The Impact of Behavioral and Economic Drivers on Gig Economy Workers

BDRM 2018

Park Sinchaisri
Gad Allon, Maxime Cohen

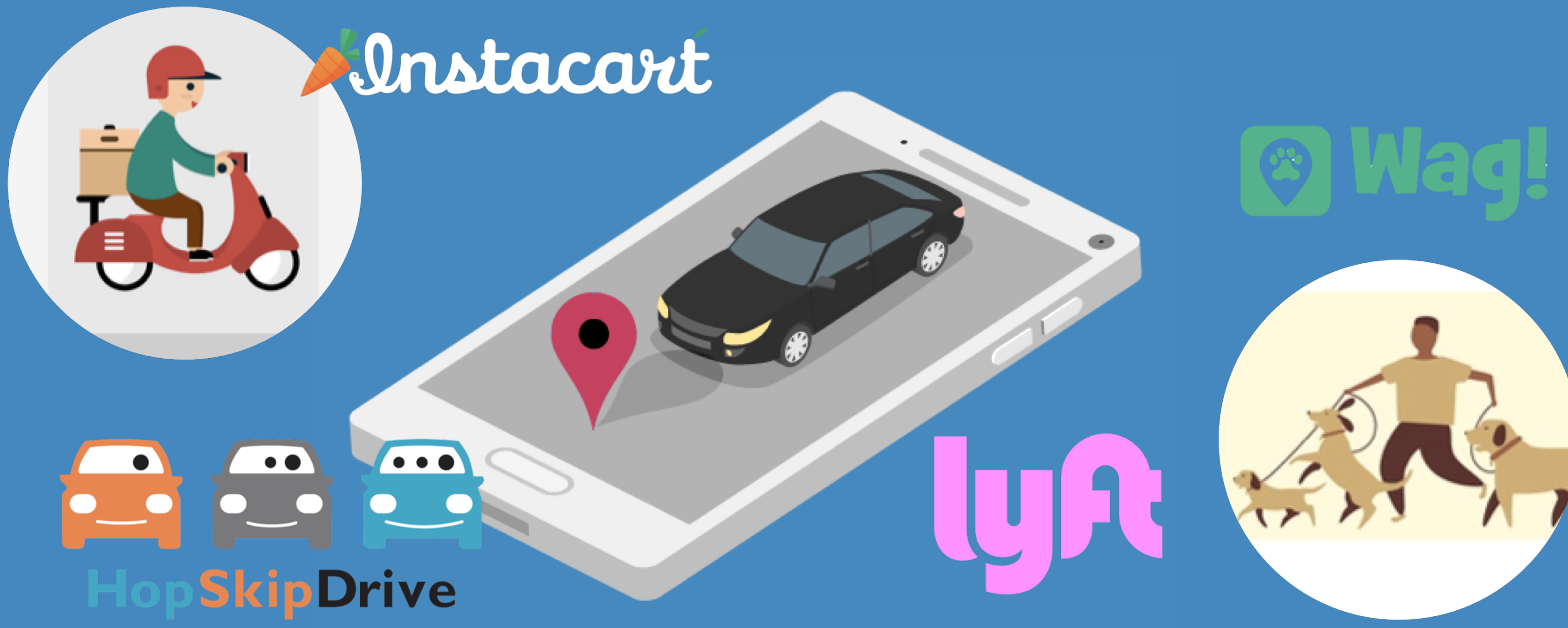
Instacart

Wag!

