



The Impact of Behavioral and Economic Drivers on Gig Economy Workers

BDRM 2018



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Demand $\xleftarrow{\text{match}}$ Supply
independent/flexible

Gig Economy



HopSkipDrive



Gig Economy

- + Labor flexibility/reduced costs
- Challenging capacity planning



Instacart



Who Will Show Up To Work?

independent/flexible

Gig Economy

- + Labor flexibility/reduced costs
- Challenging capacity planning

Existing Strategies

Real-time
“surge pricing”

Deliver by 6:15pm Decline

Mission Chinese Food
\$22.78 subtotal (2 items)

BUSY PAY: +\$1.50

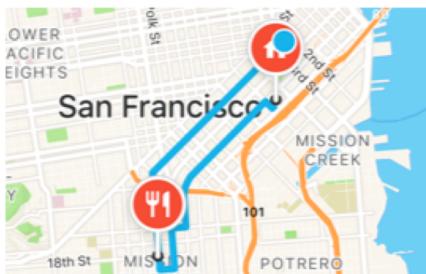
4.1 miles total

Accept Order

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San Francisco

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Accept Order

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)

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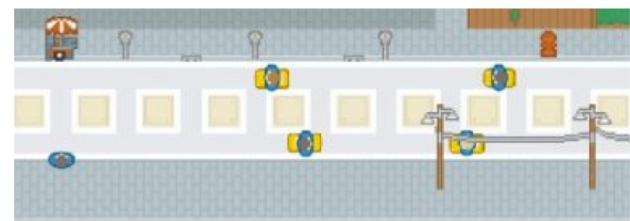
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6:00 PM–7:00 PM

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

“You’re so close to your precious target”



How Uber Uses Psychological Tricks to Push Its Drivers’ Buttons

Research Question

How do gig economy workers
make labor decisions?

Outline

Theories of
Labor Supply

Our data
Endogeneity
Selection

Approaches
Heckman + IV

Results
 $P(\text{work})/\text{Hours}$
Estimates

Implications
Optimize
Incentives

Theories of Labor Supply

Neoclassical

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

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- **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)



*Income/Hours
2nd target reached*

Crawford/Meng
(2011)



*Income/Hours
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Farber
(2015)



*Hours
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*Hours
targeting*

Chen/Sheldon
(2016)

Sheldon
(2016)

