The Impact of Behavioral and Economic Drivers on Gig Economy Workers

MSOM 2018

Park Sinchaisri
Gad Allon, Maxime Cohen

Gig Economy

Instacart

Wag!

caviar

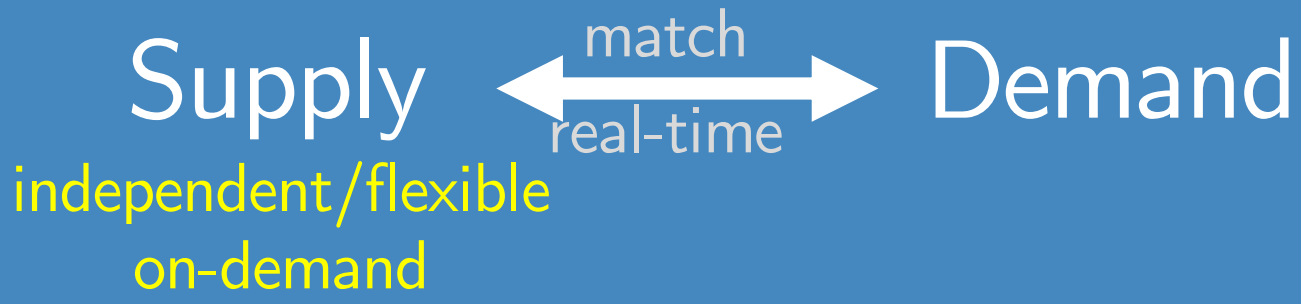
lyft

POSTMATES

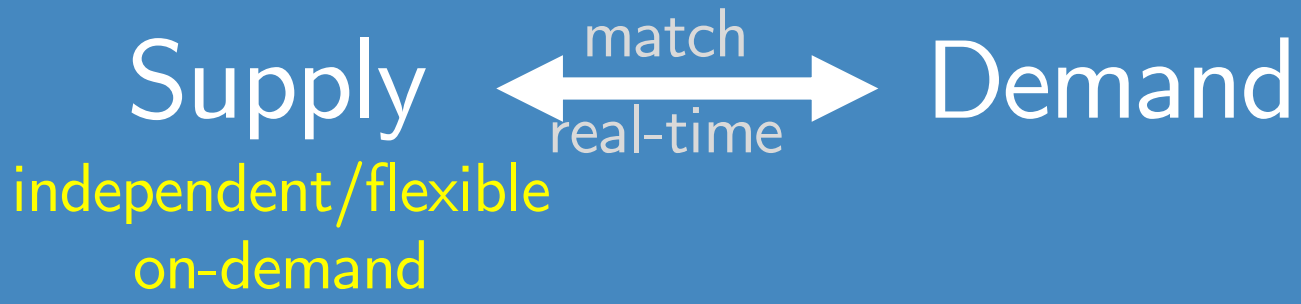
HopSkipDrive

handy

Gig Economy


Supply
match
real-time
Demand
independent/flexible
on-demand

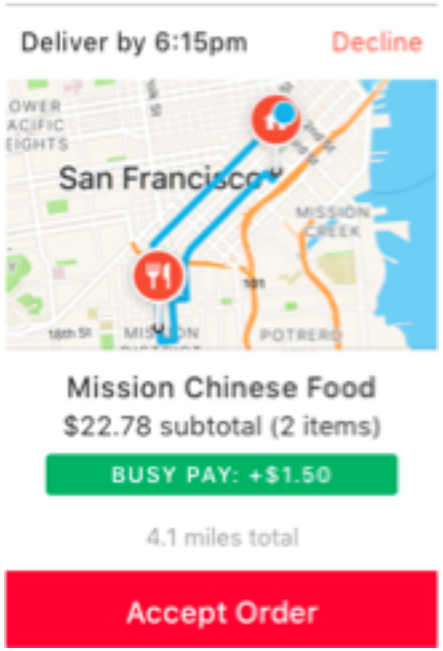
Gig Economy



Capacity planning is challenging

In Practice

Real-time "surge pricing"



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

In Practice

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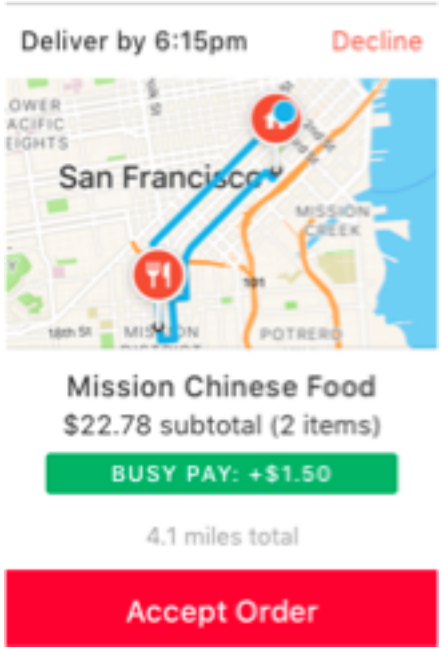

Scheduled bonus

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/

In Practice

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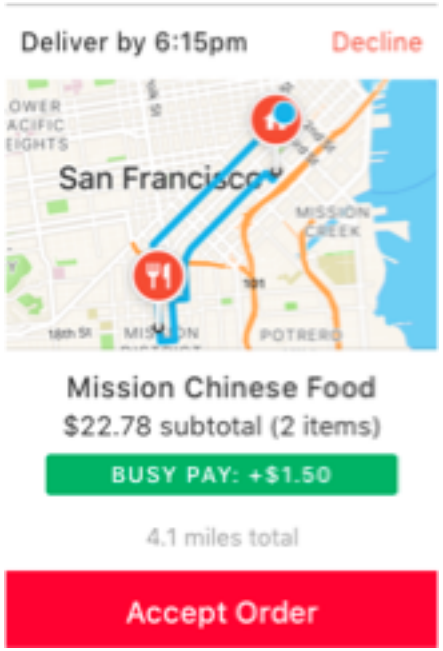

