The Impact of Behavioral and Economic Drivers on Gig Economy Workers

BDRM 2018

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Instacart

Wag!

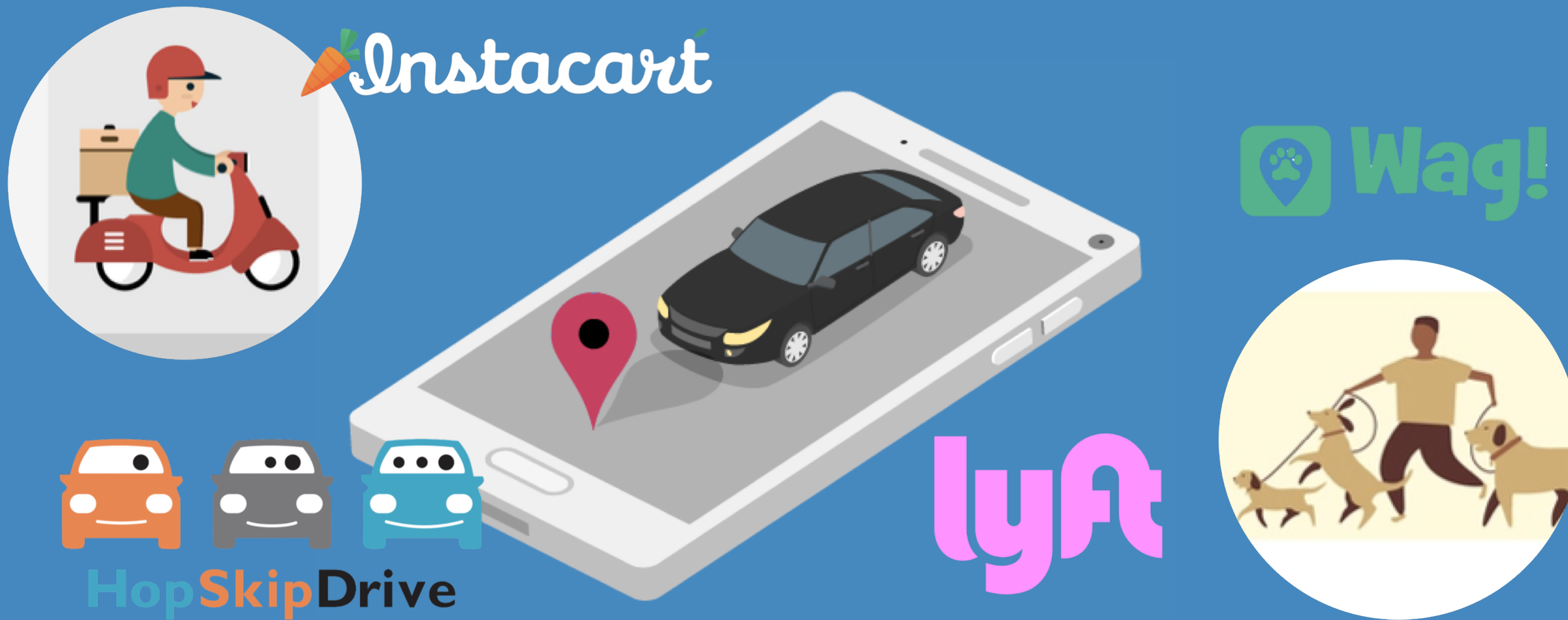
HopSkipDrive

lyft

Demand $\xleftrightarrow{\text{match}}$ Supply

independent/flexible

Gig Economy



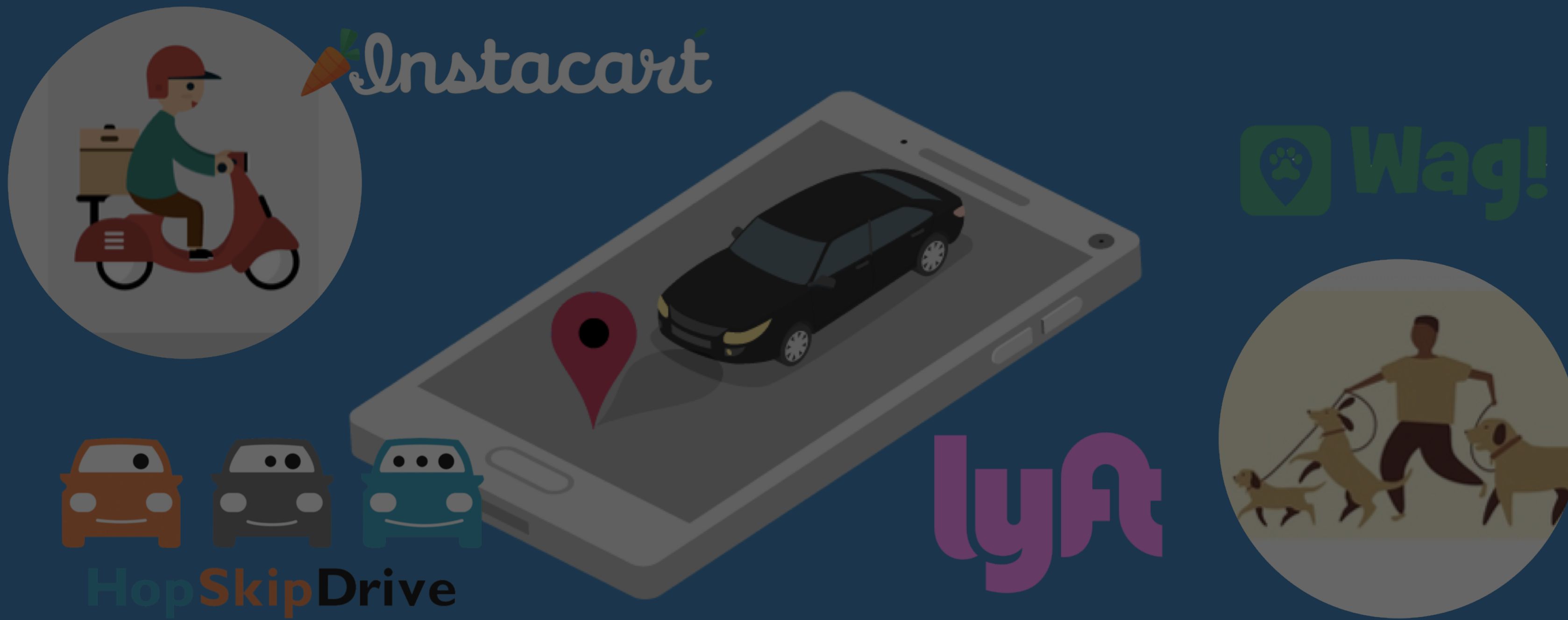
Demand $\xleftrightarrow{\text{match}}$ Supply

independent/flexible

Gig Economy