No targeting

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

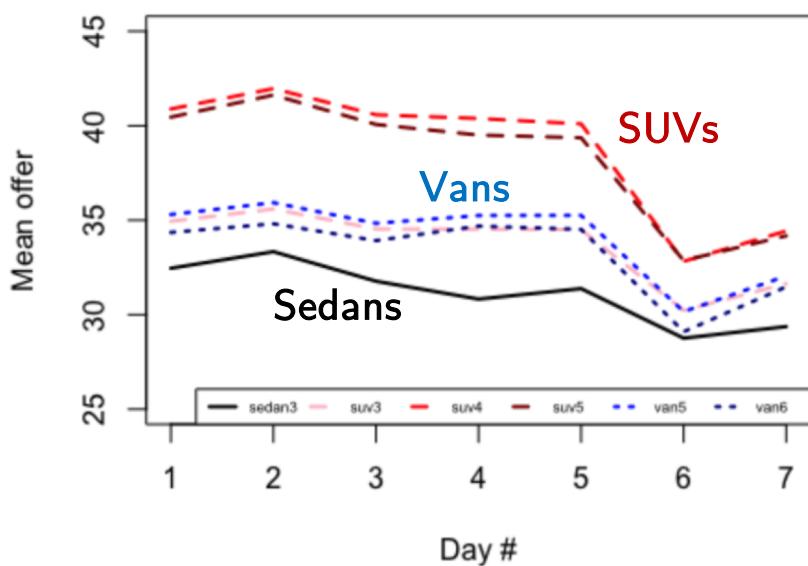
7,826

Unique drivers

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

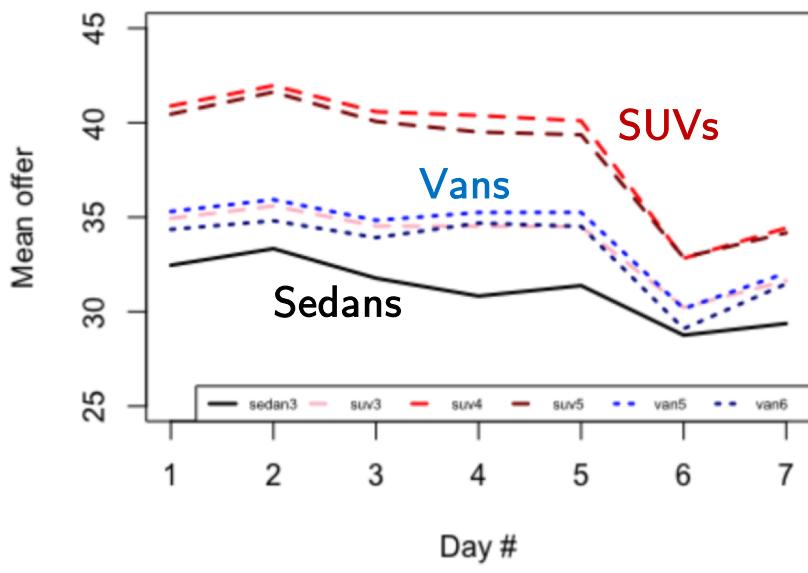
Casual vs. Professional Drivers

Offer

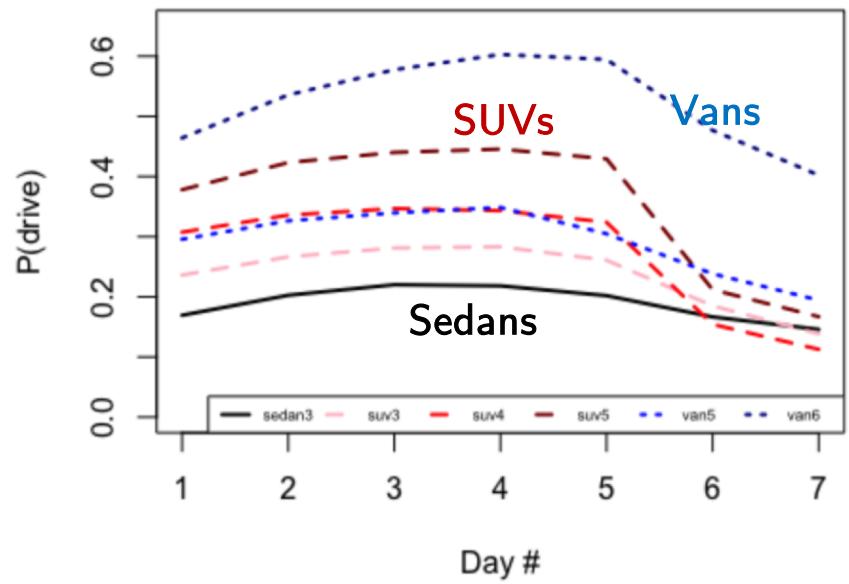


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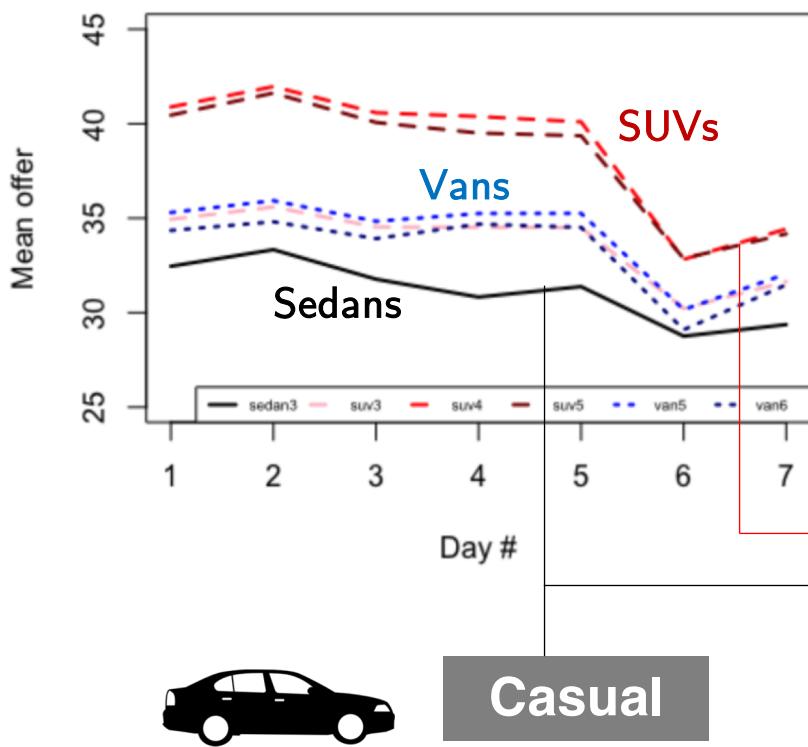


Drive?

