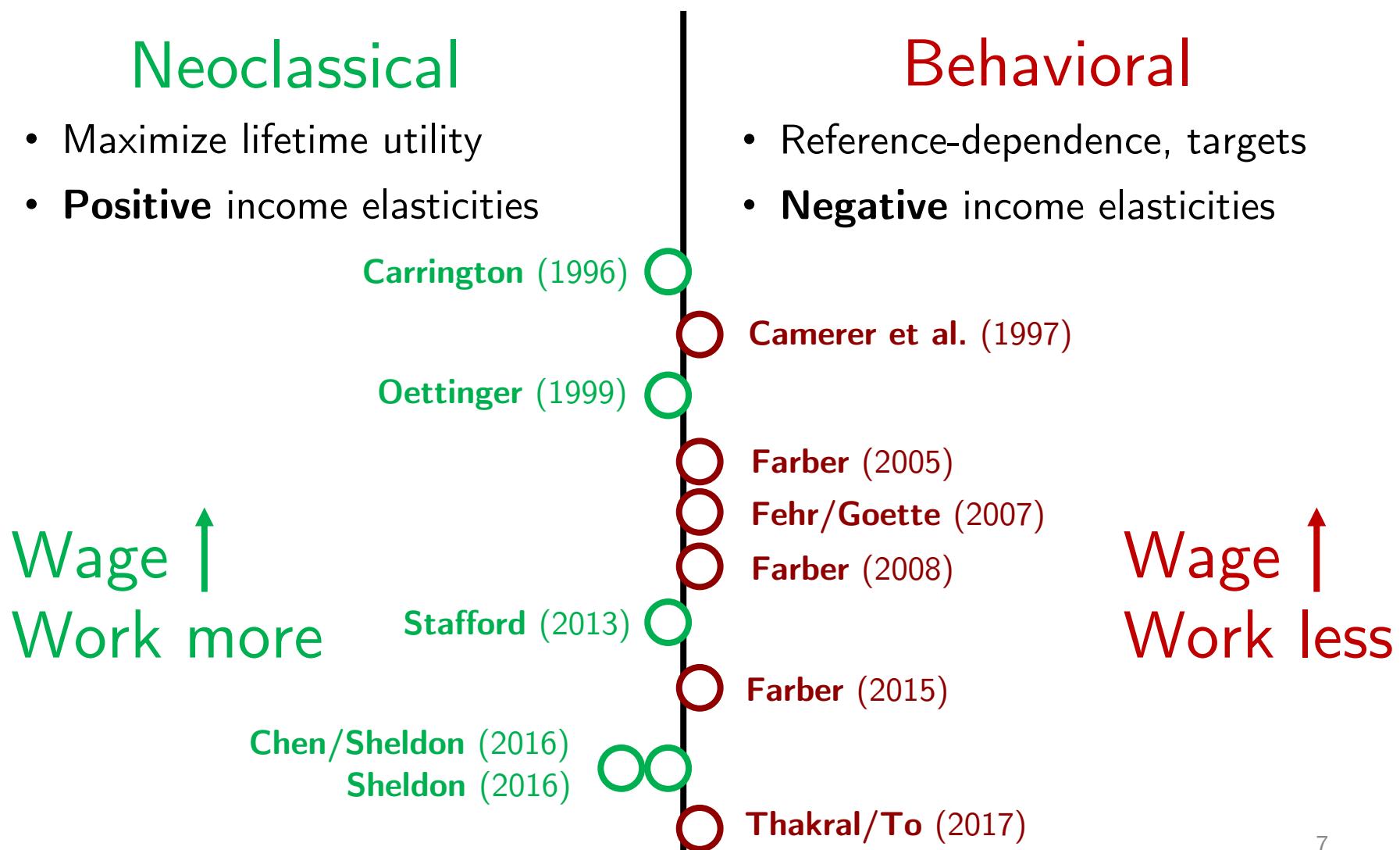
Chen/Sheldon (2016)  
Sheldon (2016)

## 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

# Data

## US ride-hailing firm

Drivers are guaranteed an hourly base rate.

# Data

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Drivers are guaranteed an hourly base rate.



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

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## US ride-hailing firm

Drivers are guaranteed an hourly base rate.



