The Impact of Behavioral and Economic Drivers on Gig Economy Workers

NYU Stern 3/28/2019

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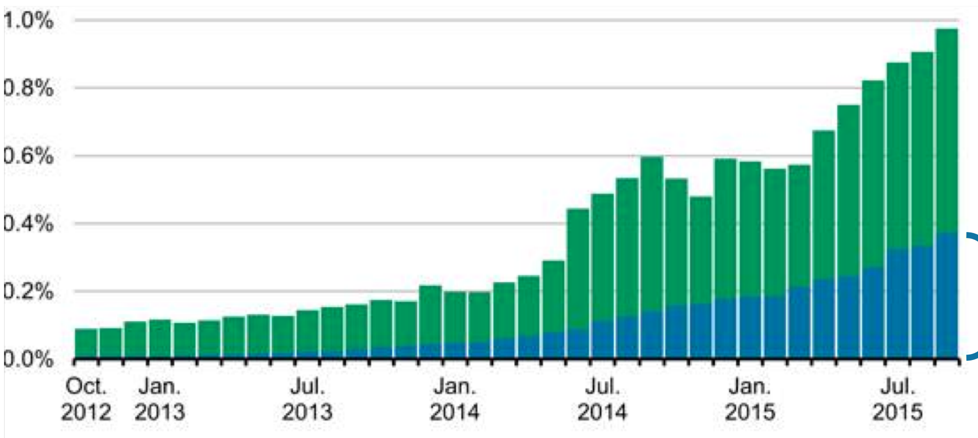
Gad Allon (Wharton), Maxime Cohen (NYU)

Gig Economy

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



Labor Platforms
Uber, TaskRabbit, ...

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

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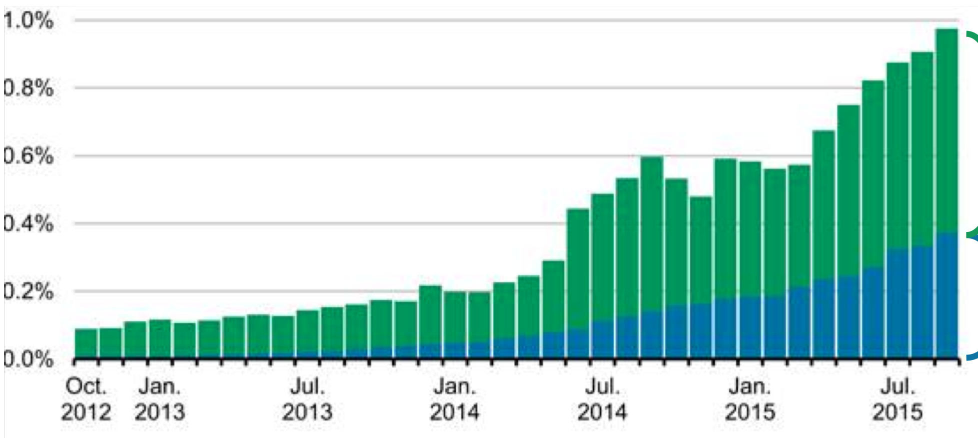

Capital Platforms
AirBnB, eBay, ...

Labor Platforms
Uber, TaskRabbit, ...

Gig Economy

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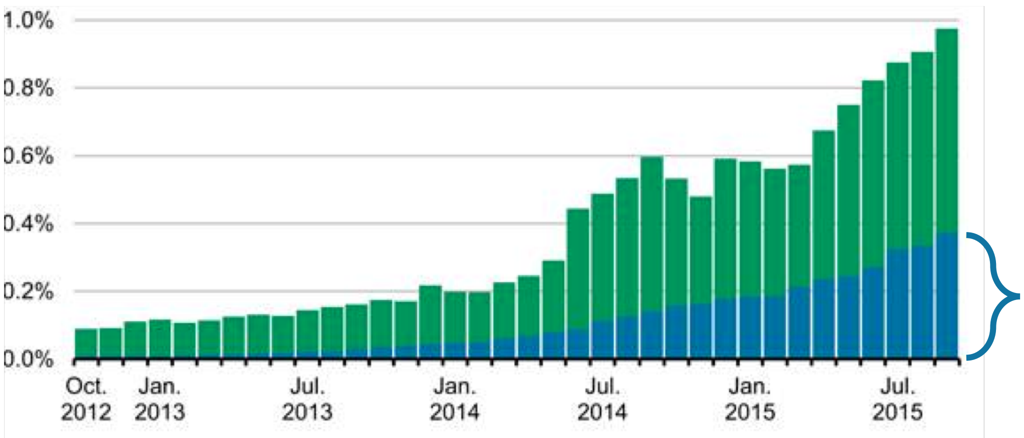


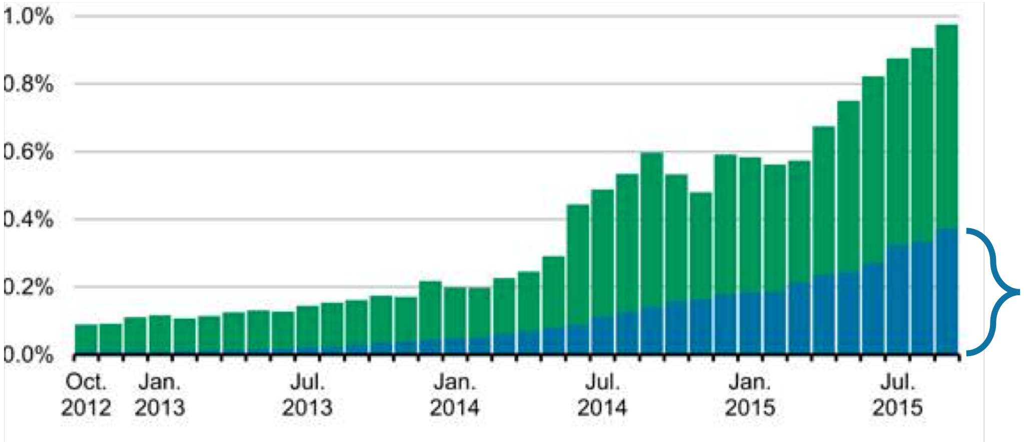
2015

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

2016 McKinsey Global Institute

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

44% primary income

~50% millennials

when to work?

how long?

which platforms?

Workers decide work schedules

2016 McKinsey Global Institute

Gig Company

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

independent/flexible
on-demand

Gig Company

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

independent/flexible
on-demand

Workforce planning is challenging

Research Questions

How do gig economy workers make labor decisions?

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

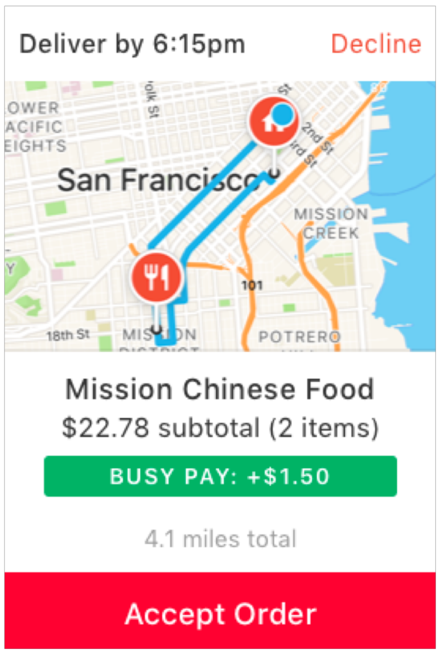
  Impact of incentive and behavioral elements on labor decisions

- Implications

  Simulation of optimal incentive re-allocation

In Practice

Real-time “surge pricing”



DOORDASH

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

In Practice

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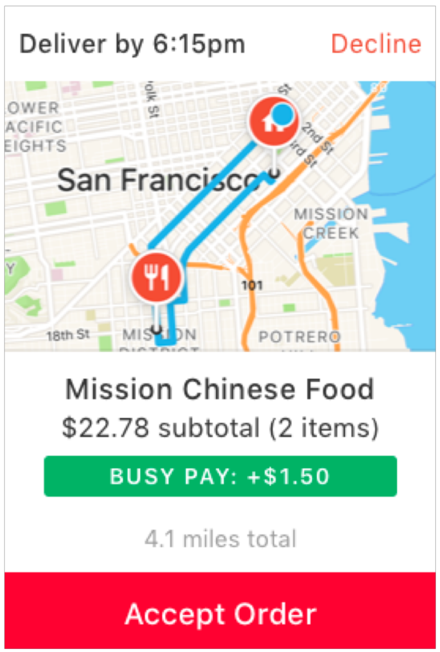

DOORDASH

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

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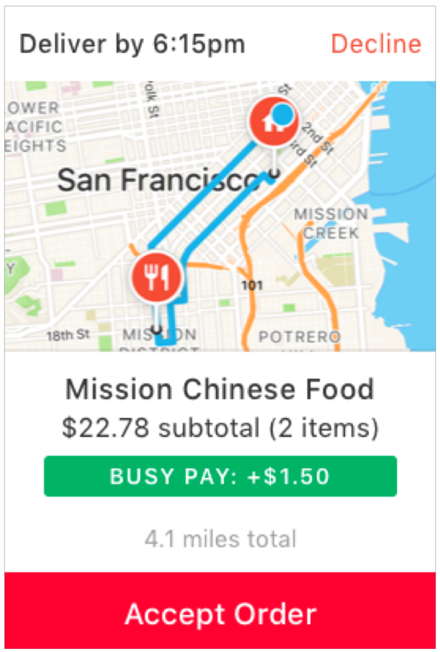

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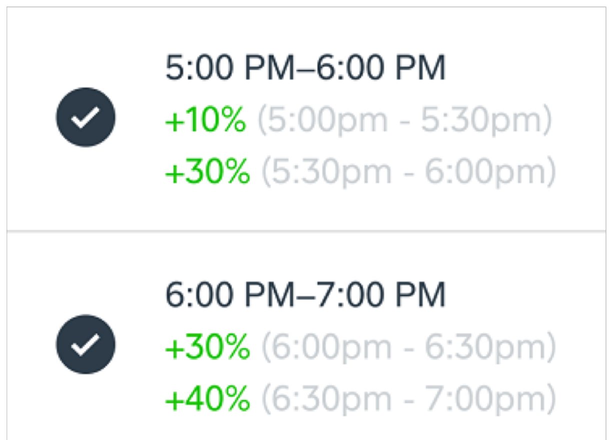
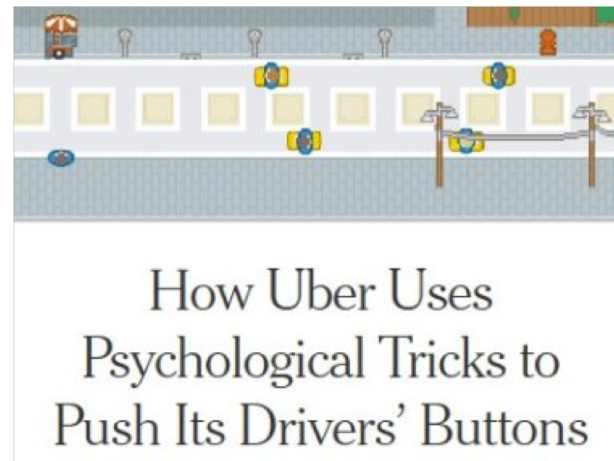


caviar

“You’re so close to your precious target”



