Understanding Gig Worker Behavior

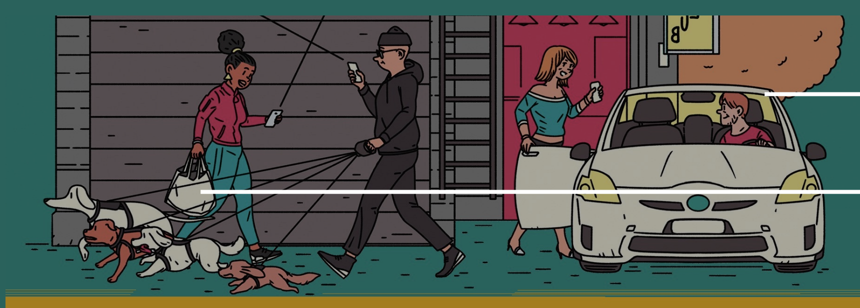
From Multihoming to Algorithm Interactions

Park Sinchaisri
UC Berkeley

Johns Hopkins Carey Business School

November 13, 2025

“Gig Economy”



ride-hailing
Uber lyft DiDi Grab

delivery
DOORDASH Uber Eats
LINEMAN deliveroo instacart
GrabFood goPuff caviar Glovo

"Gig Economy"

freelancing
remote work
Upwork
CATALANT
fastwork
Toptal
fiverr

telemedicine
Teladoc HEALTH
MDLIVE

retail
(allwork)
snag.work on-demand

local tasks
TaskRabbit
handy
TakeMeTour
BeNeat ビニート
urbansitter
GLAMSQUAD
Rover
Helpling
bTaskee

ride-hailing
Uber
lyft
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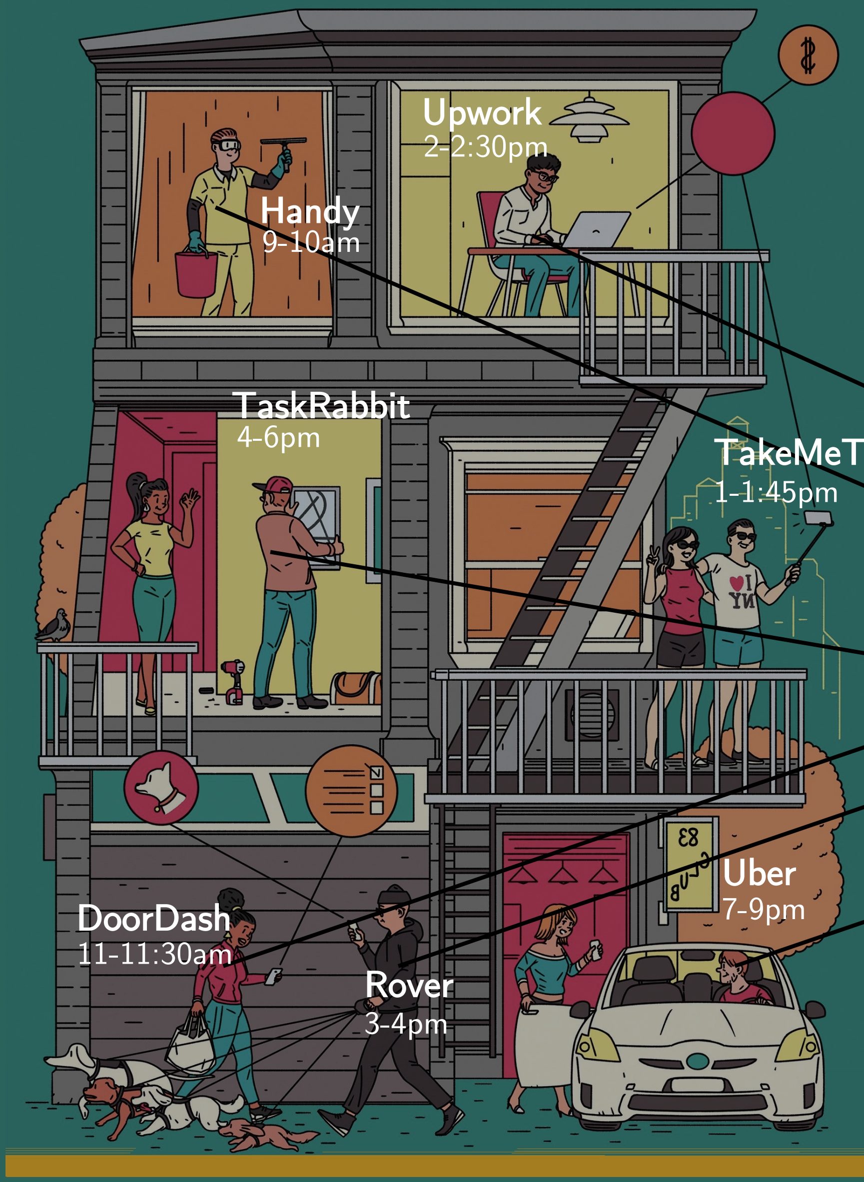
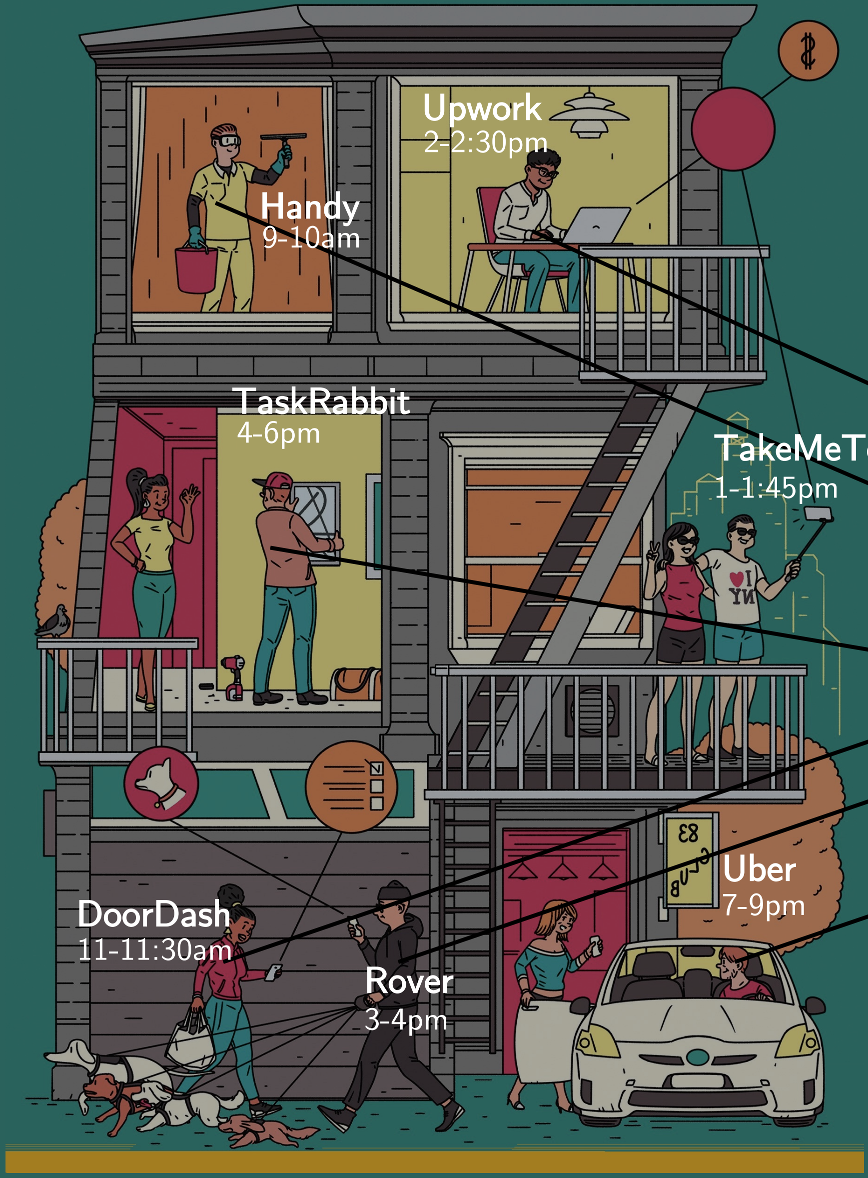


When?
How long?

Where?

#1

Flexible Work



When?
How long?

Where?

#1

Flexible Work

Improving Operations
for Future of Work

Research Overview

1 Improving Operations for Future of Work

How do on-demand workers make their work decisions?

How to design incentives and scheduling?

How do they learn, and how to help them improve faster?

Research Overview

1 Improving Operations for Future of Work

Gig Workers' Decision-Making/Incentives

- Behavioral & economic drivers on workers' labor decisions/scheduling (with Gad Allon, Maxime Cohen, M&SOM 2023)
- Multihoming, incentive schemes (with Gad Allon, Maxime Cohen, Ken Moon, Under revision for resubmission)
- Optimizing task selection/assignment (with Shunan Jiang, CSCW 2025)
- *In progress:* field experiment on incentive design with a food delivery platform, temporary on-demand teams in retail, crowdsourced workers

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Our kind industry partner

Park Sinchaisri (UC Berkeley Haas) / parksinchaisri@berkeley.edu / parksinchaisri.github.io

Research Overview

Struggling gig workers

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Our kind industry partner

People work independently /remotely

People work independently /remotely

#2

Worker Learning

Human-AI Interfaces to Improve Performance

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2 Human-AI Interfaces to Improve Performance

"Sequential Decision Making"

How to design effective human-AI interfaces?

How do humans respond to AI-generated advice?

How humans learn to use new tool (e.g., generative AI)?

Research Overview

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2 Human-AI Interfaces to Improve Performance

Tips for Sequential Decision-Making

- Learning best practices ("tip") from data
  (with Hamsa Bastani, Osbert Bastani, Management Science 2025)
- Precision of advice in uncertain env.
  (with Philippe Blaettchen, preparing for submission)
- Generative AI and productivity
  (with Sam Keppler, Clare Snyder, CSCW 2025)
- Backward planning with generative AI
  (with Sam Keppler, Clare Snyder, preparing for submission)
- Characterizing non-adoption
  (with David Lee, preparing for submission)
- *In progress: AI tips for multiple agents*

Today

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Managing **Multihoming Workers** in the Gig Economy

Park Sinchaisri
UC Berkeley

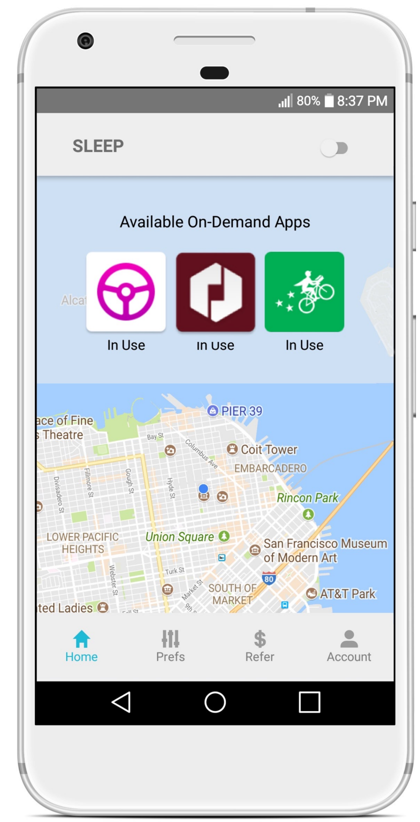
joint work with
Gad Allon, Maxime Cohen, Ken Moon

Multihoming Workers

Multihoming Workers

caviar GRUBHUB seamless goPuff
DOORDASH Uber Eats instacart Postmates
Uber lyft via

Multihoming Workers

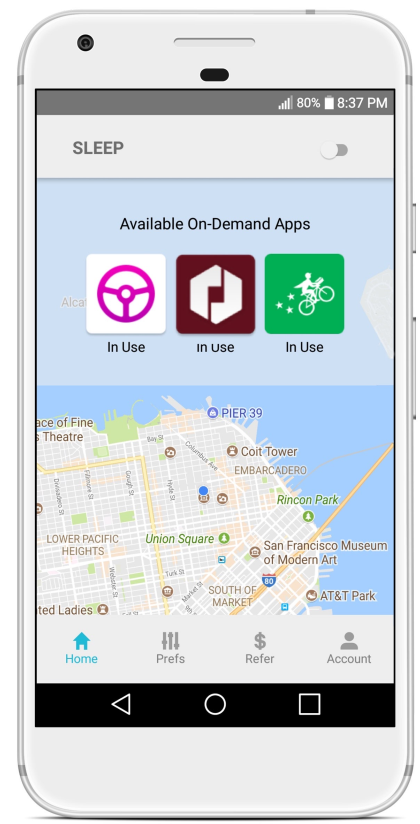


POLICY \ US & WORLD \ TRANSPORTATION

In major defeat for Uber and Lyft, New York City votes to limit ride-hailing cars

NYC becomes the first American city to restrict the explosive growth in for-hire vehicles

By Shoshana Wodinsky | Aug 8, 2018, 4:39pm EDT



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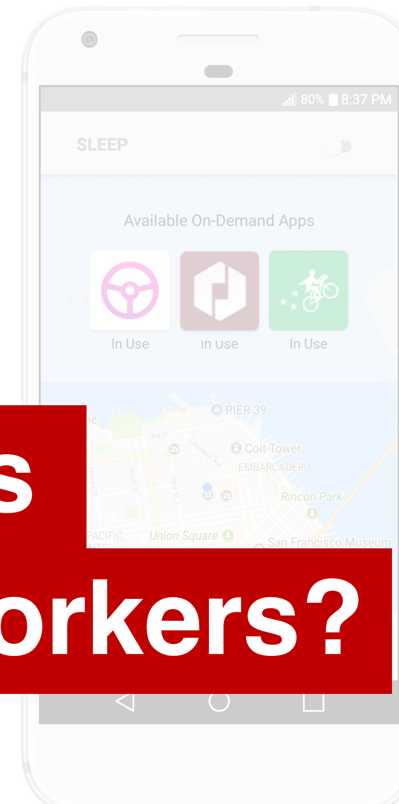
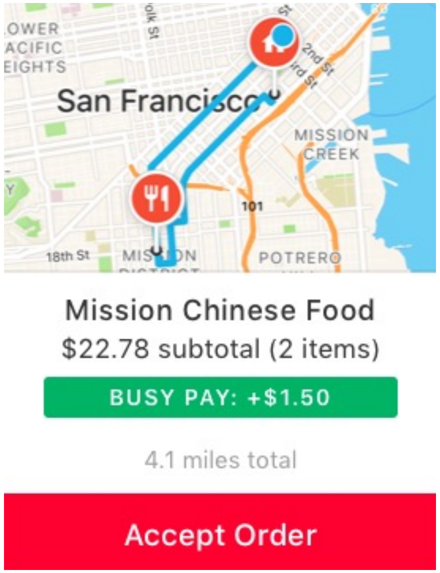
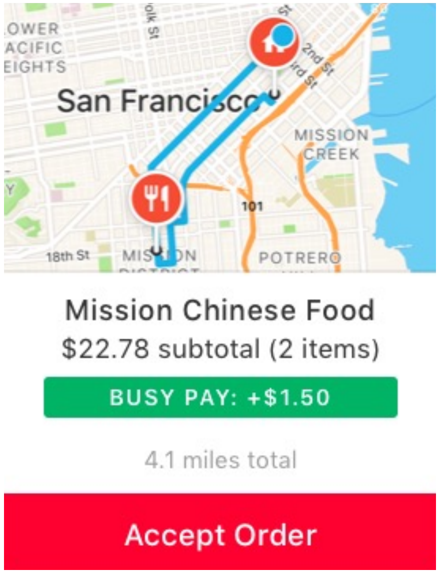


How should platforms compete for multihoming workers?



DOORDASH

How should platforms compete for multihoming workers?



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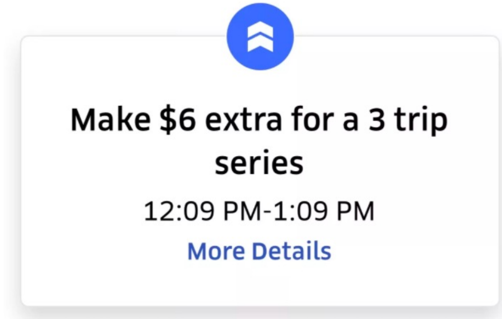
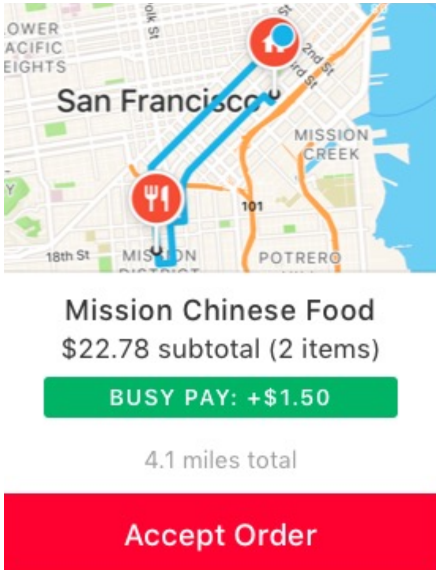
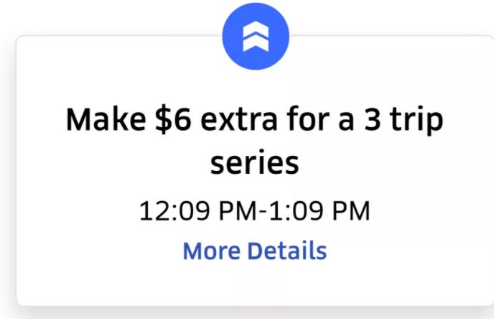


Uber

How should platforms compete for multihoming workers?