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

**5.5M**

Observations

**358**

Days

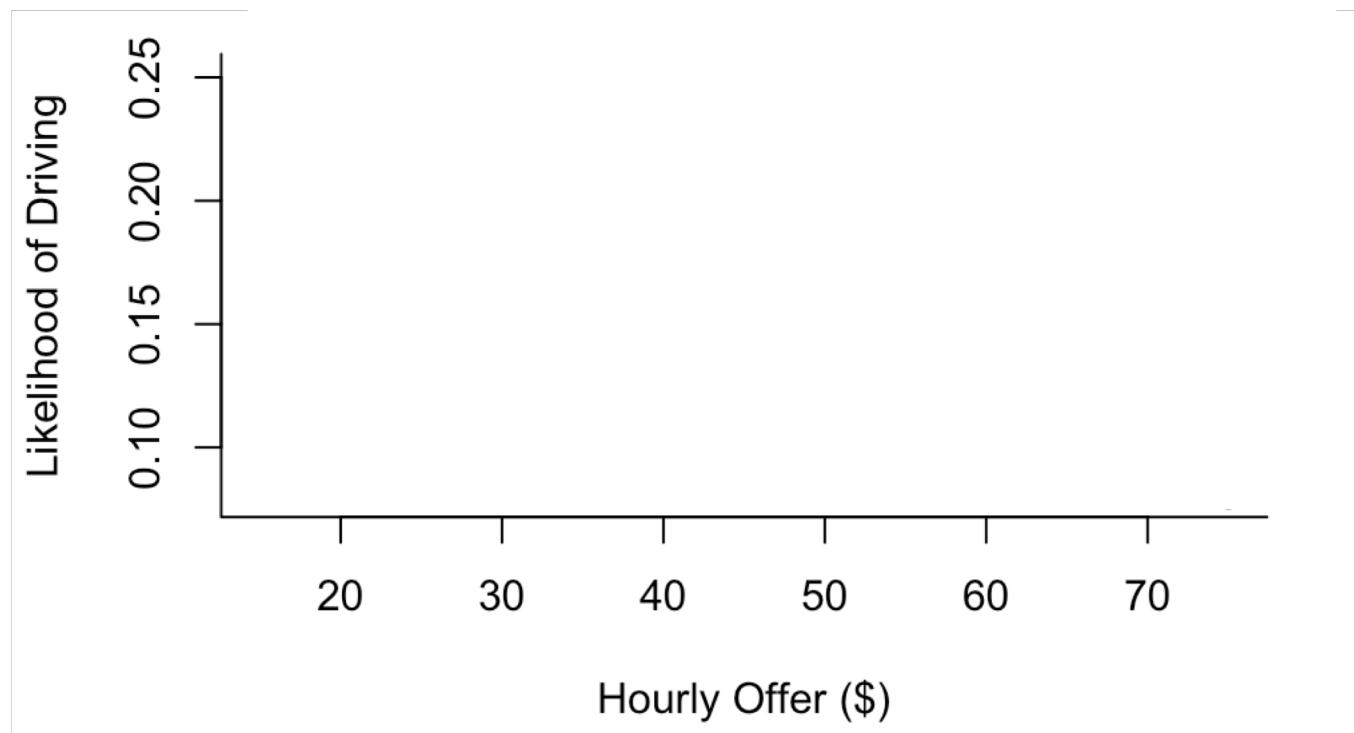
*Oct 2016 – Sep 2017*

**7,826**

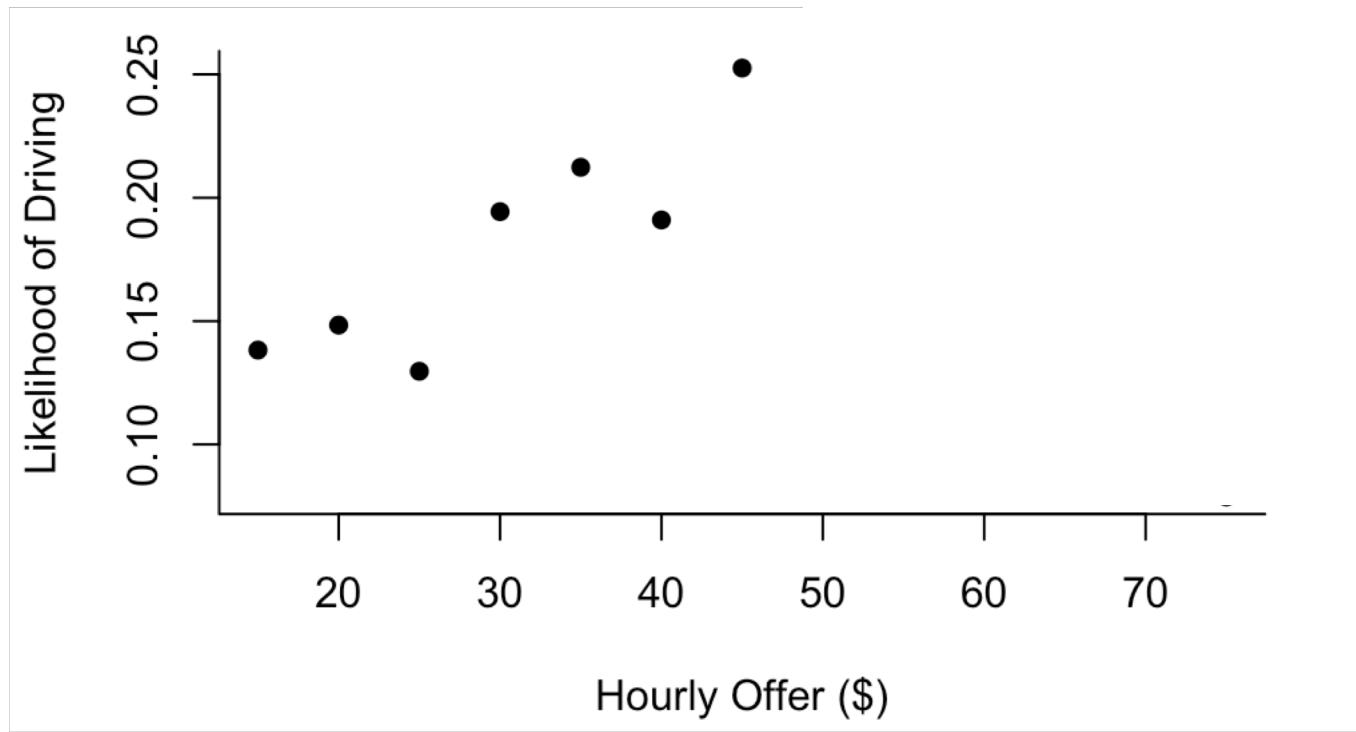
Unique drivers

SUV/Sedan/Van

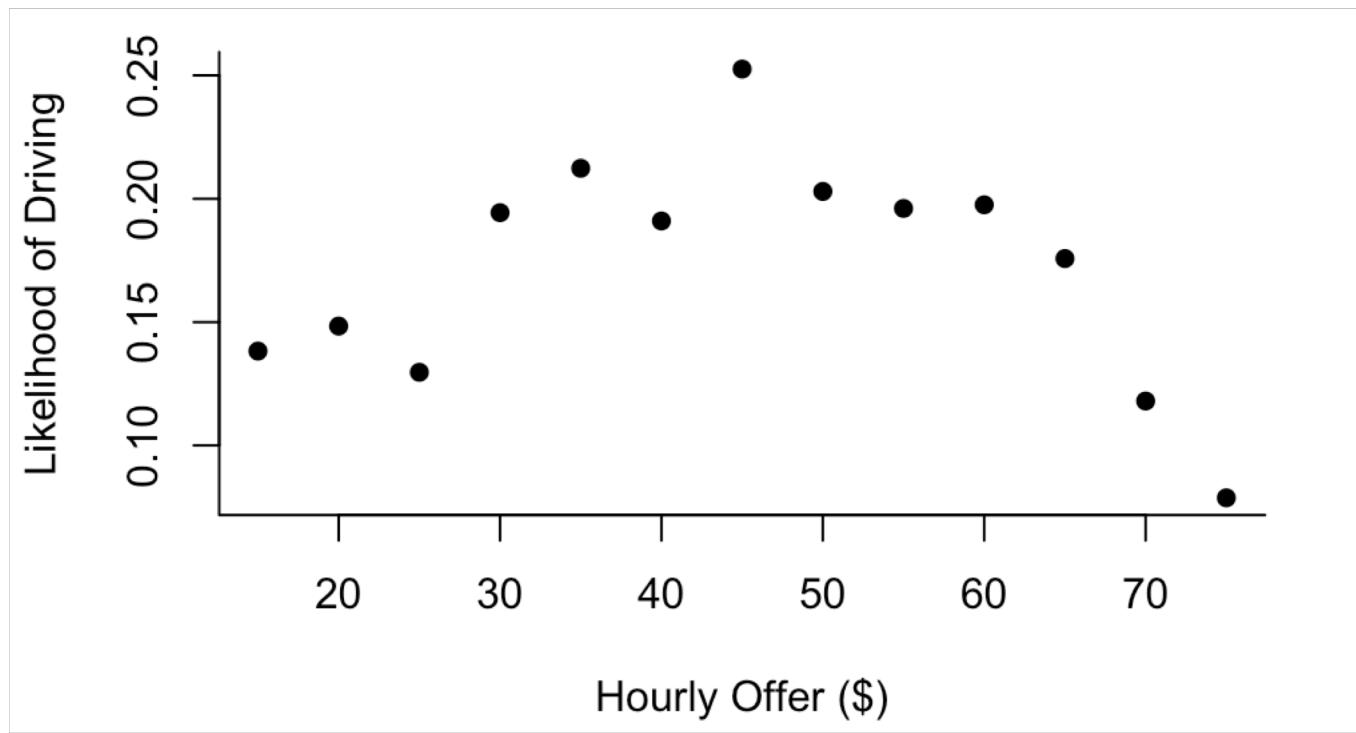
# Empirical Strategy Challenges



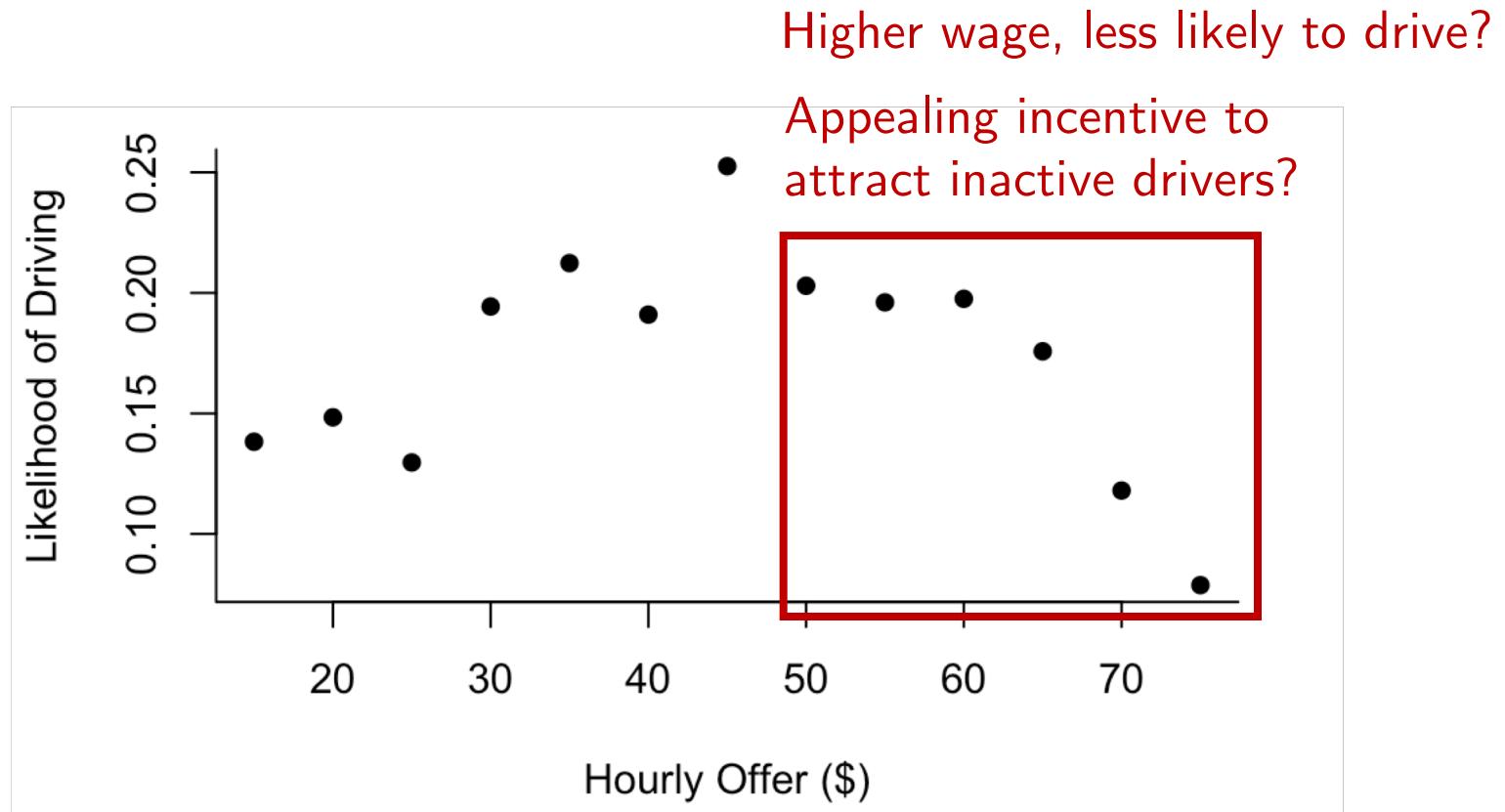
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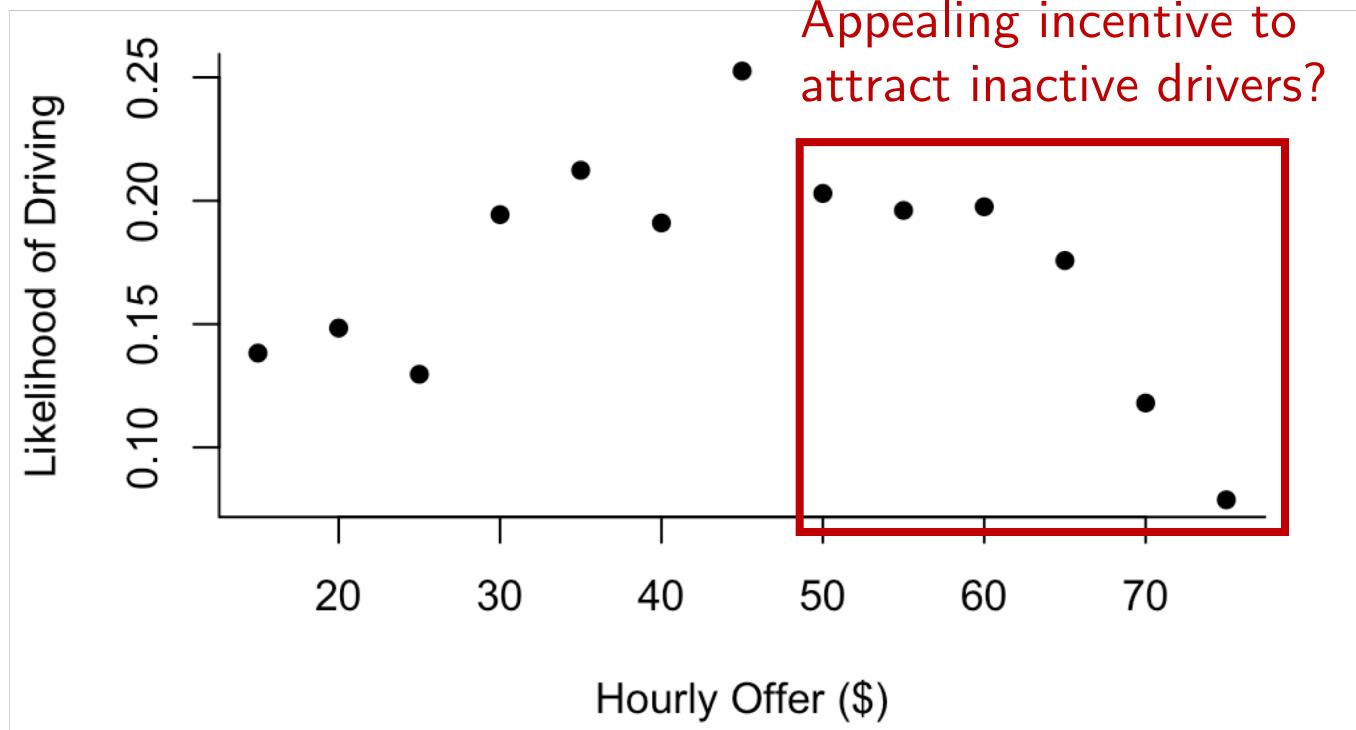