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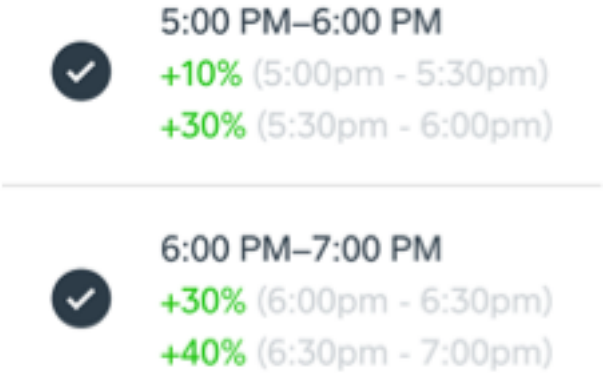
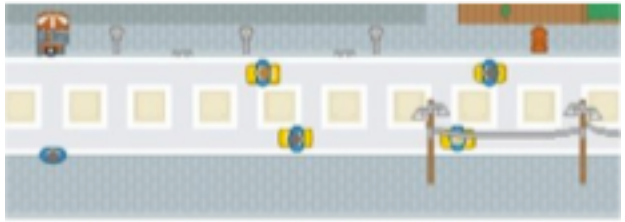


"You're so close to your precious target"



How Uber Uses Psychological Tricks to Push Its Drivers' Buttons

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https://courierhelp.trycaviar.com/customer/en/portal/articles/2821000-peak-hour-pay?b_id=9619/
https://nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html

Theories of Labor Supply

Neoclassical

- Maximize lifetime utility

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- **Positive** income elasticities

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Carrington (1996)

Oettinger (1999)

Stafford (2013)

Chen/Sheldon (2016)

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- Reference-dependence, targets

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- **Negative** income elasticities

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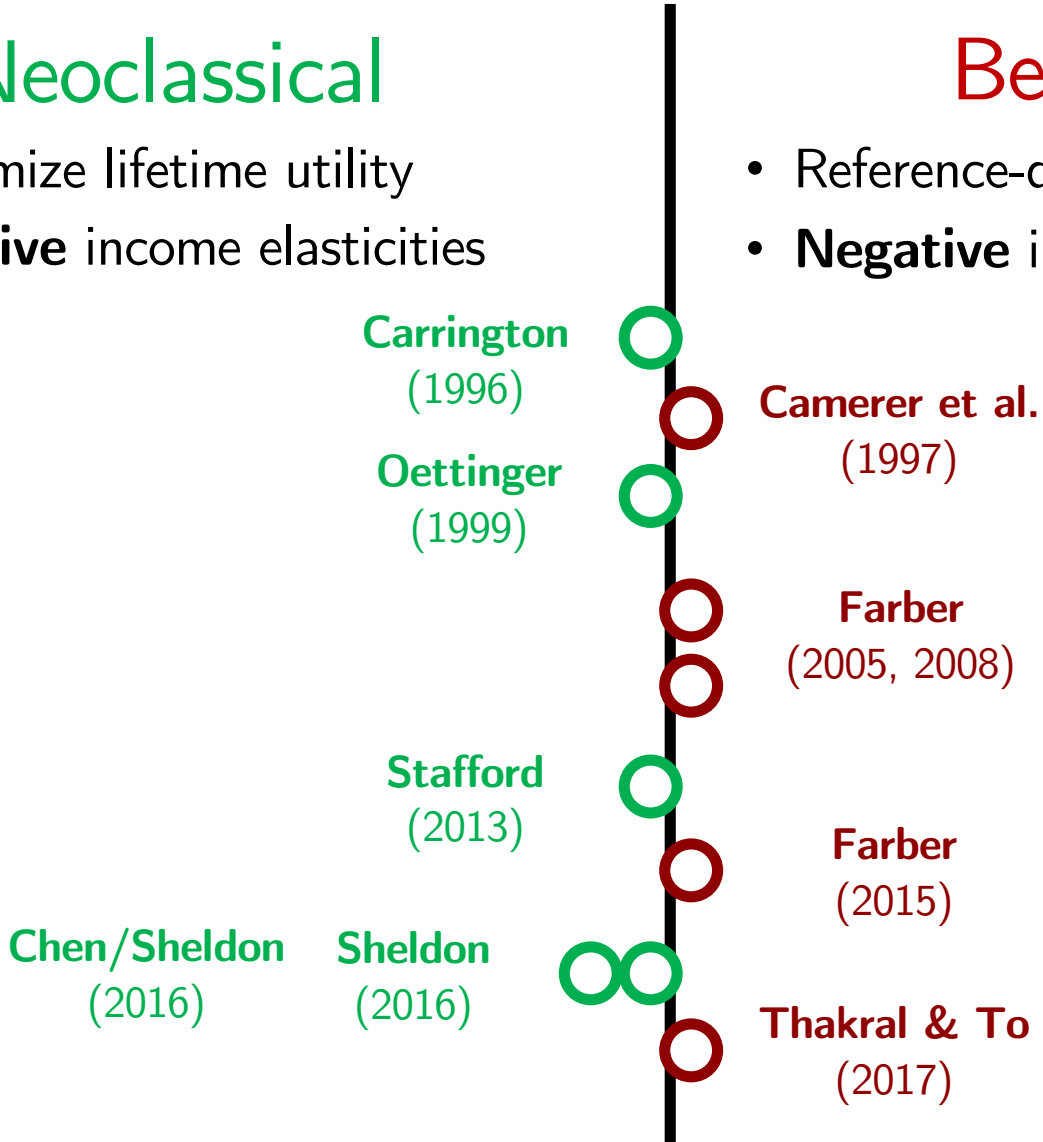

Research Questions

How do gig economy workers make labor decisions?

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How can the platform influence their decisions?

Data NYC ride-hailing firm

Drivers are guaranteed an hourly base rate.

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

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Drivers are guaranteed an hourly base rate.