DOORDASH



Uber

The New York Times

DoorDash, Shifting Business Model, Will Offer Drivers Hourly Pay

The company said the option would give couriers greater choice. It could also help DoorDash find people who will make less desirable deliveries.

How should platforms compete for multihoming workers?

How workers make multihoming decisions?

How should platforms compete for multihoming workers?

Context Ride-Hailing w/ Diff. Pay

A = Focal

B = Competitor

Context Ride-Hailing w/ Diff. Pay

A = Focal

B = Competitor

dynamic guaranteed hourly pay

(e.g., $25/hour if online between 7-9am)

Context Ride-Hailing w/ Diff. Pay

A = Focal

dynamic
guaranteed hourly
pay

(e.g., $25/hour if online
between 7-9am)

B = Competitor

dynamic
per-trip
pay

(e.g., base fare
+ extra $/minute
+ extra $/distance)

Context Gig Workers with 2 Options

(ride-hailing platforms)

A = Focal

B = Competitor

225 S 4th St
Brooklyn, NY

8:20AM

Context Gig Workers with 2 Options

(ride-hailing platforms)

A = Focal

$25/hour
7-9AM

B = Competitor

225 S 4th St
Brooklyn, NY

8:20AM

Context

Gig Workers with 2 Options

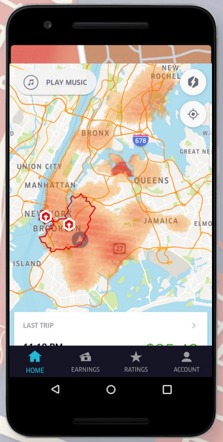
(ride-hailing platforms)

A = Focal

$25/hour

7-9AM

B = Competitor



Avg. Surge

+25%

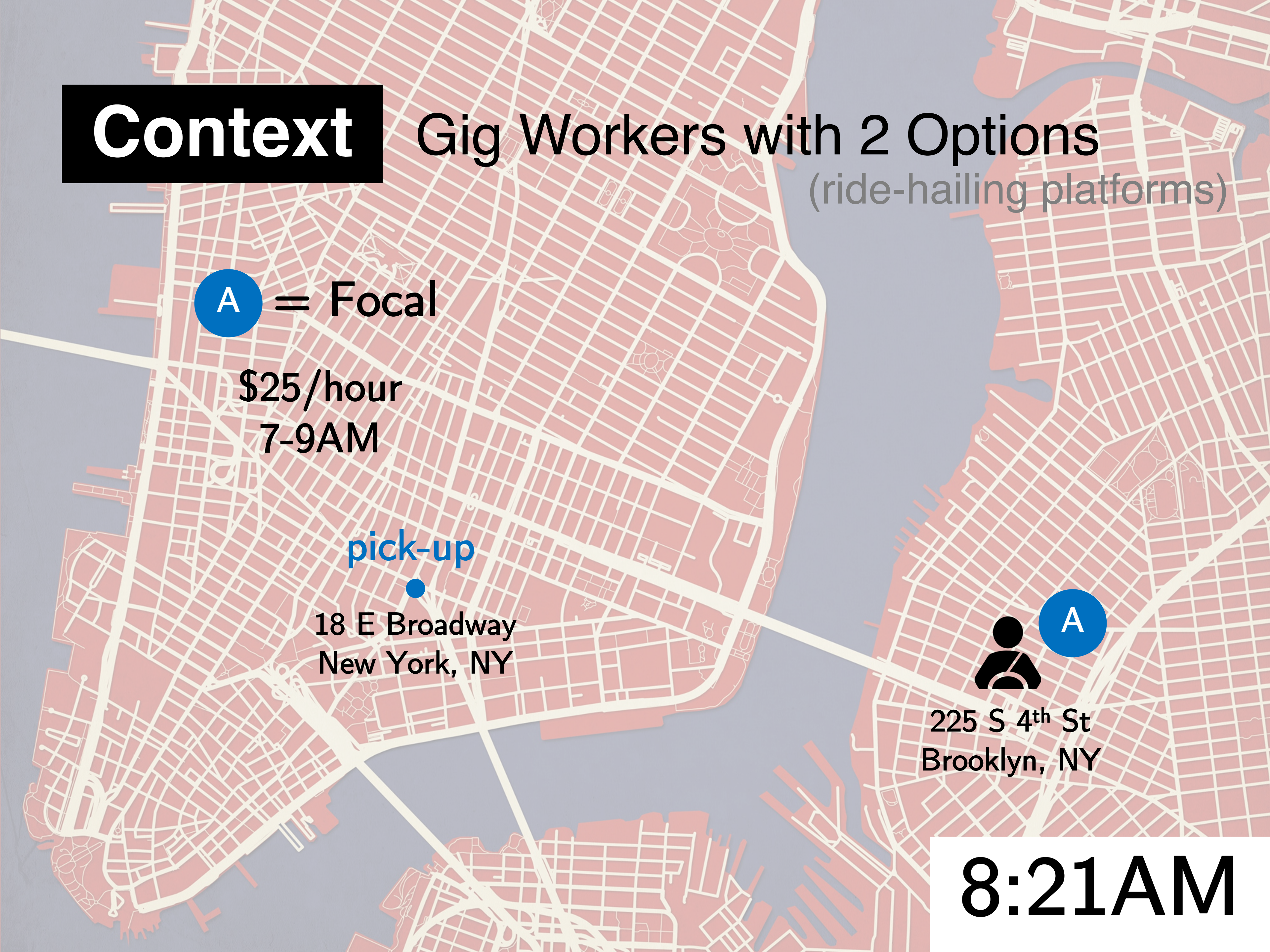
225 S 4th St

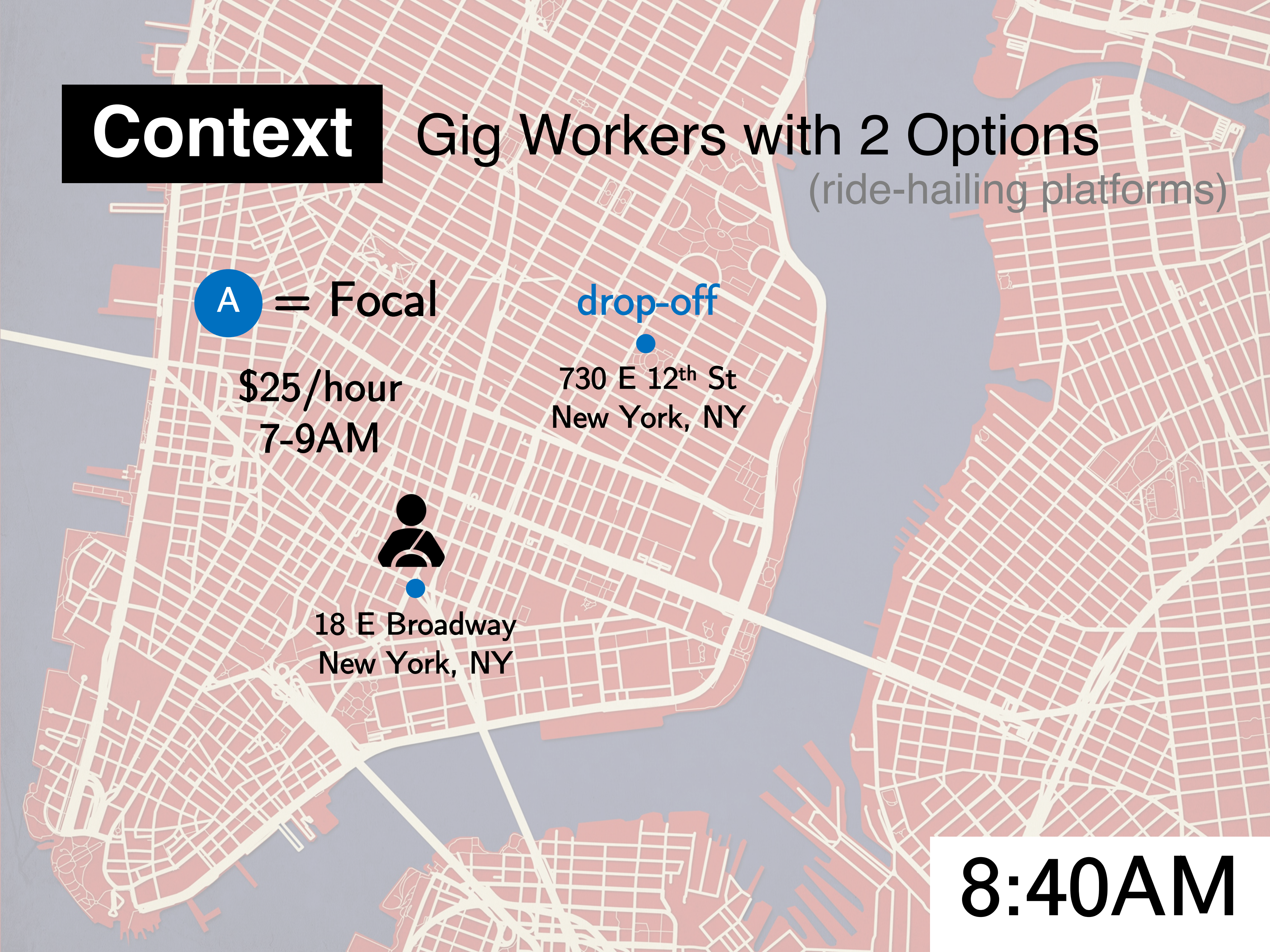
Brooklyn, NY

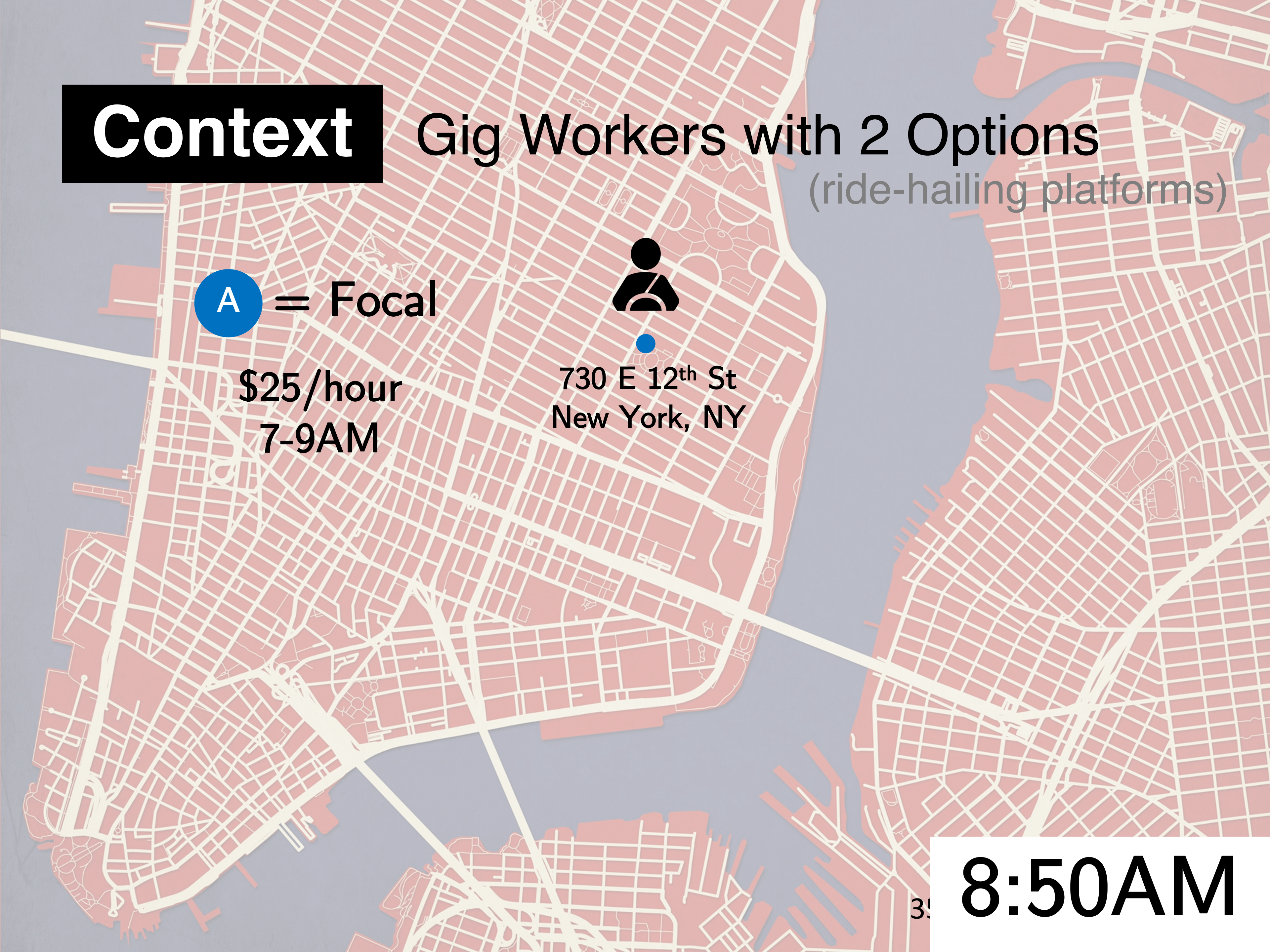
8:20AM

Context Gig Workers with 2 Options

(ride-hailing platforms)




Context
Gig Workers with 2 Options
(ride-hailing platforms)
A = Focal
$25/hour
7-9AM
drop-off
730 E 12th St
New York, NY
18 E Broadway
New York, NY
8:40AM


Context
Gig Workers with 2 Options
(ride-hailing platforms)
A = Focal
$25/hour
7-9AM
730 E 12th St
New York, NY
8:50AM

Context Gig Workers with 2 Options

(ride-hailing platforms)