# Empirical Strategy Challenges

## 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)
- **Promo** (binary): Lagged value from the same shift in the previous week  
(Villas-Boas & Winer 1999, Yang et al 2003, Archak et al 2011, Ghose et al 2012)

# Empirical Strategy Challenges

Simultaneity

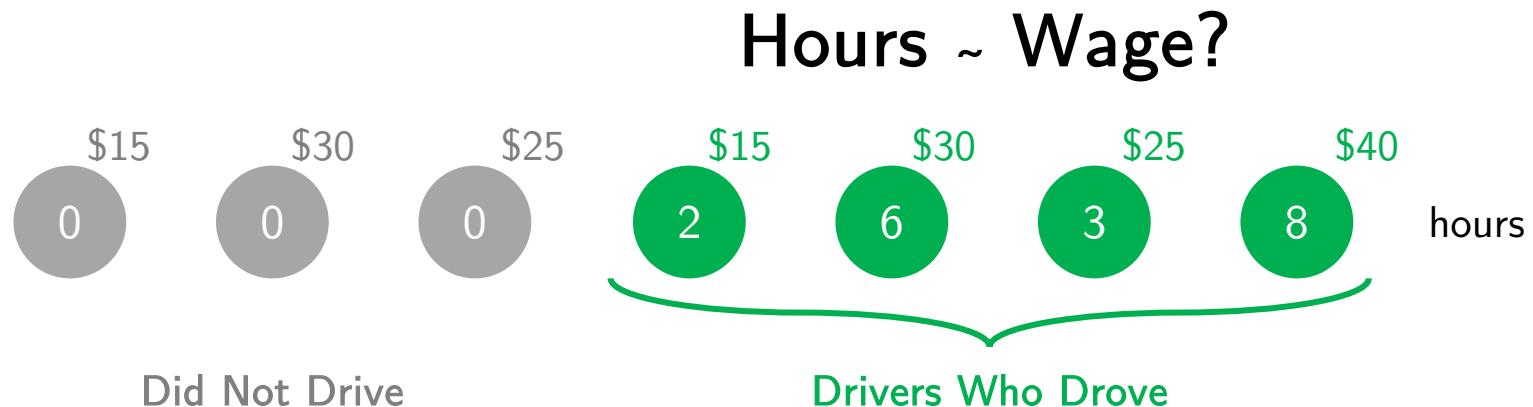
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# Empirical Strategy Challenges

