



The Impact of Behavioral and Economic Drivers on Gig Economy Workers

BDRM 2018



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Gad Allon, Maxime Cohen



Gig Economy



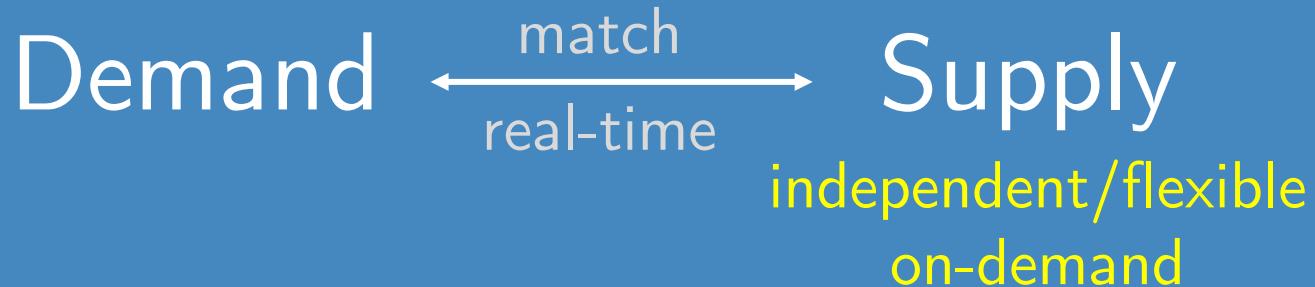
caviar



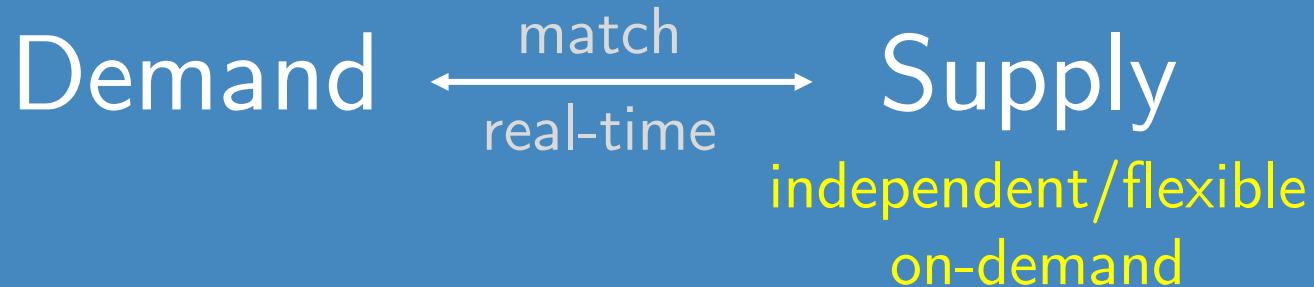
Gig Economy

Supply
independent/flexible
on-demand

Gig Economy



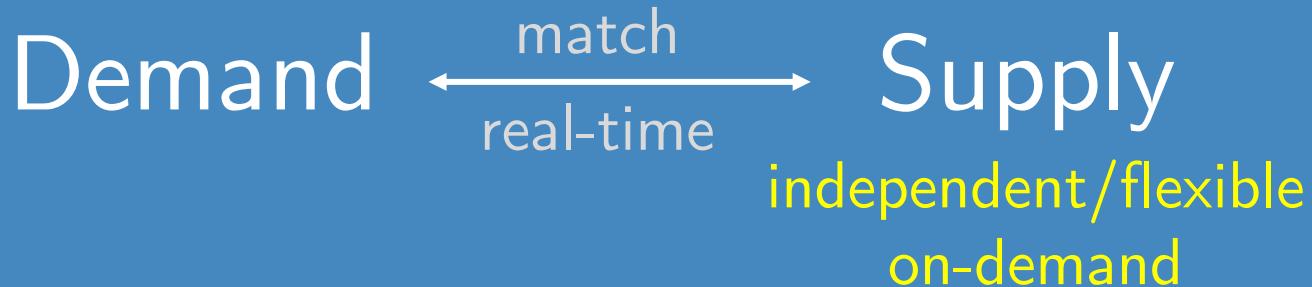
Gig Economy



For company...