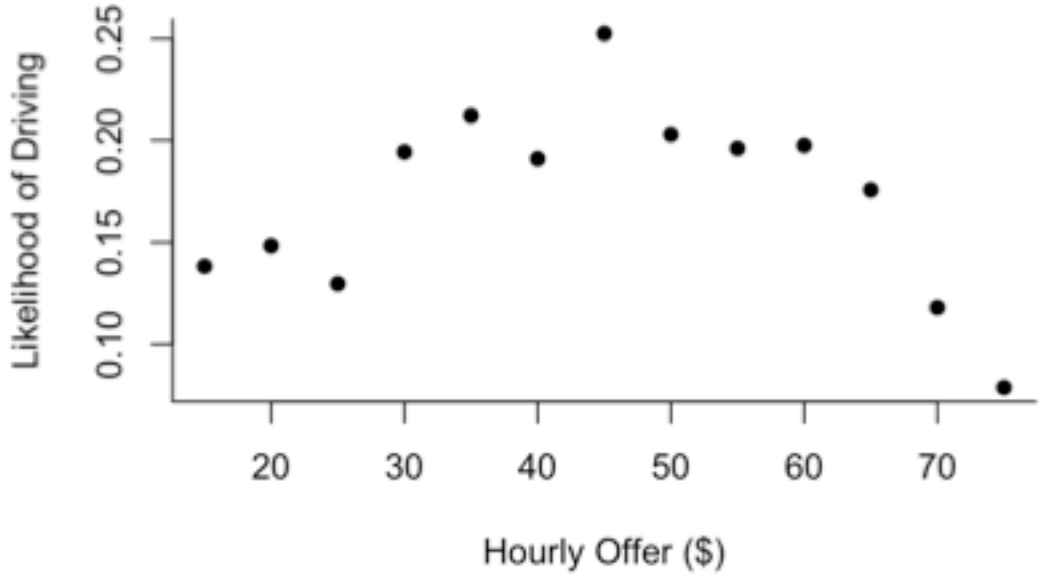
Shift-level financial incentives and driving activity *for all*

5.5M
Observations

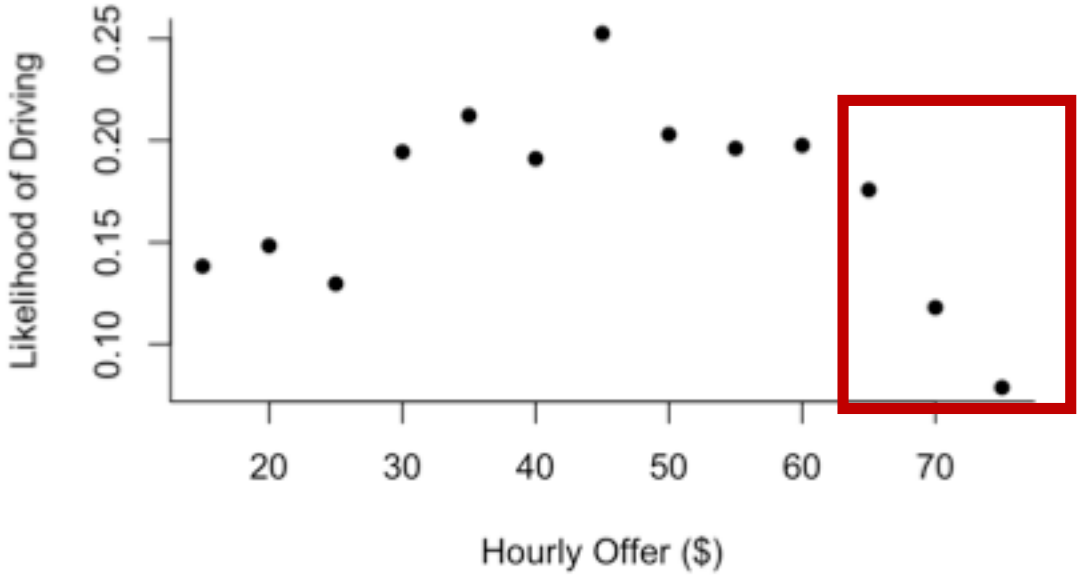
358
Days
Oct 2016 – Sep 2017

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

Challenges

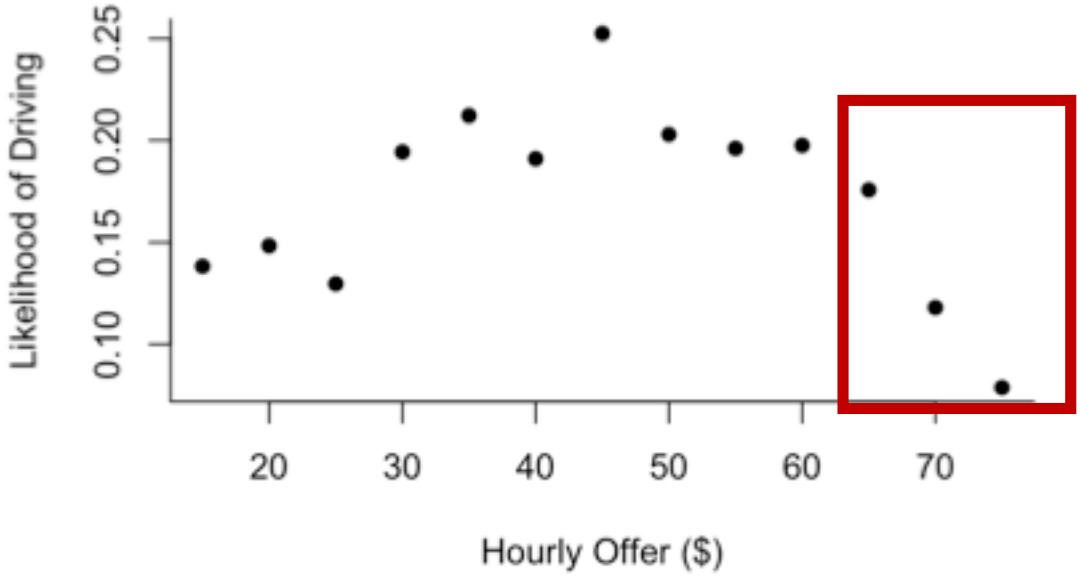

Likelihood of Driving
0.10
0.15
0.20
0.25
20
30
40
50
60
70
Hourly Offer ($)

Challenges



Higher wage, less likely to drive?