A = Focal

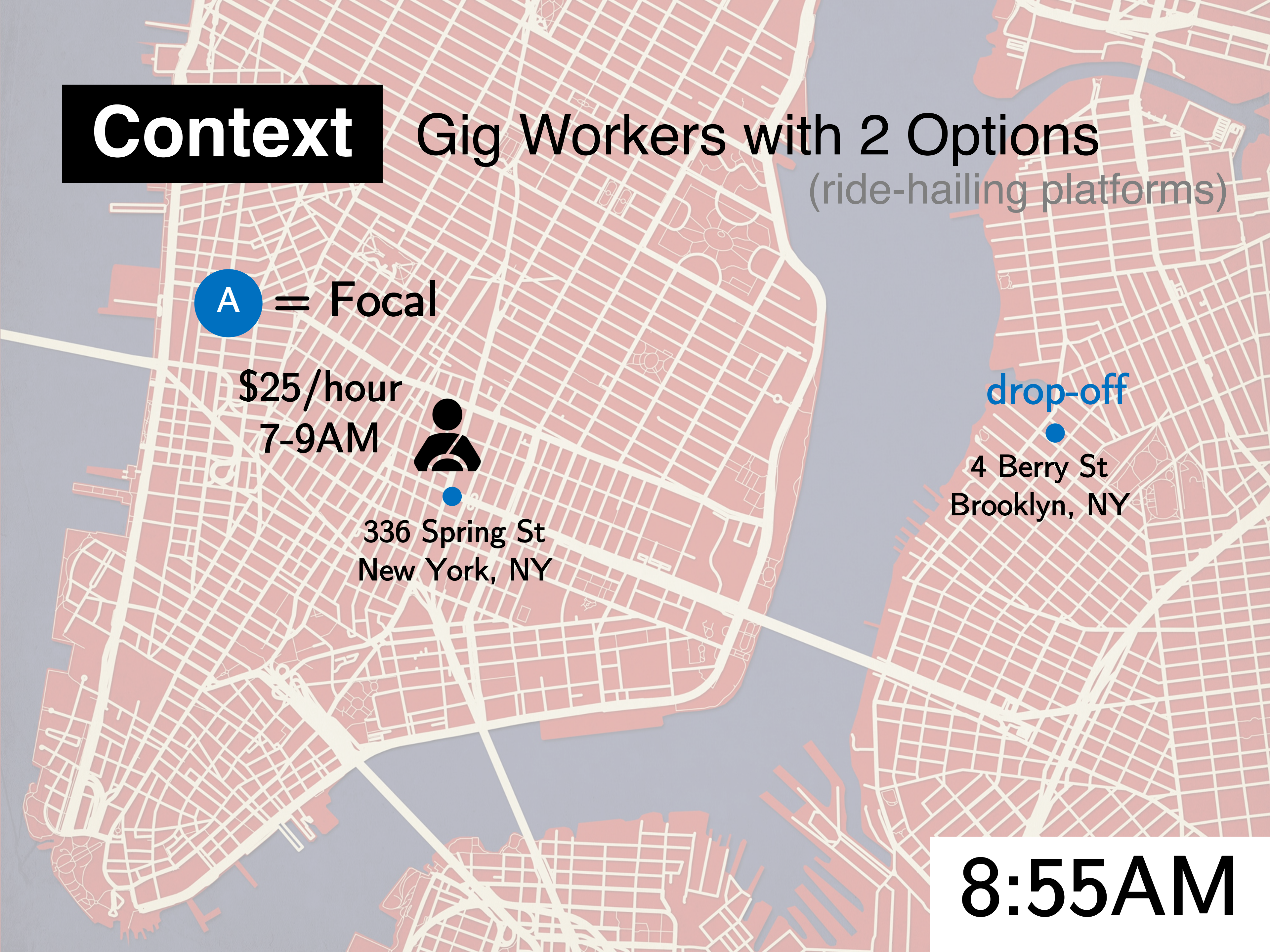
$25/hour
7-9AM

730 E 12th St
New York, NY

pick-up

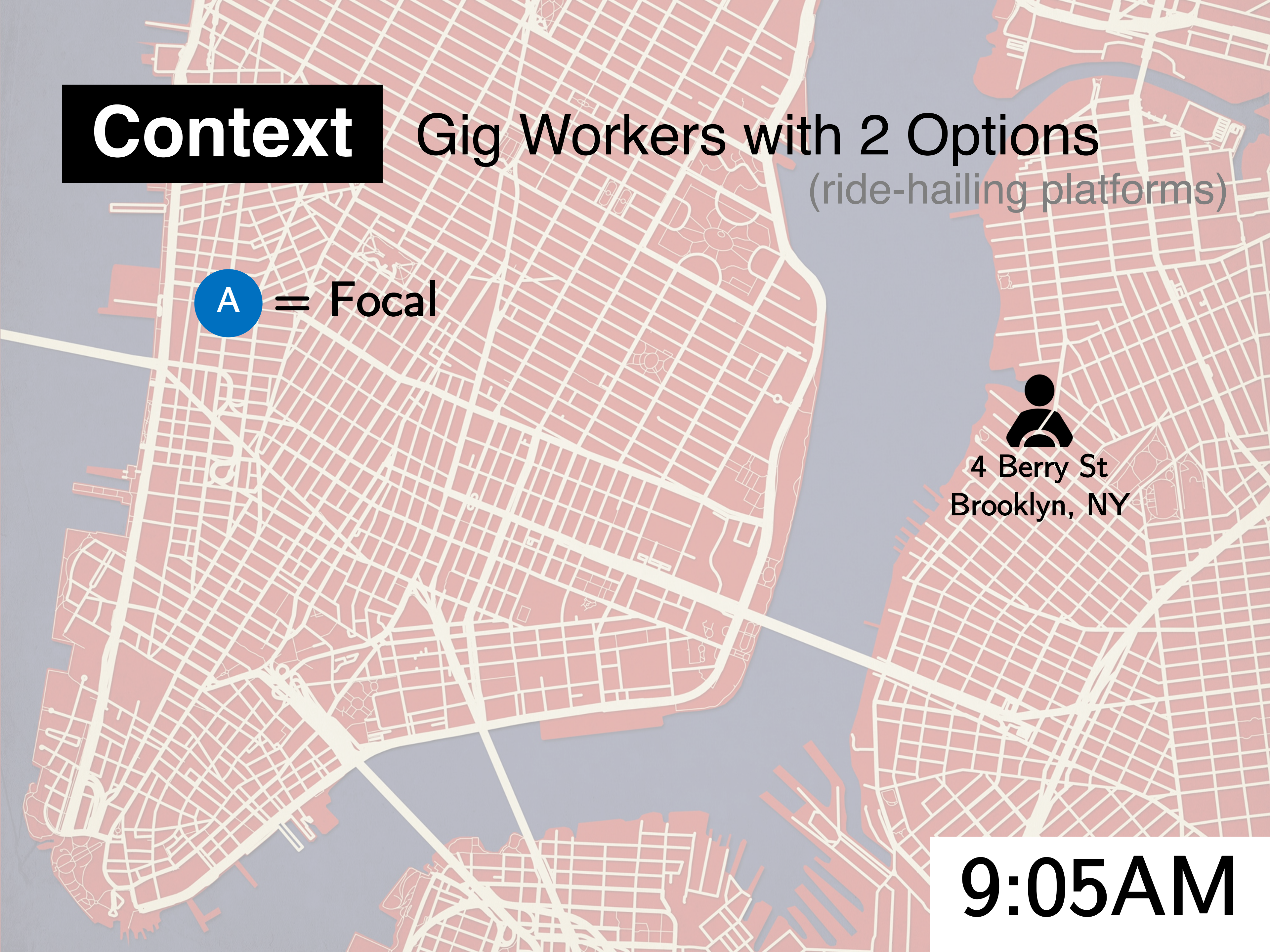
336 Spring St
New York, NY

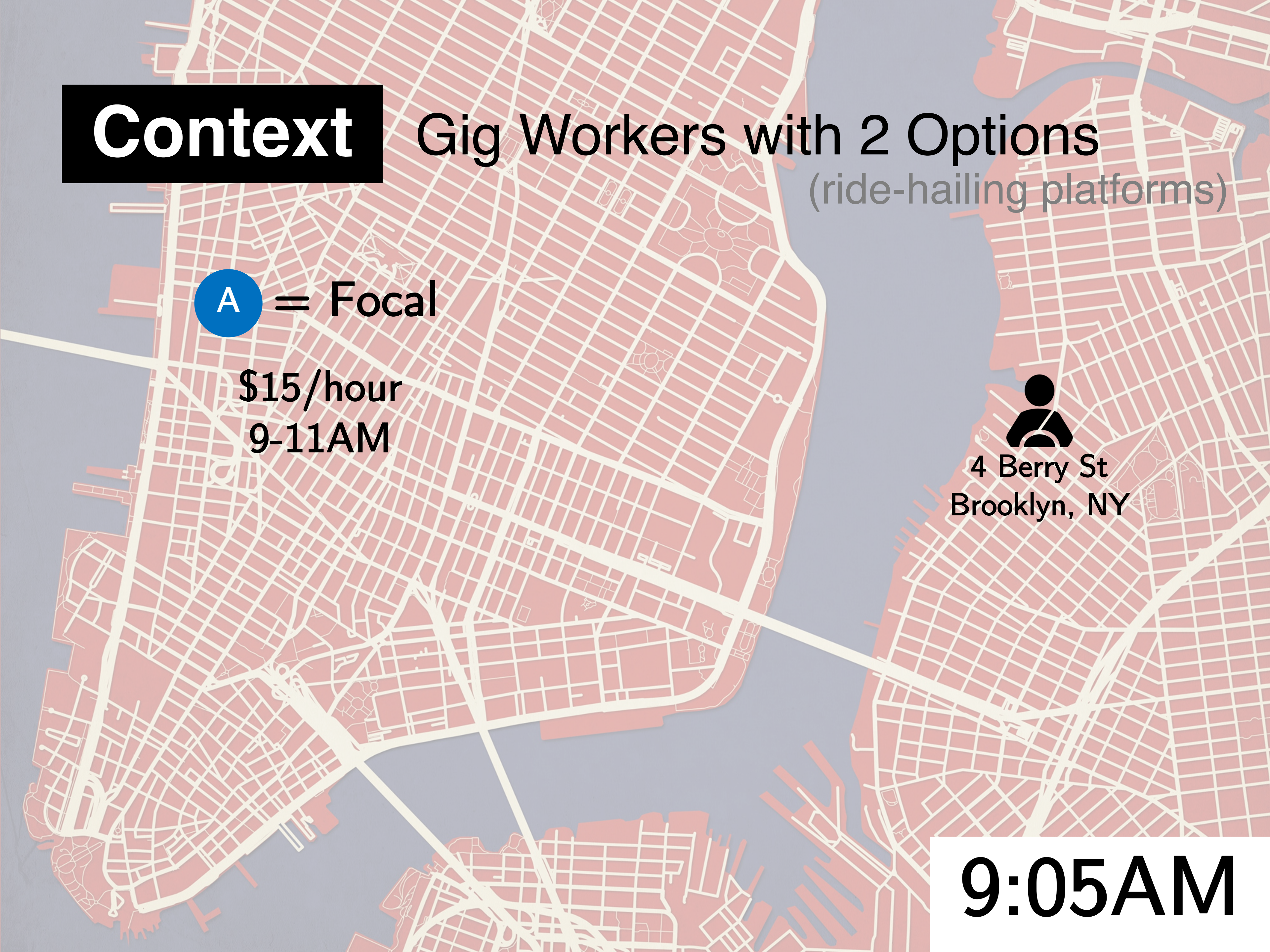
8:50AM


Context
Gig Workers with 2 Options
(ride-hailing platforms)
A = Focal
$25/hour
7-9AM
drop-off
4 Berry St
Brooklyn, NY
336 Spring St
New York, NY
8:55AM

Context Gig Workers with 2 Options

(ride-hailing platforms)




Context
Gig Workers with 2 Options
(ride-hailing platforms)
A = Focal
$15/hour
9-11AM
4 Berry St
Brooklyn, NY
9:05AM

Context

Gig Workers with 2 Options

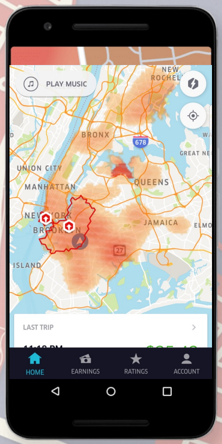
(ride-hailing platforms)

A = Focal

$15/hour
9-11AM

B = Competitor

Avg. Surge
+75%



4 Berry St
Brooklyn, NY

9:05AM

Context

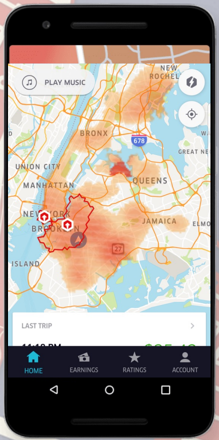
Gig Workers with 2 Options
(ride-hailing platforms)

A = Focal

$15/hour
9-11AM

B = Competitor

Avg. Surge
+75%



B

4 Berry St
Brooklyn, NY

9:06AM

Snapshot of Gig Work

Driver: Park S. 

Time	Decision/Location	Pay rate A	Pay rate B
8:21	Joined A 225 S 4^{th} St	\$25/hour	+25%
8:40	18 E Broadway A	\$25/hour	+25%
8:50	730 E 12^{th} St A	\$25/hour	+35%
8:55	336 Spring St A	\$25/hour	+50%
9:05	4 Berry St A	\$15/hour	+75%
9:06	Switched to B	\$15/hour	+75%

Snapshot of Gig Work

Driver: #123 (sedan)

Time	Decision/Location	Pay rate A	Pay rate B
8:21	Joined A 225 S 4th St	$25/hour	+25%
8:40	18 E Broadway A	$25/hour	+25%
8:50	730 E 12th St A	$25/hour	+35%
8:55	336 Spring St A	$25/hour	+50%
9:05	4 Berry St A	$15/hour	+75%
9:06	Left A d to B	$15/hour	+75%

A **Our proprietary data**

Time and location of *first* pick-up
and *last* drop-off
Guaranteed pay
July – September 2017, NYC

Public data

NYC Taxi & Limousine Commission

Snapshot of Gig Work

Driver: #123 (sedan)

Time	Decision/Location	Pay rate A	Pay rate B
8:21	Joined A 225 S 4^{th} St	\$25/hour	+25%
8:40	18 E Broadway A	\$25/hour	+25%
8	St A	\$25/hour	+35%
8	St A	\$25/hour	+50%
9:05	4 Berry St A	\$15/hour	+75%
9:06	Left A d to B	\$15/hour	+75%

Infer locations from transition matrix

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Time and location of *first* pick-up
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Time	Decision/Location	Pay rate A	Pay rate B
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8:40	18 E Broadway A	$25/hour	+25%
8	St A	$25/hour	+35%
8	St A	$25/hour	+50%
9:05	4 Berry St A	$15/hour	+
9:06	Left A d to B	$15/hour	+

Infer locations from transition matrix

Breakdown of fare rates B

A **Our proprietary data**

Time and location of *first* pick-up and *last* drop-off

Guaranteed pay

July – September 2017, NYC

Public data

Taxi & Limousine Commission

Snapshot of Gig Work

Driver: #123 (sedan)

Time	Decision/Location	Pay rate A	Pay rate B
8:21	Joined A 225 S 4th St	$25/hour	+25%
8:40	18 E Broadway A	$25/hour	
8	St A	$25/hour	
8	St A	$25/hour	+50%
9:05	4 Berry St A	$15/hour	+
9:06	Left A d to B	$15/hour	+

Infer locations
from transition matrix

Volume of trips
for all platforms
in each neighborhood

Breakdown of
fare rates B

A **Our proprietary data**

Time and location of *first* pick-up
and *last* drop-off
Guaranteed pay
July – September 2017, NYC

Public data NYC Taxi & Limousine Commission

th St

Pay rate

	A	B
	$25/hour	+25%
	$25/hour	
	$25/hour	
	$25/hour	+50%
	$15/hour	+
	$15/hour	+

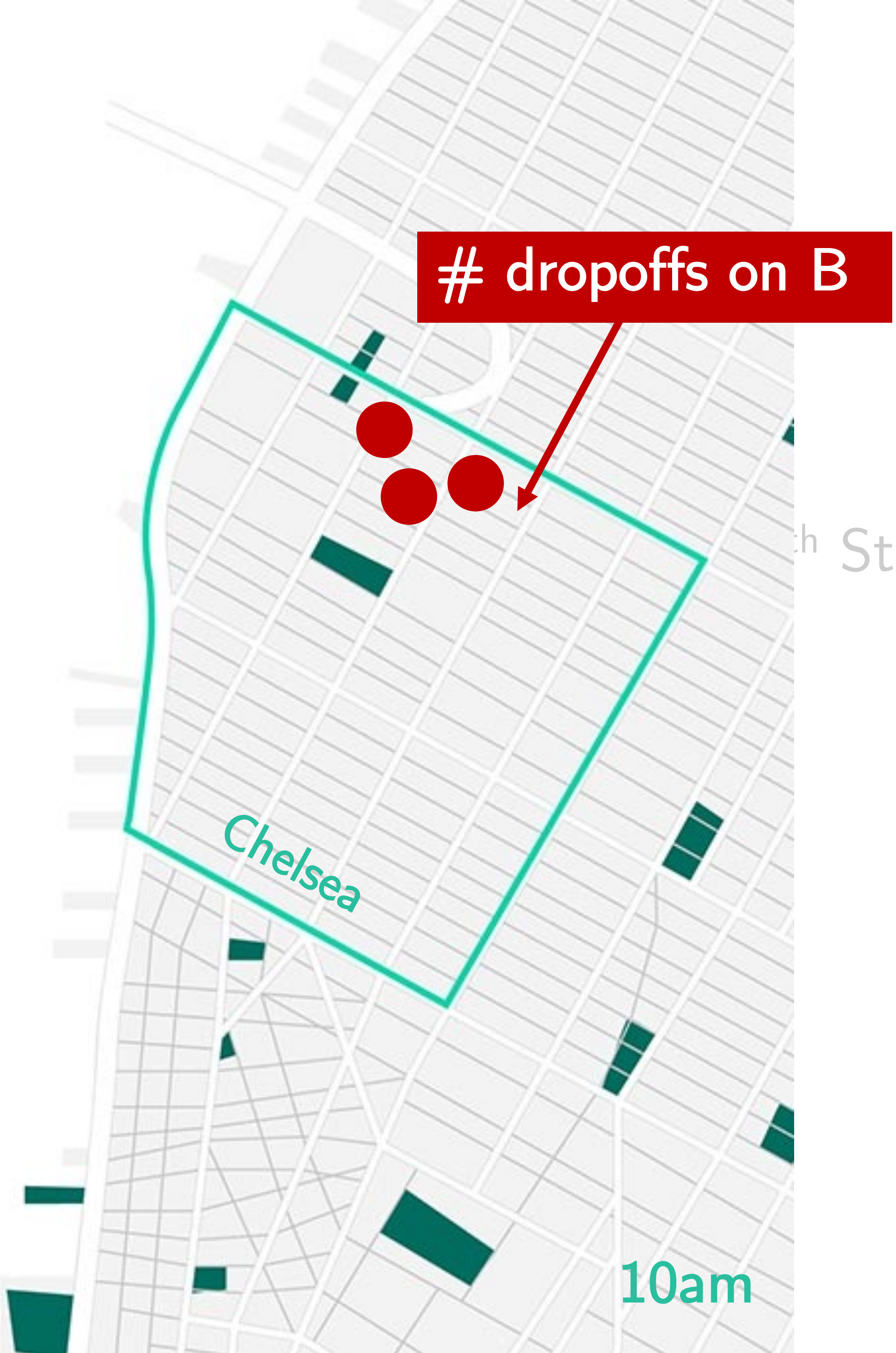
Volume of trips
for all platforms
in each neighborhood