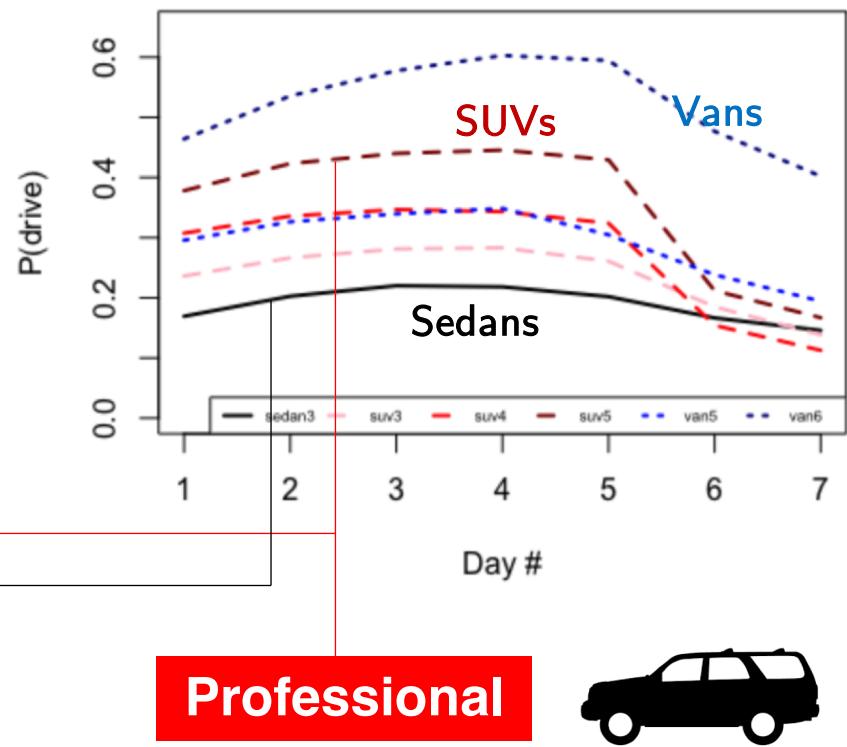


Casual vs. Professional Drivers

Offer



Drive?