+ Labor flexibility

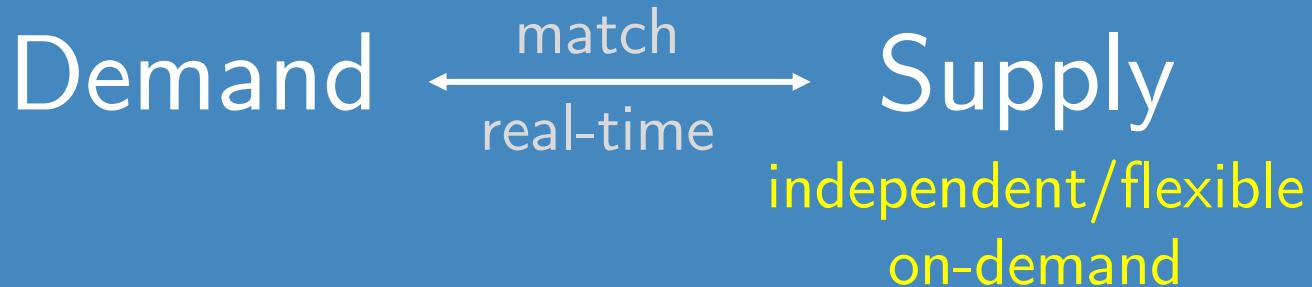
Gig Economy



For company...

- + Labor flexibility
- + Real-time incentives

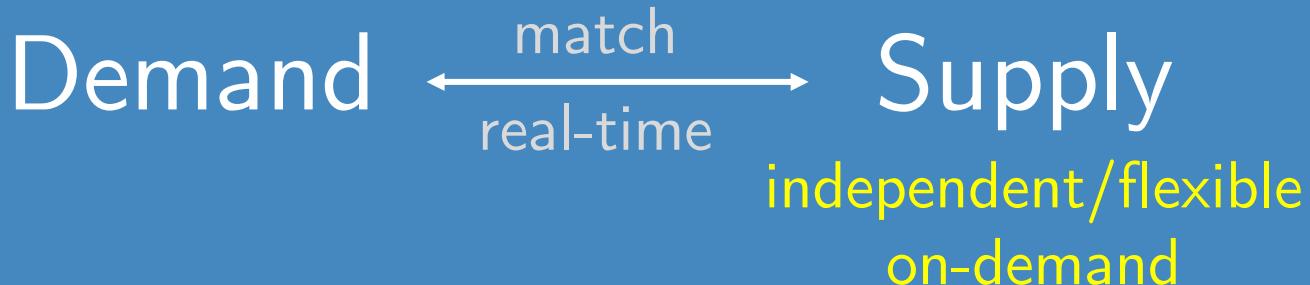
Gig Economy



For company...

- + Labor flexibility
- + Real-time incentives
- + Reduced costs

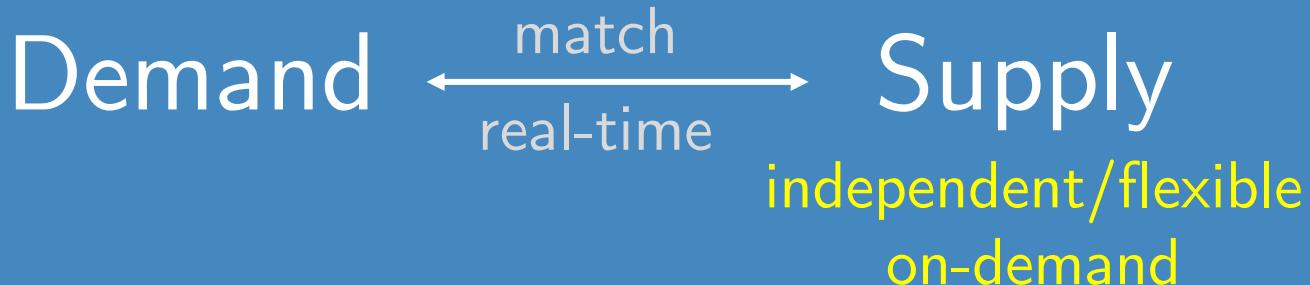
Gig Economy



For company...