Breakdown of
fare rates

B

Public data

Taxi & Limousine
Commission



Pay rate

A	B
$25/hour	+25%
$25/hour	
$25/hour	
$25/hour	+50%
$15/hour	+
$15/hour	+

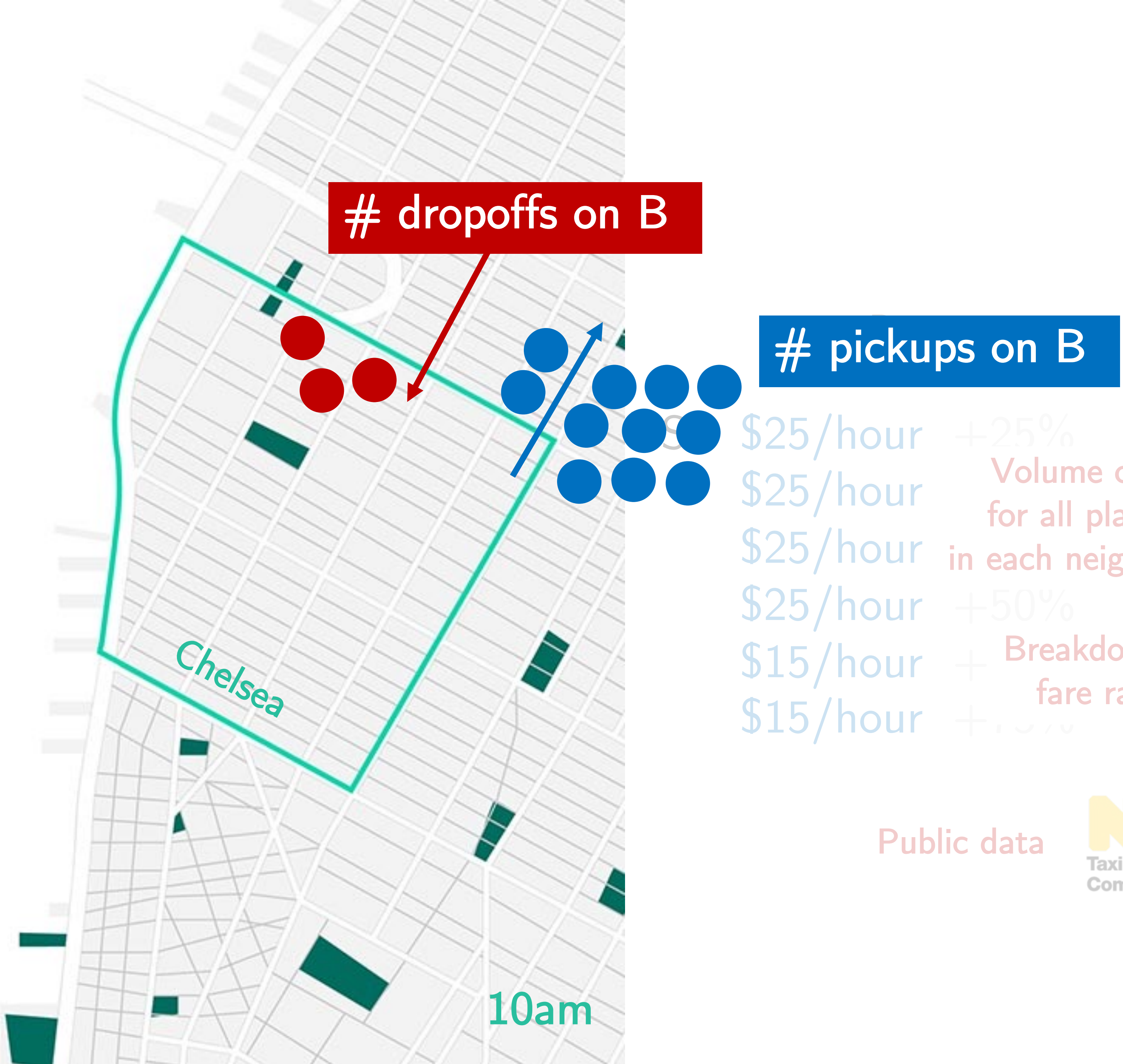
Volume of trips
for all platforms
in each neighborhood

Breakdown of
fare rates

B

Public data

Taxi & Limousine
Commission



$25/hour +25%
$25/hour
$25/hour
$25/hour +50%
$15/hour
$15/hour

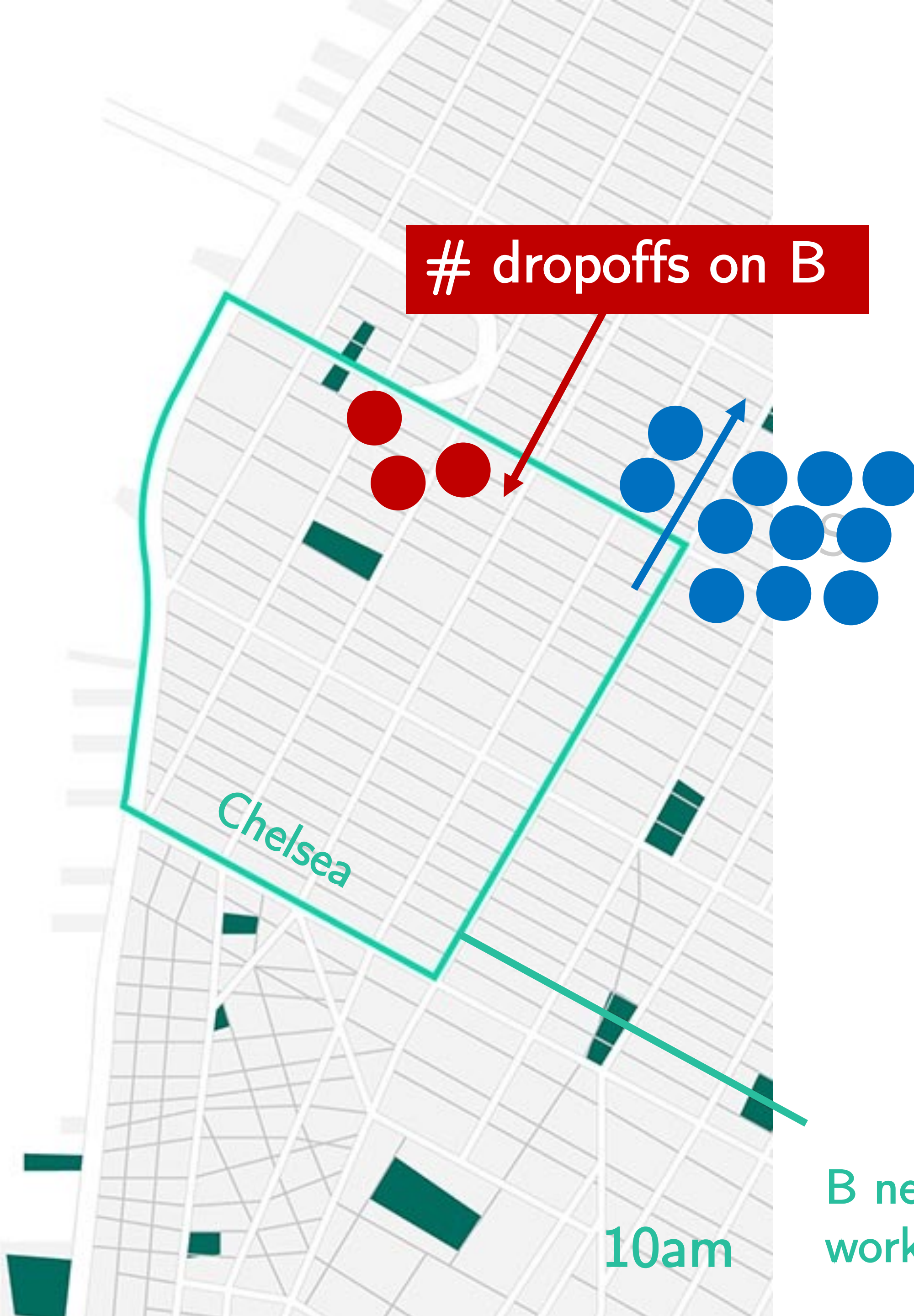
Volume of trips
for all platforms
in each neighborhood

Breakdown of
fare rates

B

Public data

Taxi & Limousine
Commission



$25/hour +25%
$25/hour
$25/hour
$25/hour +50%
$15/hour
$15/hour

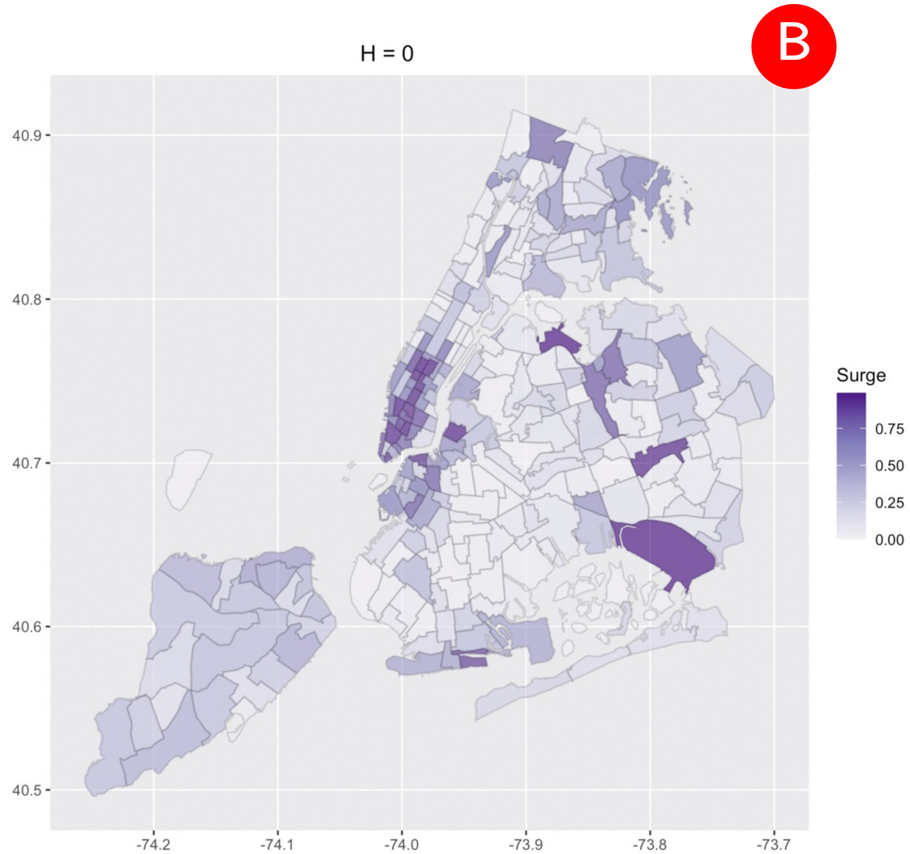
Volume of trips
for all platforms
in each neighborhood

Breakdown of
fare rates
B

Public data
NYC
Taxi & Limousine
Commission

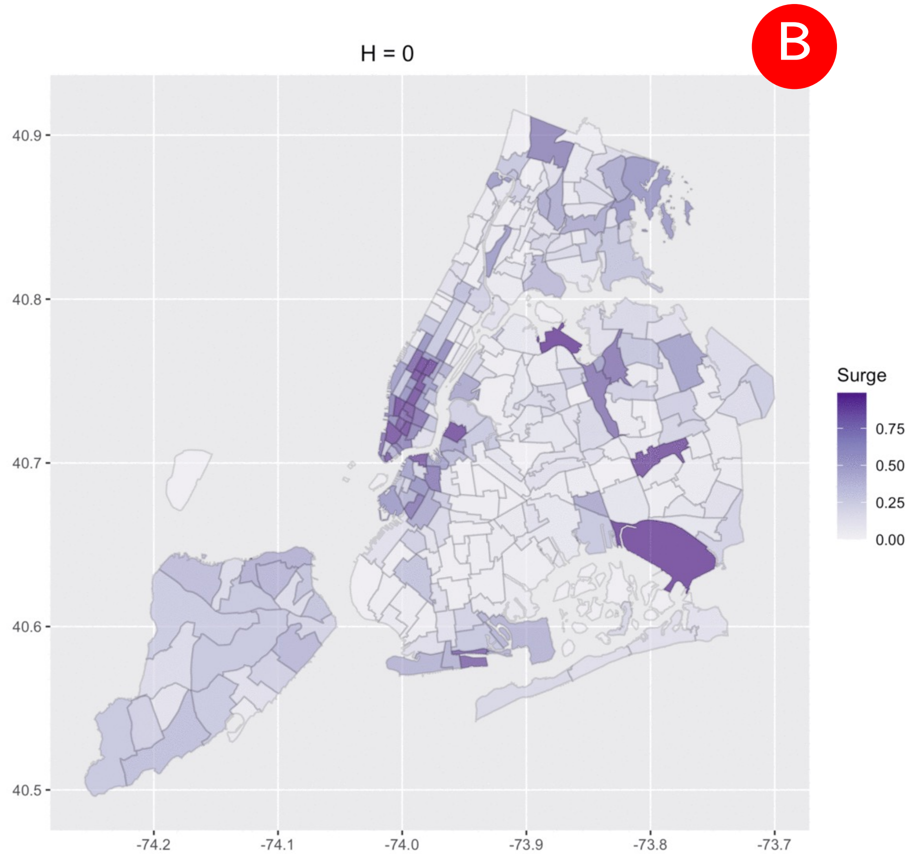
B needs to incentivize more drivers to start working here (proxy for supply shortage)

P(Supply shortage on competitor)

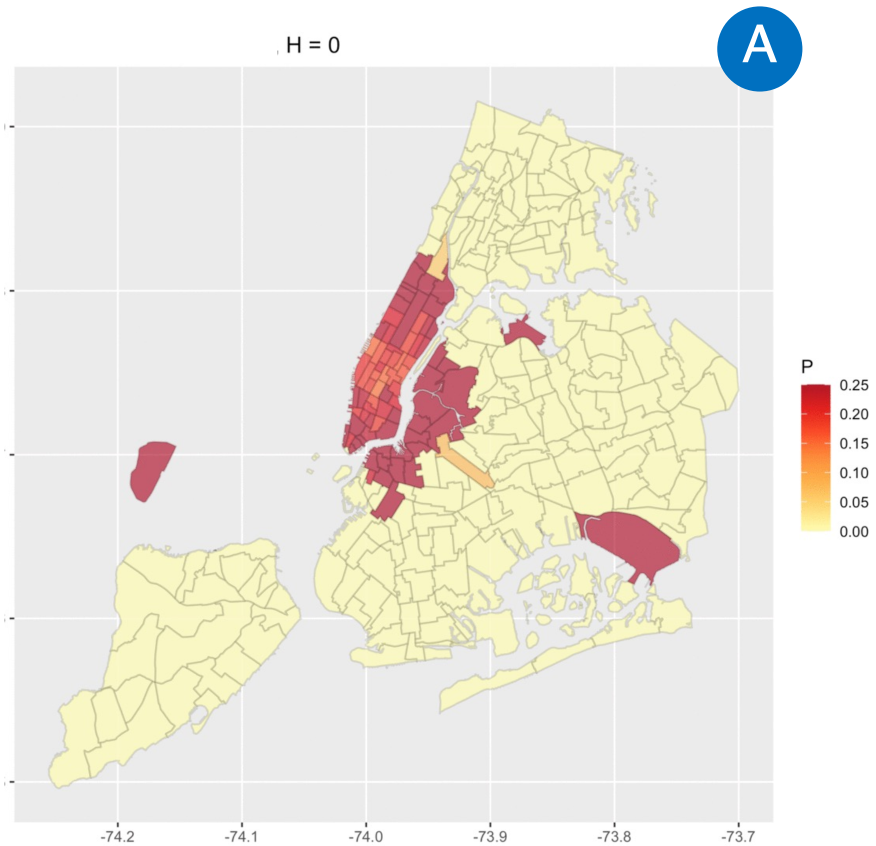


Temporal/Spatial Variations

P(Supply shortage on competitor)