## Simultaneity

Solution: Instrumental Variables

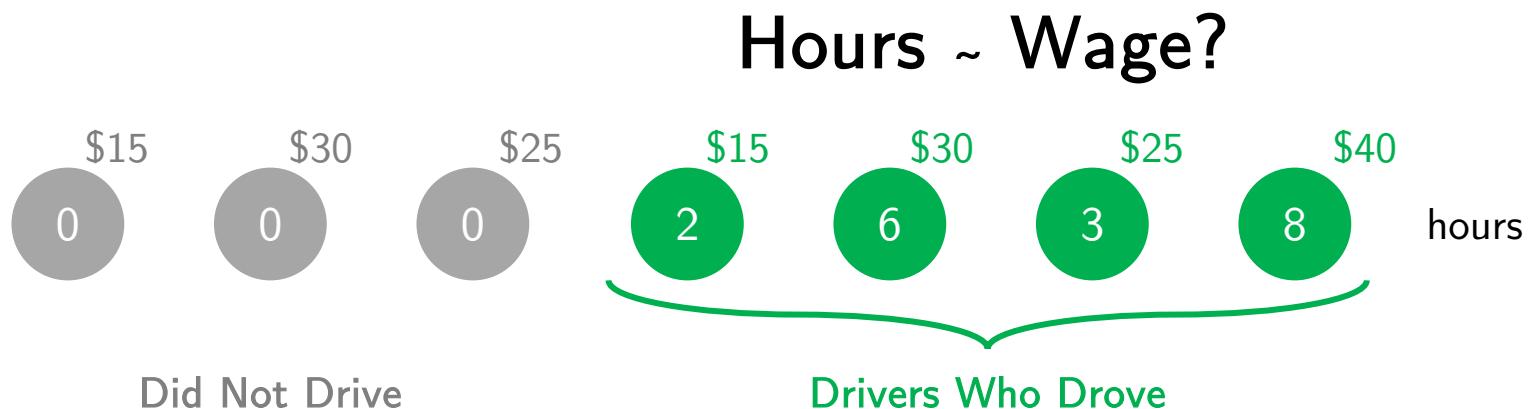


# Empirical Strategy Challenges

## Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**

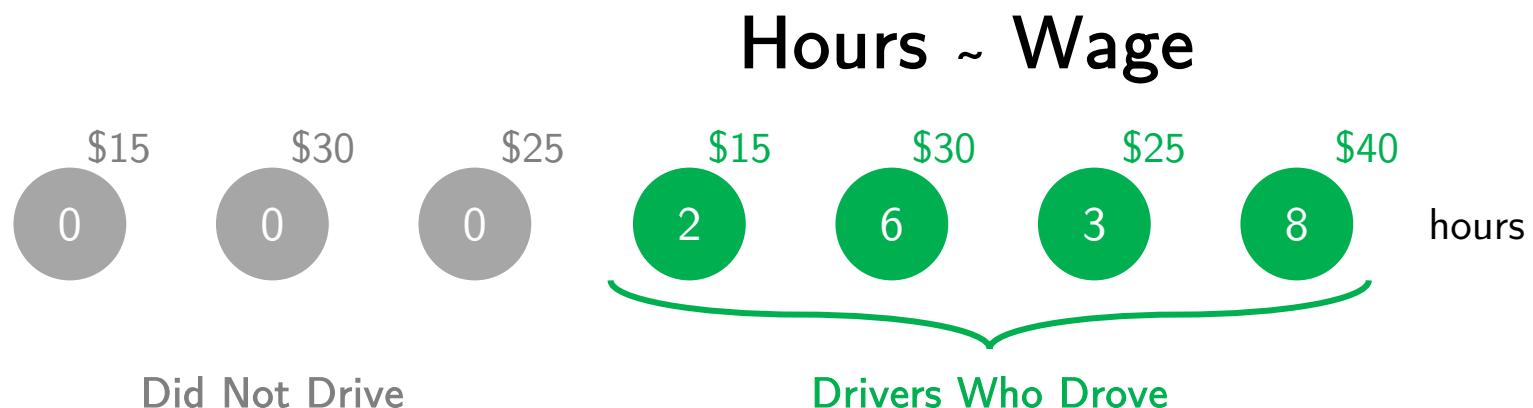


# Empirical Strategy Challenges

## Simultaneity

Solution: Instrumental Variables

## Selection Bias



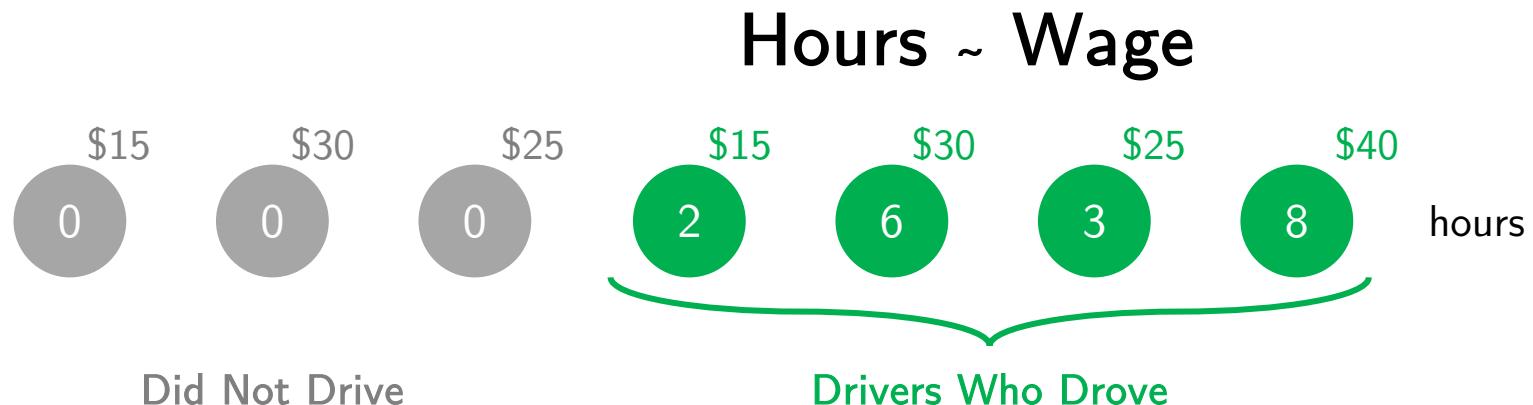
# Empirical Strategy Challenges

## 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* + *Promo*

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

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

Hourly Weather Humidity, Temp, Precipitation

Holiday, Day of Week

Month-Year FE

Past Work Habits

Total last week, same day last week, same shift last week

Driver's Experience New?

Driver's FE

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

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

+ Controls

Demand { Hourly Weather Humidity, Temp, Precipitation  
Holiday, Day of Week  
Month-Year FE

Short-term Habits { Past Work Habits  
Total last week, same day last week, same shift last week

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

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

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

Income So Far

= accumulated income since beginning of day

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

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

Income So Far  
= intensity of work

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

$P(\text{drive}) \text{ on } \textit{Offer} + \textit{Promo} + \textcolor{red}{ISF} + \textcolor{purple}{HSF} + \text{Controls}$

**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:

$P(\text{drive}) \text{ on } \textit{Offer} + \textit{Promo} + \textcolor{red}{ISF} + \textcolor{purple}{HSF} + \text{Controls}$

**Income So Far**  
= intensity of work

**Hours So Far**  
= amount of active time

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

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

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  $\textit{Earning} + \text{ISF} + \text{HSF} + \text{Controls}$

# Empirical Strategy

Heckman + IV

## 1 Work or not?

Control Function Probit:

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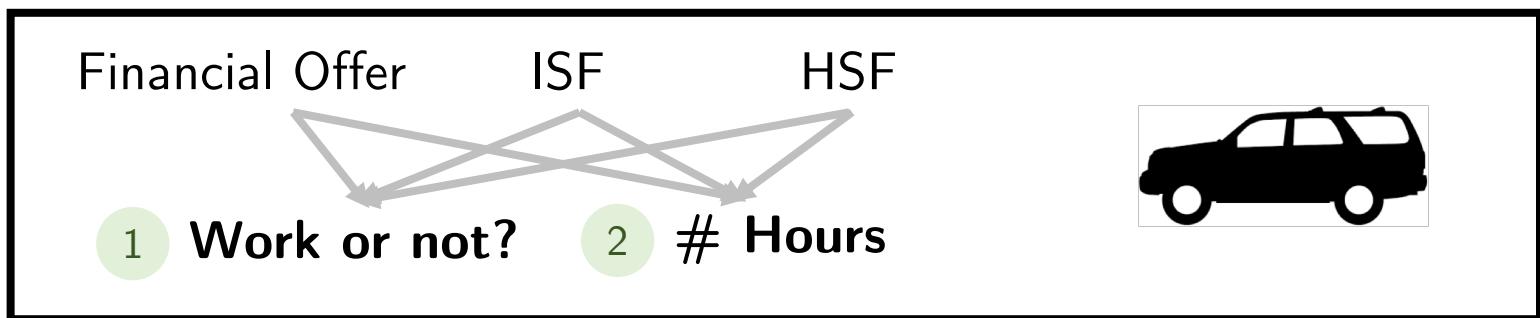
## 2 How long to work?

2SLS with Fixed Effects

# Hours on  $\textit{Earning} + \text{ISF} + \text{HSF} + \textcolor{green}{IMR} + \text{Controls}$

Inverse Mills Ratio  
= correct for selection bias

# Results



**Within-Day**

Midday



Late Night

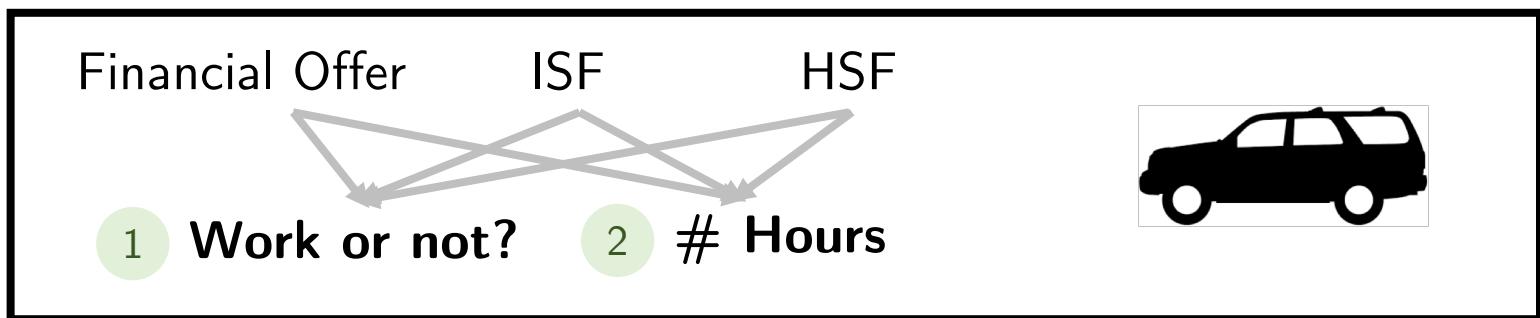
**Across-Days**

Tuesday



Sunday

# Results



**Within-Day**

Midday



**Late Night**

**Across-Days**

Tuesday



Sunday

# Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings		
Promo		
Income so far		
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)
Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far		
Hours so far		
AIC	95,856.010	72,887.620

Financial incentives and  
getting a “deal”  
encourage working

N = 166,766

# Late Night

1

	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far		-0.002*** (0.0002)
Hours so far		
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# Late Night

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	Work or not?	
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The more you've earned,  
the less likely you're going to  
continue working.

# Late Night

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	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far		
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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)
Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far	Income Target	-0.002*** (0.0002)
Hours so far		0.361*** (0.007)
AIC	95,856.010	72,887.620

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# Late Night

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	Work or not?	
	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Promo	0.229*** (0.038)	0.285*** (0.046)
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)
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Hours so far	Inertia	0.361*** (0.007)
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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)			
Promo	0.229*** (0.038)	0.285*** (0.046)			
Income so far	Income Target	-0.002*** (0.0002)			
Hours so far	Inertia	0.361*** (0.007)			
IMR					
AIC/R <sup>2</sup>	95,856.010	72,887.620			

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# Late Night

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N = 166,766

N = 18,941

# Late Night

1

2

	Work or not?		# Hours		
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Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
Promo	0.229*** (0.038)	0.285*** (0.046)			
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 <sup>2</sup>	95,856.010	72,887.620	0.313	0.324	0.957

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# Late Night

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	Work or not?		# Hours		
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Promo	0.229*** (0.038)		<b>The more you've earned, you'll drive shorter hours.</b>		
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	<b>The longer you've been active, you'll drive longer hours.</b>				
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Income so far		-0.002*** (0.0002)			-0.0002*** (0.00002)
Hours so far		0.361*** (0.007)			0.187*** (0.001)



Work or not?