\+ Labor flexibility/reduced costs

\- Challenging capacity planning



Who Will Show Up To Work?

independent/flexible

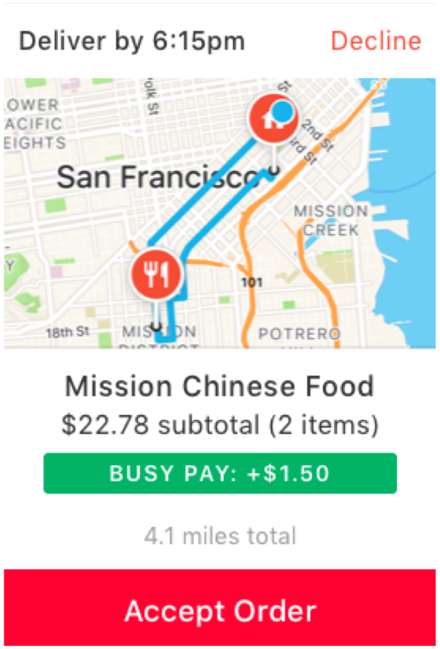
Gig Economy

+ Labor flexibility/reduced costs

- Challenging capacity planning

Existing Strategies

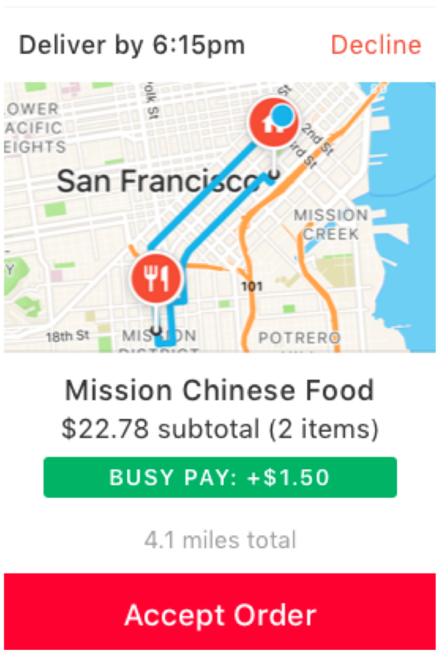
**Real-time
"surge pricing"**



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

Existing Strategies

Real-time "surge pricing"