HopSkipDrive

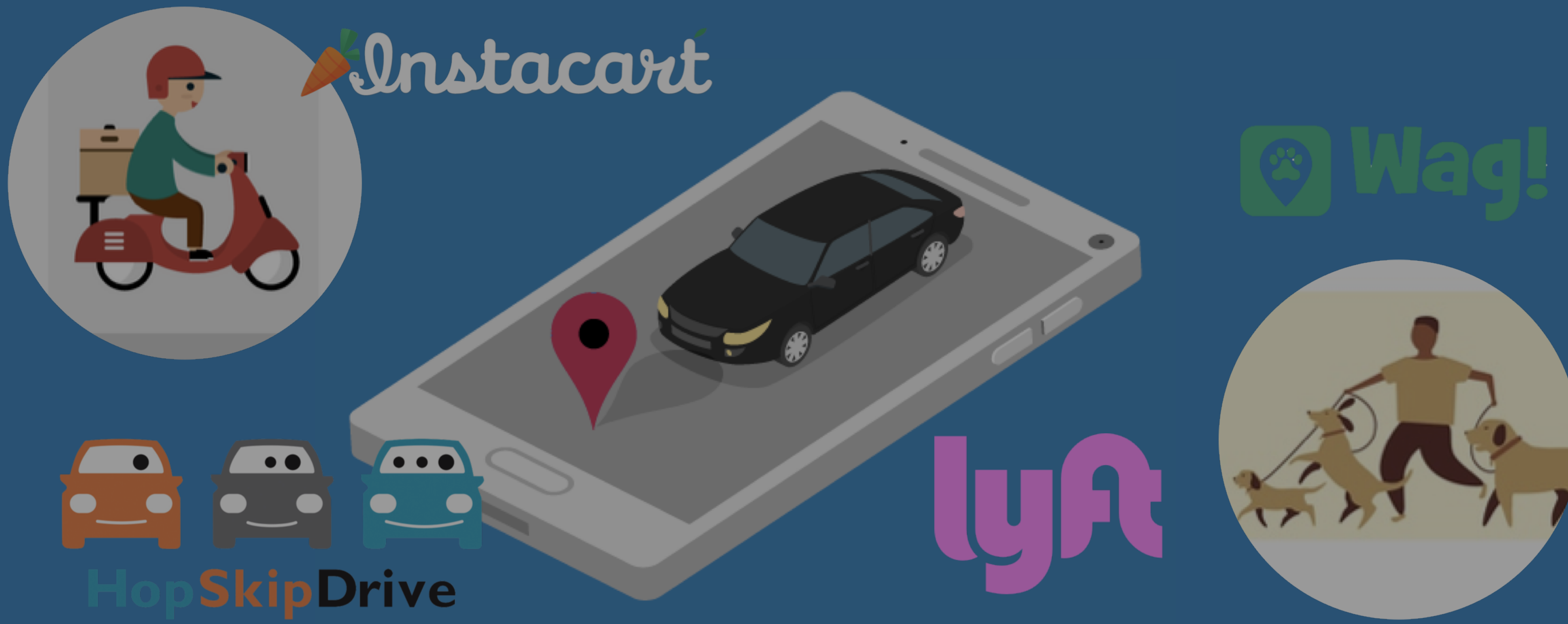
lyft

Gig Economy



Gig Economy

+ Labor flexibility/reduced costs
- Challenging capacity planning



Who Will Show Up To Work?

Gig Economy

+ Labor flexibility/reduced costs
- Challenging capacity planning

Challenging Capacity Planning

Peak

Need enough workers
when demand is high

Game nights

POSTMATES caviar

New school year

TaskRabbit handy

Slow

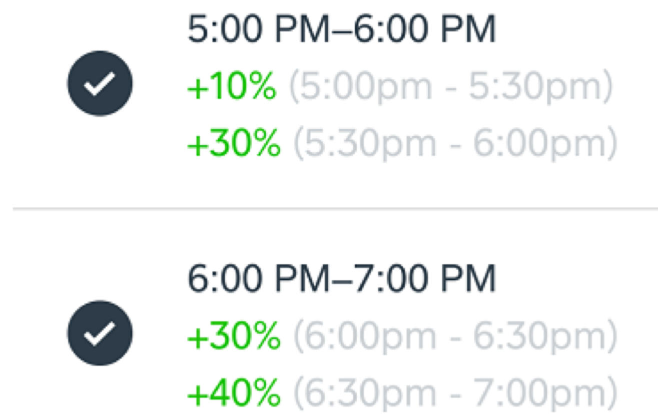
Don't want too many workers

"Guaranteed pay"

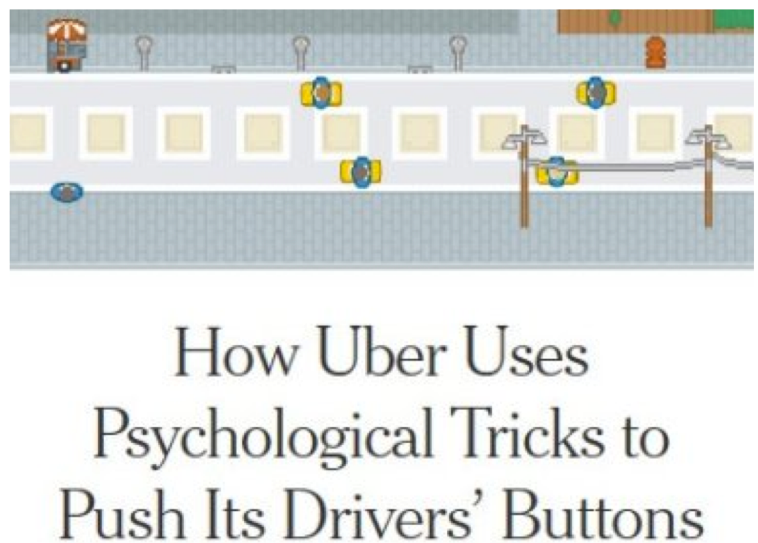
via DOORDASH

Real-time
"surge pricing"

Scheduled bonus



"You're so close to your target"



Research Question

How do gig economy workers
make labor decisions?