# Late Night

1

2

	Work or not?		# Hours		
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Income so far		-0.002*** (0.0002)			-0.0002*** (0.00002)
Hours so far		0.361*** (0.007)			0.187*** (0.001)



	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 Work or not?			2 # 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 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 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

*Neoclassical*  
**Financial Incentive**

As day/week proceeds...



encourages working

*Behavioral*  
**Income Target**

discourages working later on

*New*  
**Inertia**

encourages working

# 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*



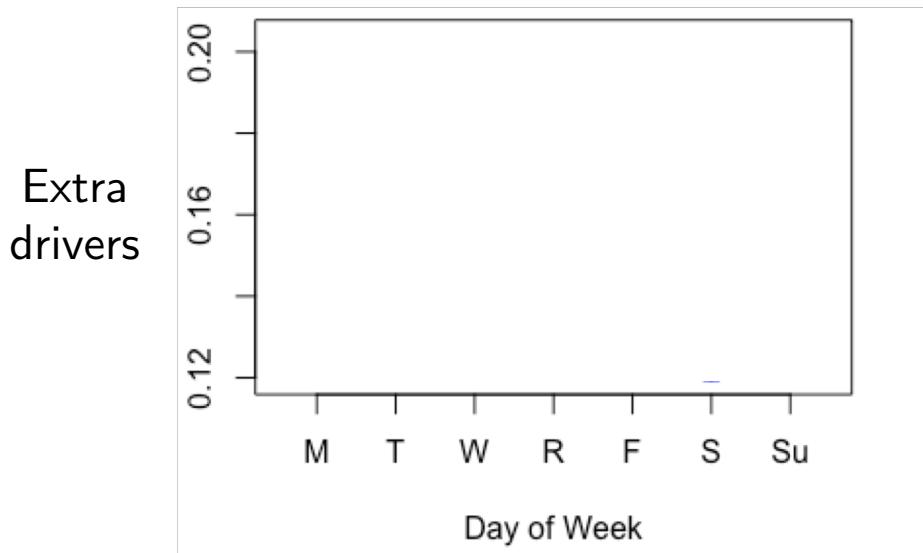
# Reallocating Incentives

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

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

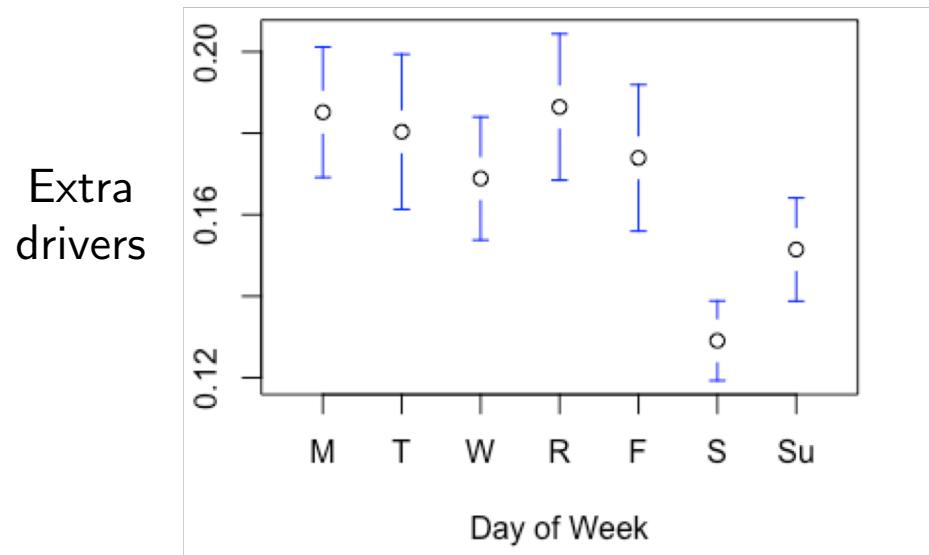
Given the same budget



# Reallocating Incentives

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

Given the same budget



Can recruit **17% more drivers**

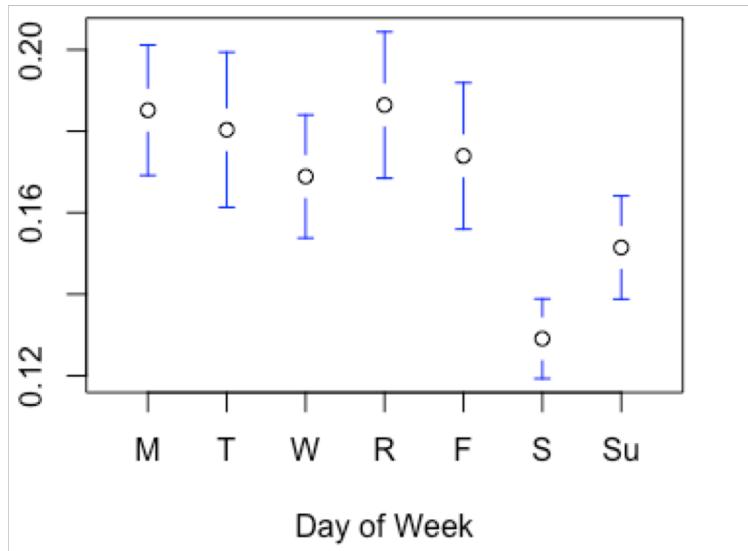
Average promo: 1.61x

# Reallocating Incentives

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

Given the same budget

Extra  
drivers

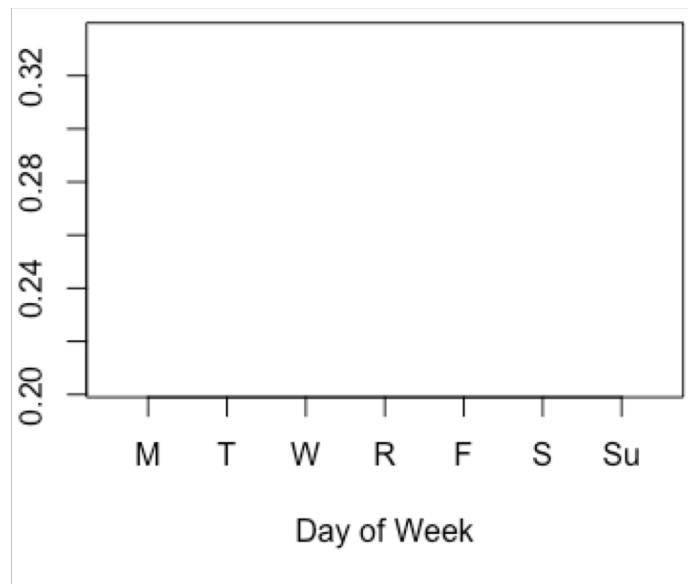


Can recruit **17% more drivers**

Average promo: 1.61x

Given the same capacity

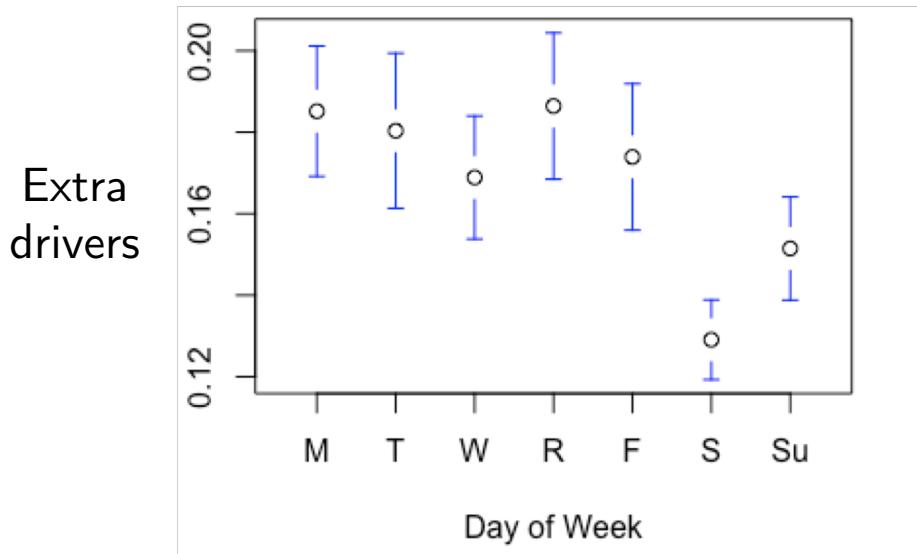
Cost  
saved



# Reallocating Incentives

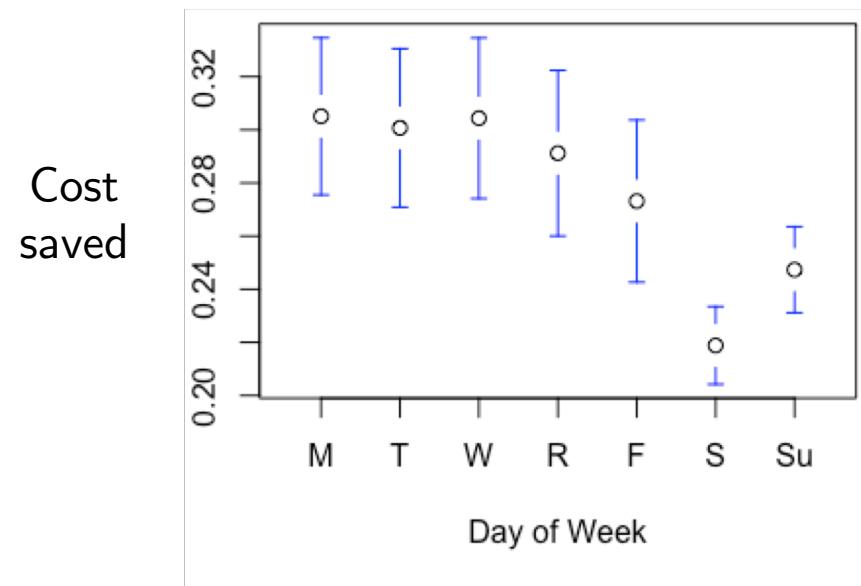
Compared to current practice from Jan to Sep 2017 out-of-sample