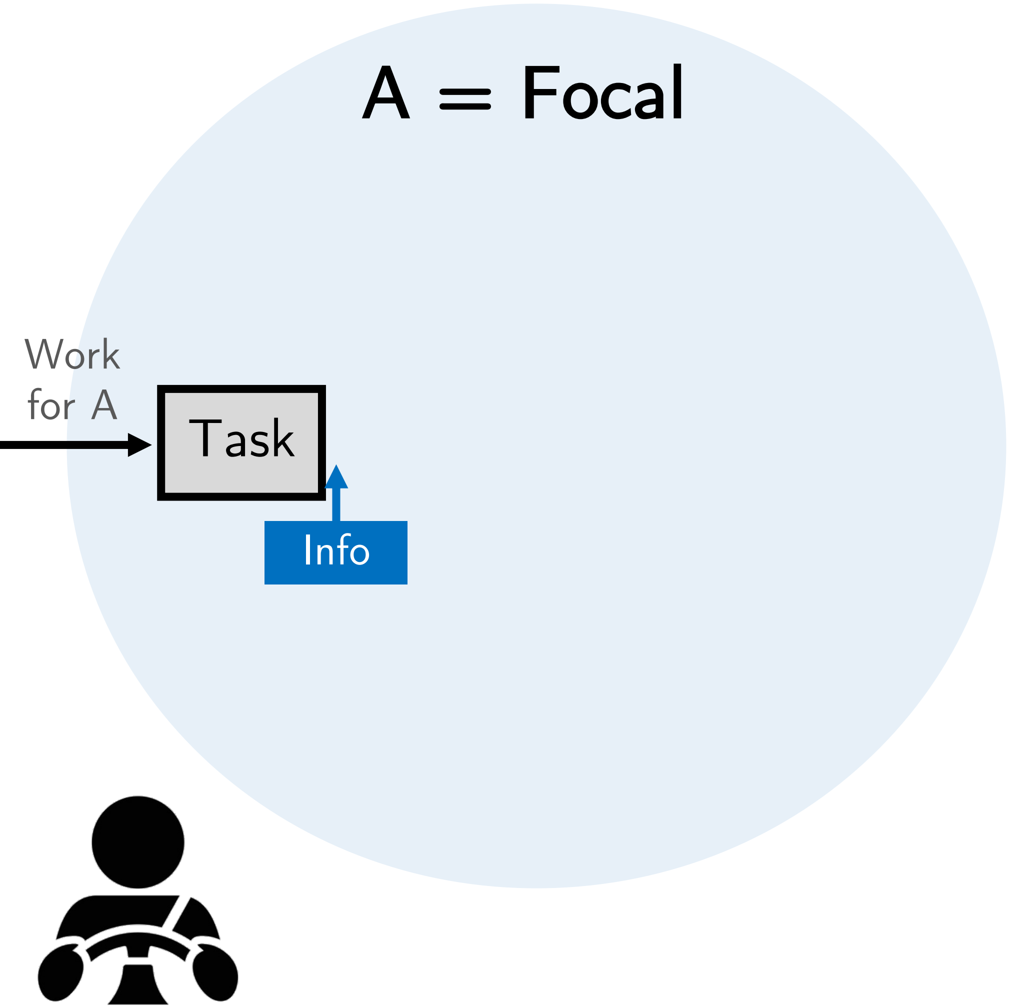


P(Leaving focal firm)



Our Model

2 firms in the same industry
Finite time horizon, every 20 mins



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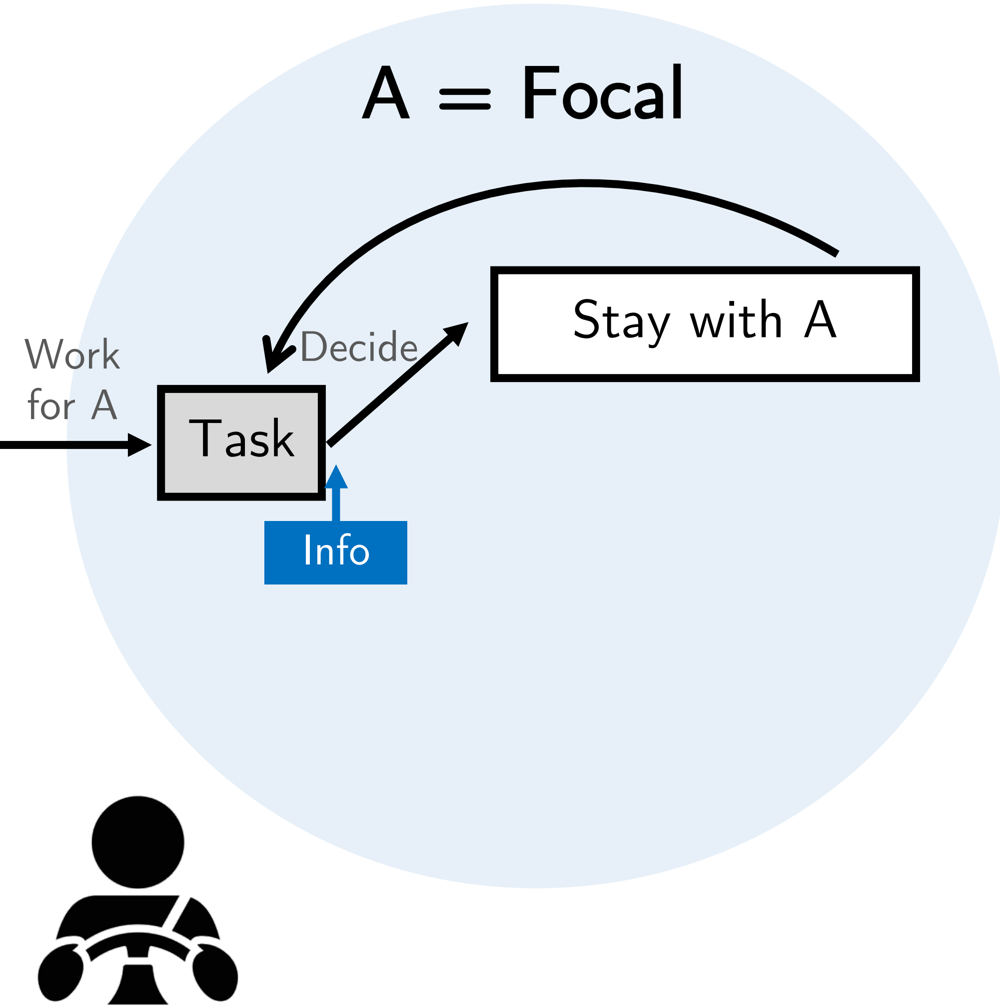
Finite time horizon, every 20 mins



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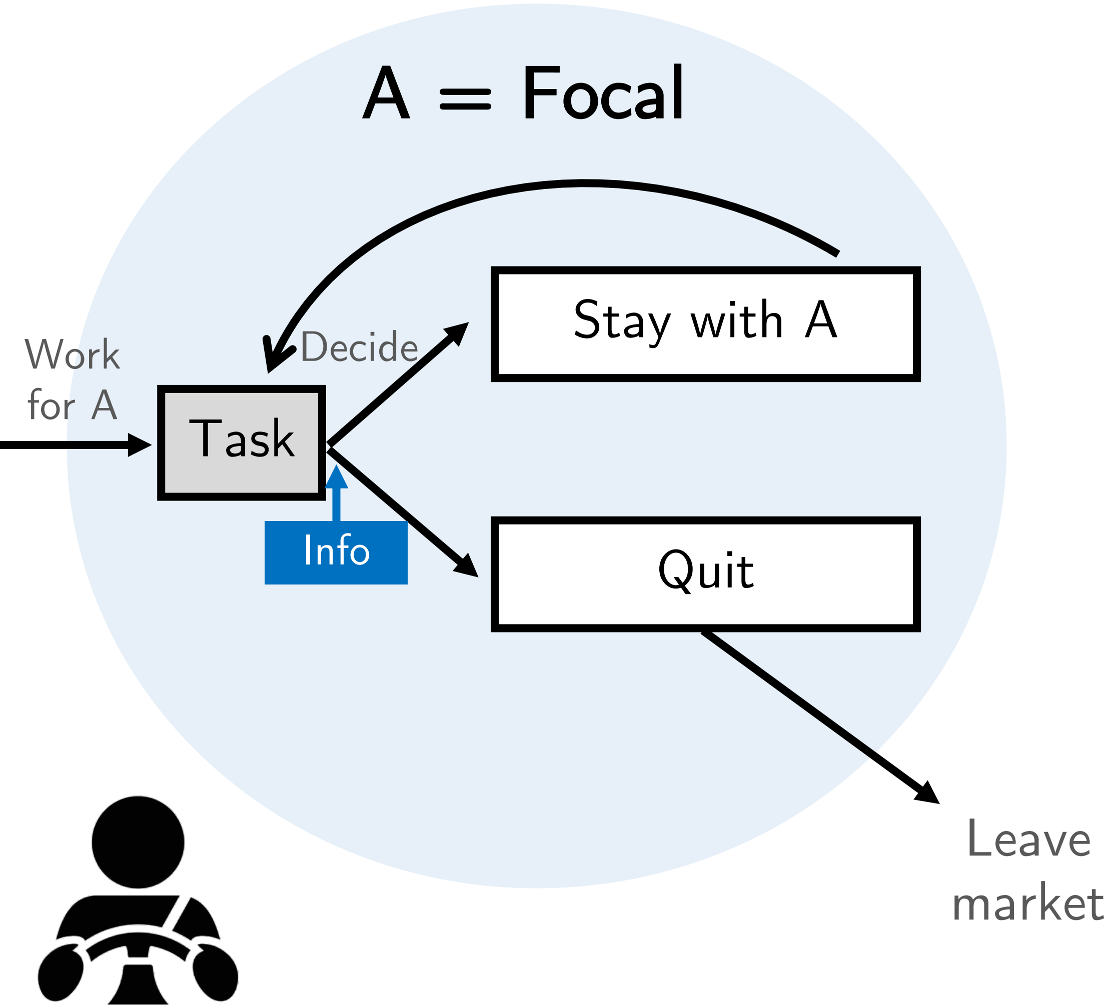

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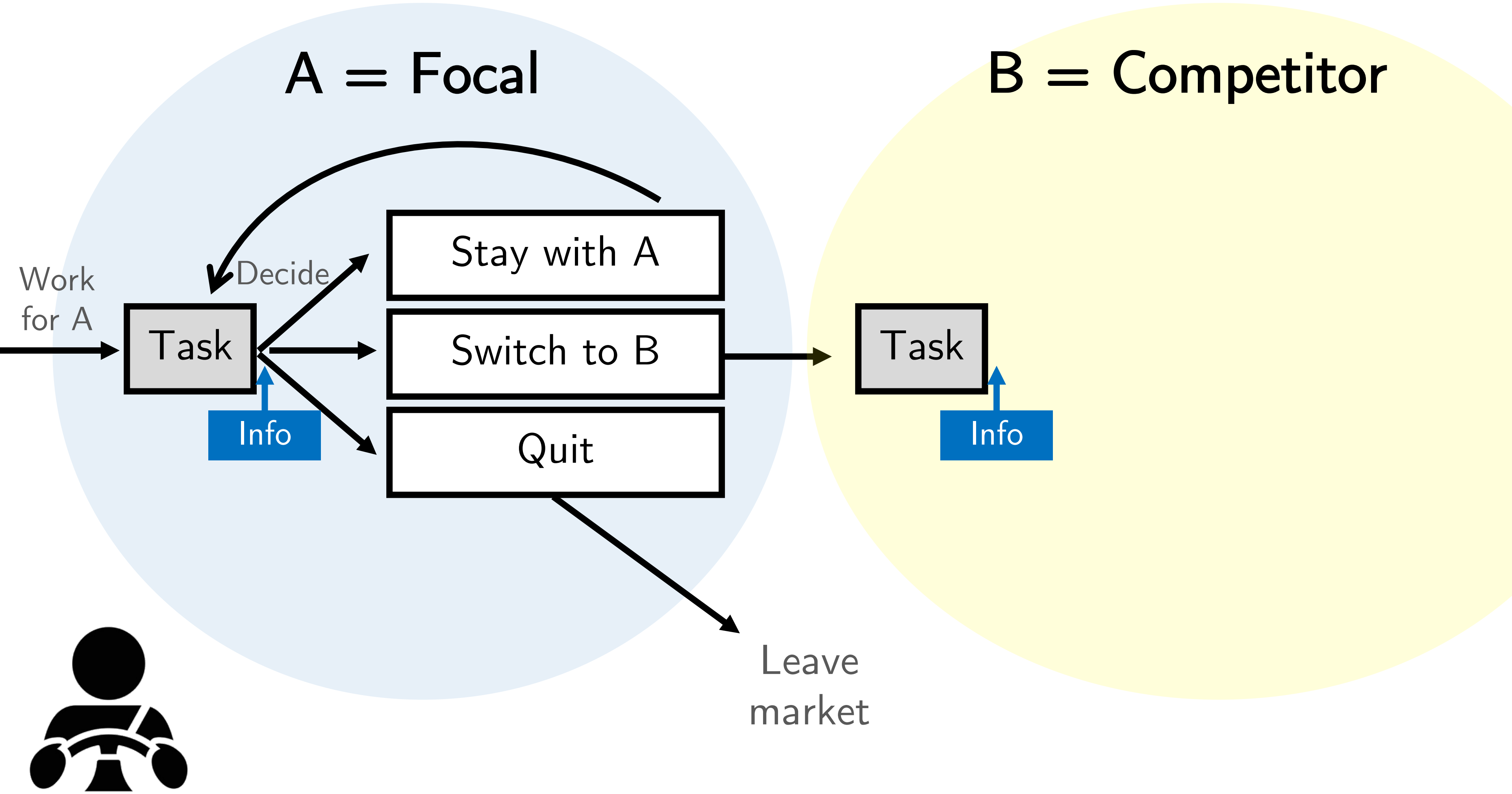
Finite time horizon, every 20 mins



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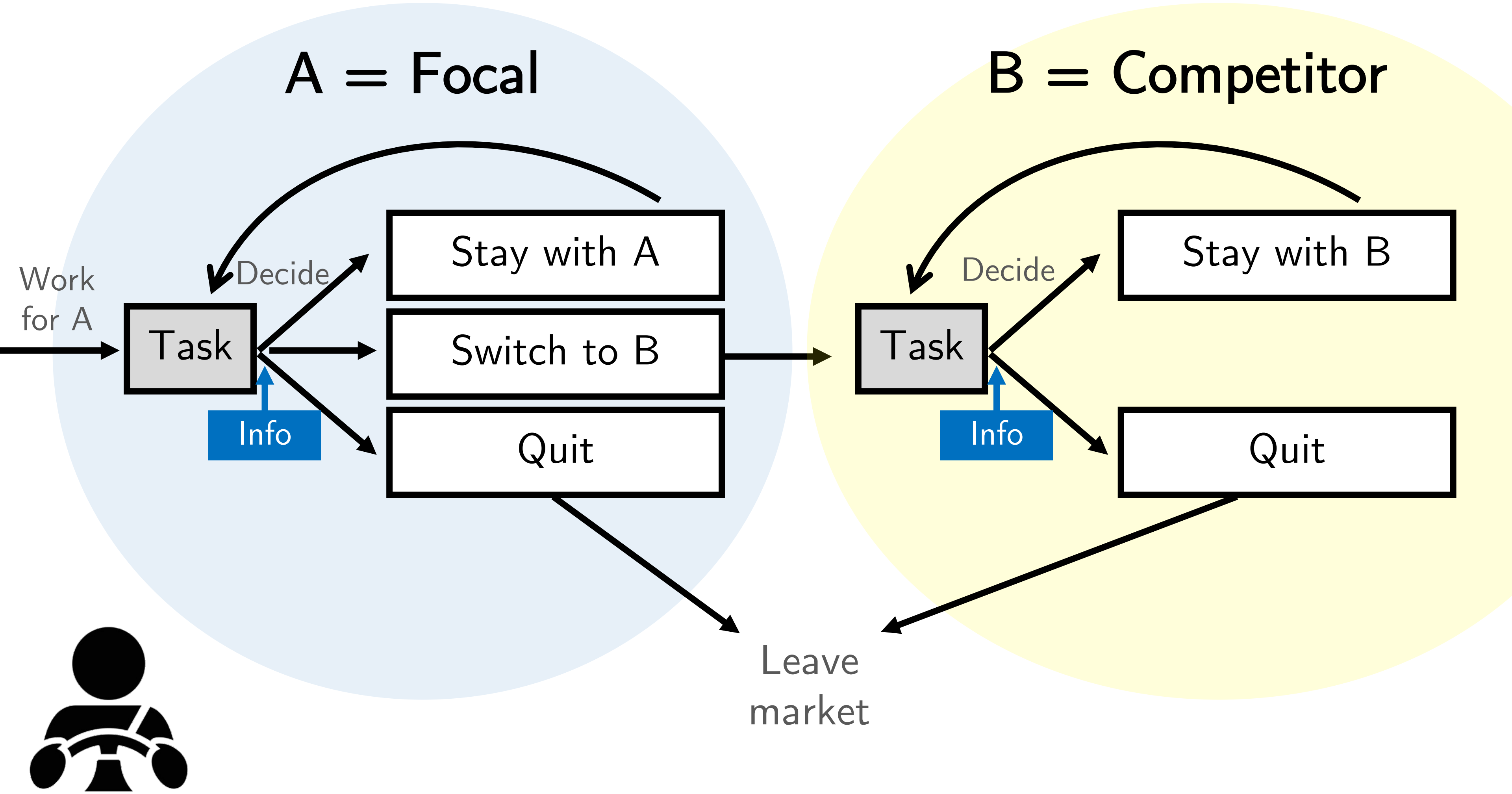
Finite time horizon, every 20 mins