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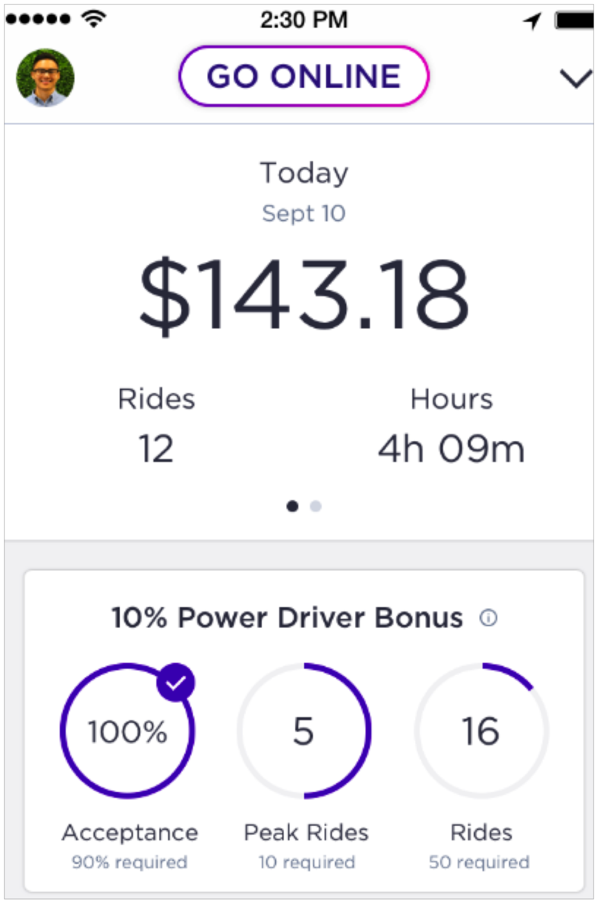
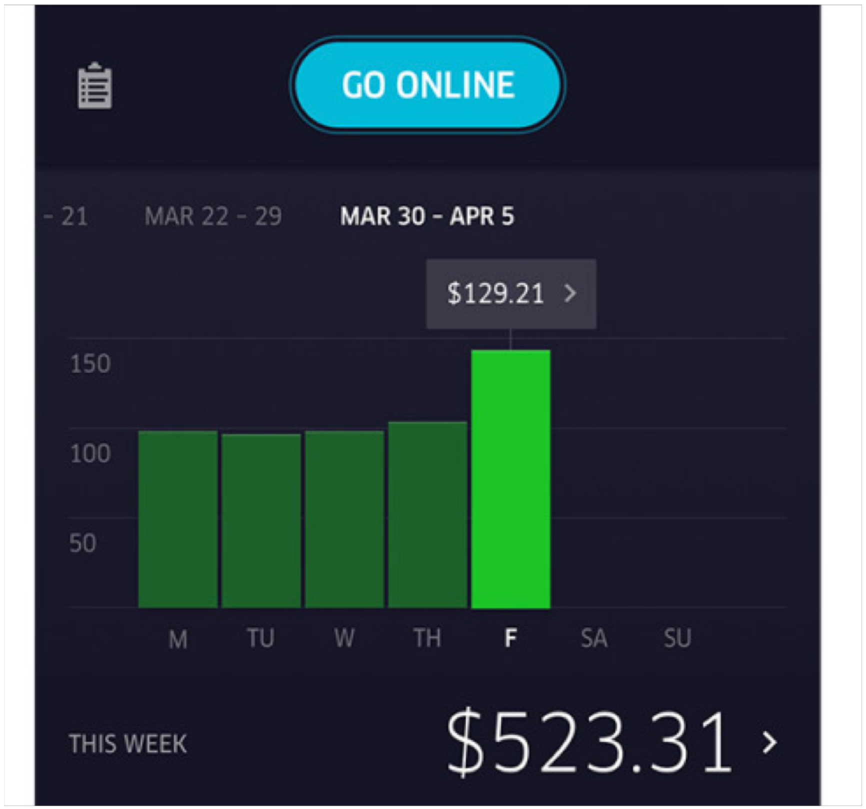
https://nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html

Driver’s View





Theories of Labor Supply

Neoclassical

- Maximize lifetime utility

Theories of Labor Supply

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

Wage $\uparrow$
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)

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Behavioral

- Reference-dependence, targets

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Wage ↑
Work more

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Behavioral

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

Wage ↑
Work less

Theories of Labor Supply

Neoclassical

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

Wage ↑
Work more

Behavioral

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

Wage ↑
Work less

Carrington (1996)

Camerer et al. (1997)

Oettinger (1999)

Farber (2005)

Fehr/Goette (2007)

Farber (2008)

Stafford (2013)

Farber (2015)

Chen/Sheldon (2016)
Sheldon (2016)

Thakral/To (2017)

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?

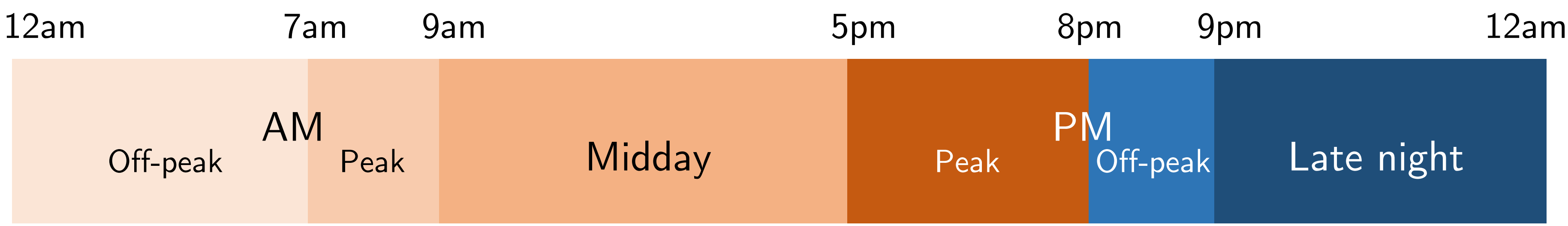
If so, how long?

Data US ride-hailing firm

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

Data US ride-hailing firm

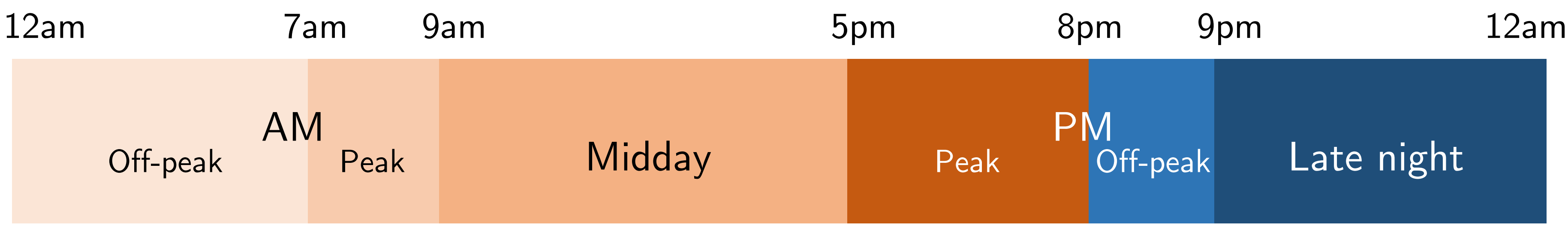
Drivers are guaranteed an hourly Base Rate + Promotions