Challenges

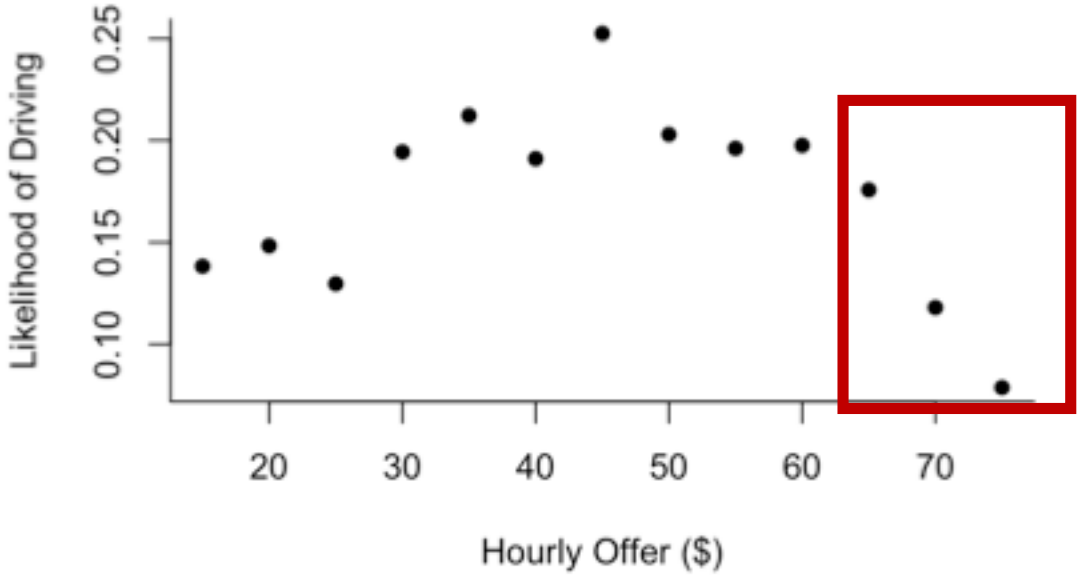


Higher wage, less likely to drive?

Use higher wage to attract inactive drivers

Challenges

Simultaneity



Higher wage, less likely to drive?

Use higher wage to attract inactive drivers

Challenges

Simultaneity

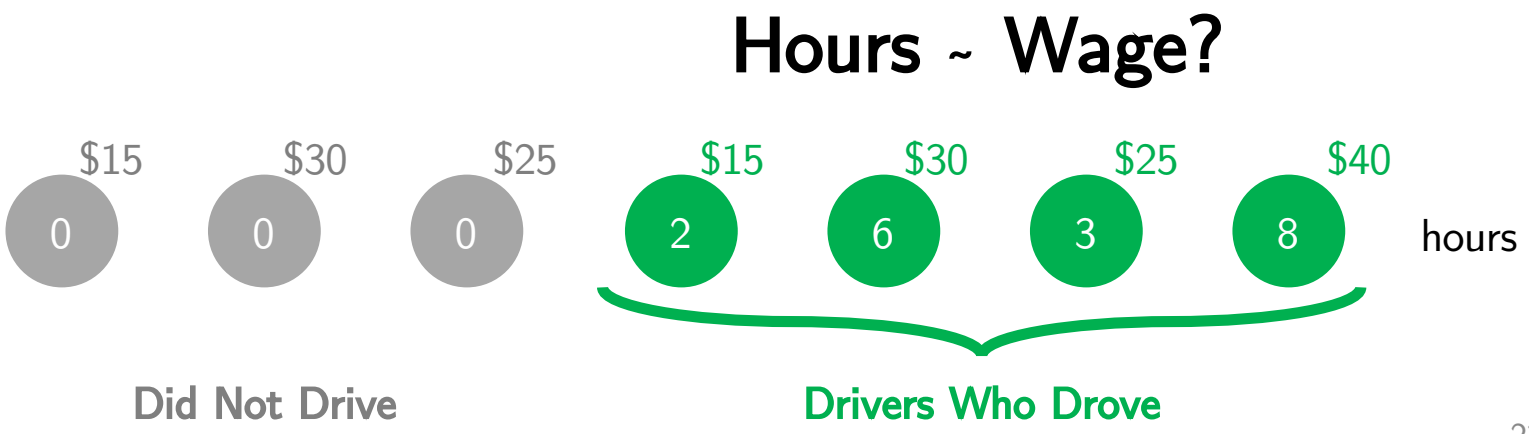
Solution: Instrumental Variables

- **Offer:** Average of other drivers' offers (Hausman 1996, Sheldon 2016, Xu et al 2017)
- **Promo** (binary): Lagged value from the same shift in the previous week (Villas-Boas & Winer 1999, Yang et al 2003, Archak et al 2011, Ghose et al 2012)