Scheduled bonus

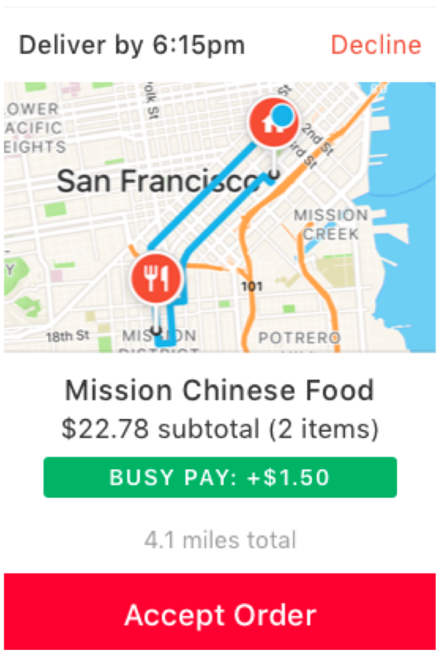
5:00 PM–6:00 PM
+10% (5:00pm - 5:30pm)
+30% (5:30pm - 6:00pm)

6:00 PM–7:00 PM
+30% (6:00pm - 6:30pm)
+40% (6:30pm - 7:00pm)

https://dasherhelp.doordash.com/busy-pay
https://courierhelp.trycaviar.com/customer/en/portal/articles/2821000-peak-hour-pay?b_id=9619/

Existing Strategies

Real-time "surge pricing"



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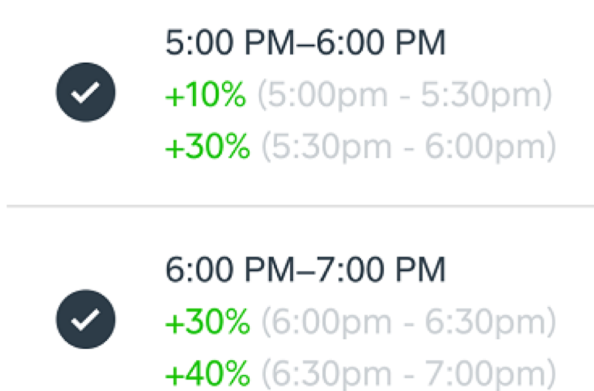
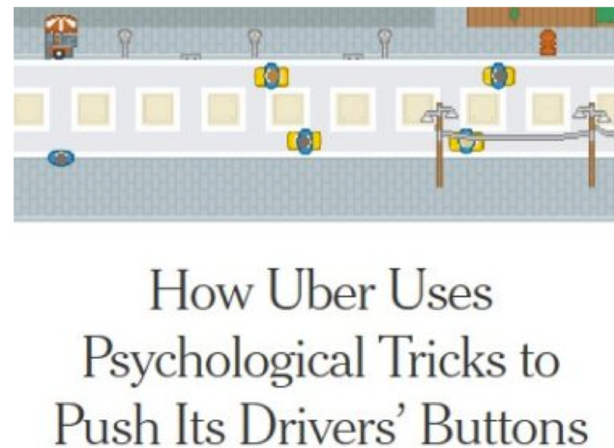


"You're so close to your precious target"



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

Research Question

How do gig economy workers make labor decisions?