Given the same budget



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

# Structural Estimation

- Goals

- Uncover the inertia behavior

- Confirm income targeting behavior

- Quantify the value of guaranteed pay

- Data

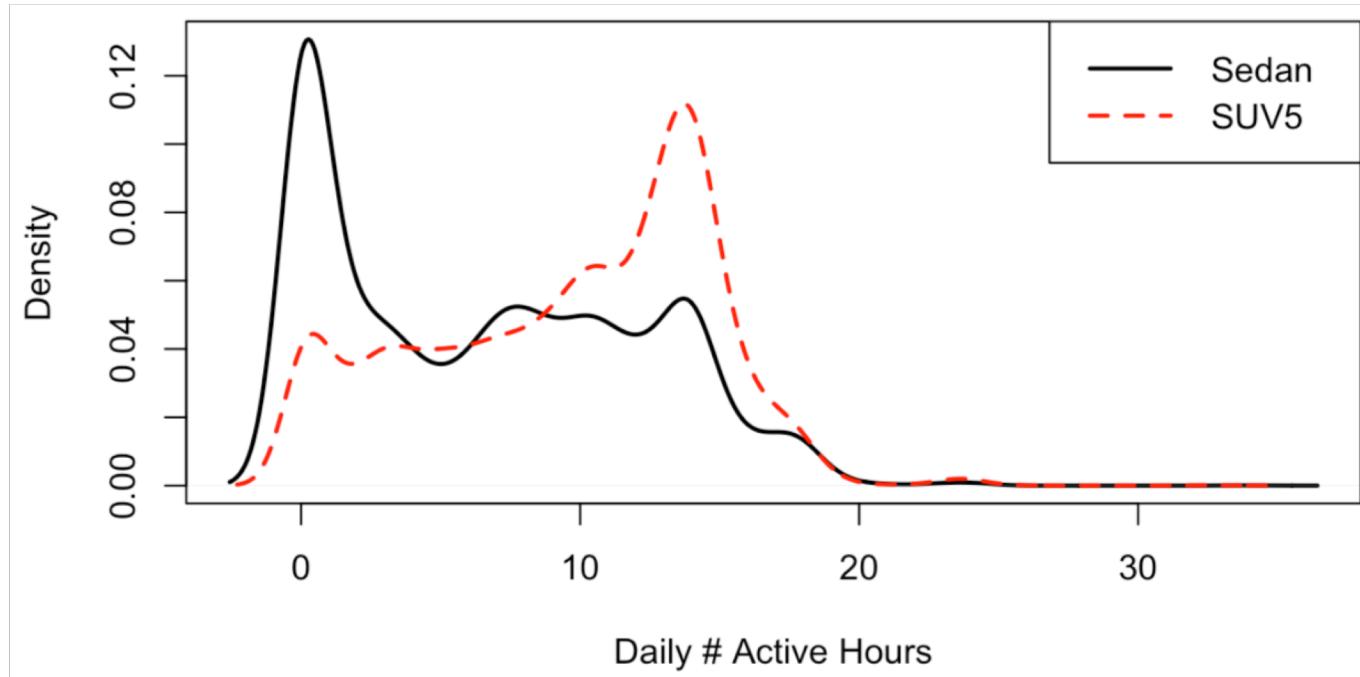
- Trip-level data for sedan and SUV drivers