= *How many would show up? How long would they stay working?*

Outline

Theories of Labor Supply	Our data Endogeneity Selection	Approaches Heckman + IV	Results P(work)/Hours Behavioral

Theories of **Labor Supply**

Neoclassical

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

Theories of **Labor Supply**

Neoclassical	Behavioral
• Maximize lifetime utility	• Reference-dependence, targeting
• **Positive** income elasticities	• **Negative** income elasticities

- **Camerer et al.** (1997) — ***Income targeting***
- **Farber** (2005) — *Income targeting but not strong*
- **Farber** (2008)
- **Crawford/Meng** (2011) — *Income/Hours 2^{nd} target reached*
- **Farber** (2015) — ***Hours targeting***

Theories of **Labor Supply**

Neoclassical

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

Behavioral

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

Camerer et al. (1997) — ***Income targeting***

Farber (2005) — *Income targeting but not strong*

Farber (2008)

Crawford/Meng (2011) — *Income/Hours 2nd target reached*

Farber (2015) — ***Hours targeting***

Chen/Sheldon (2016)

Sheldon (2016)

No targeting!

Theories of Labor Supply

Neoclassical

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

Behavioral

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

Camerer et al. (1997) — ***Income targeting***

Farber (2005) — *Income targeting but not strong*

Farber (2008)

Crawford/Meng (2011) — *Income/Hours 2nd target reached*

Farber (2015) — ***Hours targeting***

Chen/Sheldon (2016)
Sheldon (2016)

No targeting!

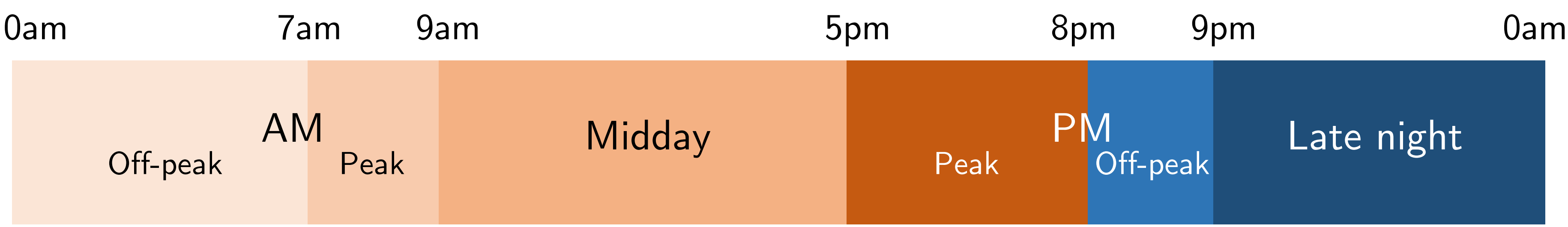
Our goal is to reconcile these two theories