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

Data US ride-hailing firm

Drivers are guaranteed an hourly Base Rate + Promotions



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

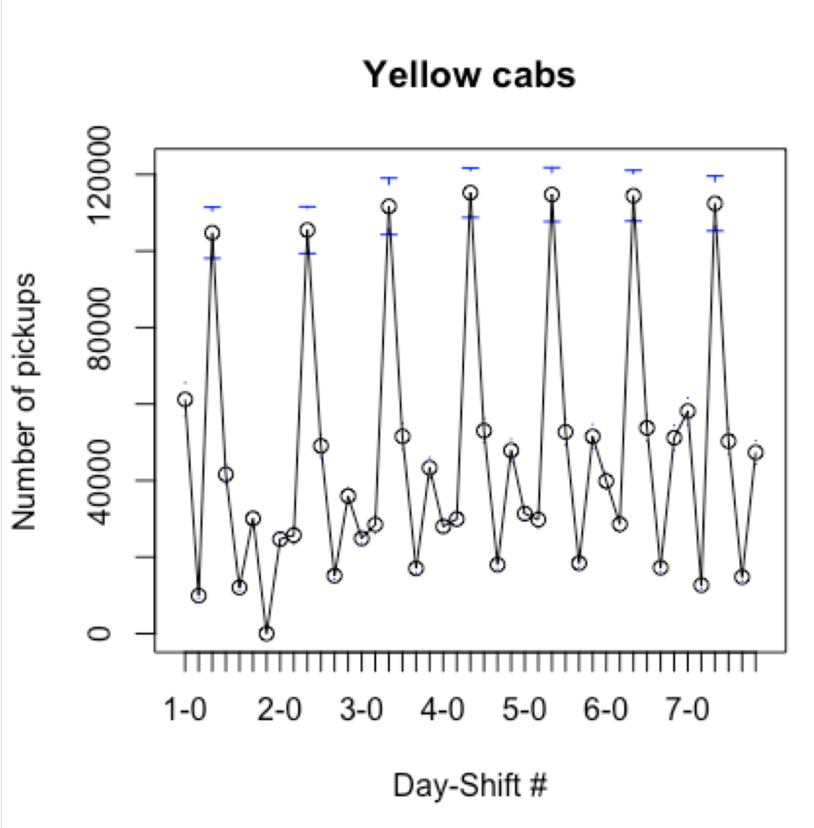
5.5M
Observations

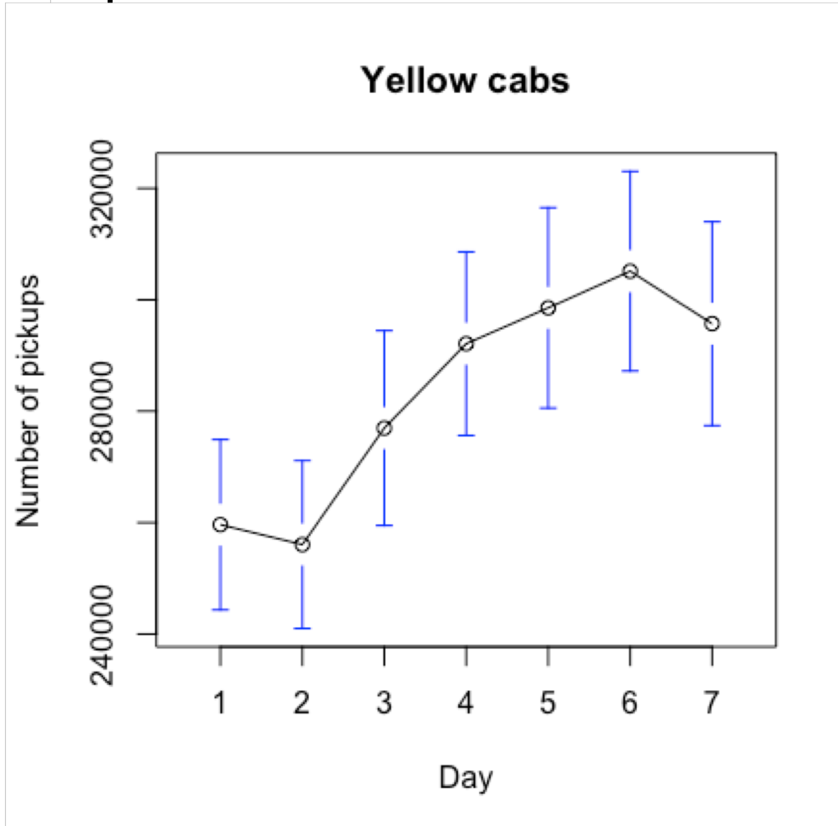
358
Days
Oct 2016 – Sep 2017

7,826
Unique drivers
SUV/Sedan/Van

TLC Data

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





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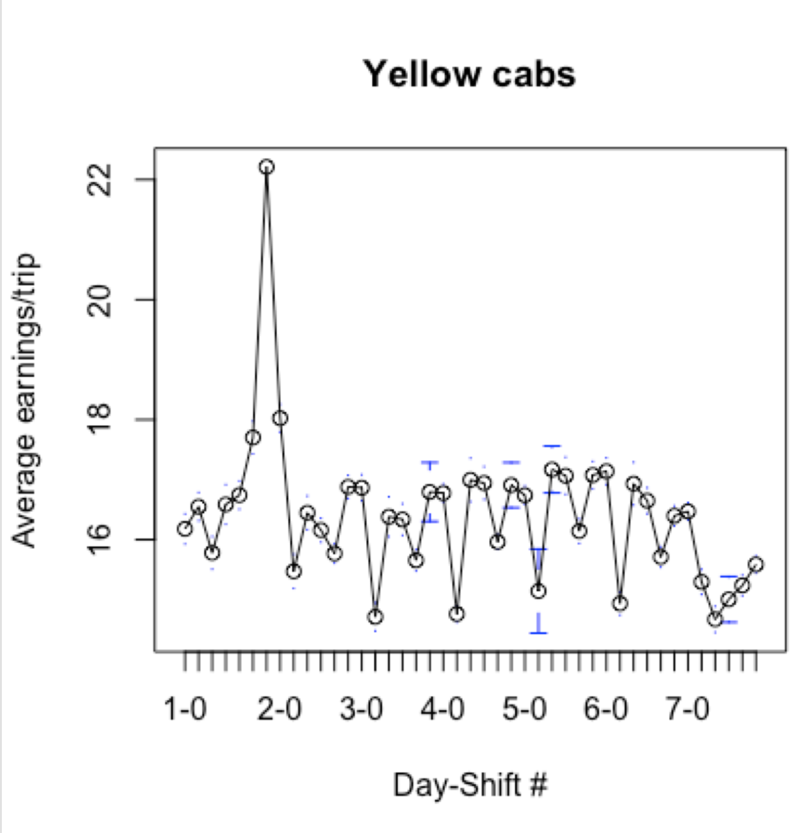

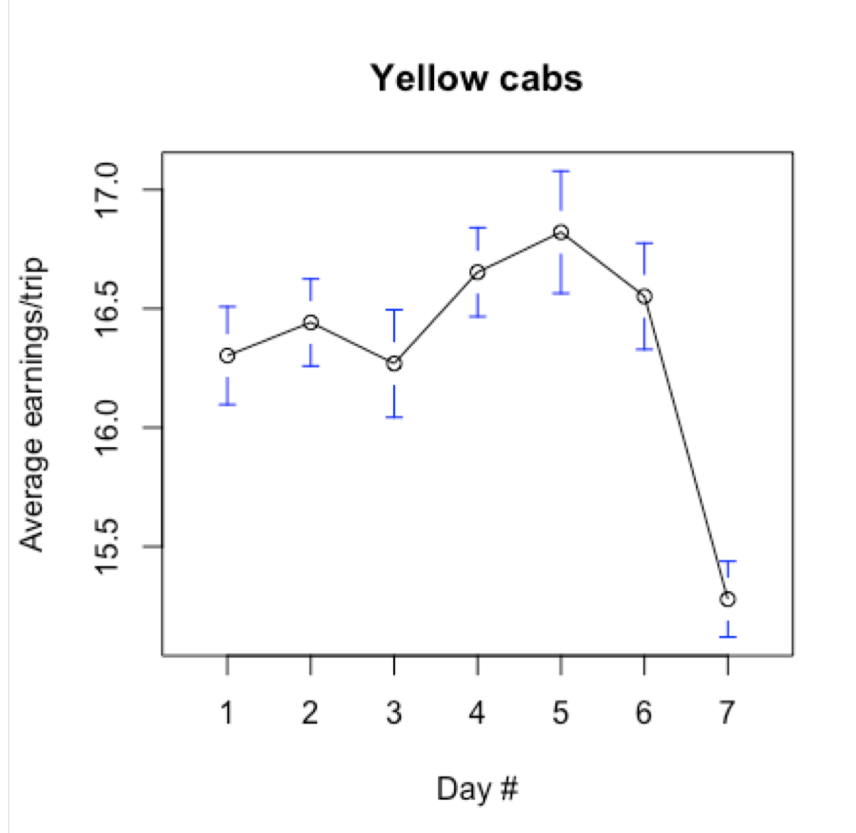

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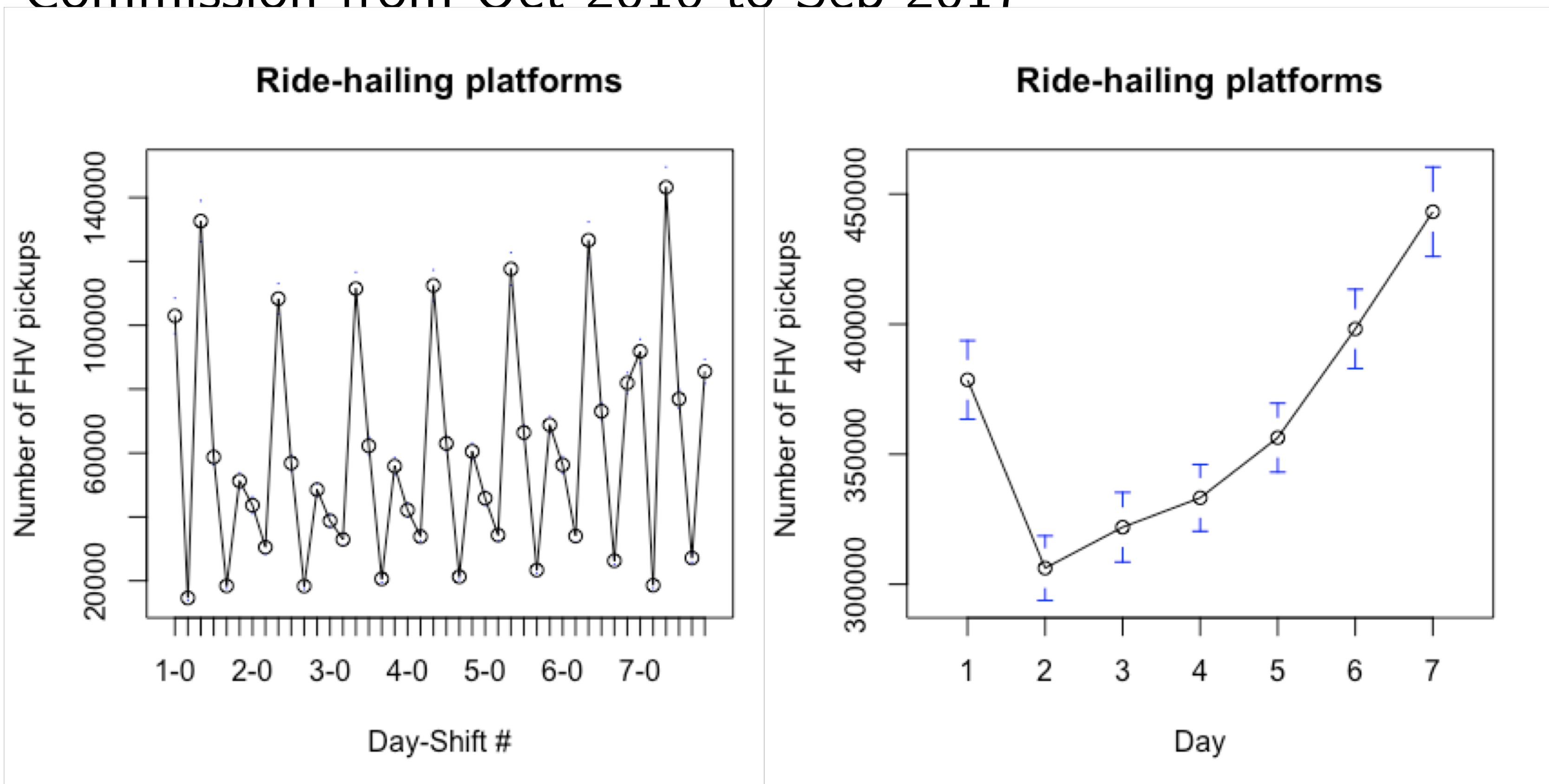