- TLC data of trips by all ride-hailing platforms

- Model

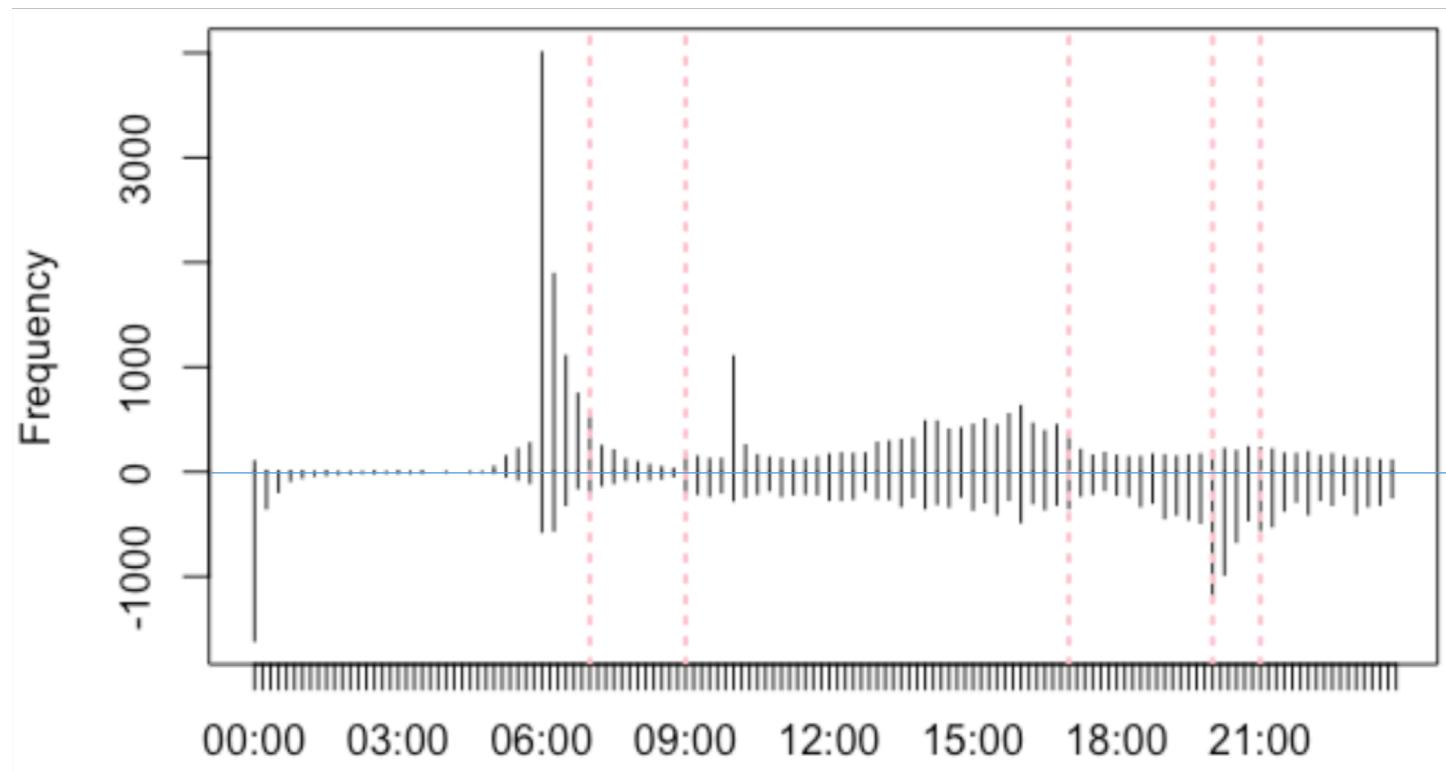
# Trip-Level Data

- Log on and off times of each driver



# Trip-Level Data

- Log on and off times of each driver



# Trip-Level Data

- Longer previous active sessions, longer new session

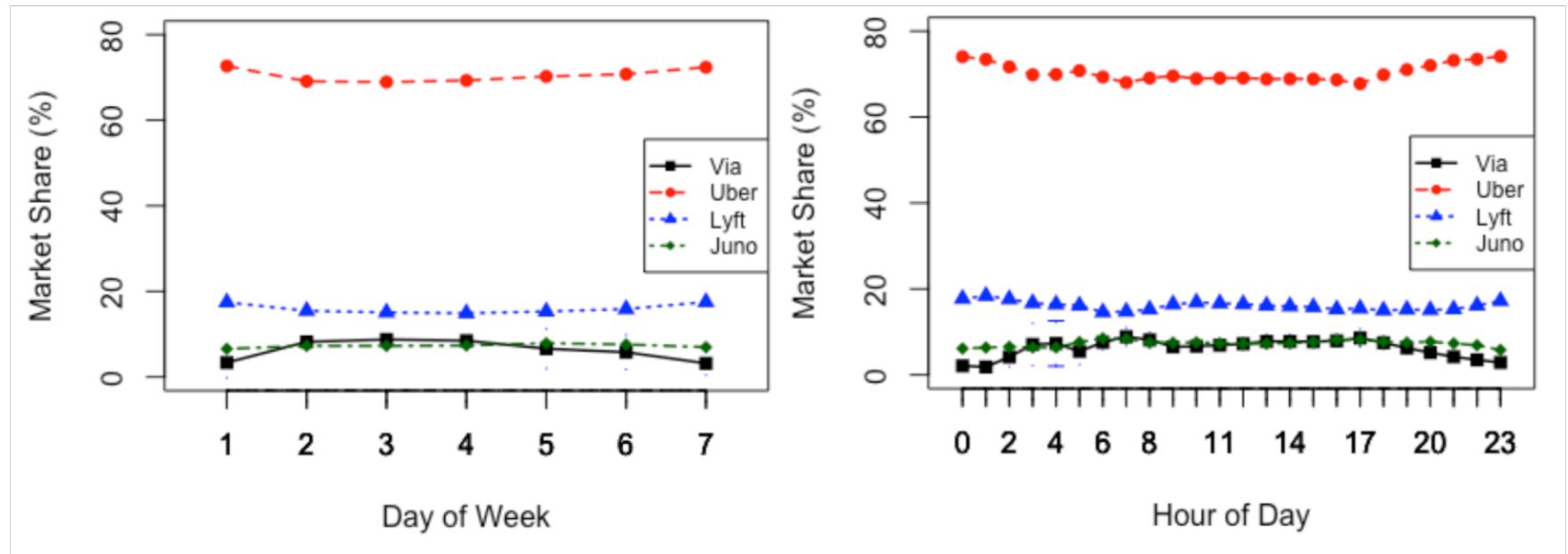
	(1) OLS	(2) Fixed Effects	(3) Fixed Effects
prevdur	0.506*** (0.005)	0.150*** (0.006)	0.133*** (0.006)
Constant	8,739.000*** (142.300)		
Control	-	-	Shift, Day of Week
Observations	24,632	24,632	24,632
R2	0.256	0.023	0.138
Adjusted R2	0.256	0.009	0.126

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

- Also, longer break, shorter next session

# TLC Data

- Pickup/drop-off locations and timestamps of each trips by all the ride-hailing platforms



# Model

- Assume finite horizon,  $t = 1, 2, \dots, T$ . Each period has length  $\Delta T$ .
- The driver knows exactly his base rate and real-time promotion information  $\rightarrow w_{i,t}$  wage per period.
- Consider 3 decisions that can be made:  $d_{i,t}$ 
  1. Work for this focal company
  2. Work for the competitor
  3. Not work at all/rest
- Assume that there is a cap of number of drivers for the focal company. Moving from competitor or not working at all to working for this company has a risk of full capacity.

# Model

## Working for the focal company

Utility function of working for period  $t$ :

$$U_{i,t}^{d=1} = \beta_w w_{i,t} - \beta_T \left( \frac{(\Delta T)^{1+\nu}}{1+\nu} \right) + f_I(I_{i,t} + w_{i,t}) + f_H(H_{i,t} + \Delta T) + \epsilon_{i,t} \quad (1)$$

The cost or disutility of working for the period of length  $\Delta T$  is  $(\Delta T)^{1+\nu}/(1+\nu)$  following the labor economics literature.  $I_{i,t}$  is the accumulated income up until period  $t$ .  $H_{i,t}$  is the accumulated time worked so far up until period  $t$ .

# Model

## Working for the competitor

Here, we assume that the driver does not know exactly the wage rate of the competitor, but he forms belief based on observed demand.

Utility of working for the competitor:

$$U_{i,t}^{d=2} = \beta_w \bar{w}_{i,t} - \beta_T \left( \frac{(\Delta T)^{1+\nu}}{1+\nu} \right) + f_I(I_{i,t} + \bar{w}_{i,t}) + f_H(H_{i,t} + \Delta T) + \eta_{i,t} \quad (2)$$

- $\bar{w}_{i,t}$  is a random variable that can be interpreted as the expected number of trips multiplied by the expected average earning per trip on the competitor's platform. It should be a function of current observed demand  $D_t$ .
- The expected value of  $\bar{w}_{i,t}$  should be strictly greater than  $w_{i,t}$ , the guaranteed wage for the first option. But it is the variance of  $\bar{w}_{i,t}$  that makes this option uncertain.

## Not working/rest

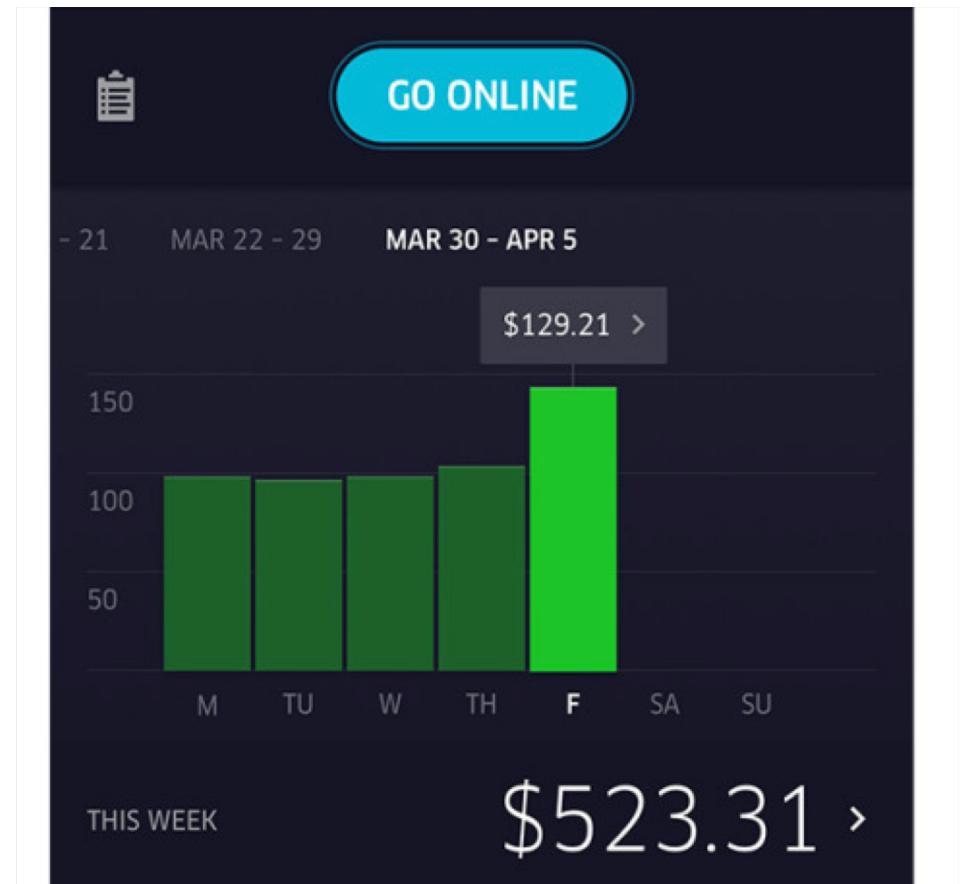
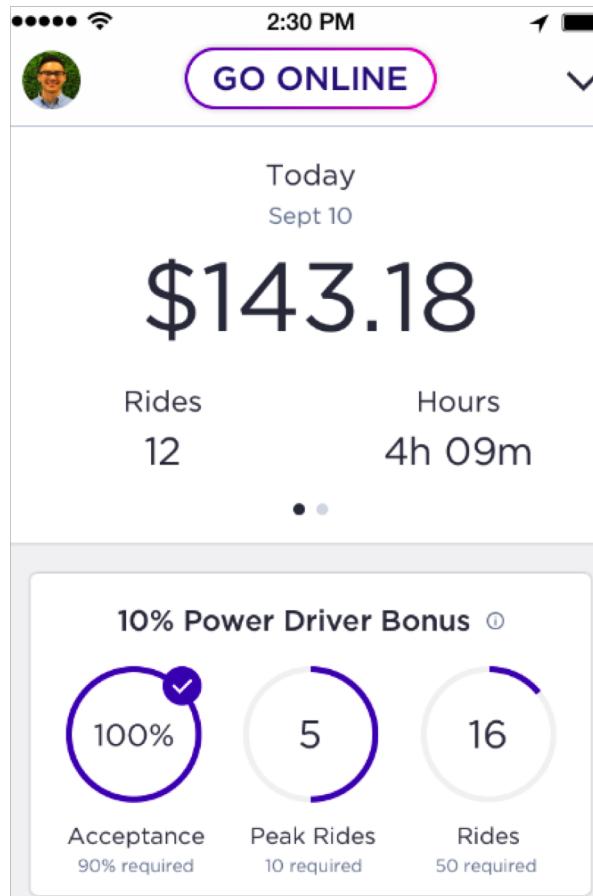
Utility of not working:

$$U_{i,t}^{d=3} = \alpha \cdot \Delta T + f_I(I_{i,t}) + f_H(H_{i,t}) + \zeta_{i,t} \quad (3)$$

$\alpha$  is the marginal benefit of having a time-off.