Challenges

Simultaneity

Solution: Instrumental Variables

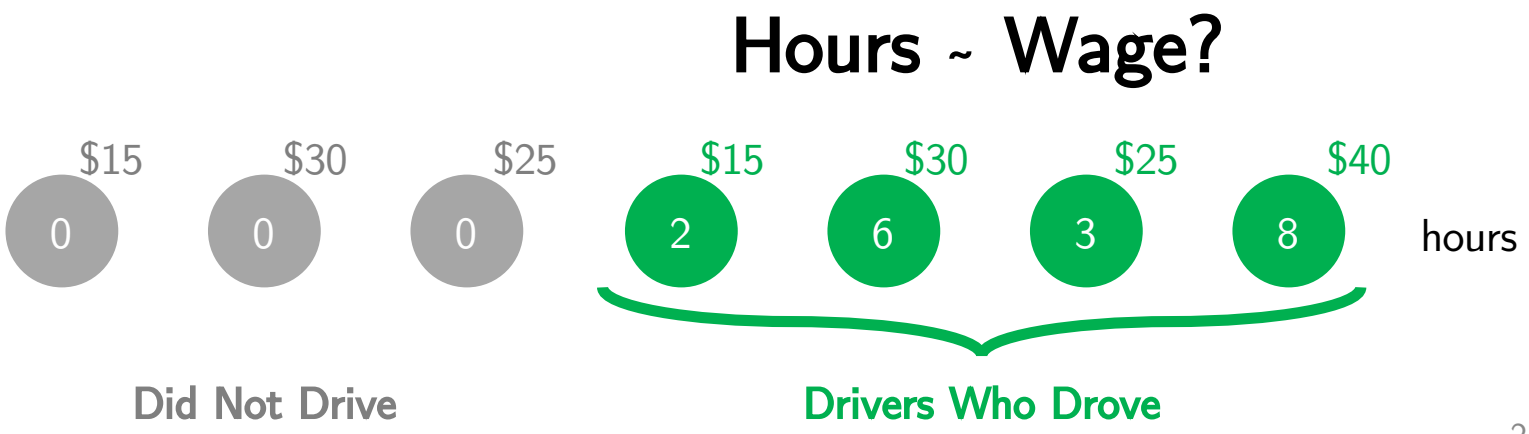


Challenges

Simultaneity

Solution: Instrumental Variables

Decision to work is **not random**



Challenges

Simultaneity

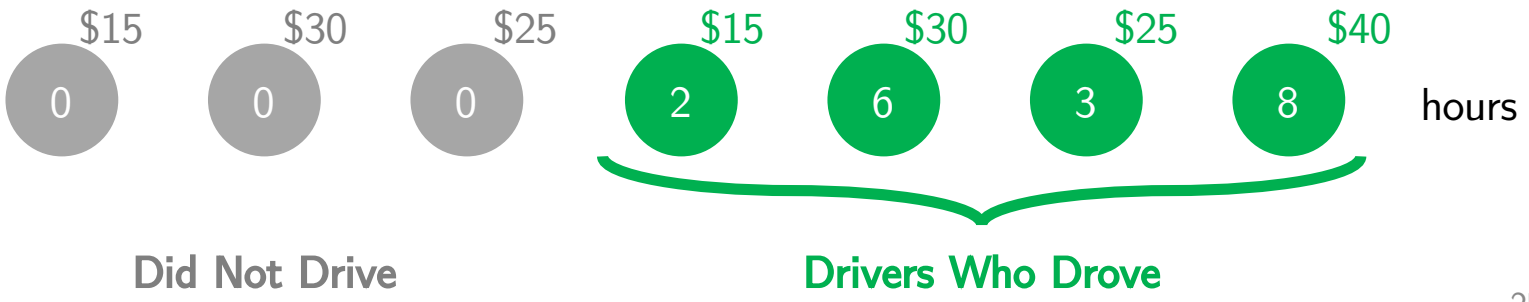
Solution: Instrumental Variables

Selection Bias

Solution: Heckman Two-Stage Method

("Heckit" - Heckman 1979)

Hours ~ Wage + Selection



Empirical Strategy

1 **Work or not?**

Control Function Probit:

P(drive) on **Offer** + **Promo** + **Controls**

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Income So Far
= intensity of work

Empirical Strategy

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Hours So Far
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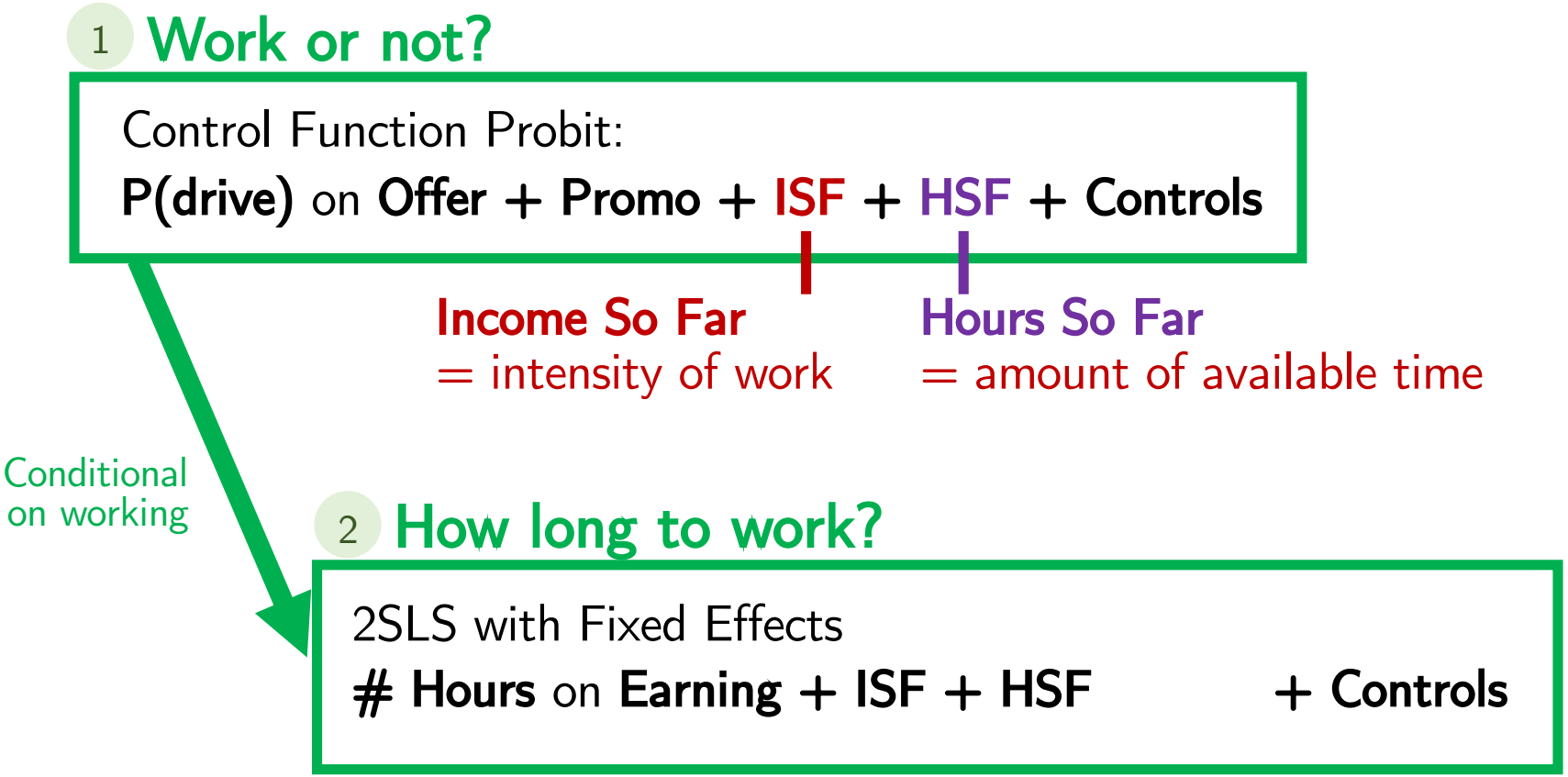