Empirical Strategy Challenges

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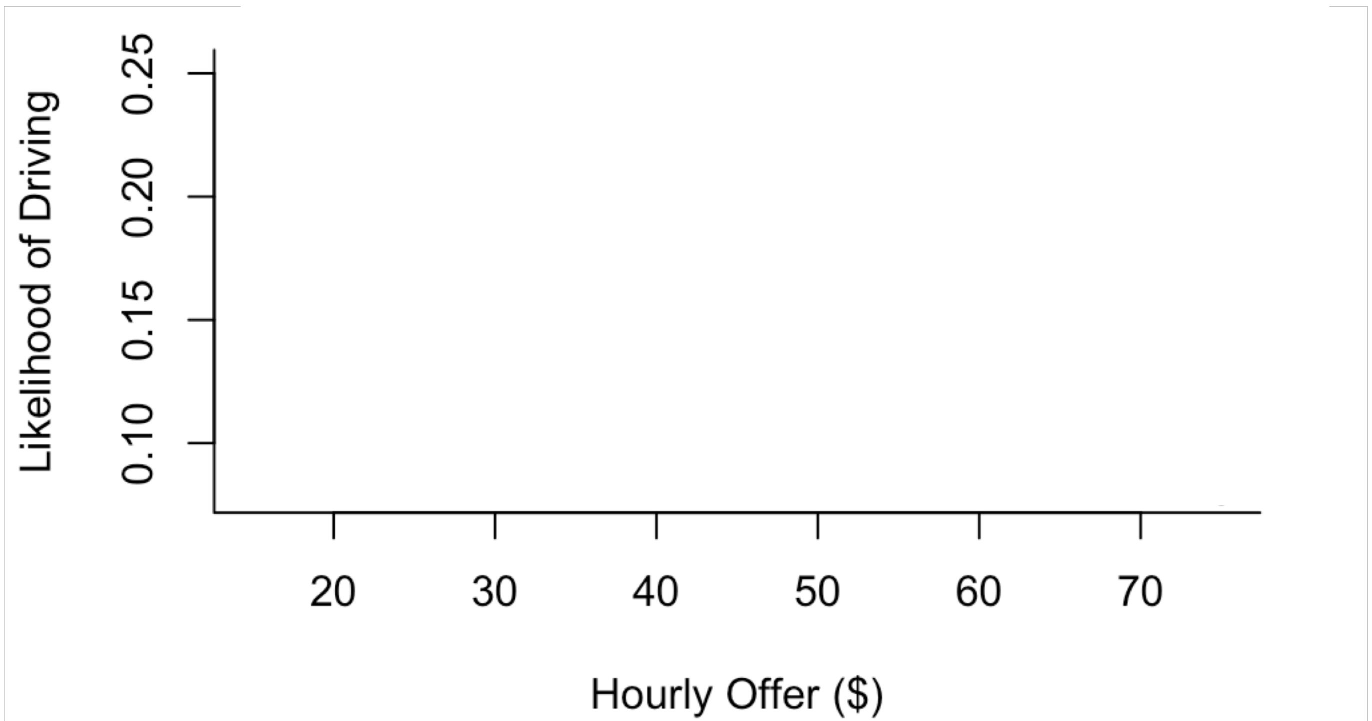

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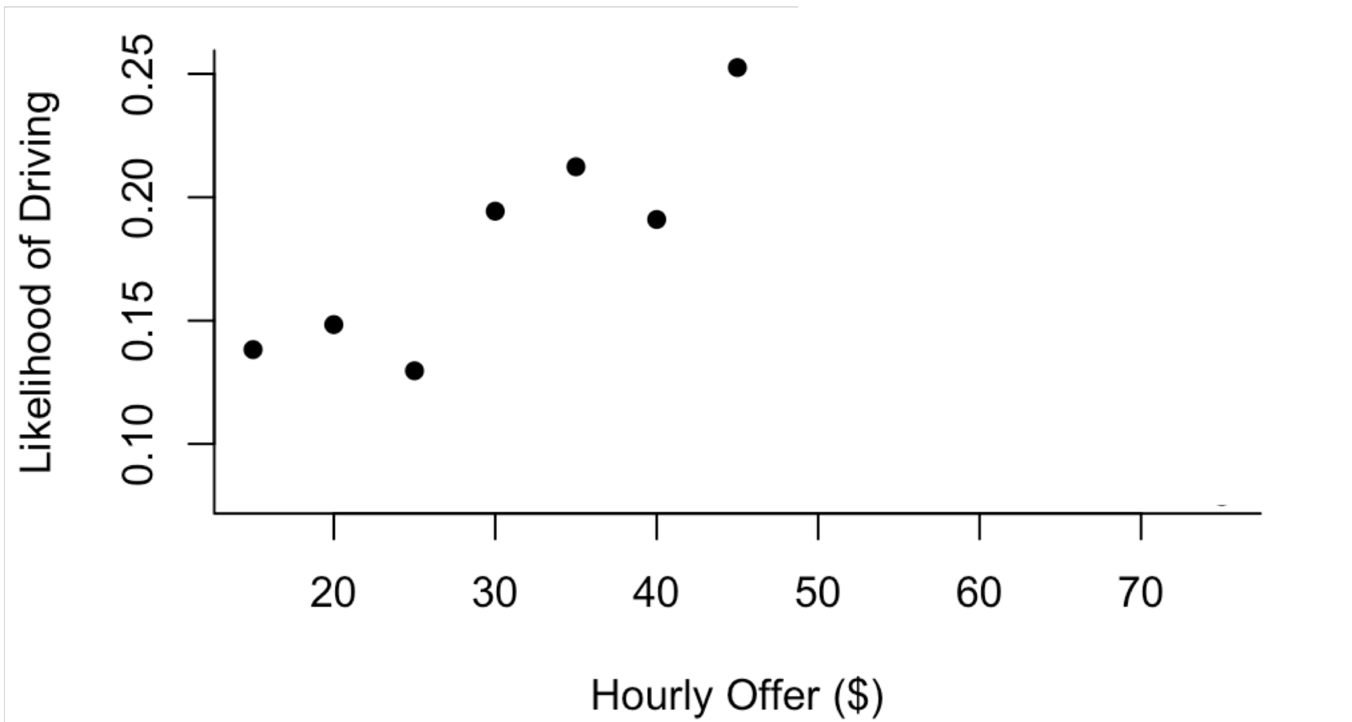

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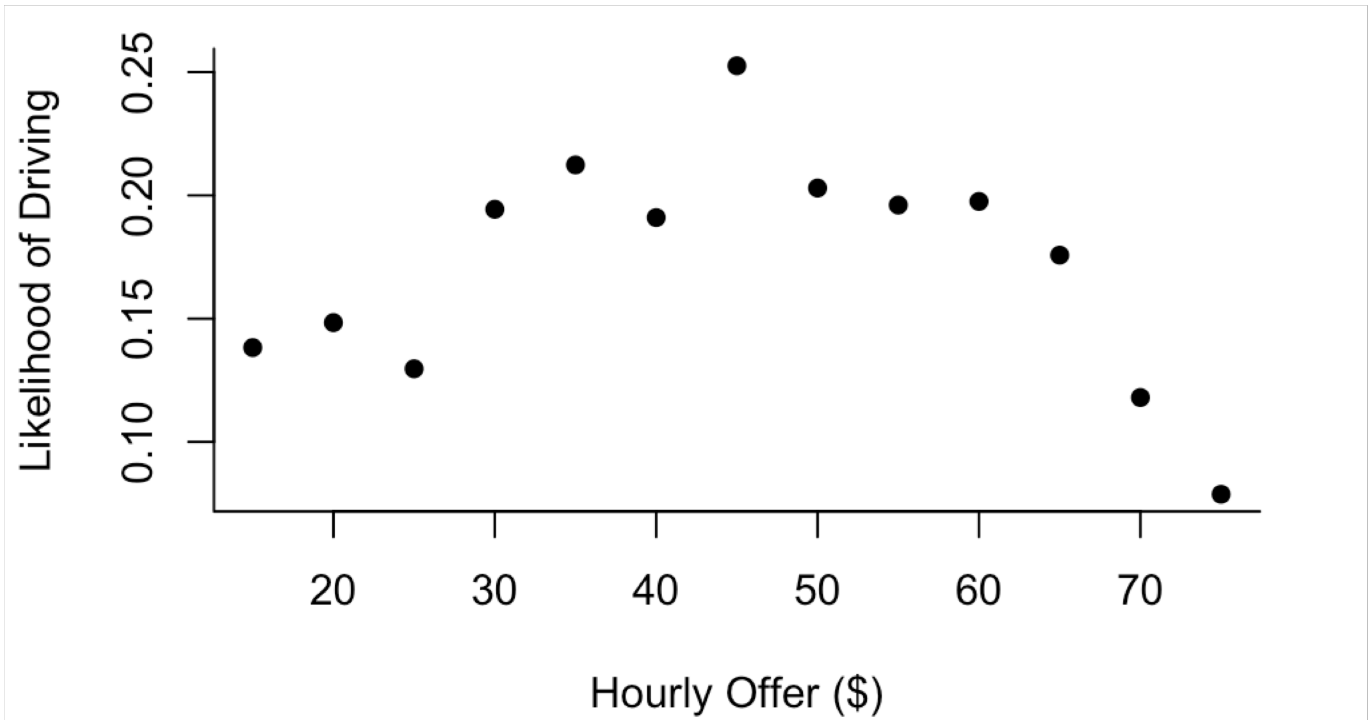
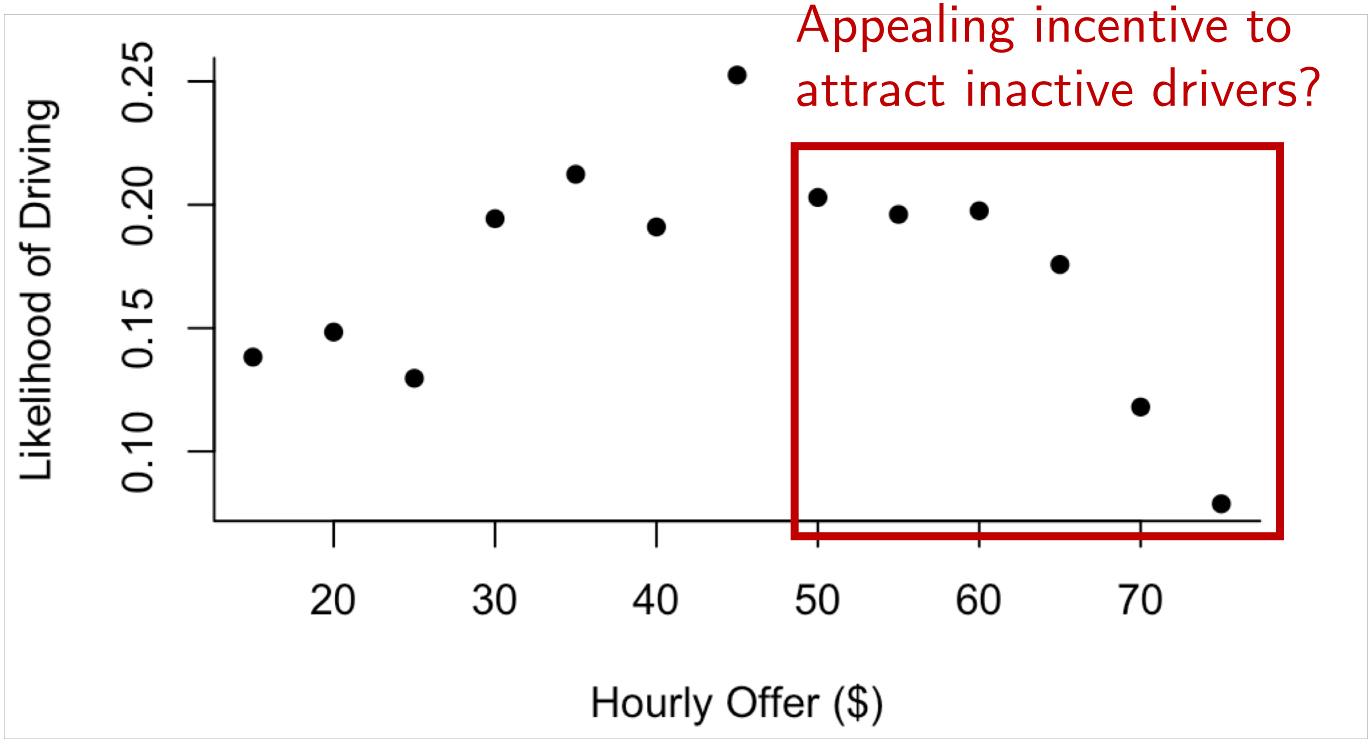


Empirical Strategy Challenges

Higher wage, less likely to drive?