Outline

Theories of Labor Supply

Our data
Endogeneity
Selection

Approaches
Heckman + IV

Results
P(work)/Hours
Estimates

Implications
Optimize
Incentives

Theories of Labor Supply

Neoclassical

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

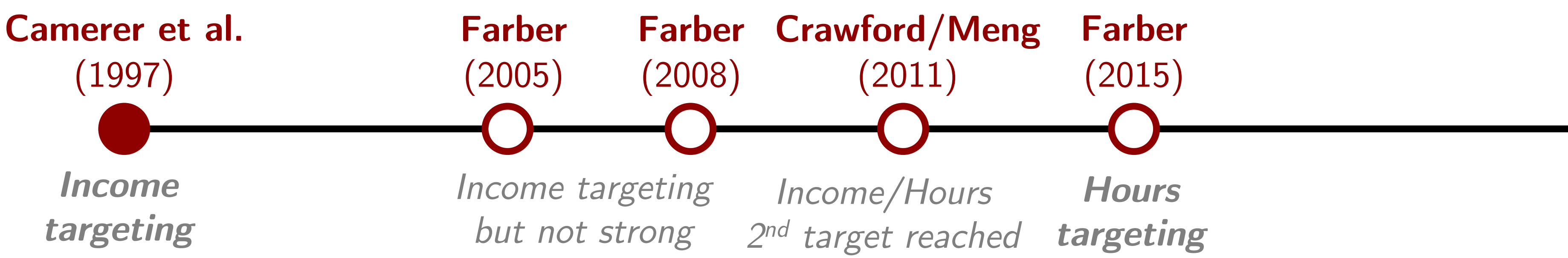
Theories of Labor Supply

Neoclassical

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

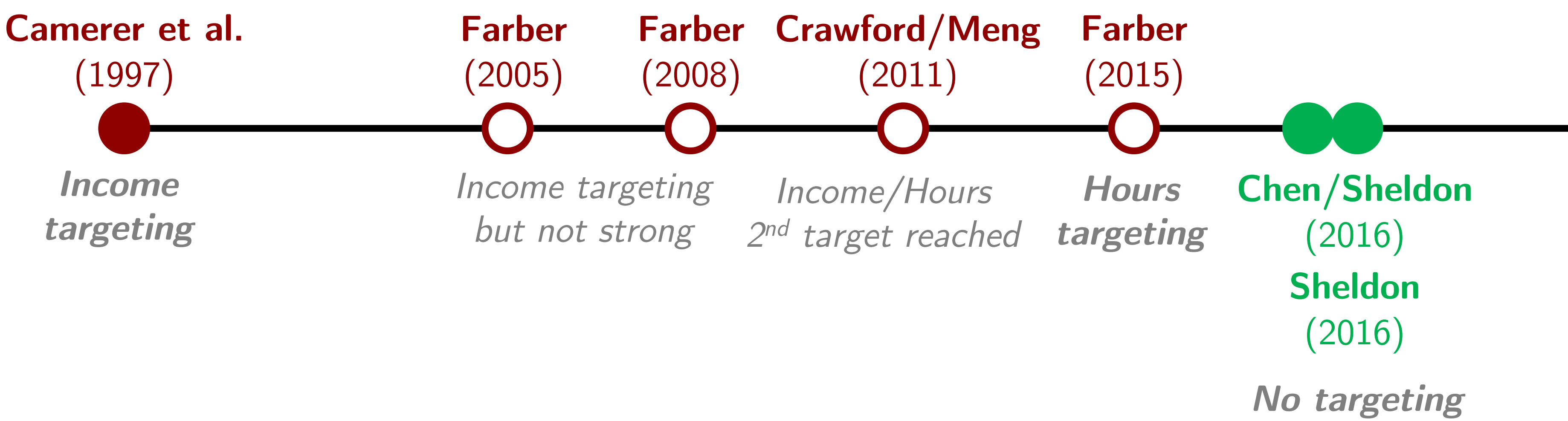
Behavioral

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



Theories of Labor Supply

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



Data NYC ride-hailing firm

Shift-level financial incentives and driving activity

Data NYC ride-hailing firm

Shift-level financial incentives and driving activity

5.5M
Observations

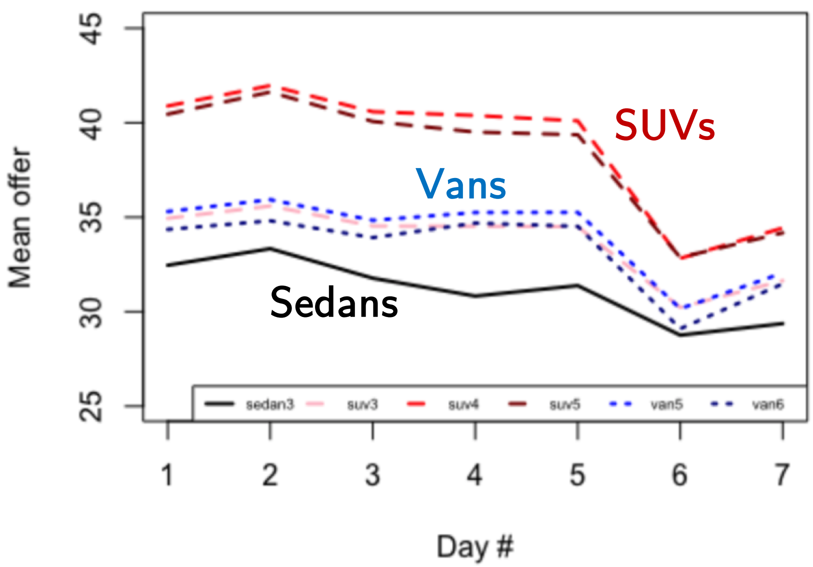
358
Days
Oct 2016 – Sep 2017

7,826
Unique drivers

- SUV (64.54%)
- Sedan (21.77%)
- Van (13.69%)