Our Dataset

A ride-hailing company based in New York City

- Drivers decide their schedules, compensated by hourly rate

Shift-level financial incentives and driving activity

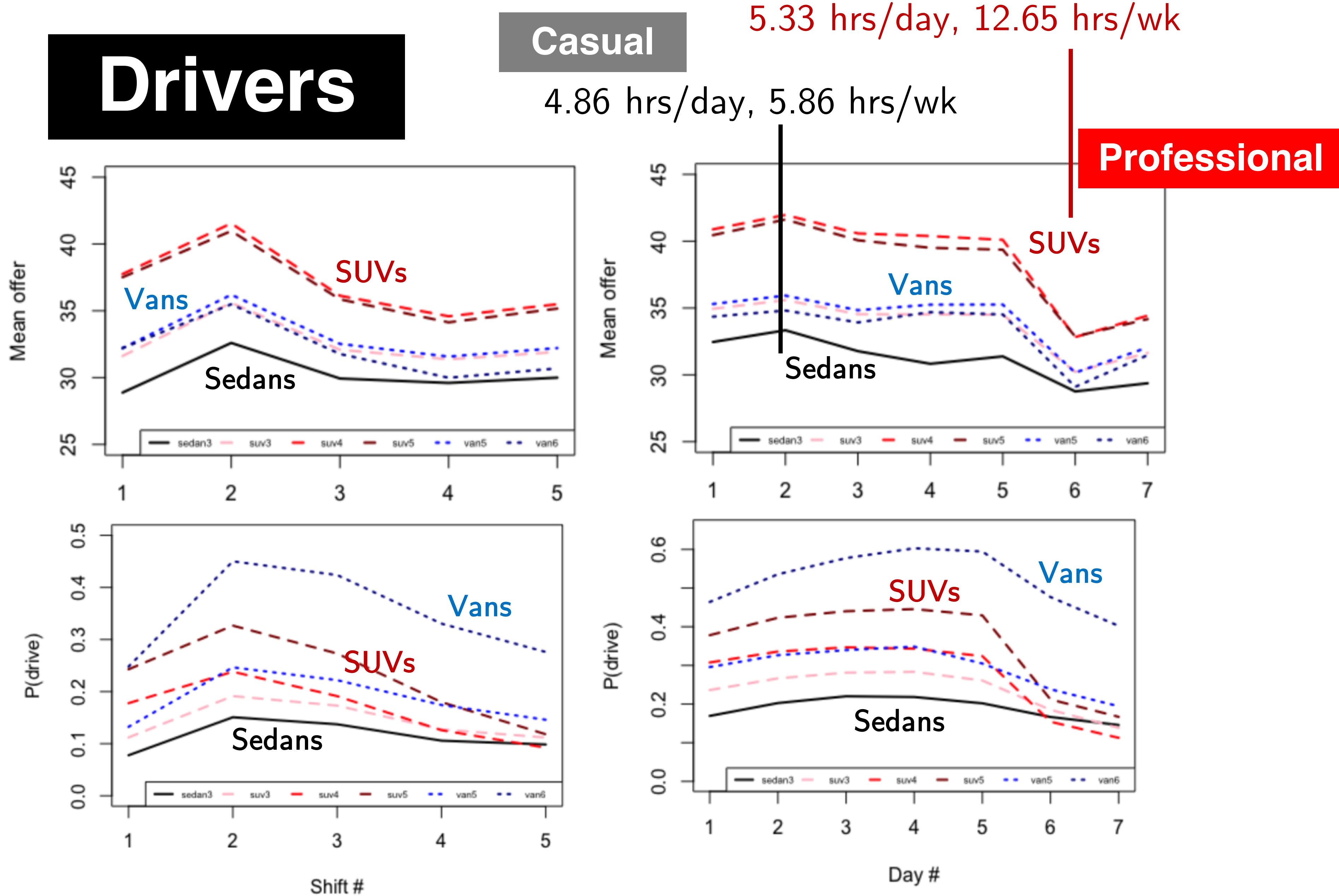


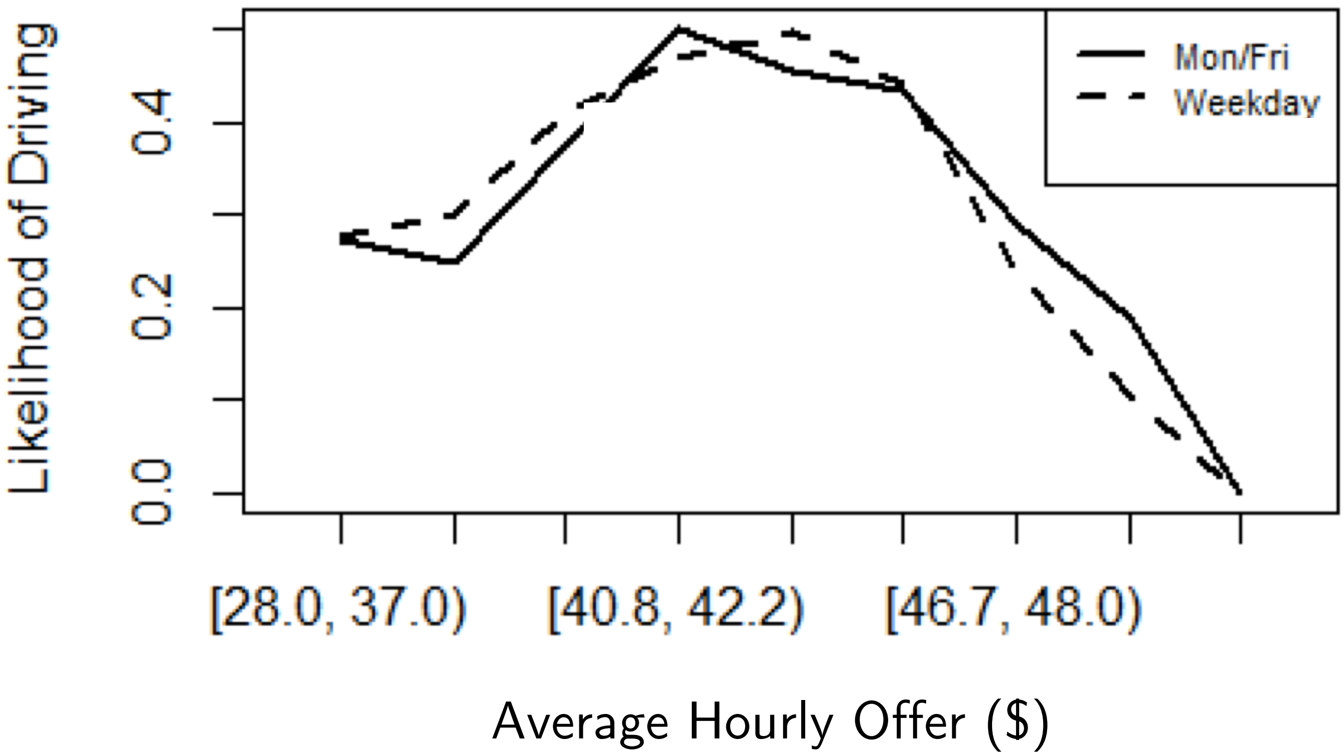
5.5M
Observations

358
Days
Oct 2016 – Sep 2017

7,826
Unique drivers
- SUV (64.54%)
- Sedan (21.77%)
- Van (13.69%)