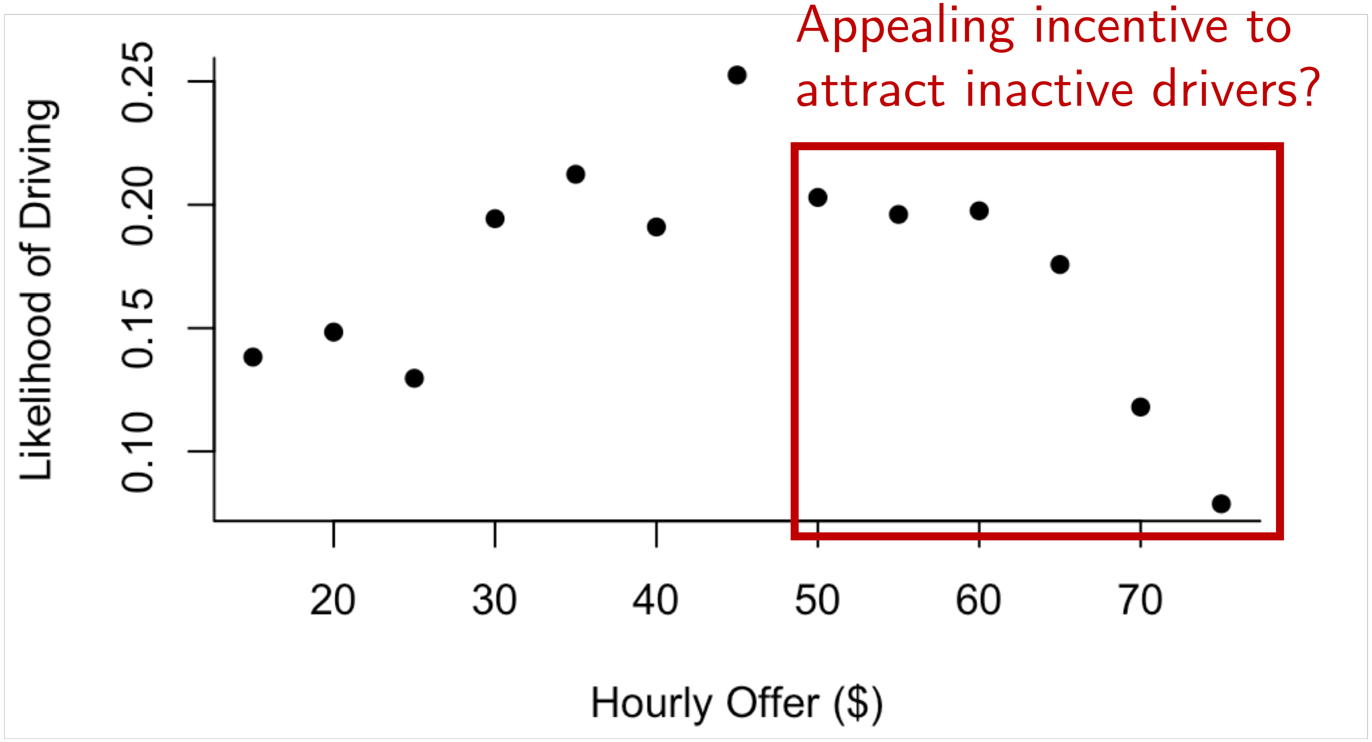
Appealing incentive to attract inactive drivers?

Empirical Strategy Challenges

Simultaneity

Higher wage, less likely to drive?

Appealing incentive to attract inactive drivers?



Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

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)
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Empirical Strategy Challenges

Simultaneity

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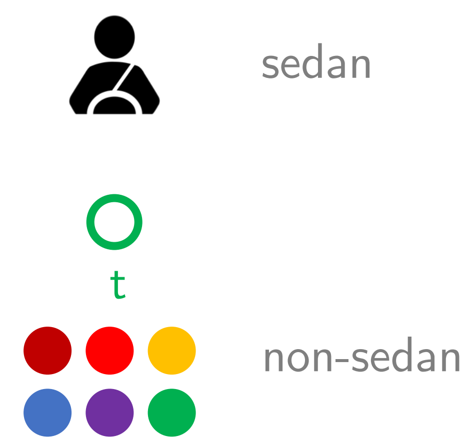

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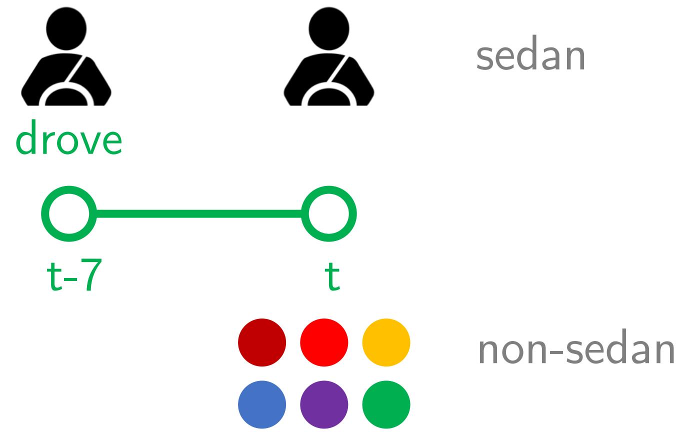

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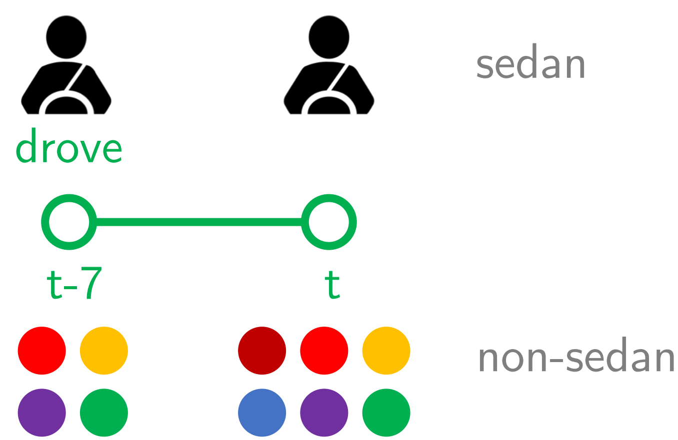

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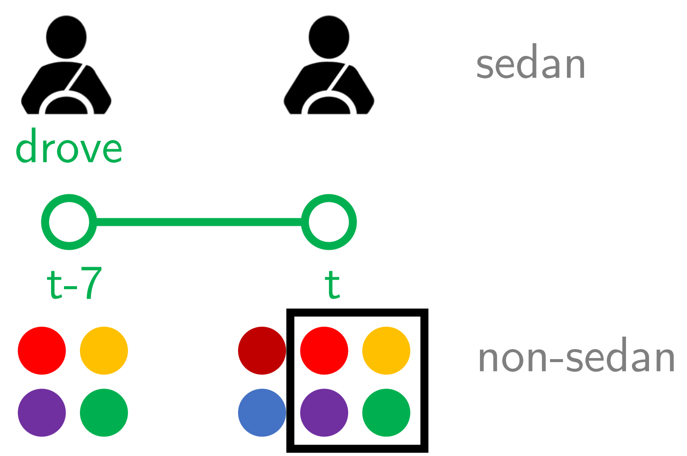

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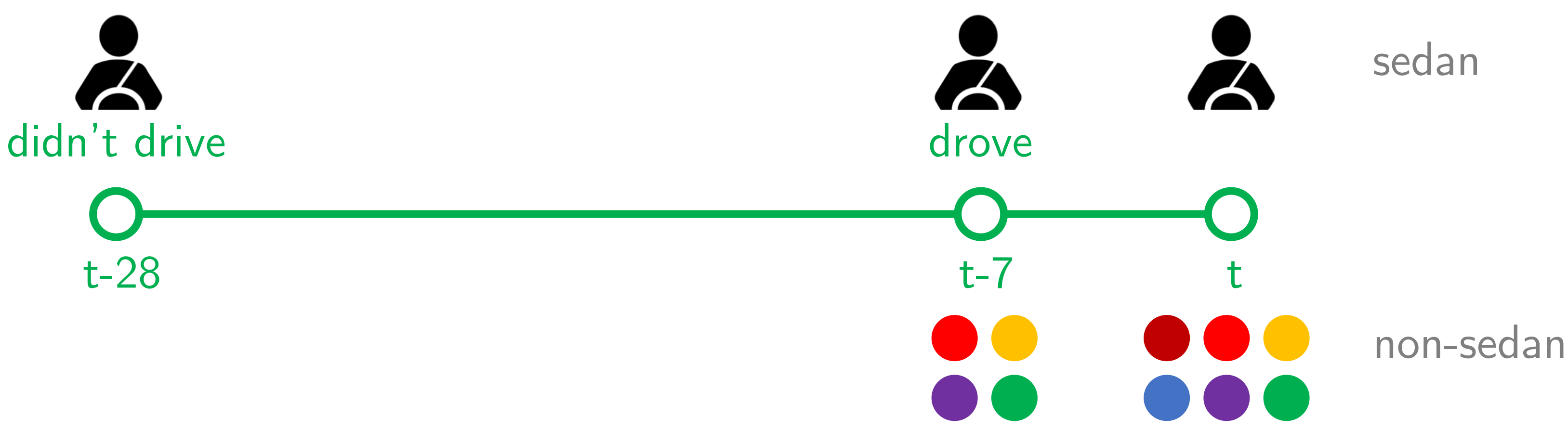