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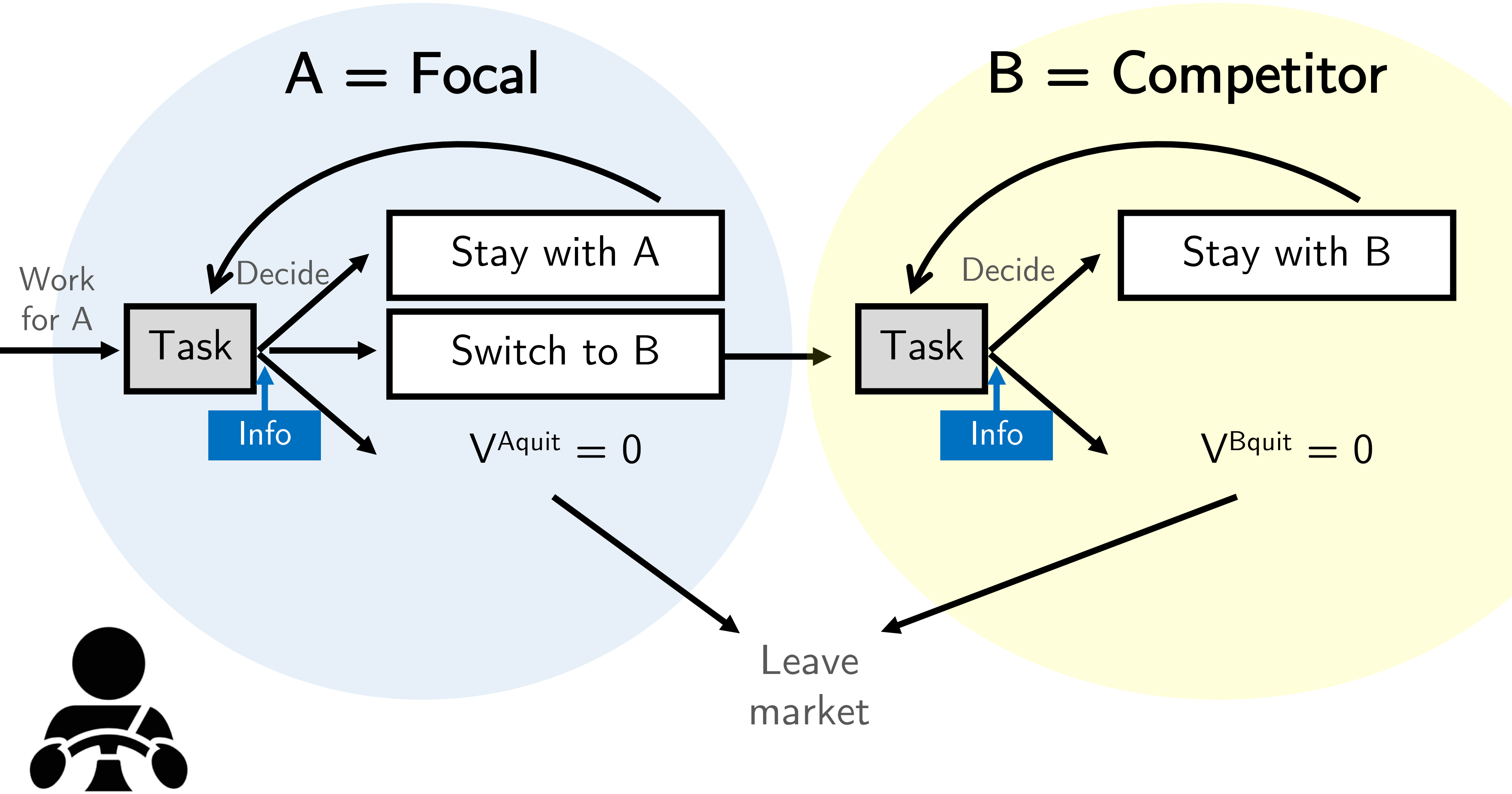
2 firms in the same industry

Finite time horizon, every 20 mins



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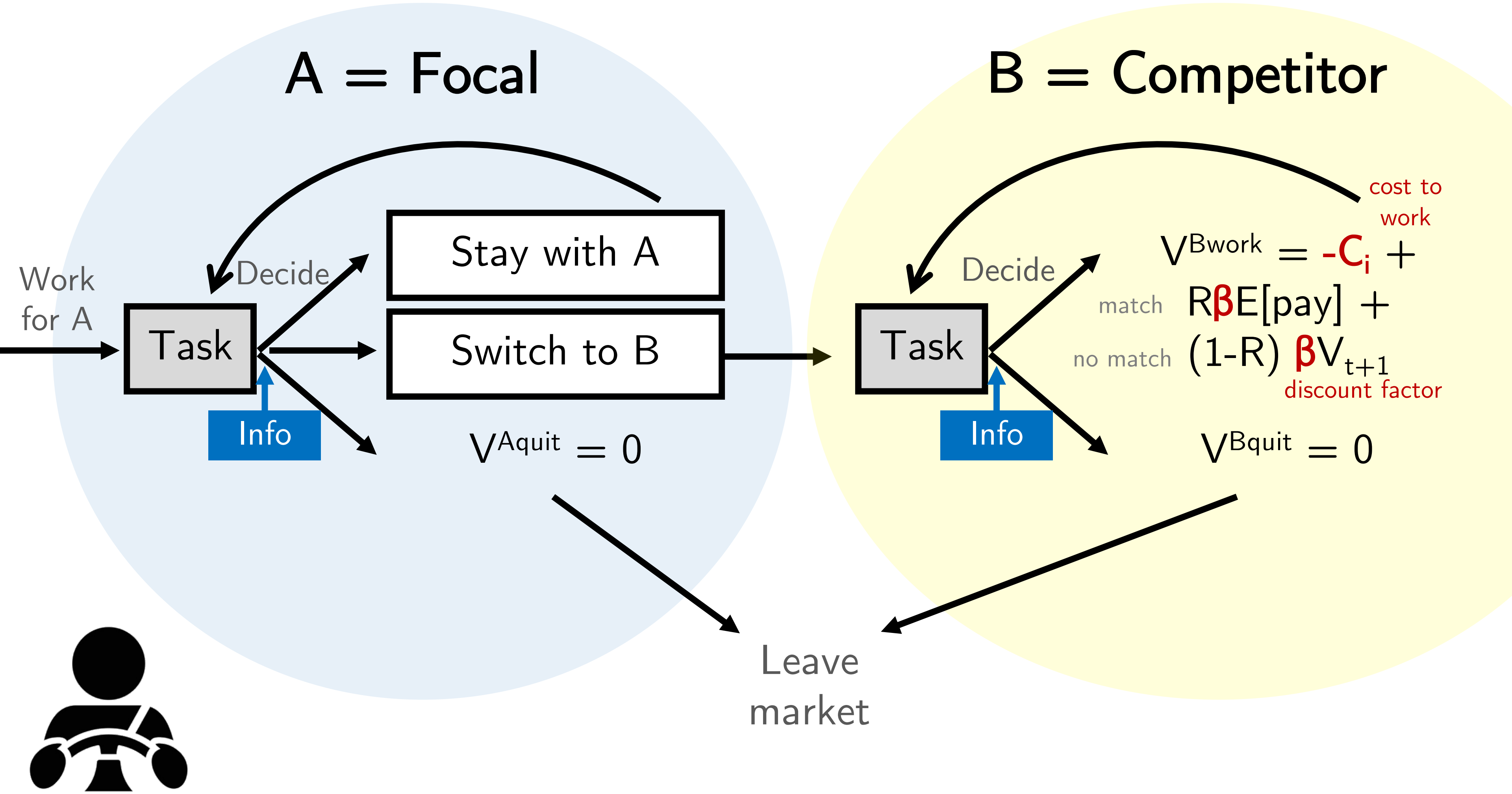
Finite time horizon, every 20 mins



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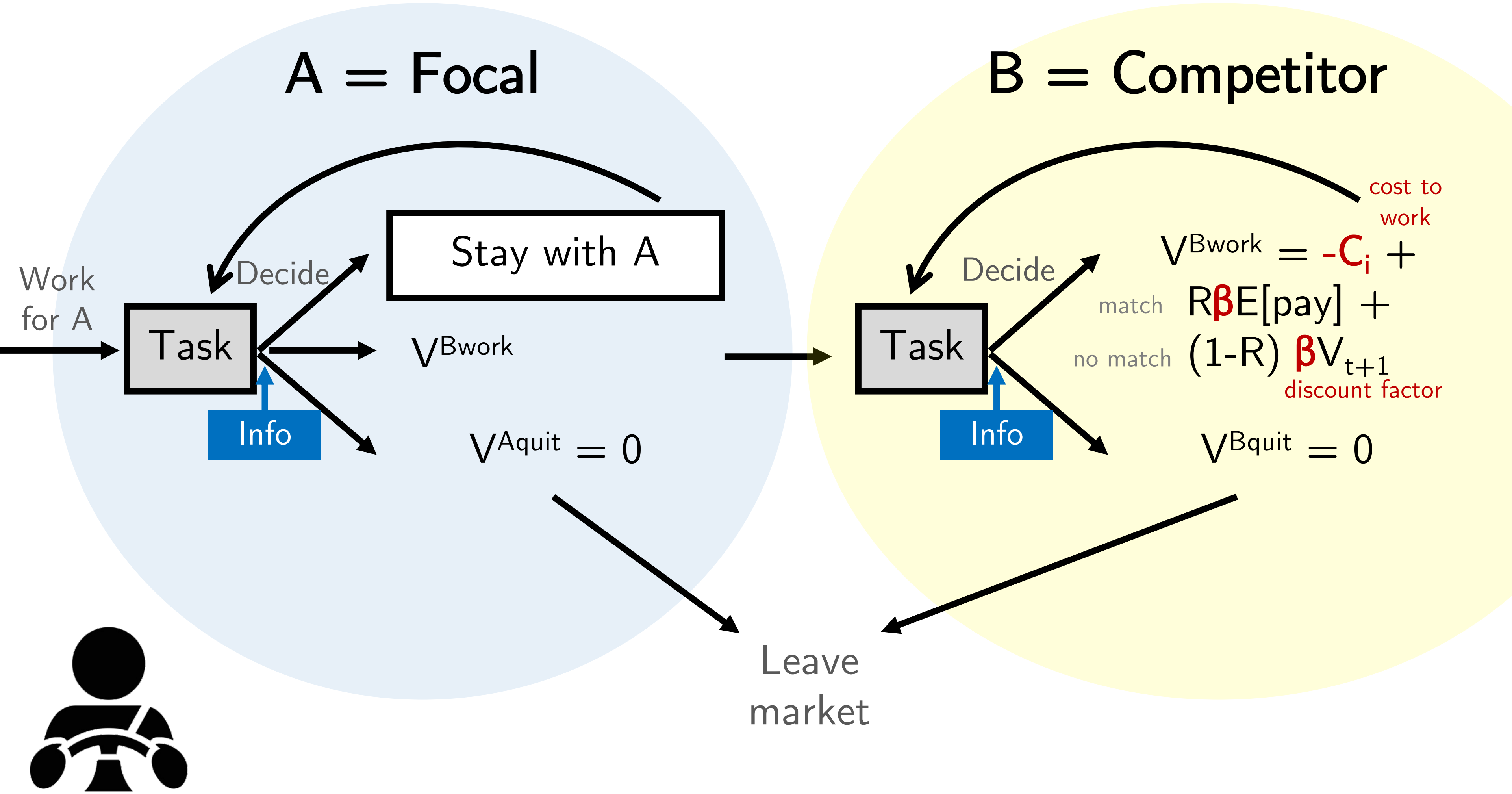
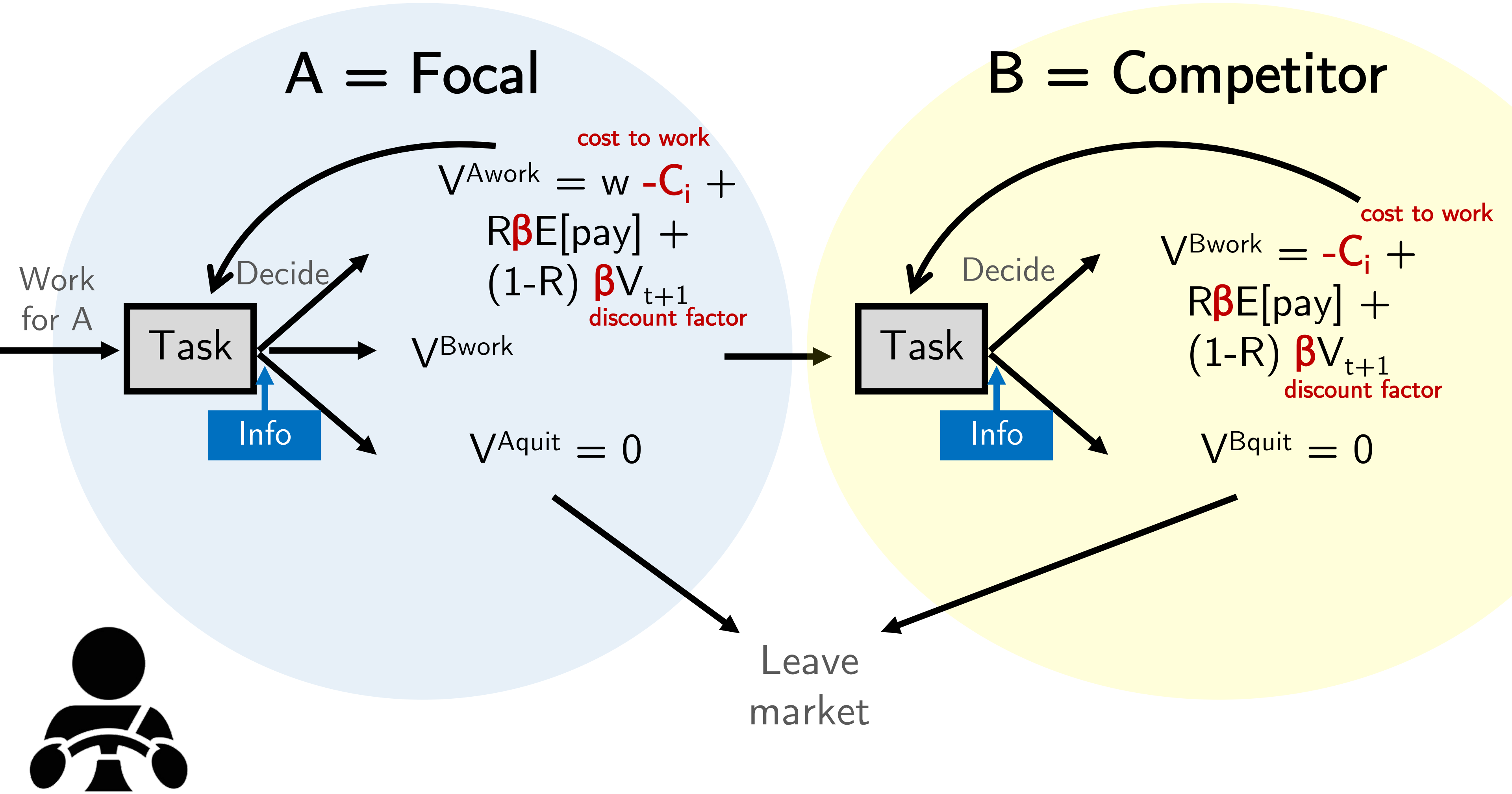


Our Model

2 firms in the same industry
Finite time horizon, every 20 mins



Our Model Drivers' Parameters

homogeneous β discount / forward-looking factor

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heterogeneous c_i cost of working for a unit time interval

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heterogeneous C_i cost of working for a unit time interval

C_1 C_2 C_3 C_4

~ Truncated Normal (μ, σ^2)