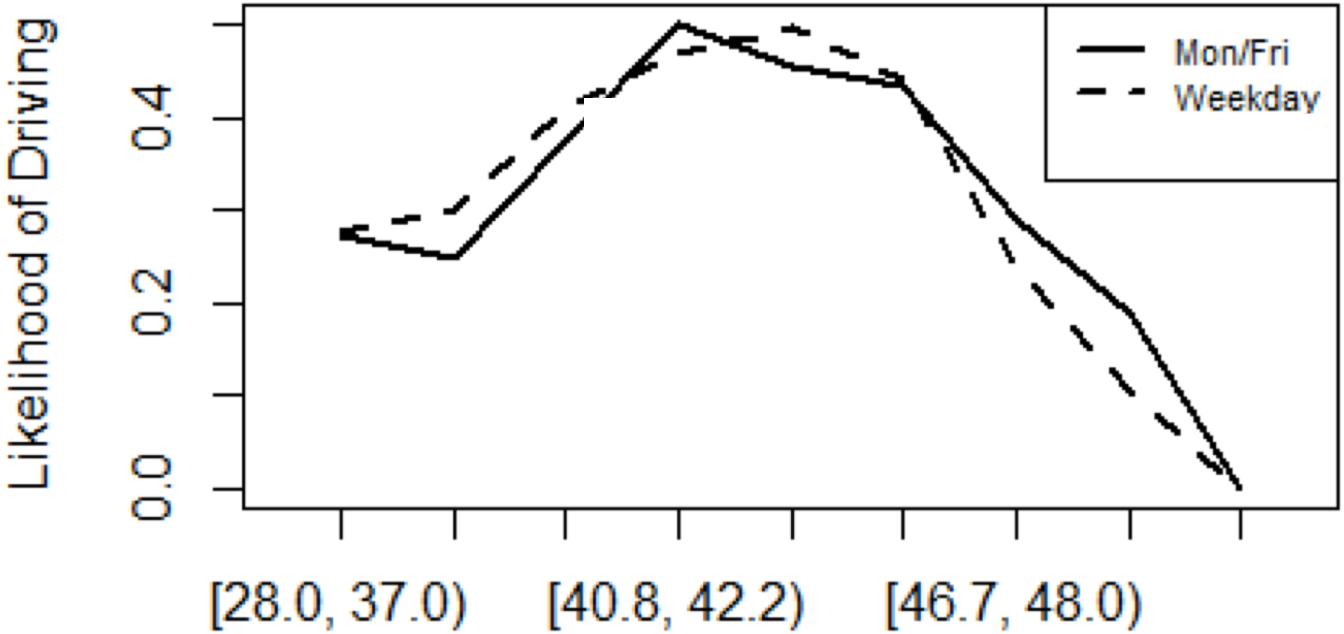
Drivers


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


Likelihood of Driving
0.0
0.2
0.4
Mon/Fri
Weekday
[28.0, 37.0)
[40.8, 42.2)
[46.7, 48.0)
Average Hourly Offer ($)

“Simultaneity”

Supply ⟷ Offer



Average Hourly Offer ($)

Approach

Instrumental Variables

- **Offer:** Average of other drivers' offers (Camerer et al. 1997, Sheldon 2016)
- **Promo**: Lagged value of *promo* from the same shift in the previous week (Villas-Boas & Winer 2001, Yang et al 2003)

Log(hours)		Camerer et al.'97		Sheldon'16	
	TRIP	*TLC1*	*TLC2*	*OLS*	*2SLS*
Log(wage)	-.319	-1.313	-.975	.14	.22

“Selection Bias”

Decision to drive or not is not random

Log(hours)	Camerer et al.’97			Sheldon’16	
	TRIP	*TLC1*	*TLC2*	*OLS*	*2SLS*
Log(wage)	-.319	-1.313	-.975	.14	.22

Approach

Heckman Two-Stage Estimation

1) Predict **choice** (drive or not?) using Probit
2) Predict **level** (how long?) using OLS

Both levels account for endogeneity using IVs discussed previously

+ Fixed effects in ”Level”

Dealing with Selection

1. Choice Equation "Drive or not?"

Probit: Estimate **P(drive)**

Inverse Mills Ratio (IMR)

Conditional on driving

2. Level Equation "How long?"

OLS: Estimate **hours**

Dealing with Selection

1. Choice Equation "Drive or not?"

IV: Estimate **hourly offer** and **promo** from IVs

Probit: Estimate **P(drive)**

$$\mathbb{P}(Drive_{it} = 1|\mathbf{X}) = \Phi(\alpha_0 + \alpha_w \hat{w}_{it} + \alpha_\psi \hat{\psi}_{it} + \alpha \mathbf{Z})$$ 1