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Control Function Probit:

P(drive) on **Offer** + **Promo** + **ISF** + **HSF** + **Controls**

Income So Far
= intensity of work

Hours So Far
= amount of available time

Conditional on working

2 How long to work?

2SLS with Fixed Effects

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

Inverse Mills Ratio
= correct for selection

Results

Compare:

1
2
vs.
1
2
+ ISF + HSF
"Targets"

Within-Day

Midday

Late Night

Across-Days

Tuesday

Sunday

Late Night

1

	Work or not?	
	Base	**+ Targets**
Hourly offer/ earnings		
Promo		
Income so far		
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)
Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far		
Hours so far		
AIC	95,856.010	72,887.620

N = 166,766

Financial incentives and getting a "deal" encourage working

Late Night

1

	Work or not?	
	Base	**+ Targets**
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)
Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far		-0.002*** (0.0002)
Hours so far		
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Hours so far		
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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

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Promo	0.229*** (0.038)	0.285*** (0.046)
Income so far	**Income Target**	-0.002*** (0.0002)
Hours so far		0.361*** (0.007)
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	Base	**+ Targets**
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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

1 2

	Work or not?		# Hours		
	Base	+ Targets	Naive	Base	+ Targets
Hourly offer/ earnings	0.008*** (0.001)	0.012*** (0.001)			
Promo	0.229*** (0.038)	0.285*** (0.046)			
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			

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Late Night

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Hours so far	**Inertia**	0.361*** (0.007)			
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AIC/R^2	95,856.010	72,887.620	0.313	0.324	0.657
	N = 166,766		N = 18,941		

Late Night

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	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)
Promo	0.229*** (0.038)	0.285*** (0.046)			
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	0.657
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Late Night

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Promo	0.229*** (0.038)				
Income so far		Income Target: -0.002*** (0.0002)			Income Target: -0.0002*** (0.00002)
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IMR					
AIC/R^2	95,856.010	72,887.620	0.313	0.324	0.657

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)
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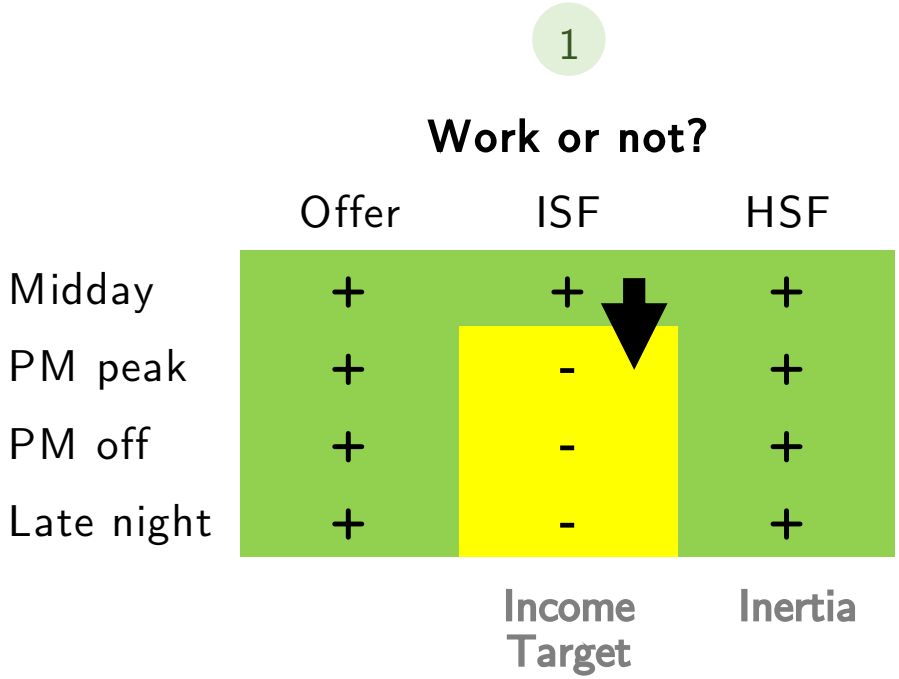
Hours so far		0.361*** (0.007)			0.187*** (0.001)

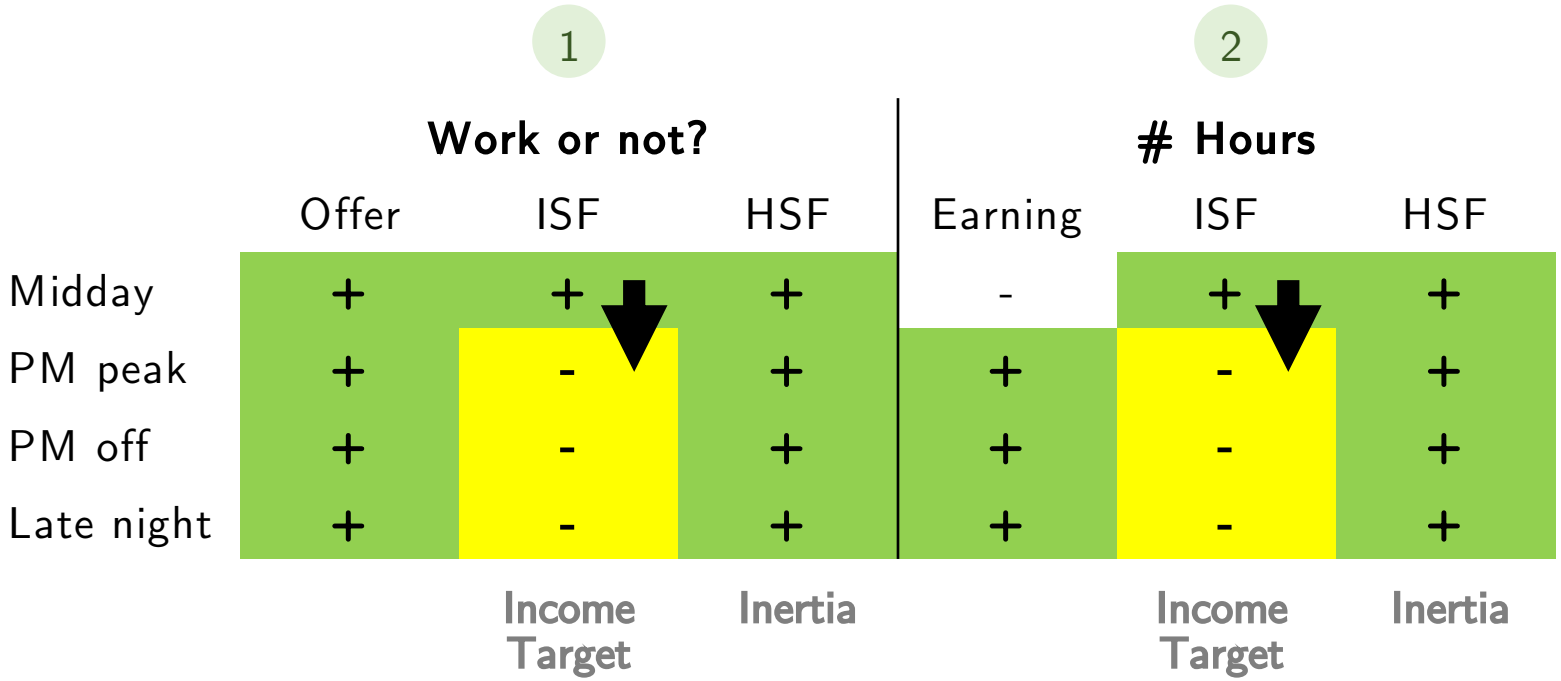
	Work or not?			# Hours		
	Offer	ISF	HSF	Earning	ISF	HSF
Late night	+	-	+	+	-	+