# Appendix

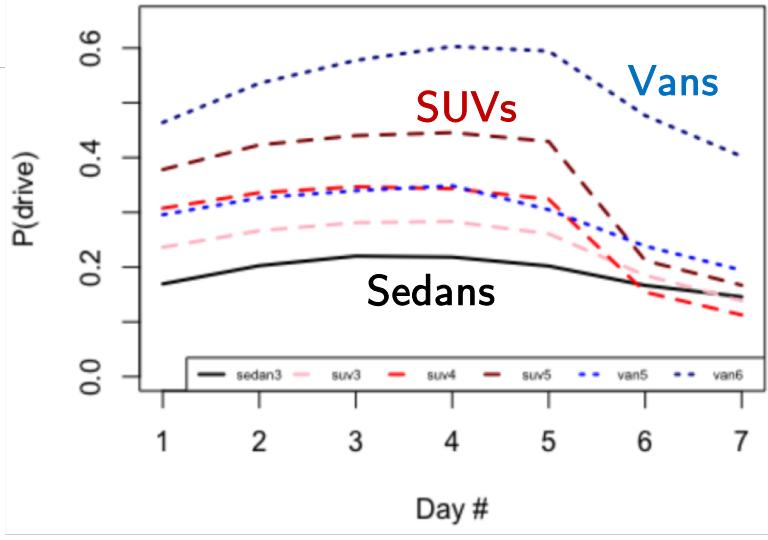
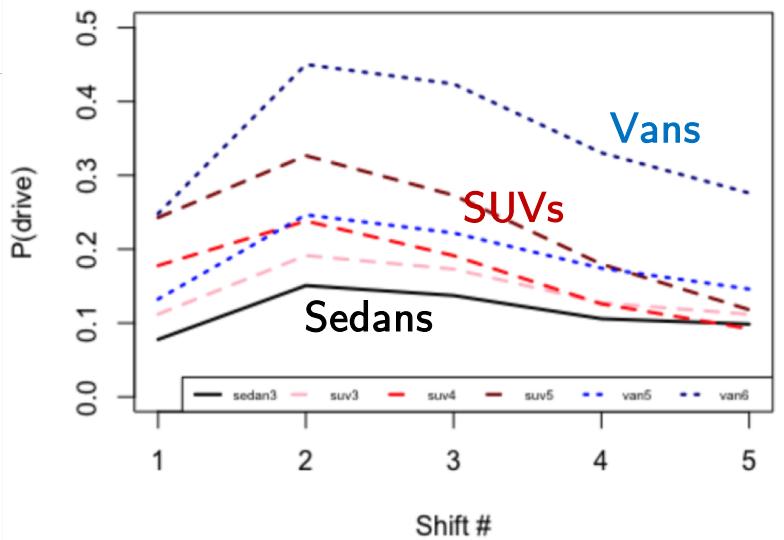
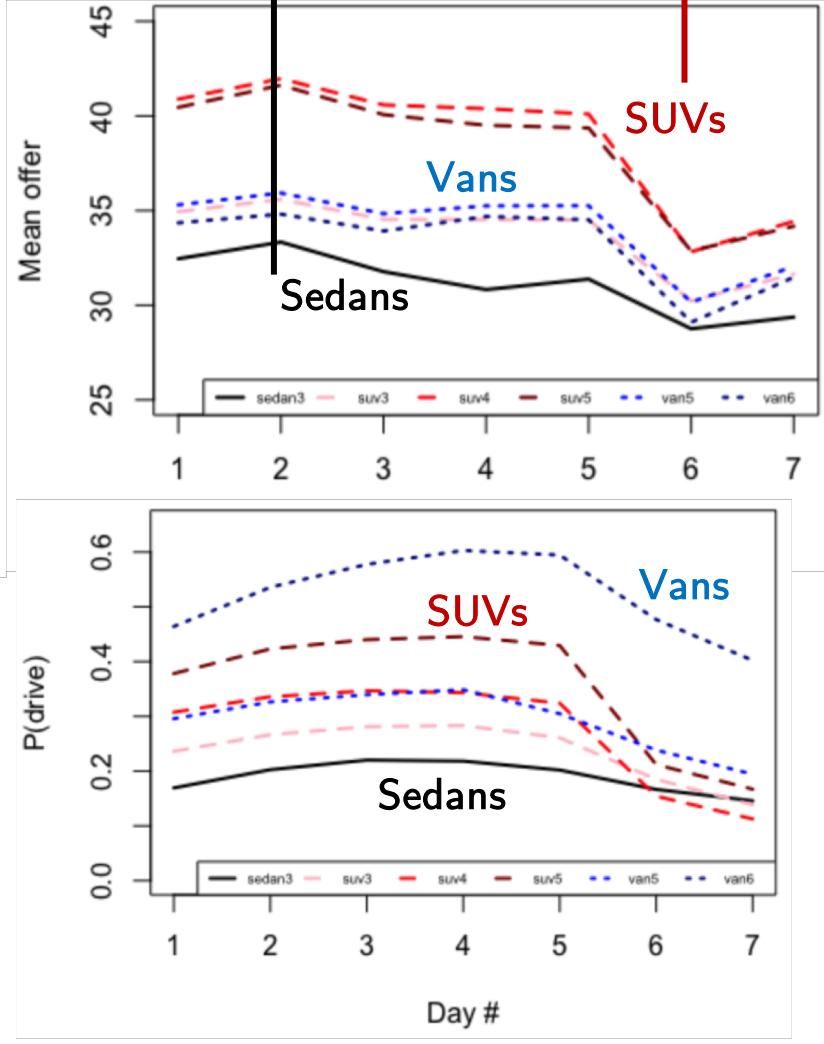
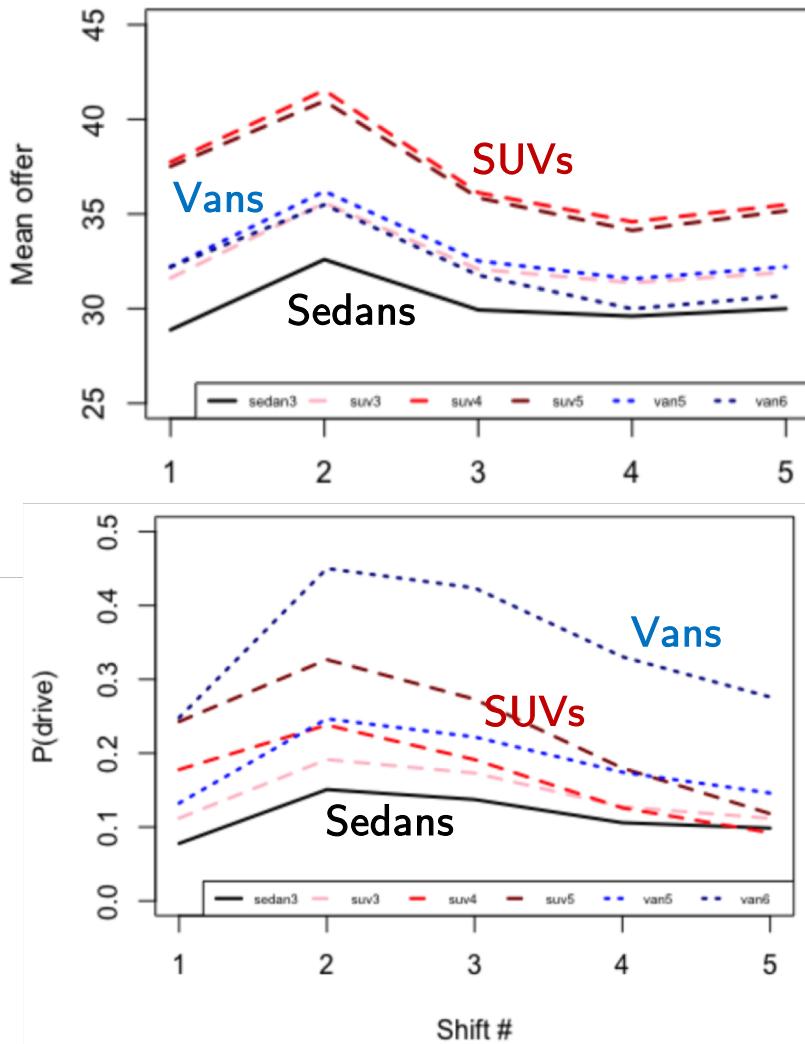
# Salience of ISF/HSF



# 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



# Heckit with IVs

## 1. Choice Equation “Drive or not?”

CF: Regress hourly offer/promo on IVs. Keep residuals

Probit: Estimate  $P(\text{drive})$

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

C

Inverse Mills Ratio (IMR)

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

Conditional on driving

## 2. Level Equation “How long?”

IV: Estimate hourly earning from IVs

OLS: Estimate hours

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

L