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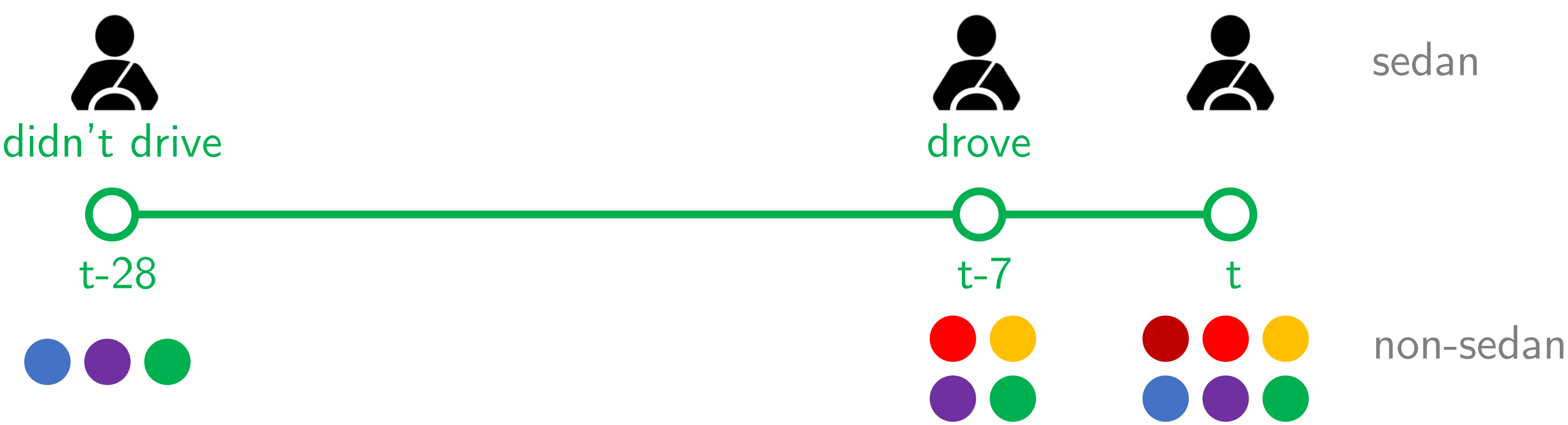

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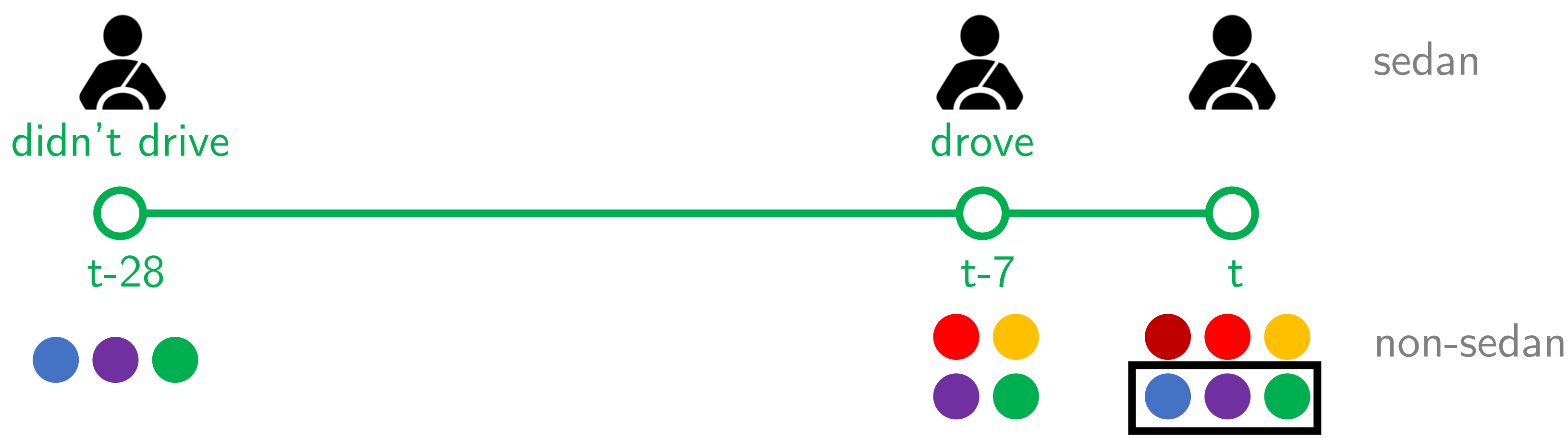


Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

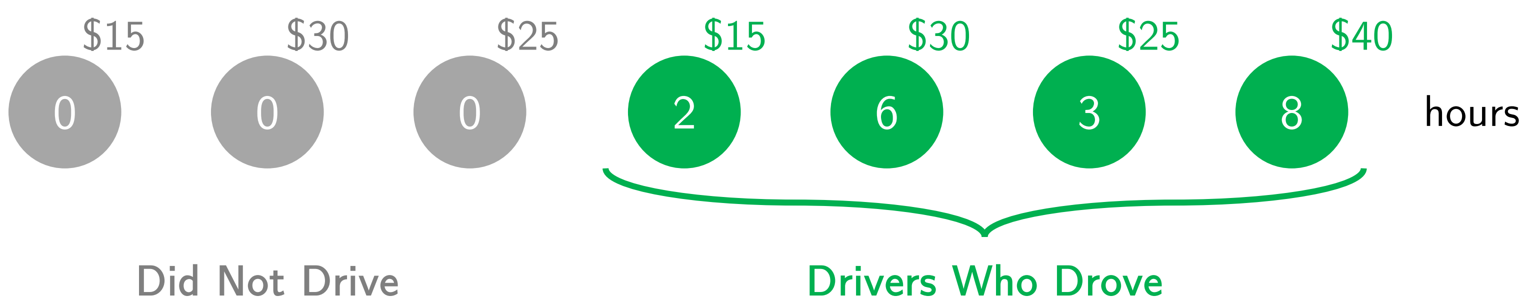
Hours ~ Wage?

Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Hours ~ Wage?



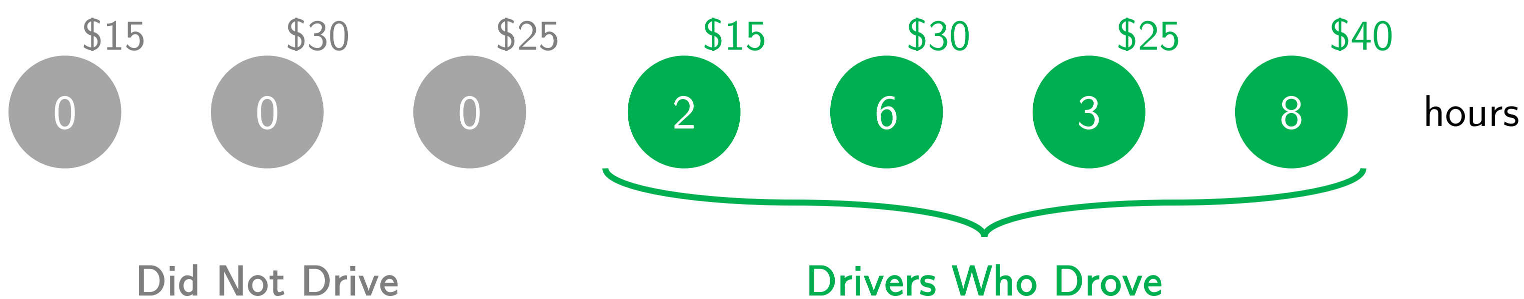
Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**

Hours ~ Wage?



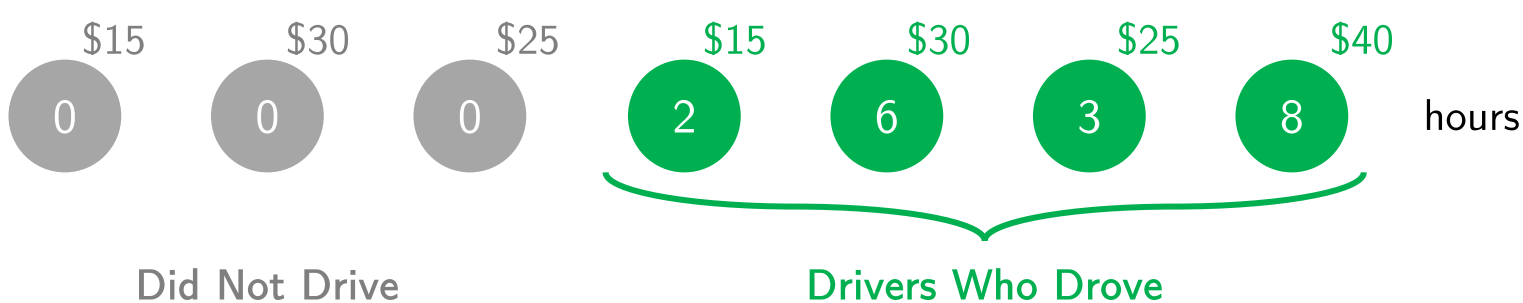
Empirical Strategy Challenges

Simultaneity

Solution: Instrumental Variables

Selection Bias

Hours ~ Wage



Empirical Strategy Challenges

Simultaneity

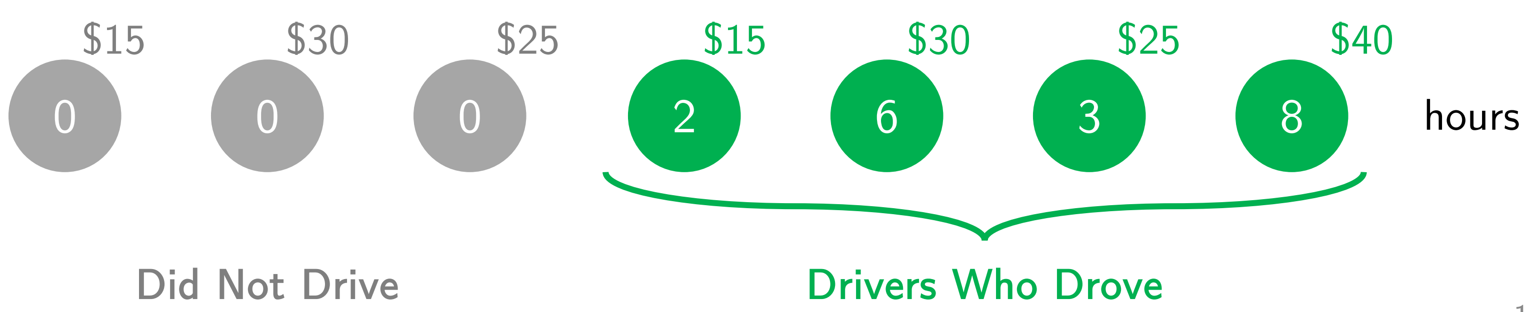
Solution: Instrumental Variables

Selection Bias

Solution: Heckman Two-Stage Method

("Heckit" - Heckman 1979)

Hours ~ Wage



Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

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

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Demand

Short-term Habits

Long-term Habits

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

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

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

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

Empirical Strategy Heckman + IV

1. **Work or not?**

Control Function Probit:

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

Income So Far
= accumulated income since beginning of day

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Income So Far
= intensity of work

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Income So Far
= intensity of work

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

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Income So Far
= intensity of work

Hours So Far
= amount of active time

Empirical Strategy Heckman + IV

1 Work or not?

Control Function Probit:

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

Income So Far
= intensity of work

Hours So Far
= amount of active time

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

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Income So Far
= intensity of work

Hours So Far
= amount of active time

Conditional on working

2 **How long to work?**

2SLS with Fixed Effects

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

Empirical Strategy Heckman + IV

1 **Work or not?**

Control Function Probit:

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

Income So Far
= intensity of work

Hours So Far
= amount of active time

Conditional
on working

2 **How long to work?**

2SLS with Fixed Effects

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

Inverse Mills Ratio
= correct for selection bias

Empirical Strategy Heckman + IV

1 Work or not?

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

Probit: Estimate **P(drive)**

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

Bias corrected with panel jackknife (Hahn & Newey 2004)

Inverse Mills Ratio (IMR)

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

Conditional on working

2 How long to work?

IV: Estimate **hourly earning** from IVs

OLS: Estimate **hours**

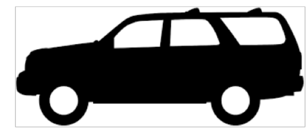
$$f(Hour_{i,t}) = \beta_{0,i} + \beta_\omega \omega_{i,t} + \boldsymbol{\beta Z_{i,t}} + \theta \lambda_{i,t} + u_{i,t}$$

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

Results

Financial Offer ISF HSF

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



Within-Day

Midday

↓

Late Night

Across-Days

Tuesday

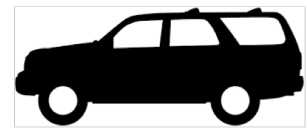
↓

Sunday

Results

Financial Offer ISF HSF

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



Within-Day

Midday

Late Night

Across-Days

Tuesday

Sunday

+	-
Positive	Negative

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	$\boxed{\text{-0.002*** (0.0002)}}$
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	$\boxed{\text{-0.002*** (0.0002)}}$
Hours so far		
AIC	95,856.010	72,887.620

N = 166,766

For average driver,
$100 additional income so far,
P(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	$\boxed{\text{-0.002*** (0.0002)}}$
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(drive) increases by 4.1%

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

Late Night

	Work or not? (1)		# Hours (2)		
	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

	Work or not? (1)		# Hours (2)		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	[illegible]	[illegible]	[illegible]	[illegible]
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					
AIC/R^2	95,856.010	72,887.620	0.313	0.324	0.913

The more you've earned, you'll drive shorter hours.

The longer you've been active, you'll drive longer hours.

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

	Work or not? (1)		# Hours (2)		
	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?

	Offer	ISF	HSF
Late night	+	-	+

Late Night

	1 Work or not?		2 # 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 Target	Inertia		Income Target	Inertia

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

Results Within Day

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

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

As day/week proceeds...

Neoclassical Financial Incentive	encourages working

Results Summary

As day/week proceeds...

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

Results Summary

As day/week proceeds...

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

Outline

- What has been done

  Practice / labor economics / OM

- Data and empirical strategy

  Dealing with endogeneity and selection bias

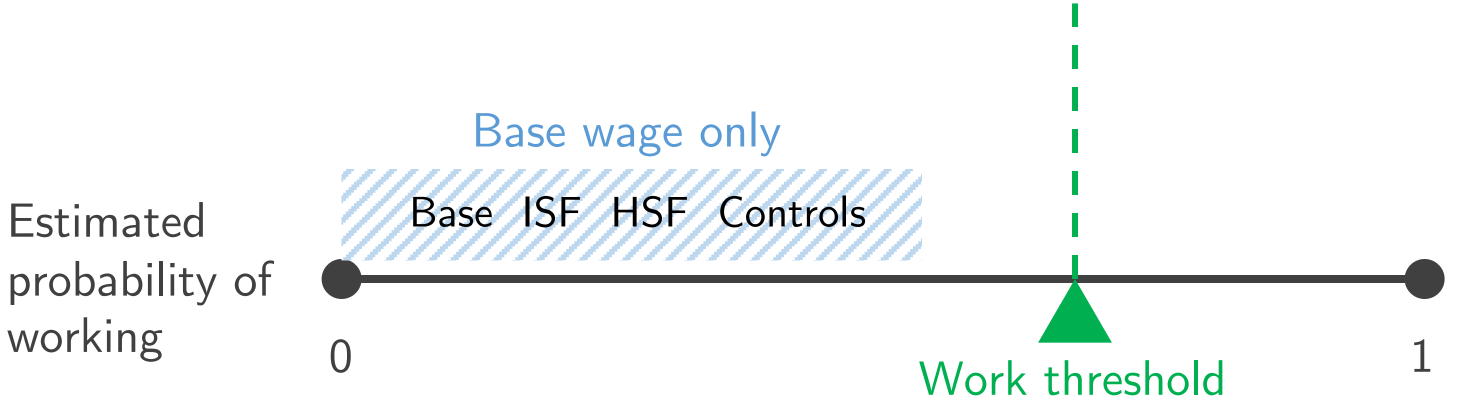
- Results

  Impact of incentive and behavioral elements on labor decisions

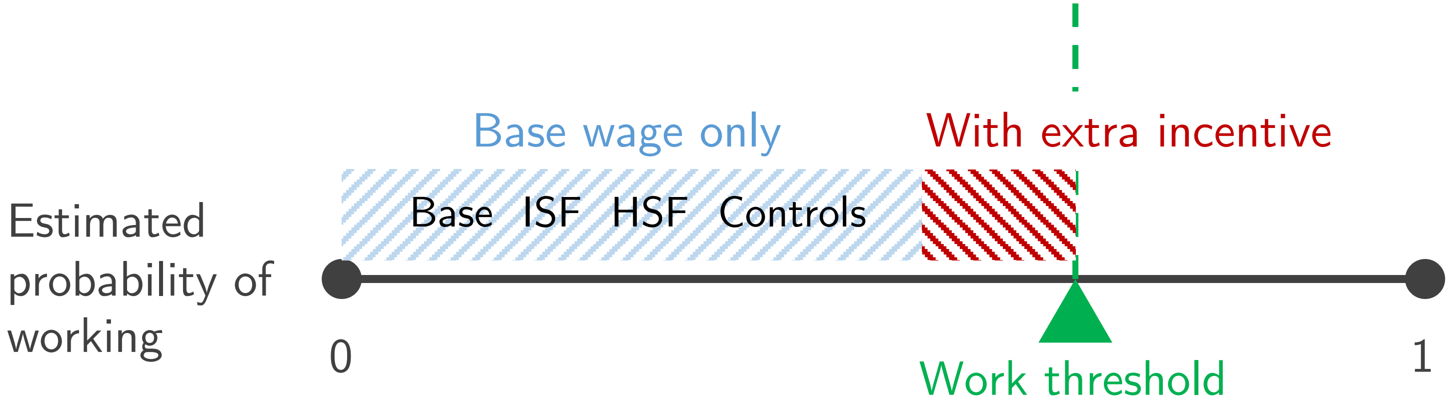
- Implications

  Simulation of optimal incentive re-allocation

Optimal Targeted Incentive

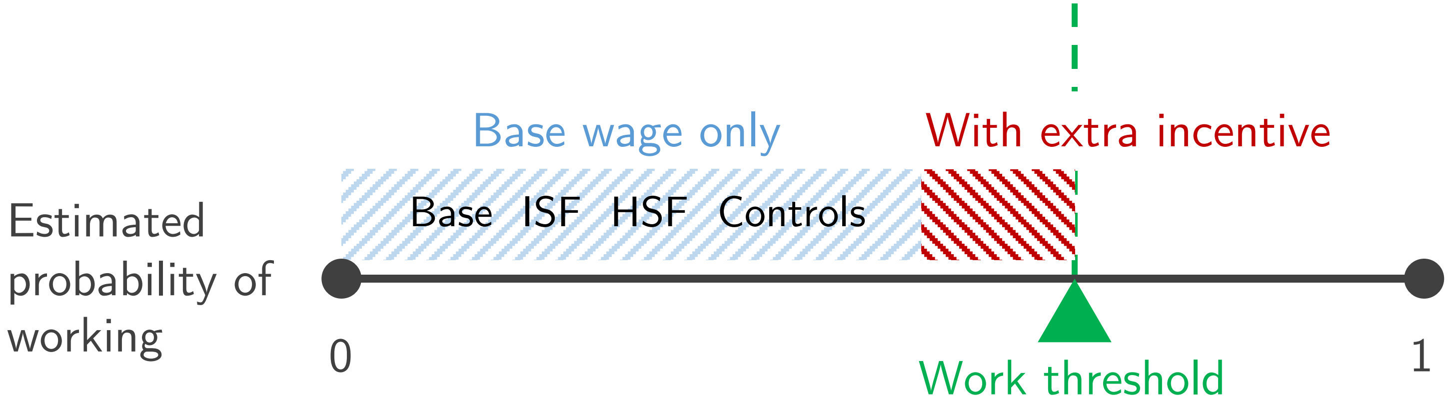


Optimal Targeted Incentive



Optimal Targeted Incentive

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



Reallocating Incentives

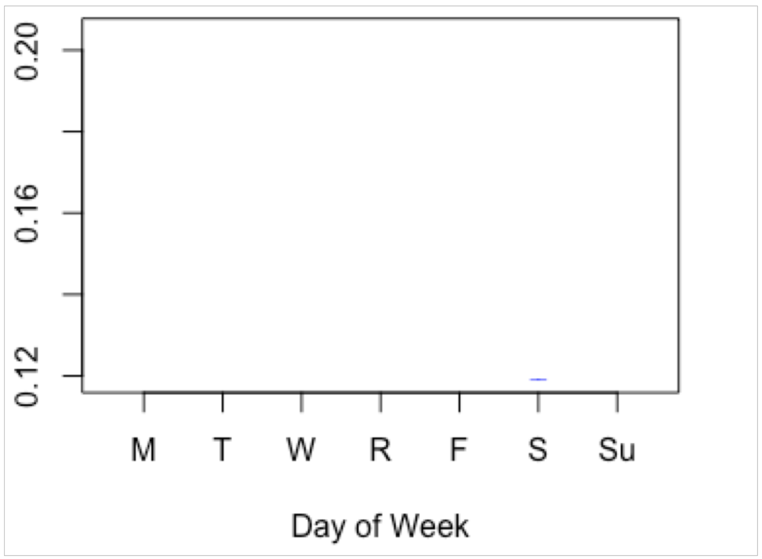
Compared to current practice from Jan to Sep 2017 out-of-sample
(Using data from Oct 2016 to right before the focal date as training)