- + Labor flexibility
- + Real-time incentives
- + Reduced costs
- Strategic players

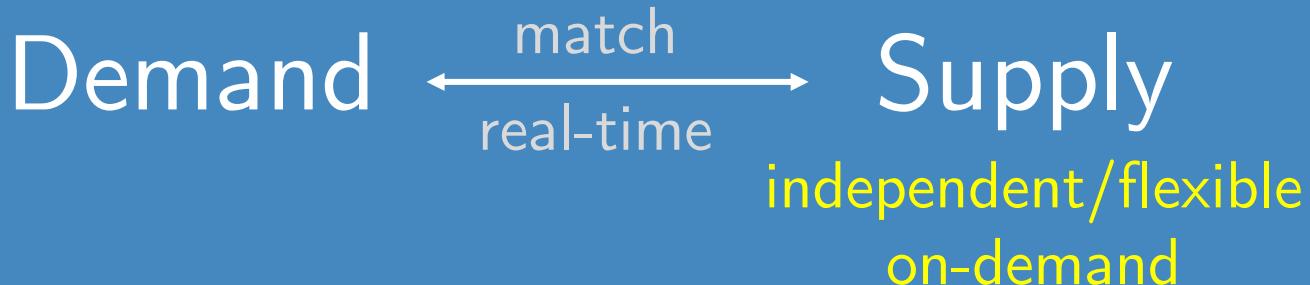
Gig Economy



For company...

- + Labor flexibility
- + Real-time incentives
- + Reduced costs
- Strategic players
- Challenging capacity planning

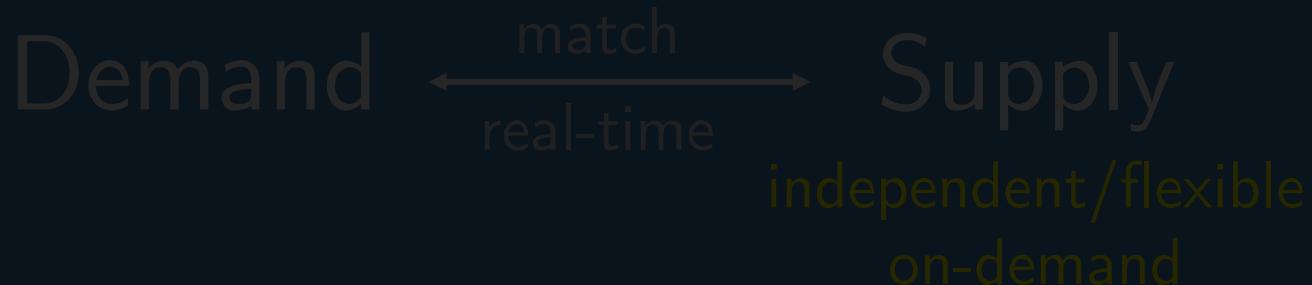
Gig Economy



For company...

- + Labor flexibility
- + Real-time incentives
- + Reduced costs
- Strategic players
- Challenging capacity planning

Gig Economy



Who Will Show Up To Work?

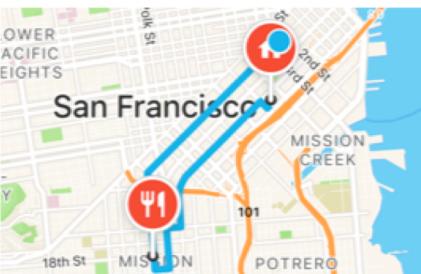
- + Labor flexibility
- + Real-time incentives
- + Reduced costs

- Strategic players
- Challenging capacity planning

Existing Strategies

Real-time
“surge pricing”

Deliver by 6:15pm Decline



Mission Chinese Food
\$22.78 subtotal (2 items)

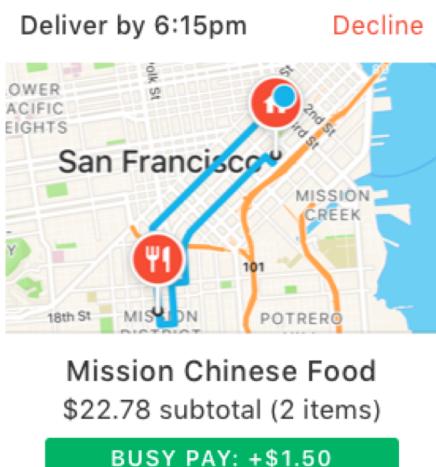
BUSY PAY: +\$1.50

4.1 miles total

Accept Order

Existing Strategies

Real-time “surge pricing”