Casual vs. Professional Drivers

Offer



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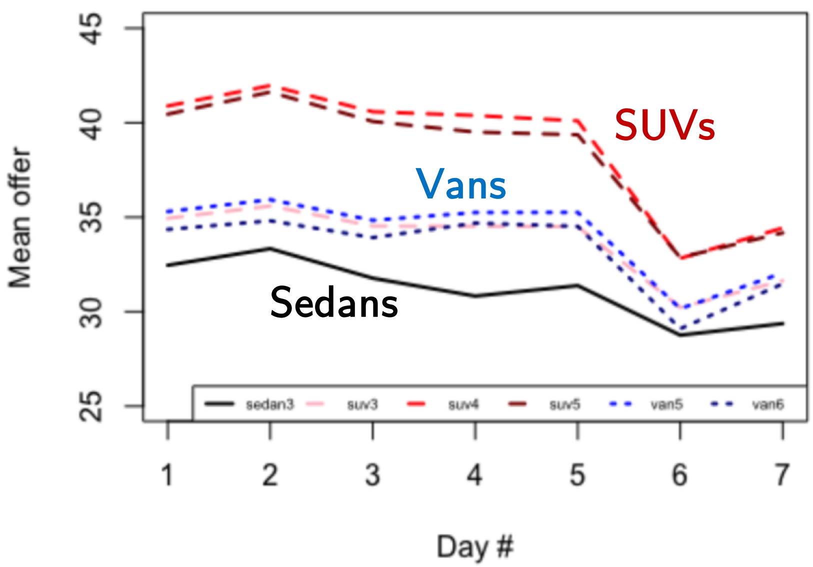
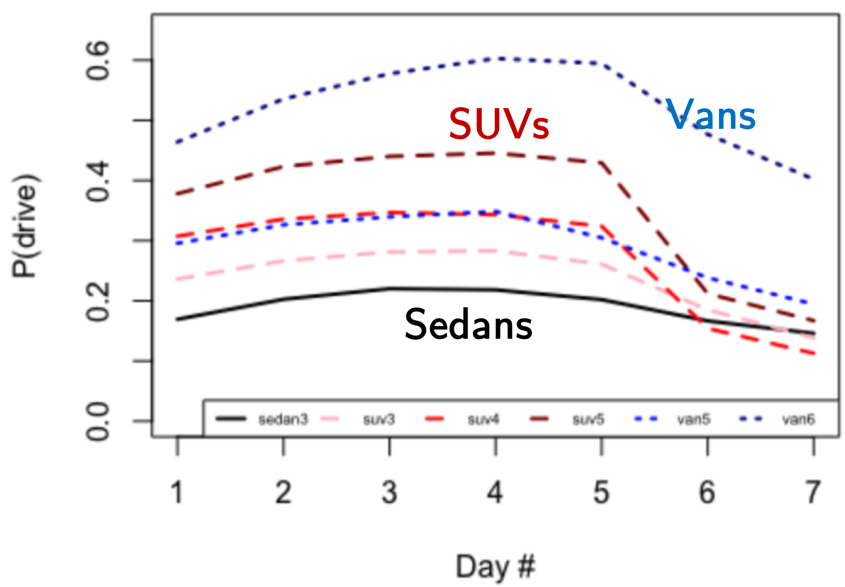
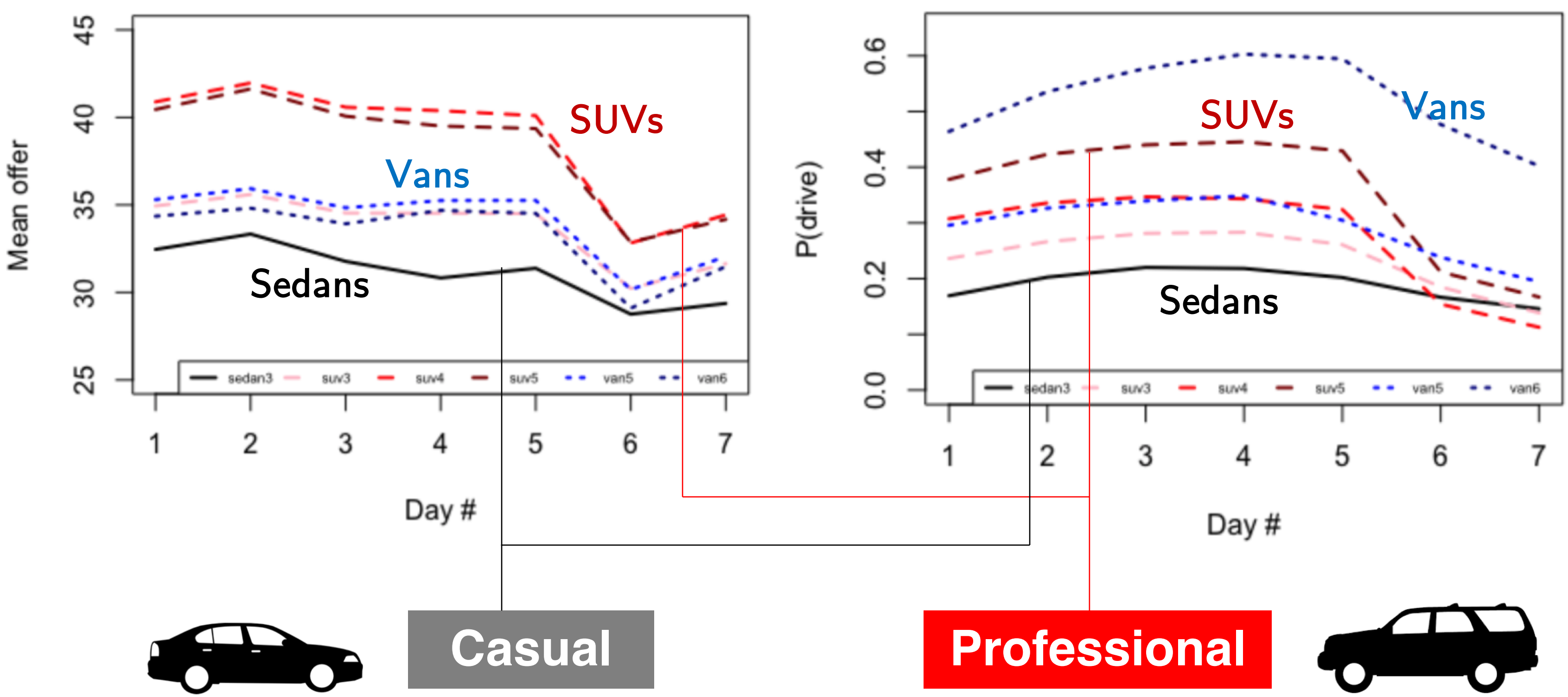