Estimation Drivers' Parameters

homogeneous β discount / forward-looking factor

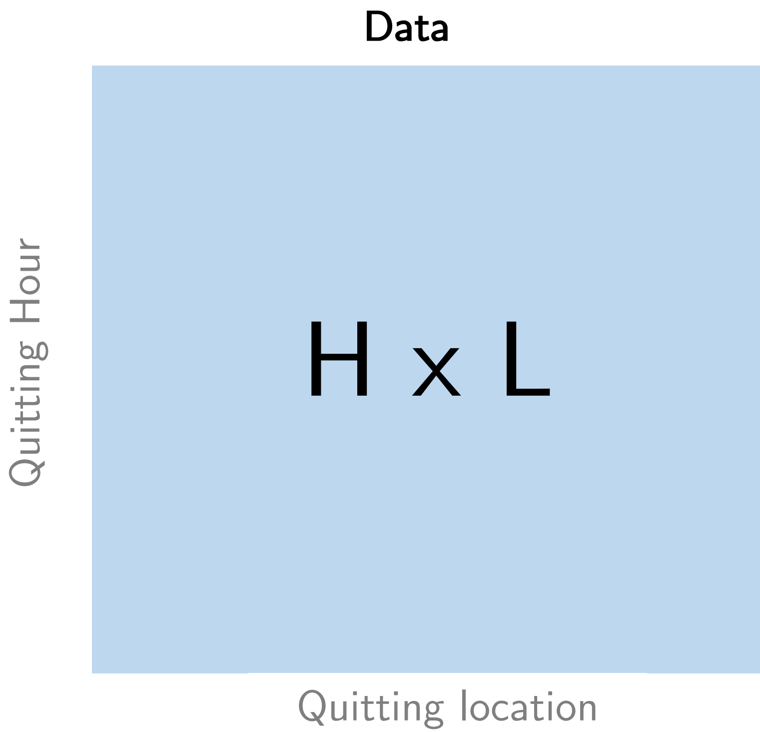
heterogeneous C_i cost of working for a unit time interval

C_1 C_2 C_3 C_4

~ Truncated Normal (μ, σ^2)

Outcome of Interest

For each day, fraction of drivers quitting at (H, L)



Hours: 7am to 11pm

(Remaining left at 11:59pm)

Location: 1 of 20 regions

Bronx, Brooklyn, Newark, Central Park, Chelsea, Downtown, Governors Island, Gramercy, Harlem, LES, LWS, Midtown, Morningside Heights, UES, UWS, Upper Manhattan, JFK, LaGuardia, Queens, Staten Island

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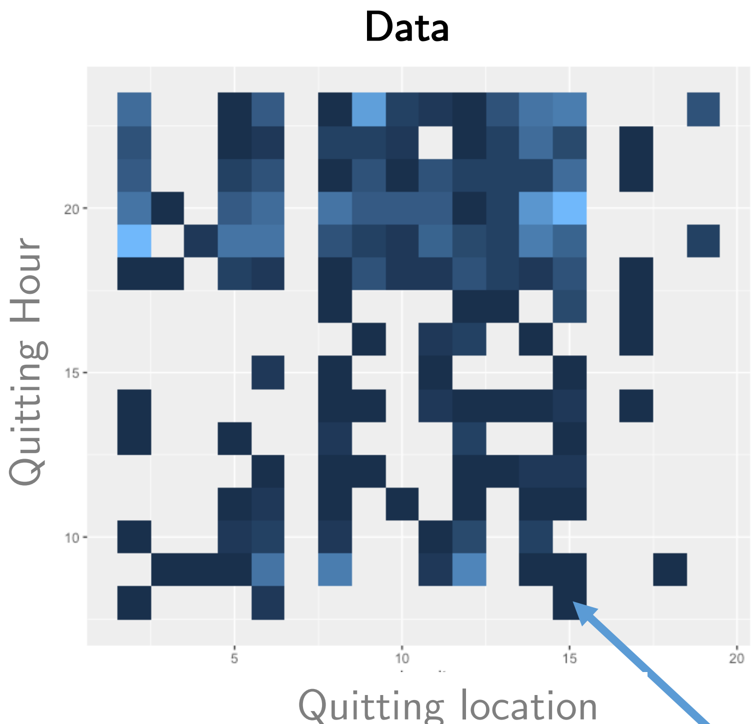

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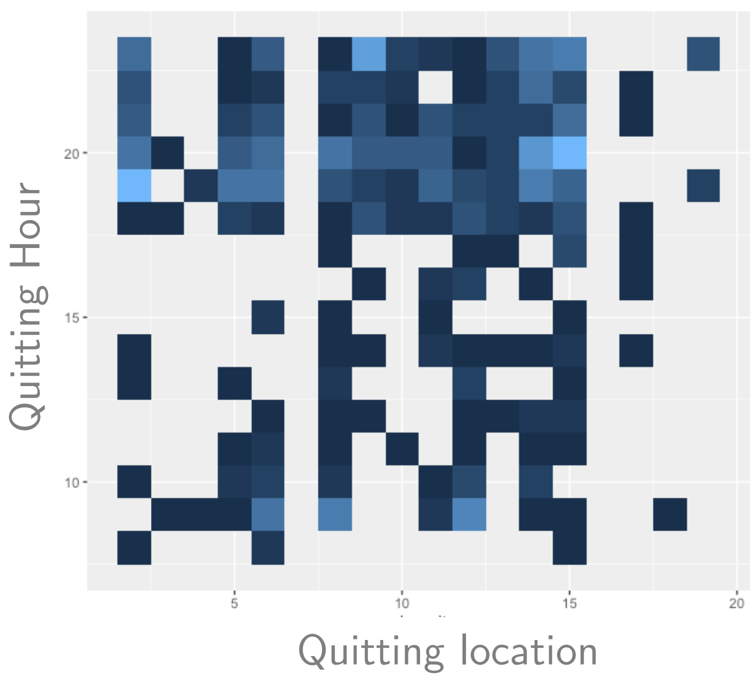
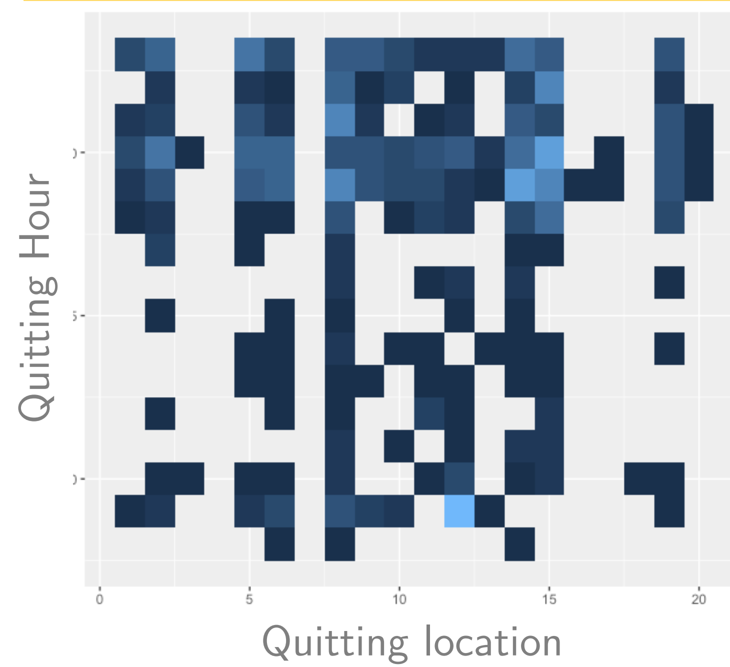
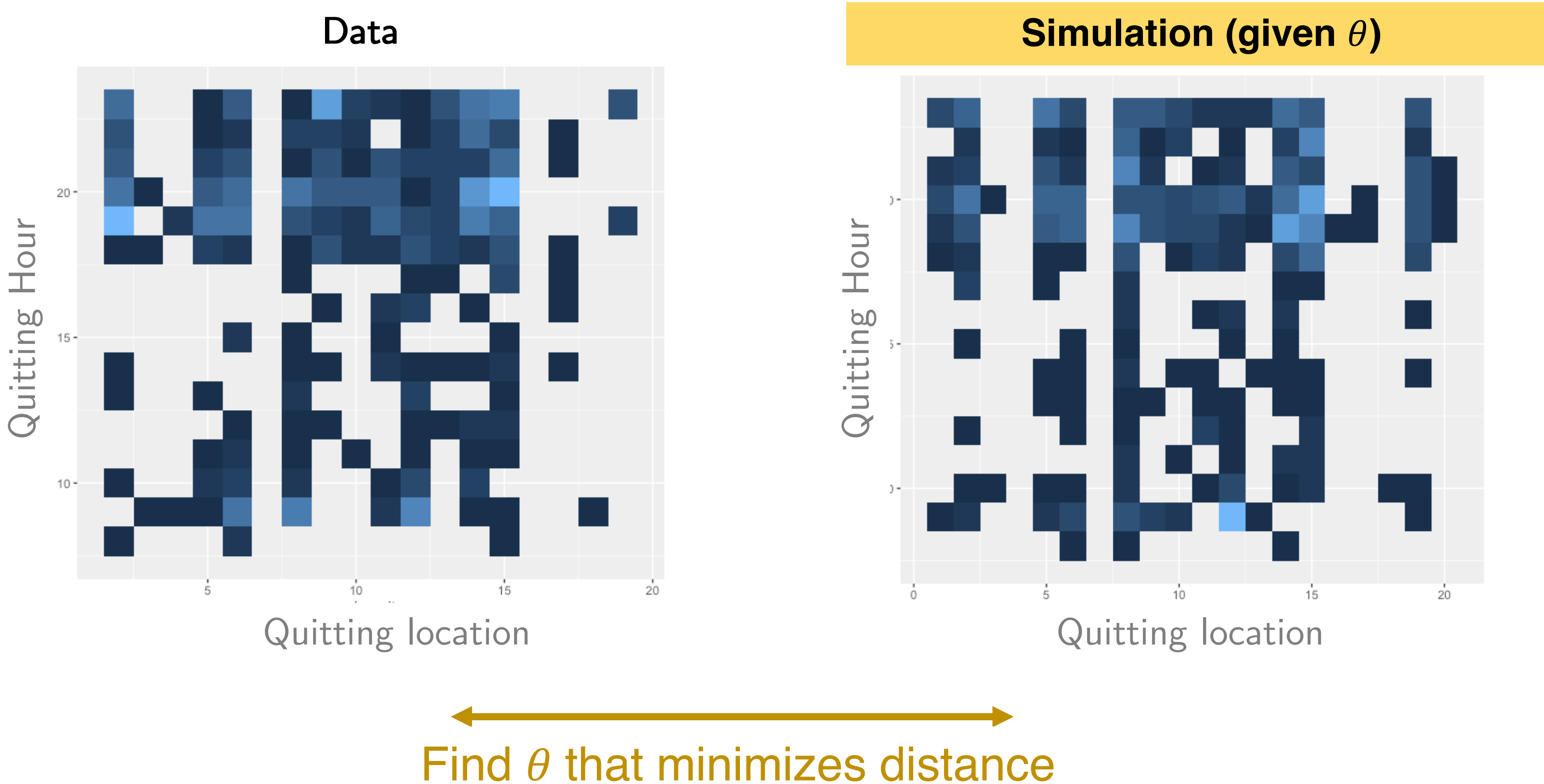
Each cell (H,L) is fraction of drivers quitting at location L and hour H: $f_{L,H}$

Data

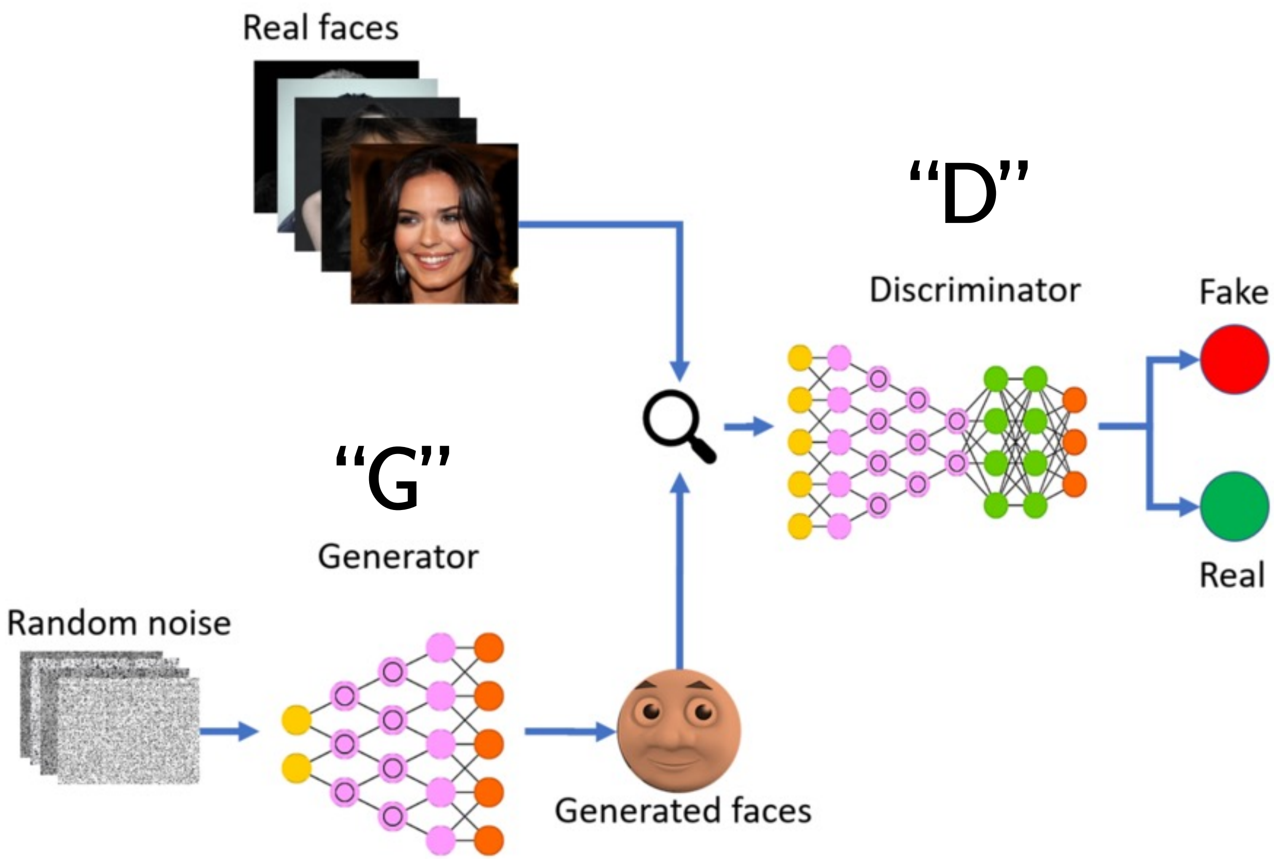


Simulation (given θ)



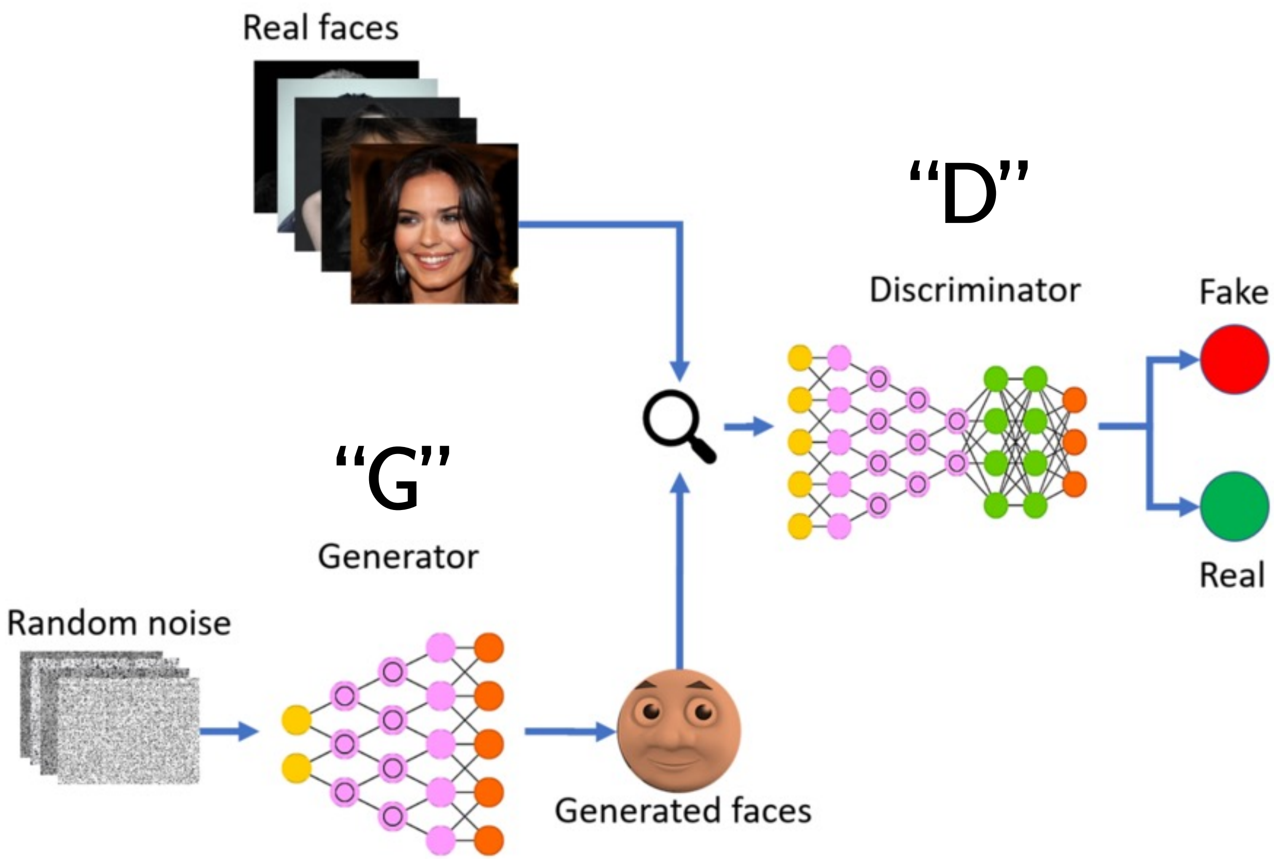

Data
Simulation (given θ)
Quitting Hour
Quitting location
Quitting Hour
Quitting location
Find θ that minimizes distance