Scheduled bonus

5:00 PM–6:00 PM

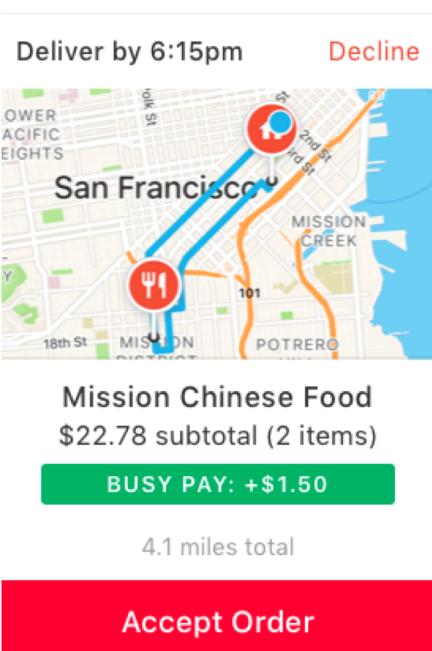
+10% (5:00pm - 5:30pm)
+30% (5:30pm - 6:00pm)

6:00 PM–7:00 PM

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

Existing Strategies

Real-time “surge pricing”



Scheduled bonus

5:00 PM–6:00 PM

+10% (5:00pm - 5:30pm)

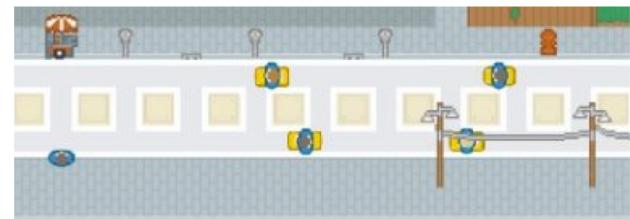
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“You’re so close to
your precious target”



How Uber Uses
Psychological Tricks to
Push Its Drivers’ Buttons

Research Questions

How do gig economy workers
make labor decisions?

Research Questions

How do gig economy workers
make labor decisions?

How to influence their 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

Theories of Labor Supply

Neoclassical

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

Theories of Labor Supply

Neoclassical

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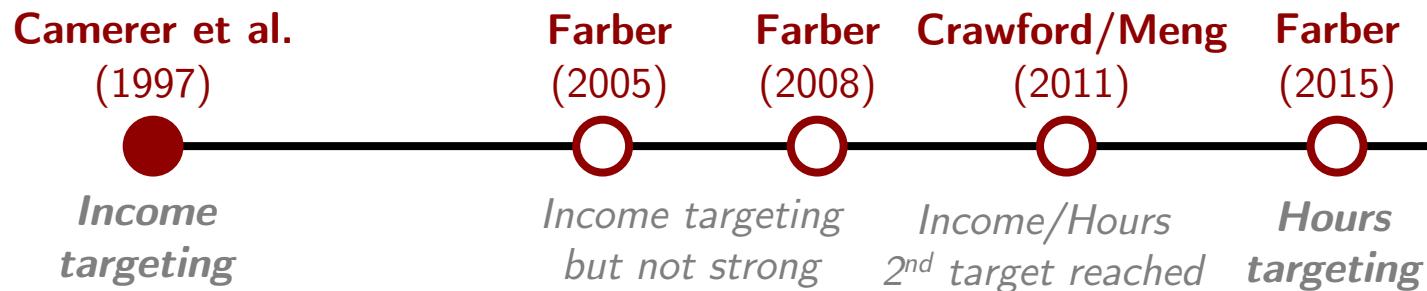
Camerer et al.
(1997)



Theories of Labor Supply

Neoclassical

- Maximize lifetime utility
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Theories of Labor Supply

Neoclassical

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

Behavioral

- Reference-dependence, targeting

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*

Theories of Labor Supply

Neoclassical

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

Behavioral

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

Camerer et al.
(1997)



*Income
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Farber
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*Income targeting
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Farber
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Theories of Labor Supply

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*Income/Hours
2nd target reached*

Farber
(2015)



*Hours
targeting*

Chen/Sheldon
(2016)

Sheldon
(2016)