Drive?



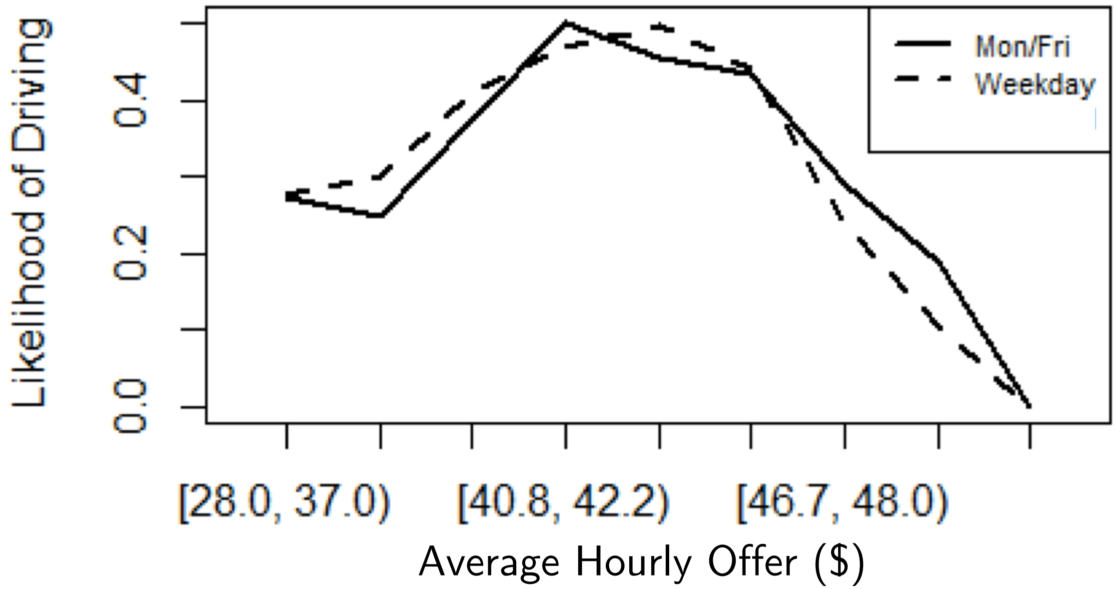
Casual vs. Professional Drivers

Offer **Drive?**

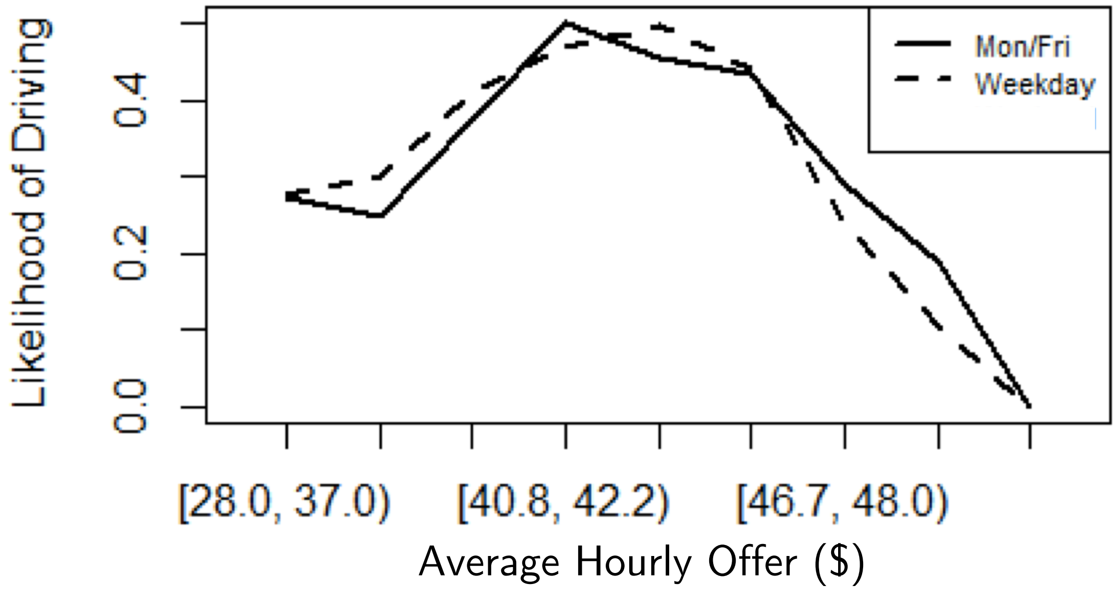


Econometric Challenges

- Simultaneity
- Sample Selection Bias


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



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

Log(hours)	Camerer et al.'97			Sheldon'16	
	TRIP	*TLC1*	*TLC2*	*OLS*	*2SLS*
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Approach

Heckman Two-Stage Estimation

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

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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**

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

Dealing with **Selection**

1. Choice Equation "Drive or not?"

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

Probit: Estimate **P(drive)**

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

C

Inverse Mills Ratio (IMR)

Conditional on driving

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C

Inverse Mills Ratio (IMR)

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

Conditional on driving

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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**

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

L

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

Daily/Weekly Targets

Monday is the first day of the week. No drivers work overnight.

1) Base

C
L

2) Income Targeting

C
L
+ Income earned so far (ISF)

3) Time Targeting

C
L
+ Hours worked so far (HSF)

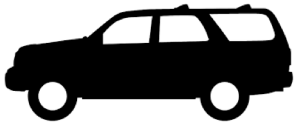
4) Income + Time Targeting

C
L
+ ISF + HSF

Results

Compare:

C L vs. C L + ISF + HSF

 vs. 

Within-Day

Midday

↓

Late Night

Across-Days

Tuesday

↓

Sunday

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)

N = 195,274

N = 166,766

Results Choice

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Income so far	-	-0.0005 (0.0003)	-	-0.002*** (0.0002)
Hours so far	-	0.414*** (0.011)	-	0.361*** (0.007)
AIC	92,276.680	63,823.450	95,856.010	72,887.620