Inverse Mills Ratio (IMR)

Conditional on driving

2. Level Equation "How long?"

OLS: Estimate **hours**

Z include past work frequency, experience, holiday, temperature, precipitation, humidity

Dealing with **Selection**

1. Choice Equation "Drive or not?"

IV: Estimate **hourly offer** and **promo** from IVs

Probit: Estimate **P(drive)**

$$\mathbb{P}(Drive_{it} = 1|\mathbf{X}) = \Phi(\alpha_0 + \alpha_w \hat{w}_{it} + \alpha_\psi \hat{\psi}_{it} + \alpha \mathbf{Z})$$

1

Inverse Mills Ratio (IMR)

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

Conditional on driving

2. Level Equation "How long?"

OLS: Estimate **hours**

Z include past work frequency, experience, holiday, temperature, precipitation, humidity

Dealing with Selection

1. Choice Equation "Drive or not?"

IV: Estimate **hourly offer** and **promo** from IVs

Probit: Estimate **P(drive)**

$$\mathbb{P}(Drive_{it} = 1|\mathbf{X}) = \Phi(\alpha_0 + \alpha_w \hat{w}_{it} + \alpha_\psi \hat{\psi}_{it} + \alpha \mathbf{Z})$$

1

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**

$$f(Hour_{it}) = \beta_0 + \beta_\omega \hat{\omega}_{it} + \beta \mathbf{Z} + \beta_\lambda \lambda_{it} + \epsilon_{it}$$

2

Z include past work frequency, experience, holiday, temperature, precipitation, humidity

Daily/Weekly Targets

Monday is the first day of the week. Assume no drivers work overnight.

Base	Income Targeting	Time Targeting
1 2	1 2 + Income earned so far	1 2 + Hours worked so far

$\underbrace{\text{Income Targeting} \quad \text{Time Targeting}}_{\text{Income + Time Targeting}}$

Daily/Weekly Targets

Monday is the first day of the week. Assume no drivers work overnight.

Base	Income Targeting	Time Targeting
1 2	1 2 + Income earned so far	1 2 + Hours worked so far

$\underbrace{\text{Income Targeting} \quad \text{Time Targeting}}_{\text{Income + Time Targeting}}$

1 **CHOICE**

$$\mathbb{P}(Drive_{it} = 1|\mathbf{X}) = \Phi(\alpha_0 + \alpha_w \hat{w_{it}} + \alpha_\psi \hat{\psi_{it}} + \alpha \mathbf{Z} + \alpha_\tau \begin{cases} \text{-} \\ \text{IncomeSoFar} \\ \text{HoursSoFar} \\ \text{ISF + HSF} \end{cases})$$

2 **LEVEL**

$$f(Hour_{it}) = \beta_0 + \beta_\omega \hat{\omega_{it}} + \beta \mathbf{Z} + \beta_\lambda \lambda_{it} + \alpha_\tau \begin{cases} \text{-} \\ \text{IncomeSoFar} \\ \text{HoursSoFar} \\ \text{ISF + HSF} \end{cases} + \epsilon_{it}$$

Results Choice

$$\mathbb{P}(Drive_{it}=1|\mathbf{X}) = \Phi(\alpha_0 + \alpha_w \hat{w}_{it} + \alpha_\psi \hat{\psi}_{it} + \alpha \mathbf{Z} + \alpha_\tau \left\{ \begin{array}{l} \text{-} \\ \text{ISF + HSF} \end{array} \right.)$$

Late Night	Sedan		SUV	
	Base	+ Targets	Base	+ Targets
Hourly offer	0.008*** (0.001)	0.011*** (0.001)	0.008*** (0.001)	0.012*** (0.001)
Promo	0.421*** (0.040)	0.407*** (0.049)	0.229*** (0.038)	0.285*** (0.046)

Results Choice

$$\mathbb{P}(Drive_{it}=1|\mathbf{X}) = \Phi(\alpha_0+\alpha_w\hat{w}_{it}+\alpha_\psi\hat{\psi}_{it}+\alpha\mathbf{Z}+\alpha_\tau\left\{\begin{array}{l} - \\ \text{ISF + HSF}\end{array}\right.)$$

Late Night	Sedan		SUV	
	Base	+ Targets	Base	+ Targets
Hourly offer	0.008*** (0.001)	0.011*** (0.001)	0.008*** (0.001)	0.012*** (0.001)
Promo	0.421*** (0.040)	0.407*** (0.049)	0.229*** (0.038)	0.285*** (0.046)
Income so far	-	-0.0005 (0.0003)	"Fatigue" -	-0.002*** (0.0002)
Hours so far	-	0.414*** (0.011)	"Inertia" -	0.361*** (0.007)
AIC	92,276.680	63,823.450	95,856.010	72,887.620