No targeting

Data

NYC ride-hailing firm

Drivers are **paid by hour** not by trip

Data

NYC ride-hailing firm

Drivers are **paid by hour** not by trip



Shift-level financial incentives and driving activity

Data

NYC ride-hailing firm

Drivers are **paid by hour** not by trip



Shift-level financial incentives and driving activity

5.5M

Observations

358

Days

Oct 2016 – Sep 2017

7,826

Unique drivers

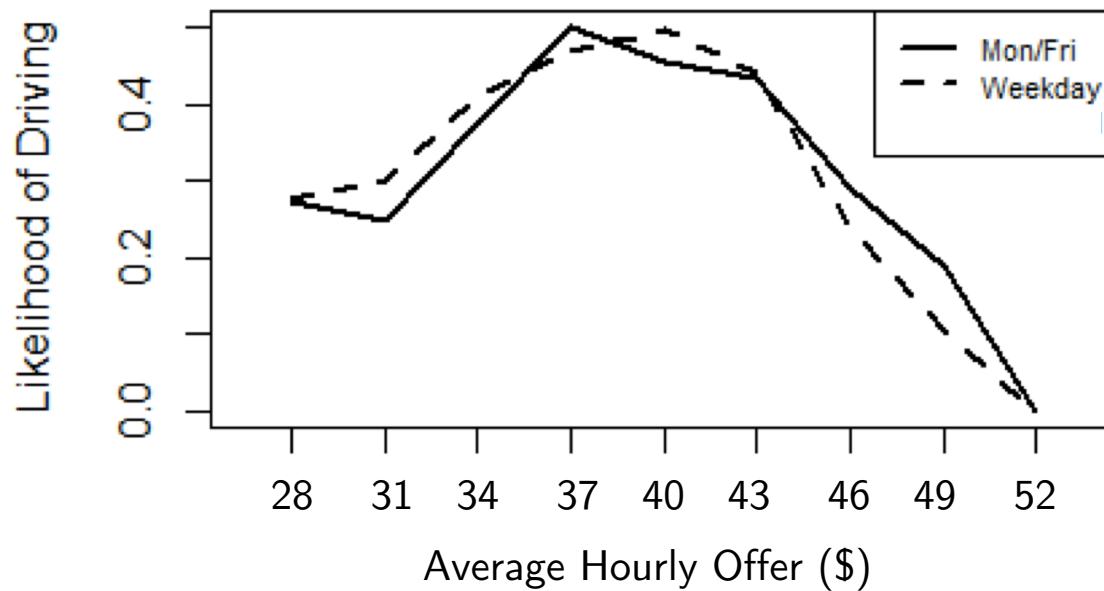
- SUV (64.54%)
- Sedan (21.77%)
- Van (13.69%)

Data generated from real-time sophisticated algorithms and randomized experiments

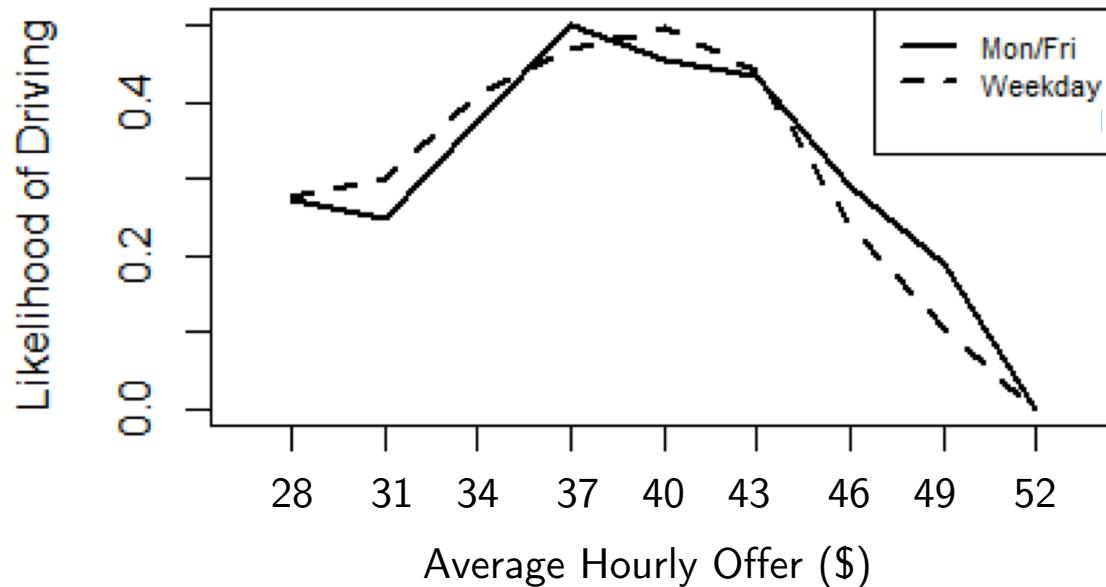
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Econometric Challenges