Results Across Shifts



Income targeting effect kicks in later in the day.

Results Across Shifts



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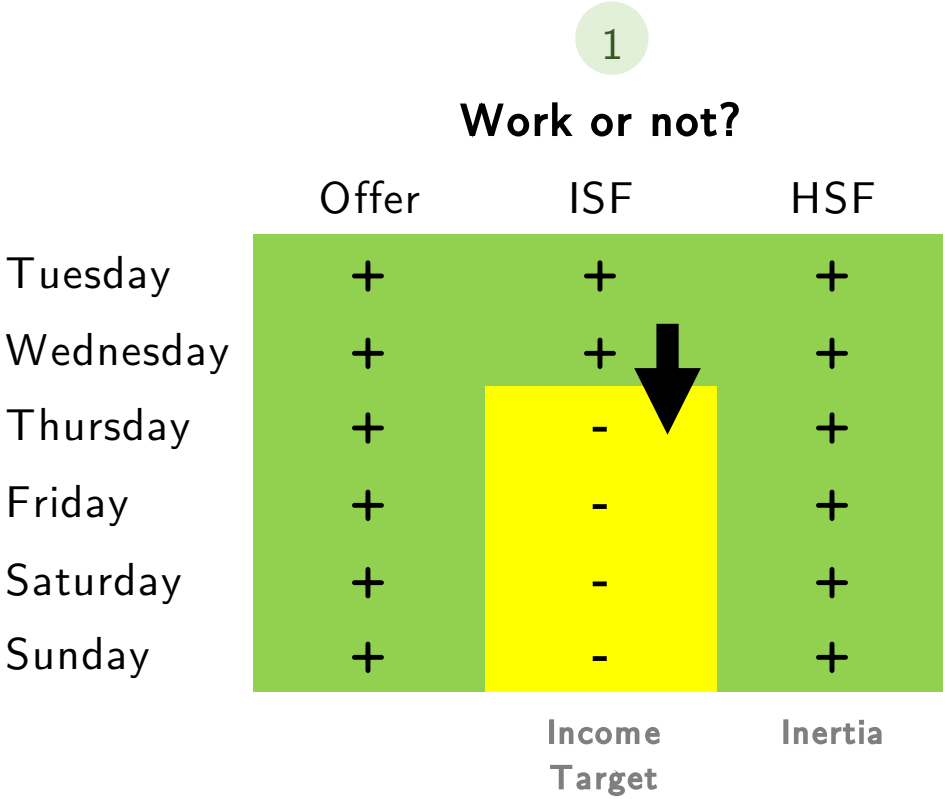
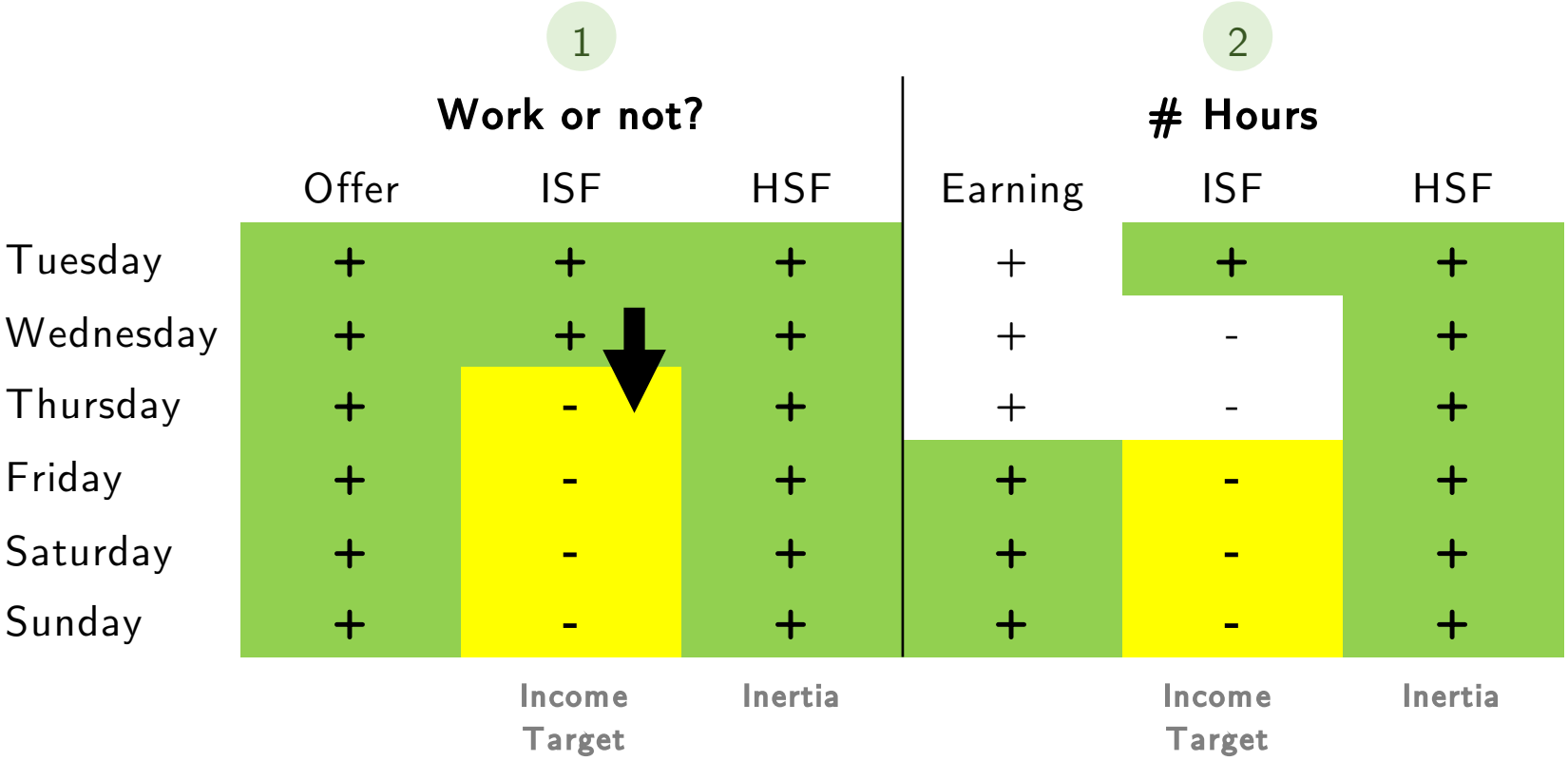
Results Across Days