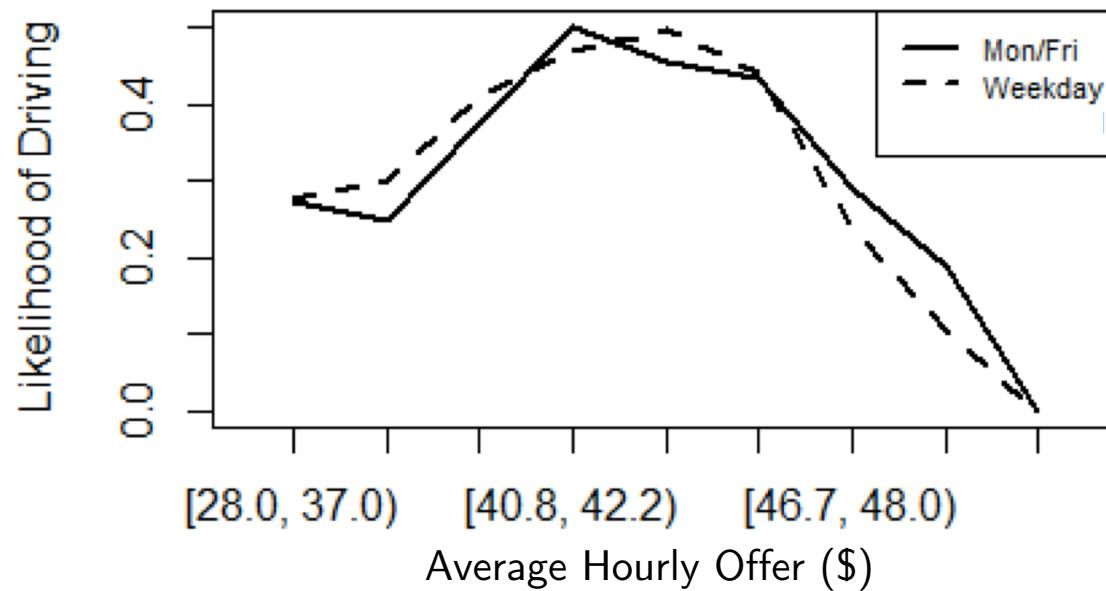
Casual



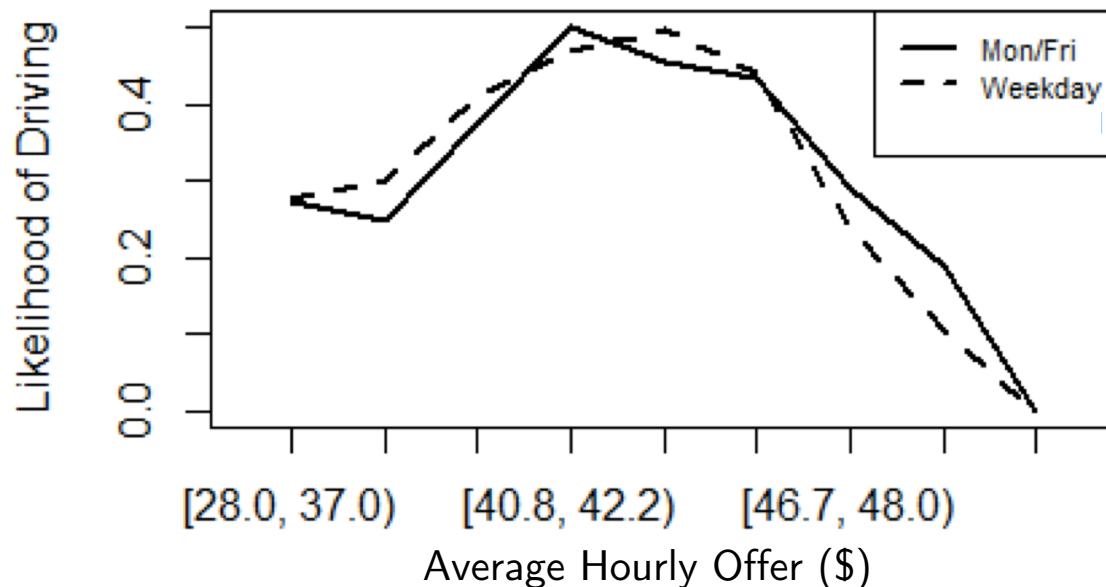
Professional

Econometric Challenges

- Simultaneity
- Sample Selection Bias



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			
	<i>TRIP</i>	<i>TLC1</i>	<i>TLC2</i>	<i>OLS</i>	<i>2SLS</i>
Log(wage)	-.319	-1.313	-.975	.14	.22

Selection Bias

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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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- 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 $P(\text{drive})$

Inverse Mills Ratio (IMR)

Conditional on
driving

2. Level Equation “How long?”

OLS: Estimate hours

Dealing with Selection

1. Choice Equation “Drive or not?”

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

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Inverse Mills Ratio (IMR)

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

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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

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

L

Daily/Weekly Targets

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

1) Base



2) Income Targeting



+ Income earned so far
(ISF)

3) Time Targeting



+ Hours worked so far
(HSF)

4) Income + Time Targeting



+ ISF + HSF

Results

Compare:



vs.



+ ISF + HSF



vs.



Within-Day

Midday



Late Night

Across-Days

Tuesday



Sunday

Daily/Weekly Targets

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Compare:



vs.



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vs.



Results Choice

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

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

N = 17,515

N = 18,941

Results Level

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

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ISF	-	-	-	-0.0003*** (0.00003)	-	-	-0.0002*** (0.00002)
HSF	-	-	-	0.197*** (0.001)	-	Inertia	-
IMR	-	***	***	***	-	***	***
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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



SUV	Choice			Level		
	Offer	ISF	HSF	Earning	ISF	HSF
Midday	+	+	+	-	+	+
PM peak	+	-	+	+	-	+
PM off-peak	+	-	+	+	-	+
Late night	+	-	+	+	-	+



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



Fatigue	Inertia	Income Target	Inertia
---------	---------	---------------	---------