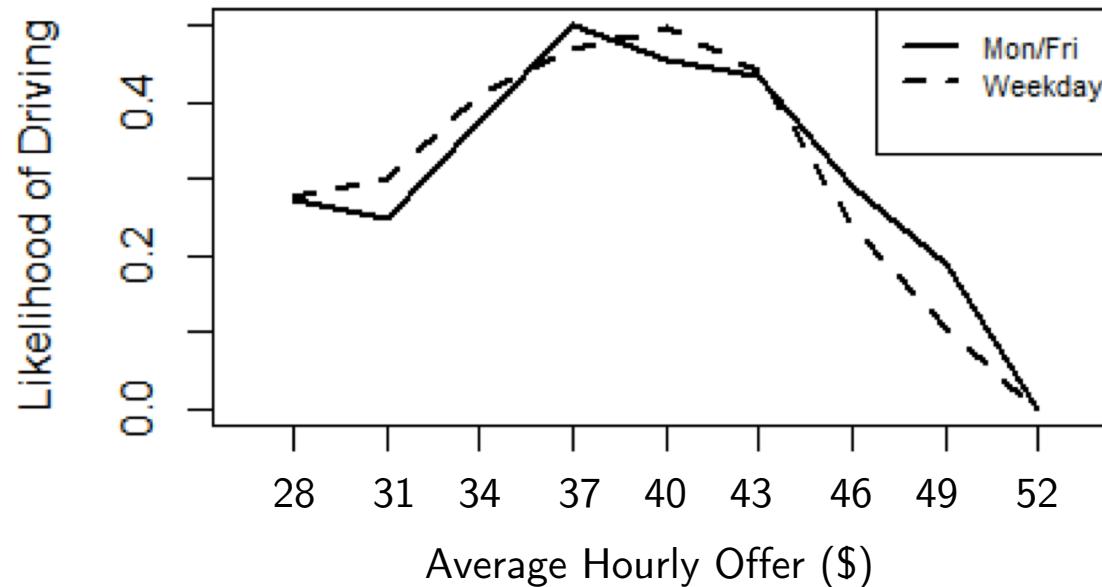
- Simultaneity
- Sample Selection Bias



Simultaneity



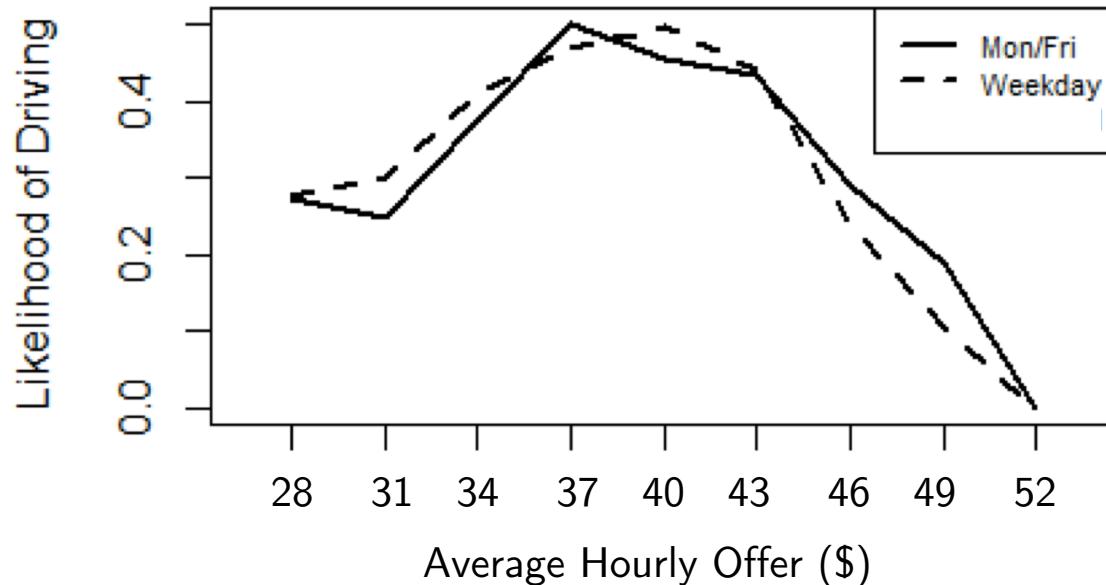
Simultaneity



Approach

Instrumental
Variables

Simultaneity

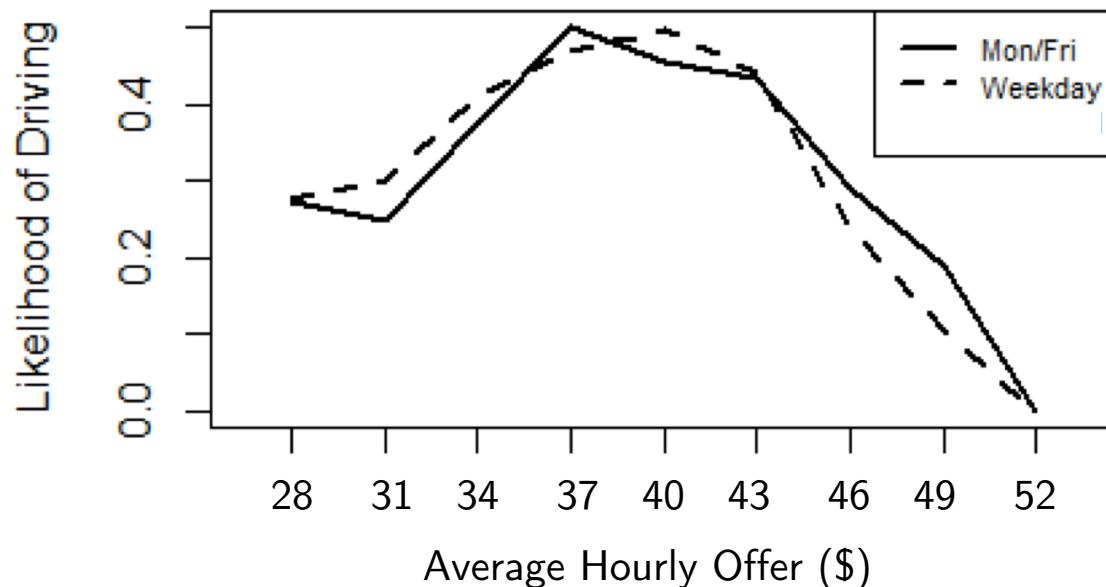


Approach

Instrumental Variables

- **Offer:** Average of other drivers' offers
(Camerer et al. 1997, Sheldon 2016)

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

Log(hours)	Camerer et al.'97		Sheldon'16	
	<i>TRIP</i>	<i>TLC1</i>	<i>TLC2</i>	<i>OLS</i>
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Approach

Heckman
Two-Stage
Estimation

(Heckman 1979)

Selection Bias

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Approach

- 1) Predict **choice** (drive or not?) using Probit

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Two-Stage
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Approach

Heckman Two-Stage Estimation

(Heckman 1979)

- 1) Predict **choice** (drive or not?) using Probit
 - Compute Inverse Mills Ratio (IMR)

Selection Bias

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Approach

Heckman Two-Stage Estimation

(Heckman 1979)

- 1) Predict **choice** (drive or not?) using Probit
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- 2) Predict **level** (how long?) using OLS with IMR as an additional regressor

Selection Bias

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Approach

Heckman
Two-Stage
Estimation
(Heckman 1979)

- 1) Predict **choice** (drive or not?) using Probit
 - Compute Inverse Mills Ratio (IMR)
- 2) Predict **level** (how long?) using OLS with IMR as an additional regressor

Both levels account for endogeneity using IVs
Individual and time 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

Inverse Mills Ratio (IMR)

Conditional on driving

2. Level Equation “How long?”

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Dealing with Selection

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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?”

OLS: Estimate hours

Dealing with Selection

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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

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

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

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

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

Late Night	Sedan		SUV	
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Results Level

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

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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		Naive	Base	+ Targets	Naive	Base	+ Targets
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ISF	-	-	-	-0.0003*** (0.00003)	-	-	-0.0002*** (0.00002)
HSF	-	-	-	0.197*** (0.001)	-	Inertia	-
IMR	-	***	***	***	-	***	***
Adjusted R ²	0.617	0.617	0.976		0.313	0.324	0.957