Income targeting effect kicks in later in the week.

Results Across Days



Financial incentives and income target effect are not significant for weekdays.

Who Should Get Promotion?

Who Should Get Promotion?

Ranking each driver by her
minimum driving-inducing incentive

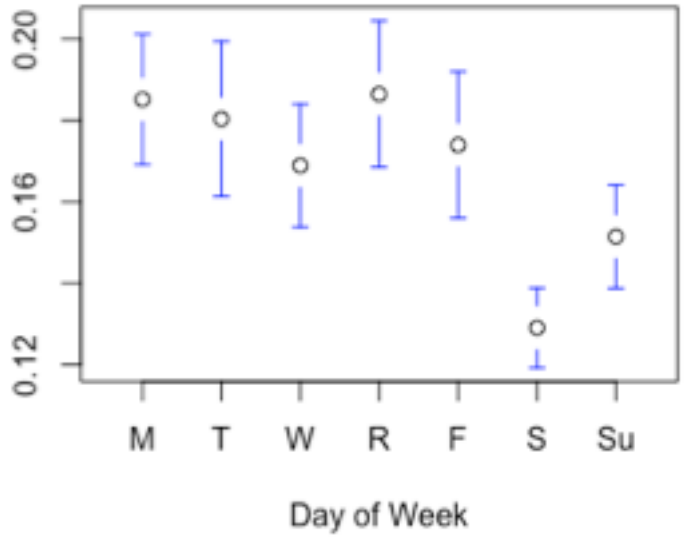
= *how much to trigger working decision*

Optimizing Incentives

Compared to current practice from January to September 2017

Given the same budget

Extra drivers



Can recruit **17% more drivers**

Average promo: 1.61x

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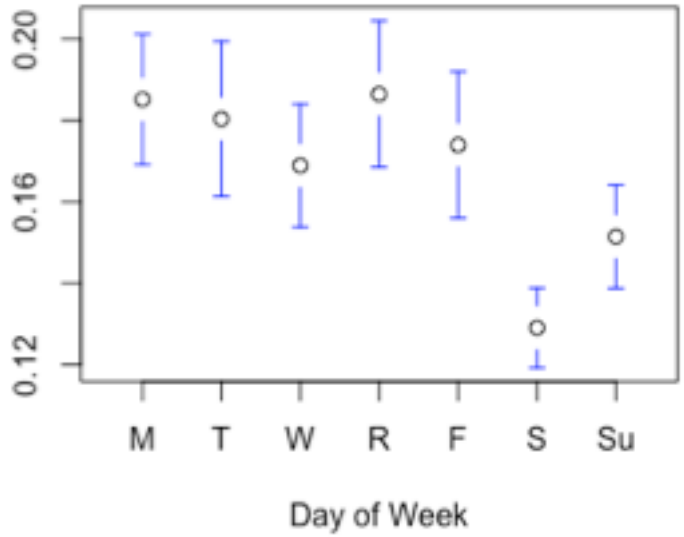
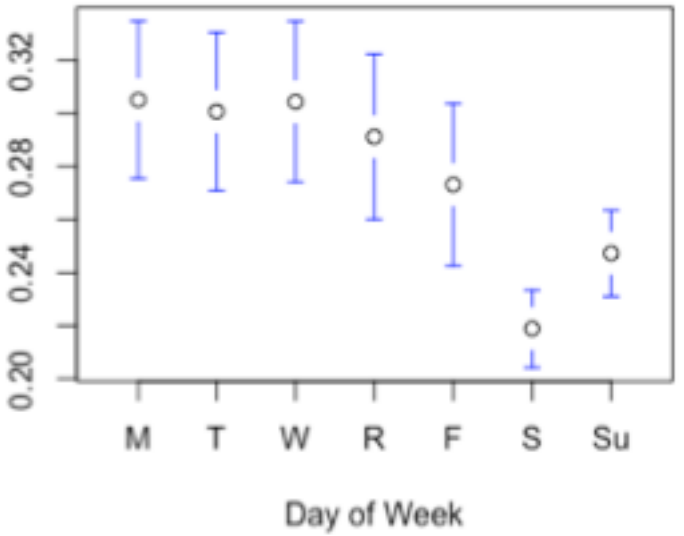


Can recruit **17% more drivers**
Average promo: 1.61x

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 two-stage Heckman estimation w/ IVs and fixed effects

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- Modified two-stage Heckman estimation w/ IVs and fixed effects

Findings

- Decisions depend on driver type and time
- Offer and inertia can increase work activity
- Income targeting has a positive effect early on and then switches to a negative effect 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

Heckit with IVs

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)

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

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