N = 195,274 N = 166,766

Results Level

$$f(Hour_{it}) = \beta_0 + \beta_\omega \hat{\omega}_{it} + \beta \mathbf{Z} + \beta_\lambda \lambda_{it} + \alpha_\tau \left\{ \begin{array}{l} - \\ \text{ISF + HSF} \end{array} \right. + \epsilon_{it}$$

Late Night	Sedan			SUV		
	Naive	Base	+ Targets	Naive	Base	+ Targets
Hourly earnings	-0.008*** (0.001)	0.002 (0.001)	0.003*** (0.0003)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)

Results Level

$$f(Hour_{it}) = \beta_0 + \beta_\omega \hat{\omega}_{it} + \beta \mathbf{Z} + \beta_\lambda \lambda_{it} + \alpha_\tau \begin{cases} - \\ \text{ISF + HSF} \end{cases} + \epsilon_{it}$$

Late Night	Sedan			SUV		
	Naive	**Base**	**+ Targets**	**Naive**	**Base**	**+ Targets**
Hourly earnings	-0.008*** (0.001)	0.002 (0.001)	0.003*** (0.0003)	-0.010*** (0.001)	-0.001 (0.001)	0.001*** (0.0002)
ISF	-	-	$\boxed{\text{-0.0003*** (0.00003)}}$	**“Income Target”** -	-	$\boxed{\text{-0.0002*** (0.00002)}}$
HSF	-	-	$\boxed{\text{0.197*** (0.001)}}$	**“Inertia”** -	-	$\boxed{\text{0.187*** (0.001)}}$
IMR	-	***	***	-	***	***
Adjusted R^2	0.617	0.617	0.976	0.313	0.324	0.957

N = 17,515 (Sedan)

N = 18,941 (SUV)

Results Across Shifts

No significant difference among driver types

	Choice			Level		
SUV	Offer	ISF	HSF	Earning	ISF	HSF
Midday	+	+	+	-	+	+
PM peak	+	-	+	+	-	+
PM off-peak	+	-	+	+	-	+
Late night	+	-	+	+	-	+
		Fatigue	Inertia		Income Target	Inertia

Sedan	Offer	ISF	HSF	Earning	ISF	HSF
Midday	+	+	+	+	+	+
+PM peak	+	-	+	+	-	+
PM off-peak	+	-	+	+	-	+
Late night	+	-	+	+	-	+
		Fatigue	Inertia		Income Target	Inertia

Results Across Days

	Choice			Level		
SUV	Offer	ISF	HSF	Earning	ISF	HSF
Tuesday	+	+	+	+	+	+
Wednesday	+	+	+	+	-	+
Thursday	+	-	+	+	-	+
Friday	+	-	+	+	-	+
Saturday	+	-	+	+	-	+
Sunday	+	-	+	+	-	+

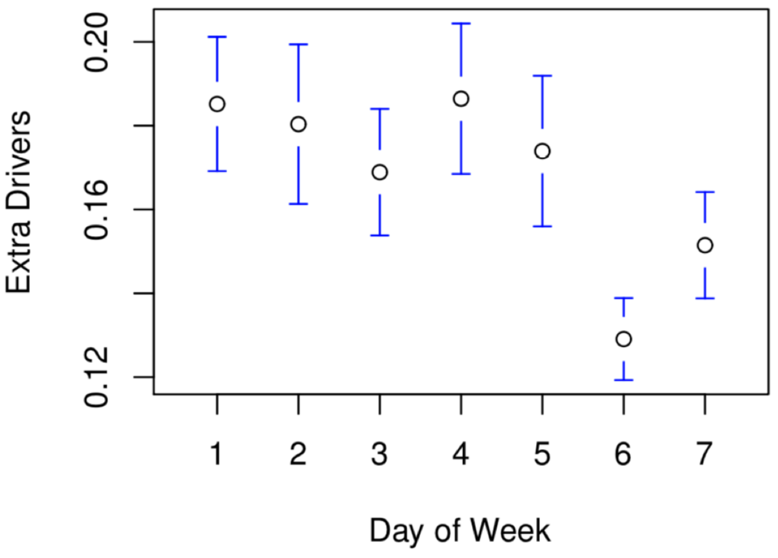
Sedan	Offer	ISF	HSF	Earning	ISF	HSF
Tuesday	+	+	+	-	-	+
Wednesday	+	+	+	-	-	+
Thursday	+	+	+	-	+	+
Friday	+	+	+	+	-	+
Saturday	+	-	+	+	-	+
Sunday	+	-	+	+	-	+

Income Target

Optimizing Incentives

Using the insights we obtain, we propose algorithm for optimal allocation of financial incentives