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

N = 17,515

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Results Across Shifts



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

Results Across Shifts



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

Fatigue Inertia Fatigue Inertia

Results Across Days



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



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

Results Across Days



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



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

Results Across Days



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



Optimizing Incentives

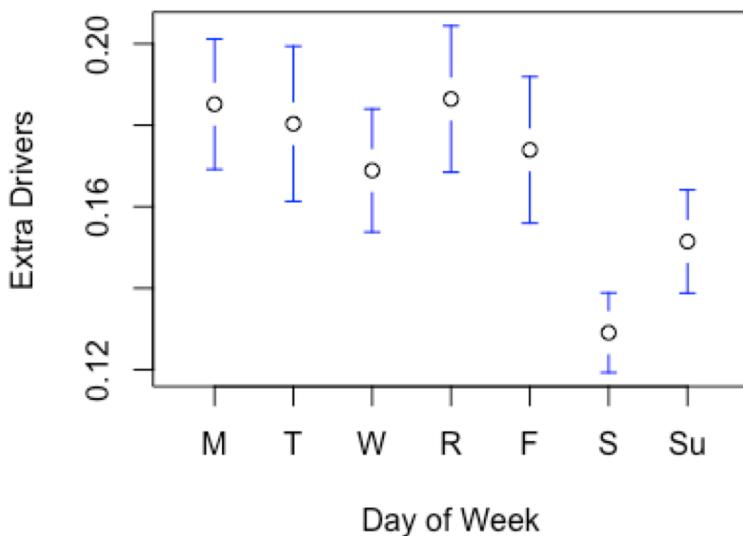
Using the insights we obtain, we propose algorithm for optimal allocation of financial incentives:

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



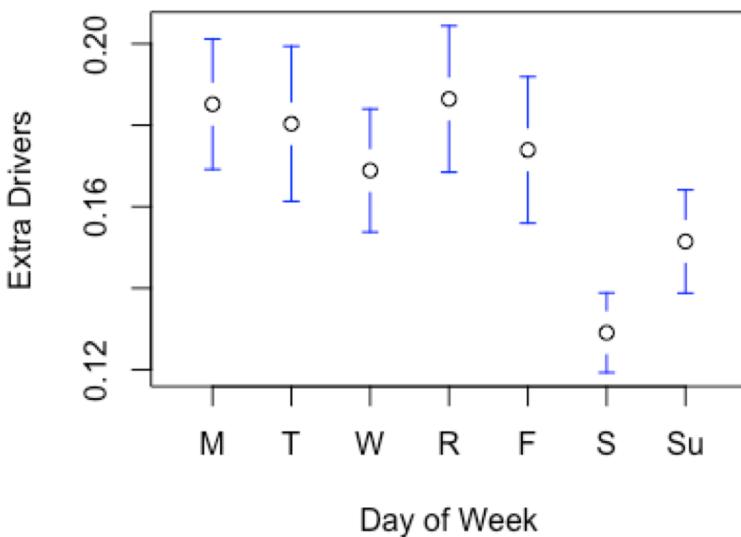
Can recruit **17% more drivers**

Average promo: 1.61x

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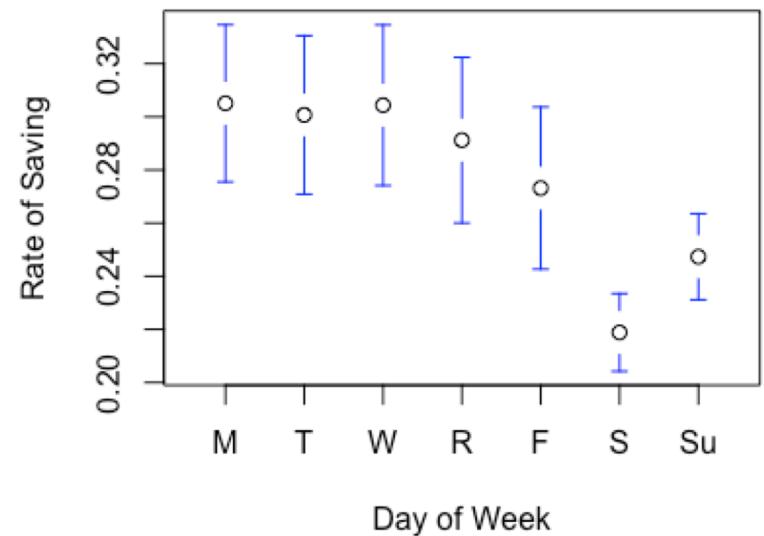
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Given the same budget



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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/ IVs and FEs

Findings

- Decisions depend on driver type and time
- Offer and inertia can increase work activity
- Fatigue or income target affects how long they will work, from positively early on to negatively later in the day or week
- Compared to the company's current practice, our approach can improve service capacity by 17% at the same cost or maintain the same capacity at 28% less cost