Reallocating Incentives

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

Given the same budget

Extra drivers

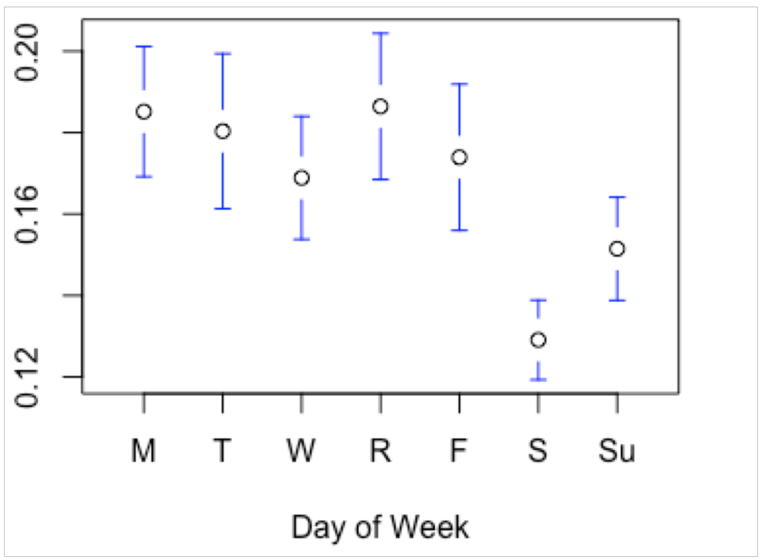


Reallocating Incentives

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

Given the same budget

Extra drivers



Can recruit **17% more drivers**

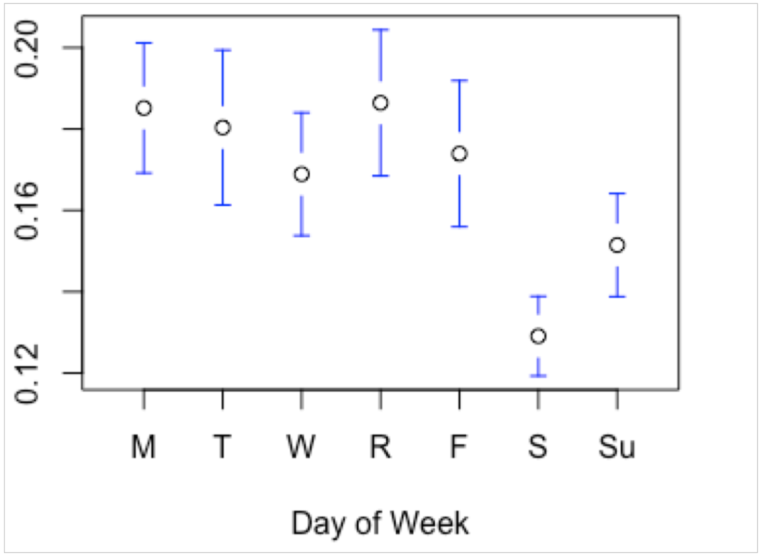
Average promo: 1.61x

Reallocating Incentives

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

Given the same budget

Extra drivers

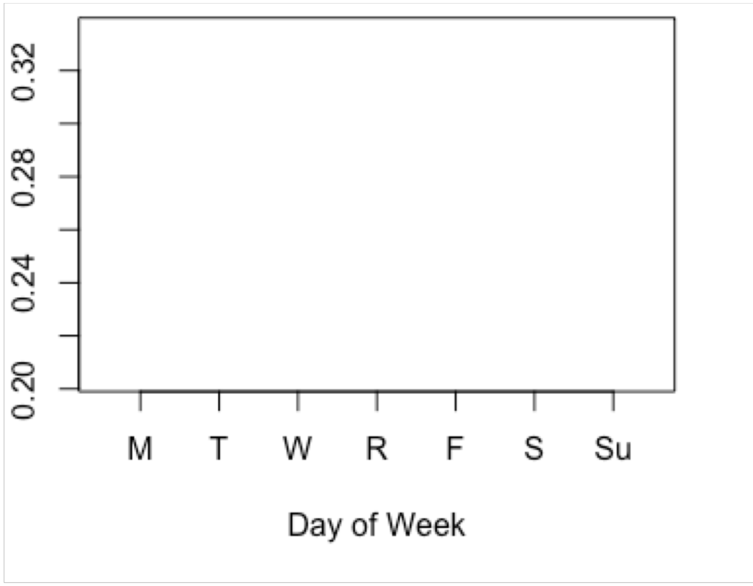


Can recruit **17% more drivers**

Average promo: 1.61x

Given the same capacity

Cost saved

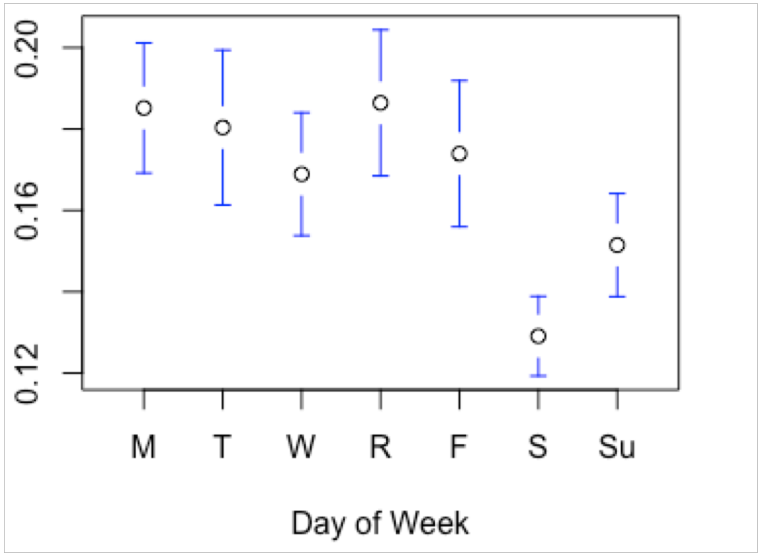


Reallocating Incentives

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

Given the same budget

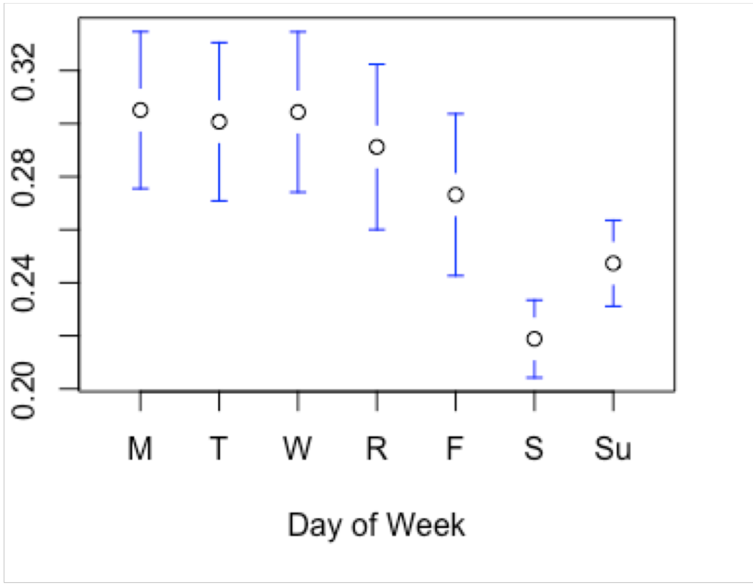
Extra drivers



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

Given the same capacity

Cost saved



Costs 28% less to maintain capacity

Summary

How do gig economy workers make labor decisions?

Approach

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

Findings

As day/week proceeds...

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

Implications

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

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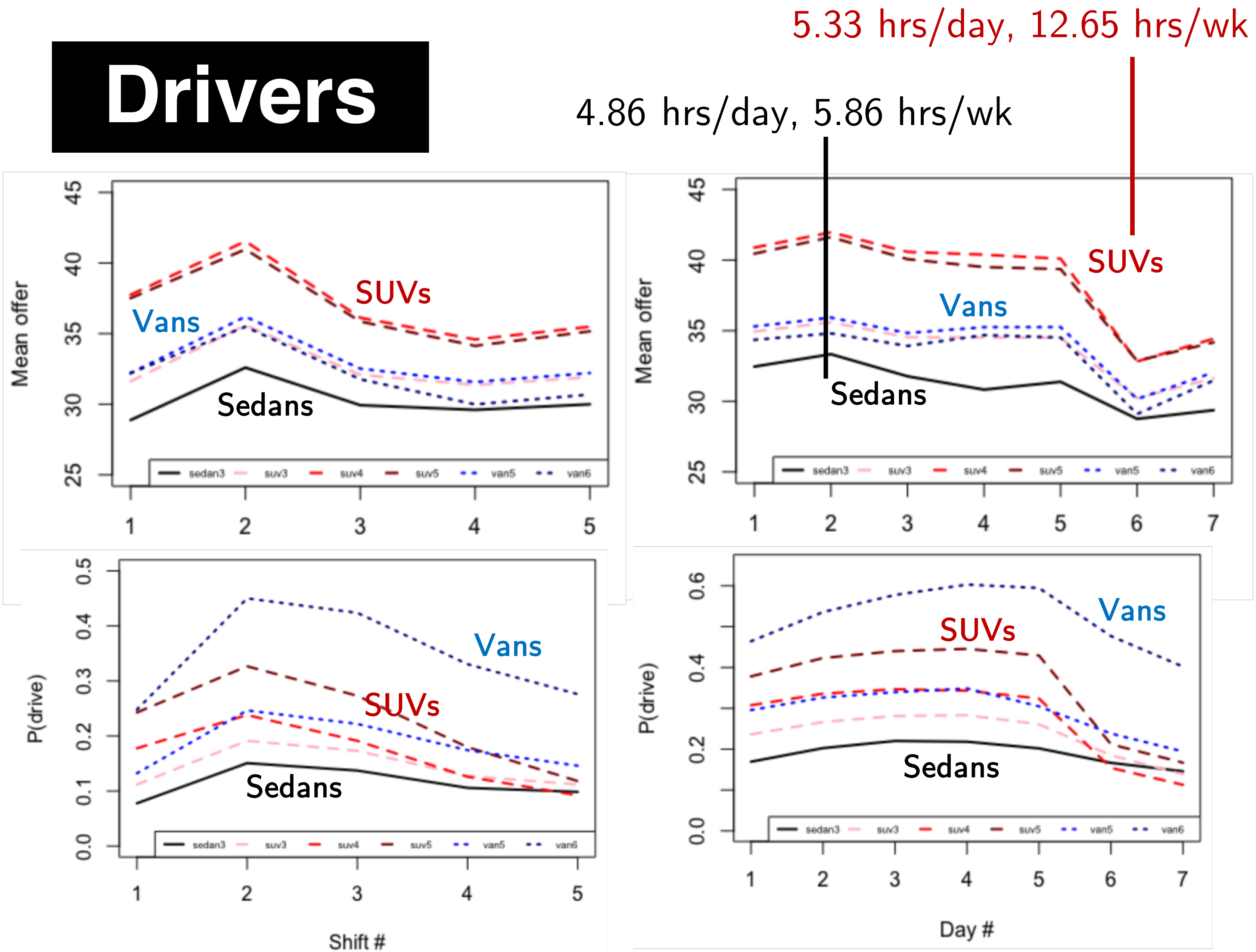
Appendix

Drivers



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

Gig Economy x Retail

Baker Retailing Center

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

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

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

snag.work on-demand

Wonolo

coople

(allwork)

Heckman Sample Selection

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

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

From this process, the researcher can observe

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

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

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

The probability of y_i not censored is

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

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

Heckman Sample Selection

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

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

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

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

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

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

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

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.