Results Across Days



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



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

Results Across Days



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Optimizing Incentives

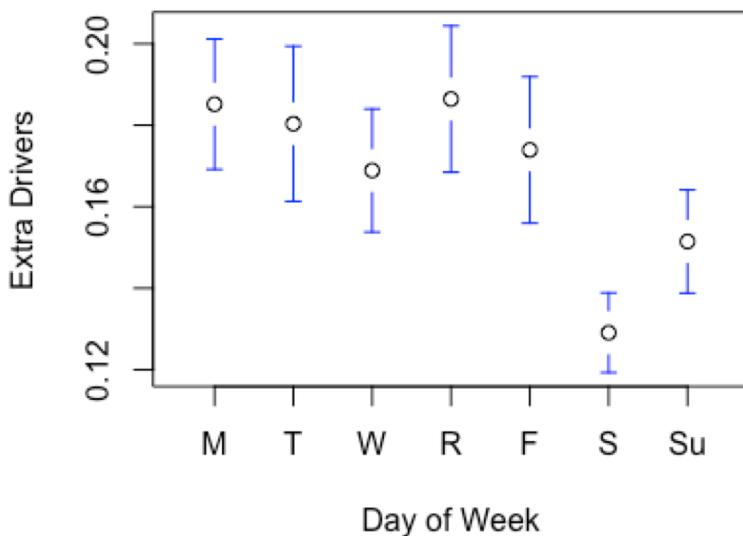
Using the insights we obtain, we propose algorithm for optimal allocation of financial incentives:

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



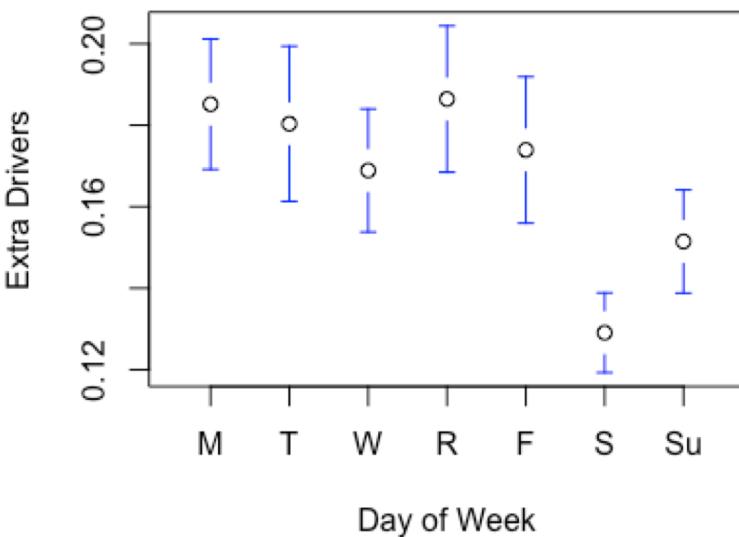
Can recruit **17% more drivers**

Average promo: 1.61x

Optimizing Incentives

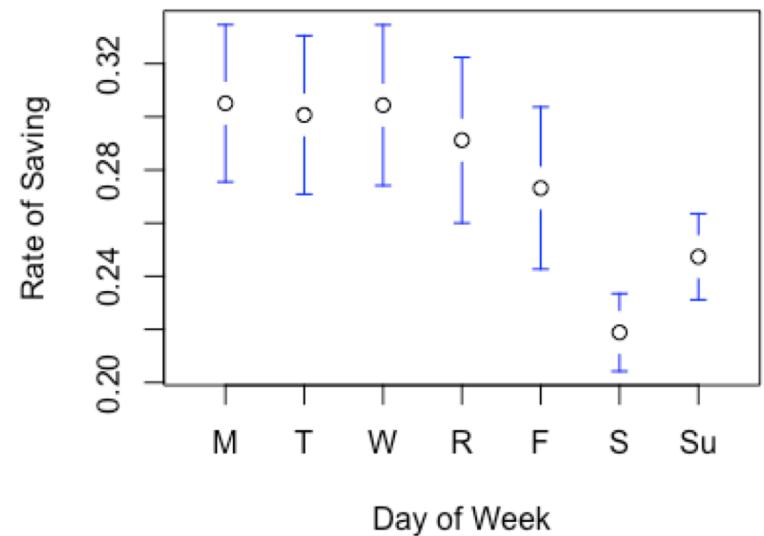
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Given the same budget



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**