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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

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

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)
IMR	-	***	***	-	***	***
Adjusted R^2	0.617	0.617	0.976	0.313	0.324	0.957

N = 17,515

N = 18,941

Results Level

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

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)
ISF	-	-	-0.0003*** (0.00003)	-	-	-0.0002*** (0.00002)
HSF	-	-	0.197*** (0.001)	- Inertia	-	0.187*** (0.001)
IMR	-	***	***	-	***	***
Adjusted R^2	0.617	0.617	0.976	0.313	0.324	0.957

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

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	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	-	-	-0.0003*** (0.00003)	- Income Targeting	-	-0.0002*** (0.00002)
HSF	-	-	0.197*** (0.001)	- Inertia	-	0.187*** (0.001)
IMR	-	***	***	-	***	***
Adjusted R^2	0.617	0.617	0.976	0.313	0.324	0.957

N = 17,515

N = 18,941

Results Across Shifts

		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	+	-	+	+	-	+
		Fatigue	Inertia		Income Target	Inertia

	Choice			Level		
Sedan	Offer	ISF	HSF	Earning	ISF	HSF
Tuesday	+	+	+	-	-	+
Wednesday	+	+	+	-	-	+
Thursday	+	+	+	-	+	+
Friday	+	+	+	+	-	+
Saturday	+	-	+	+	-	+
Sunday	+	-	+	+	-	+
		Fatigue	Inertia		Income Target	Inertia

Results Across Days

	Choice			Level		
SUV	Offer	ISF	HSF	Earning	ISF	HSF
Tuesday	+	+	+	+	+	+
Wednesday	+	+	+	+	-	+
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Friday	+	-	+	+	-	+
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		Fatigue	Inertia		Income Target	Inertia

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Sedan	Offer	ISF	HSF	Earning	ISF	HSF
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Friday	+	+	+	+	-	+
Saturday	+	-	+	+	-	+
Sunday	+	-	+	+	-	+
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Results Across Days

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Sunday	+	-	+	+	-	+
		Fatigue	Inertia		Income Target	Inertia