Given the same budget



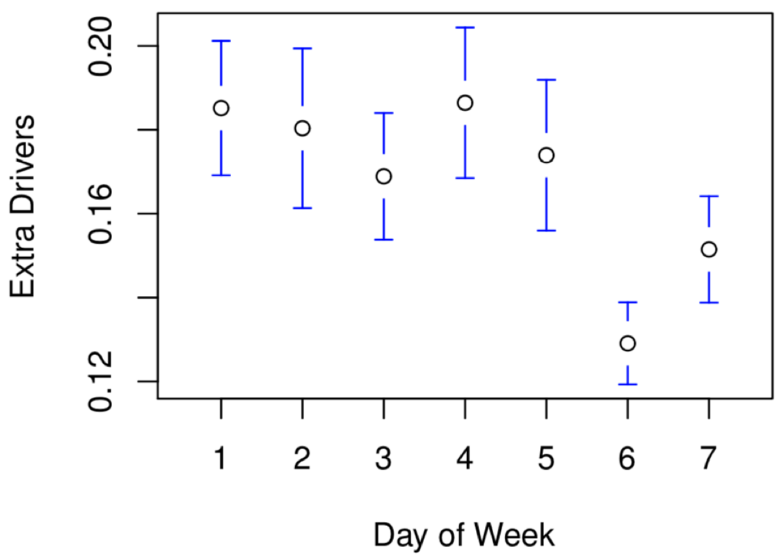
Can recruit **17% more drivers**

Average promo: 1.61x

Optimizing Incentives

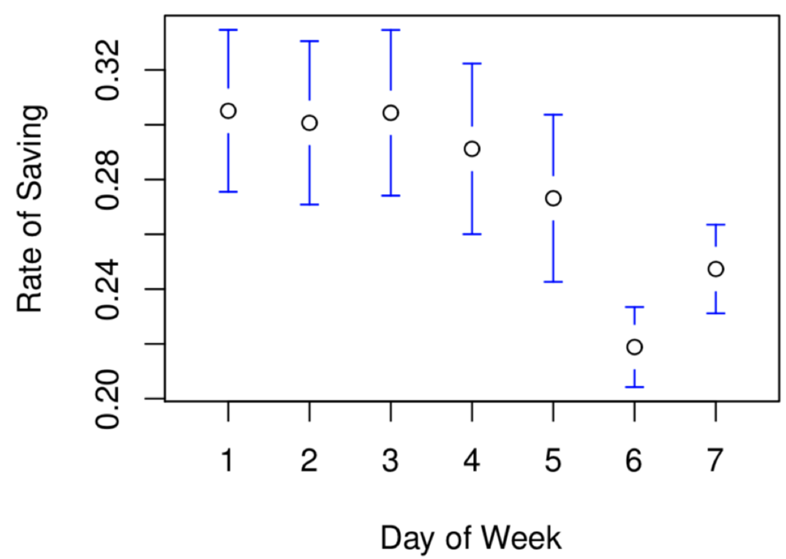
Using the insights we obtain, we propose algorithm for optimal allocation of financial incentives

Given the same budget



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

Given the same capacity



Costs 28% less to maintain capacity

Summary

Research question:

- How gig economy workers make labor decisions?
  How they are influenced by behavioral elements?

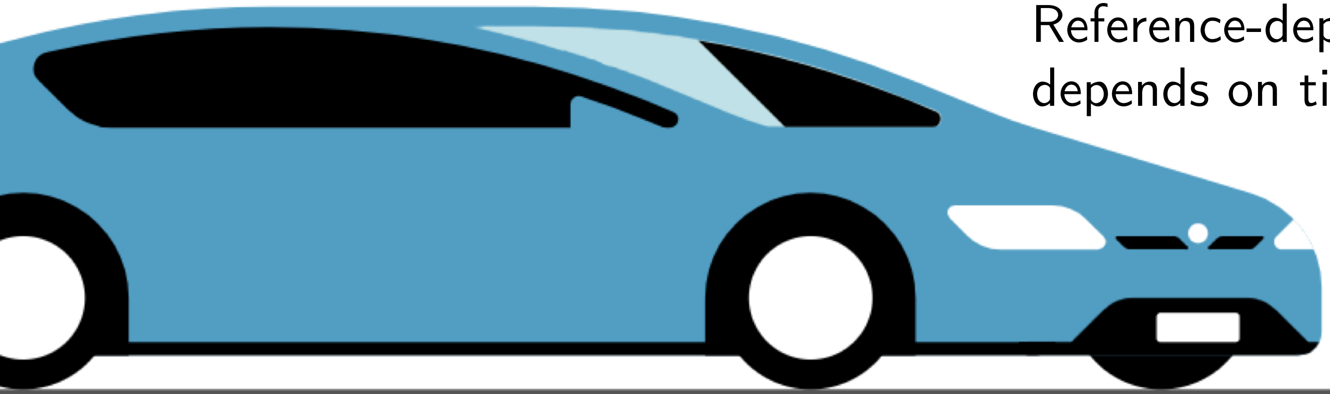
Approach:

- Shift-level data from ride-hailing company
- Two-stage Heckman estimation with instrumental variables

Findings:

- To bring workers to work, **offer** and **inertia** can increase the participation. **Fatigue/targeting** affect how long they will work.

  Reference-dependence preference depends on time and vehicle type



Appendix