Optimizing Incentives

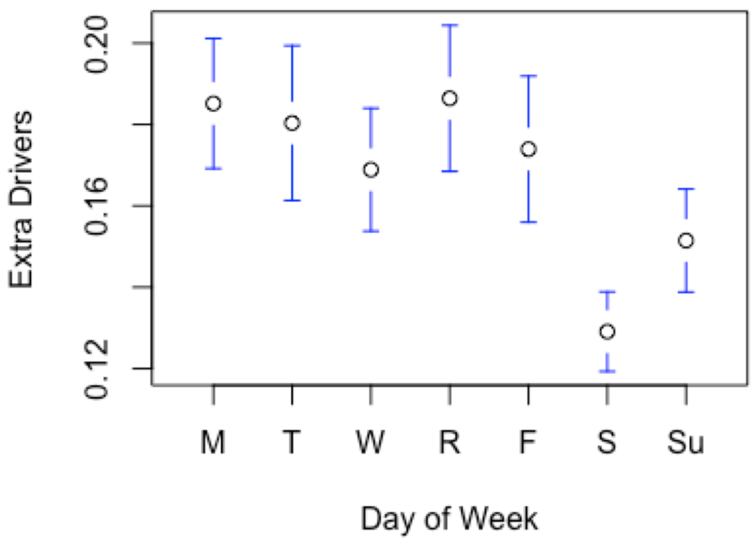
Using the insights we obtain, we propose algorithm for optimal allocation of financial incentives:

Ranking each driver by her
minimum driving-inducing incentive

Optimizing Incentives

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

Given the same budget



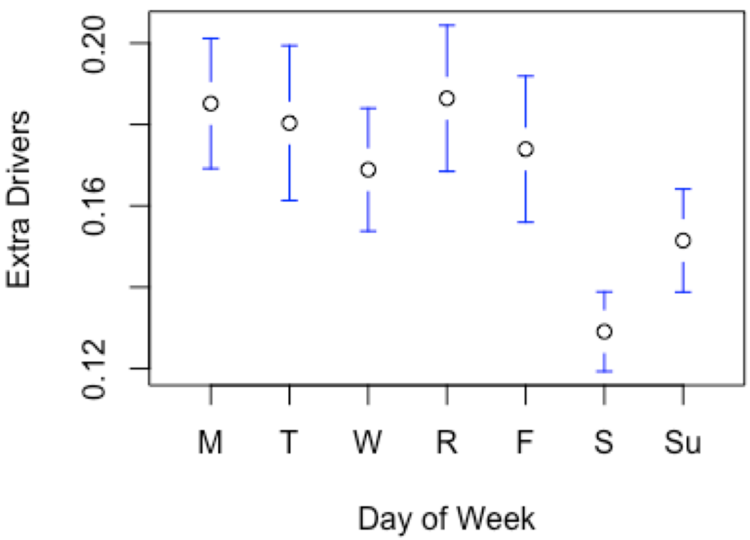
Can recruit **17% more drivers**

Average promo: 1.61x

Optimizing Incentives

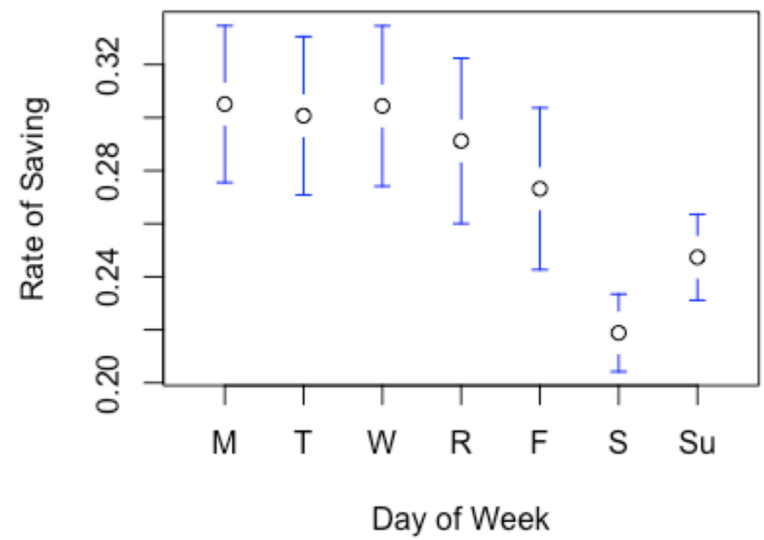
Using the insights we obtain, we propose algorithm for optimal allocation of financial incentives

Given the same budget



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

Given the same capacity



Costs 28% less to maintain capacity

Summary

How do gig economy workers make labor decisions?

Approach:

- Shift-level data from ride-hailing company
- Two-stage Heckman estimation w/ instrumental variables & fixed effects

Findings: Decisions depend on driver type and time

- **Offer** and **inertia** can increase work activity
- **Fatigue** and **income target** affect how long they will work

- Our approach can **improve service capacity by 17%** at the same cost or maintain the same capacity **at 28% less cost**