Gen. Adversarial Networks



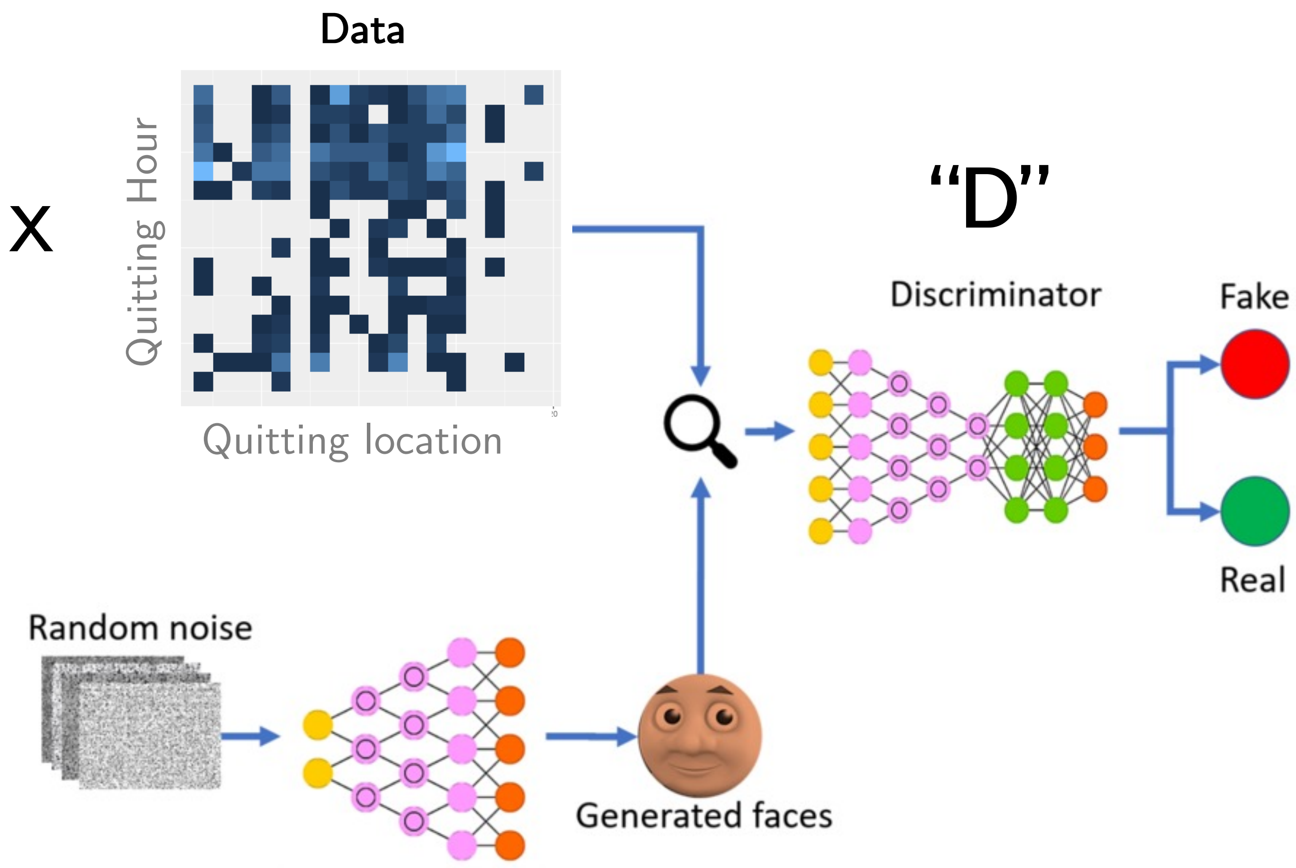
$$\min_{\{generator\}} \max_{\{discriminator\}} \textit{classification accuracy}.$$

Adversarial Estimation

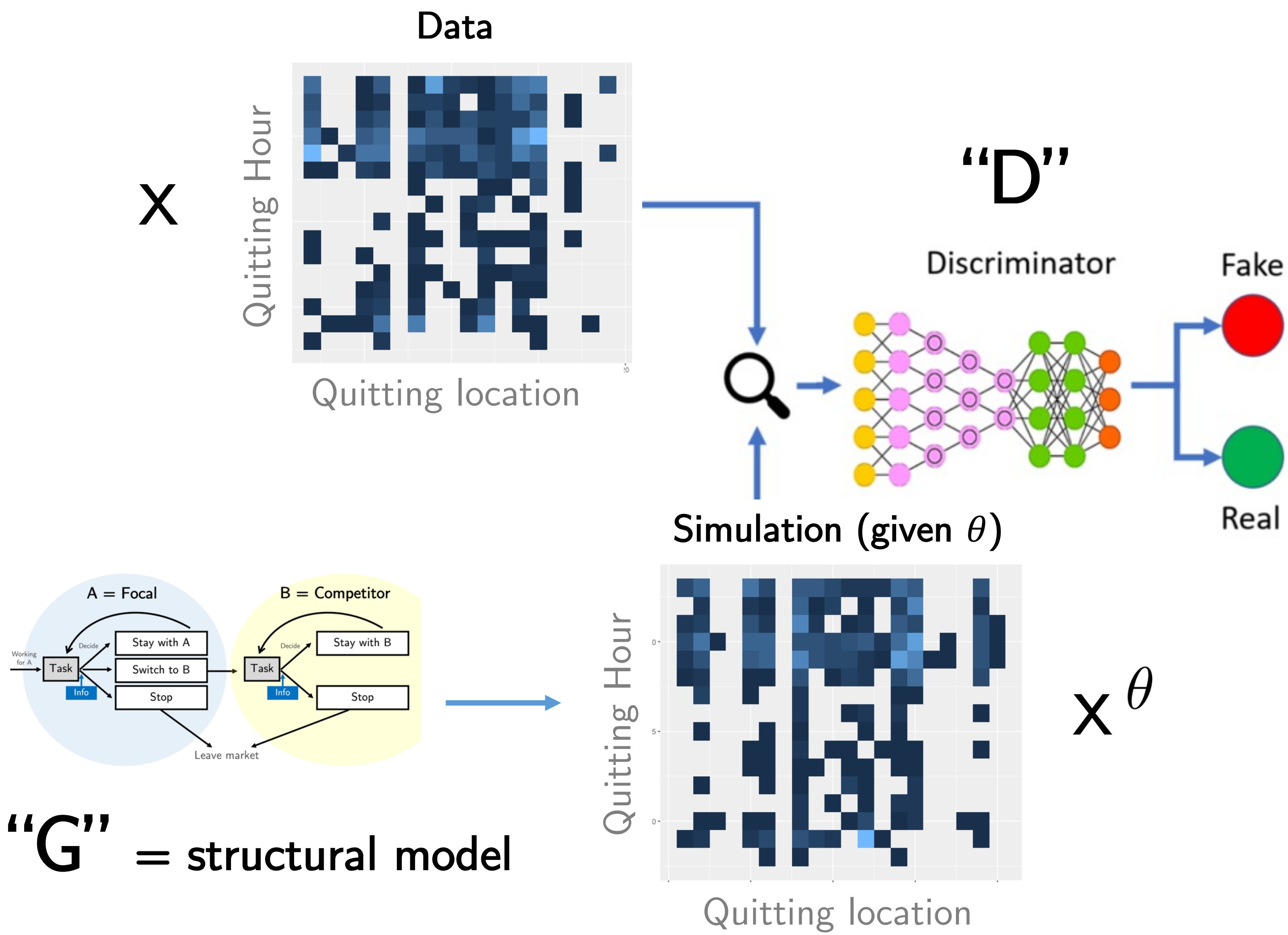


Kaji, Manresa & Pouliot (2020)

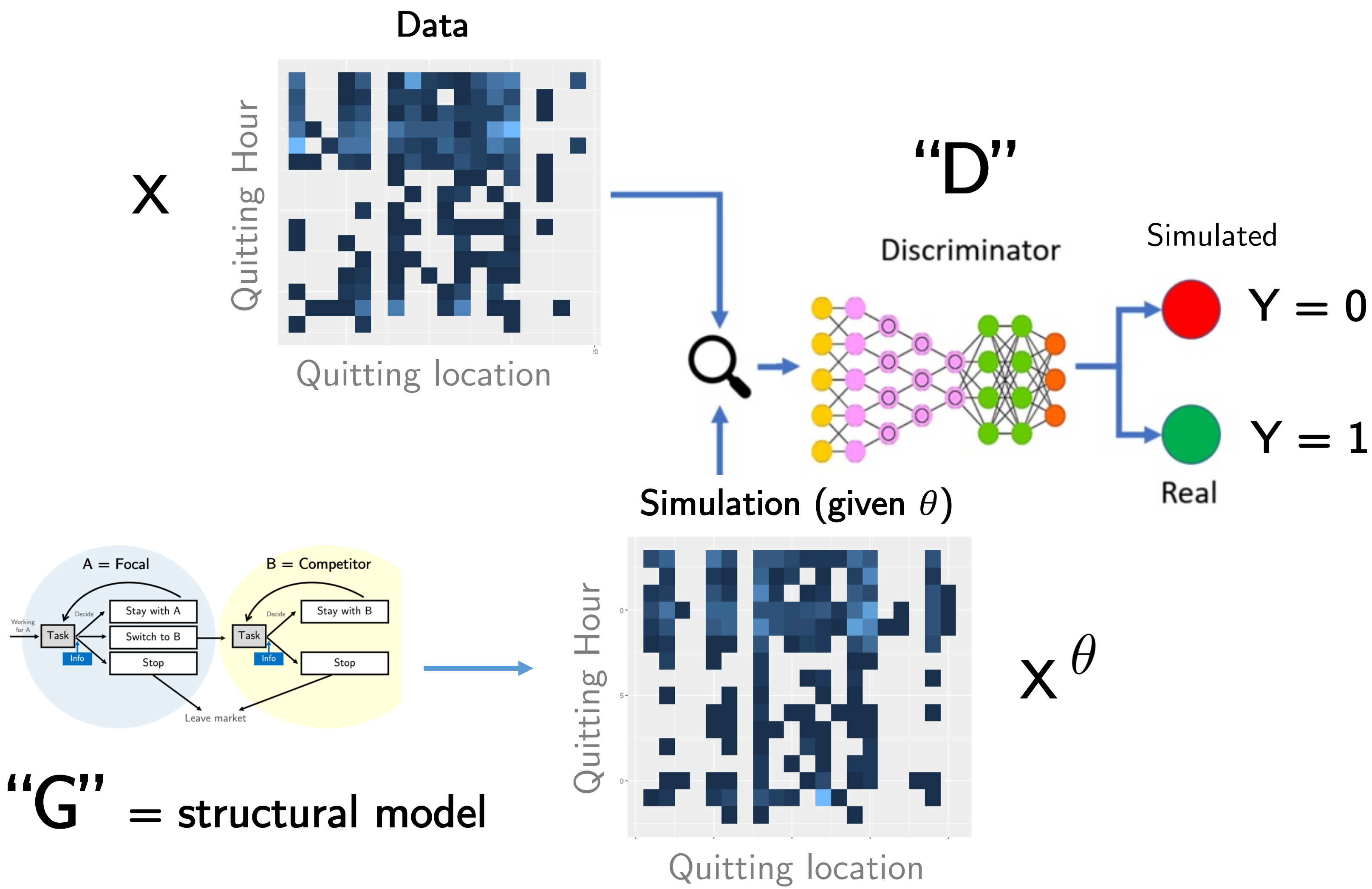
Adversarial Estimation



Adversarial Estimation

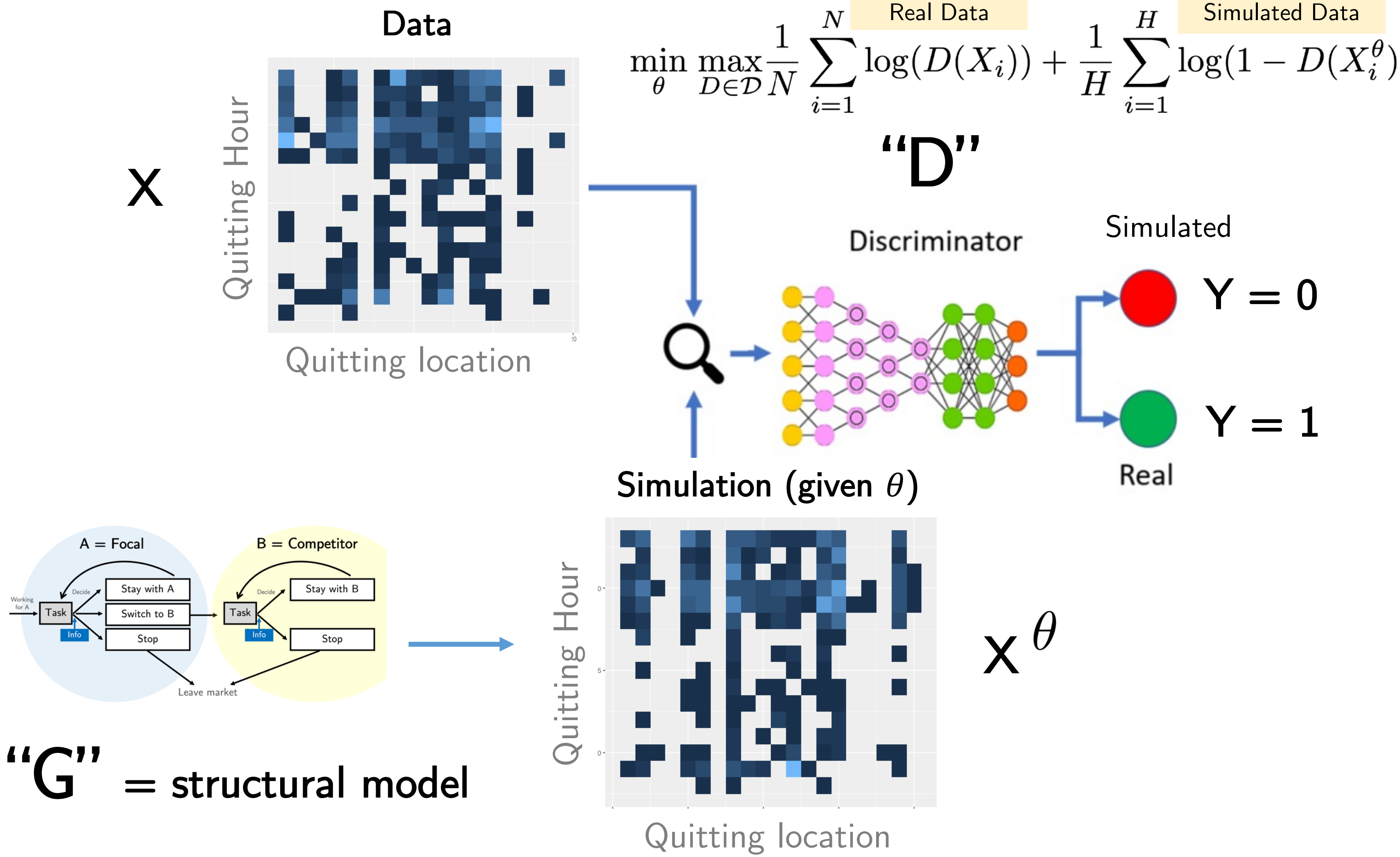


Adversarial Estimation



Adversarial Estimation

$$\min_{\theta} \max_{D \in \mathcal{D}} \underbrace{\frac{1}{N}\sum_{i=1}^{N} \log(D(X_i))}_{\text{Real Data}} + \underbrace{\frac{1}{H}\sum_{i=1}^{H} \log(1 - D(X_i^{\theta}))}_{\text{Simulated Data}}$$



Estimation Results

Discount factor	Population distribution of cost	
$\beta = 0.94985$	$\mu = 0.55358$	$\sigma = 0.664725$
(0.00187)	(0.01145)	(0.01197)

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$1 in 2 hours
→ 73 cents now

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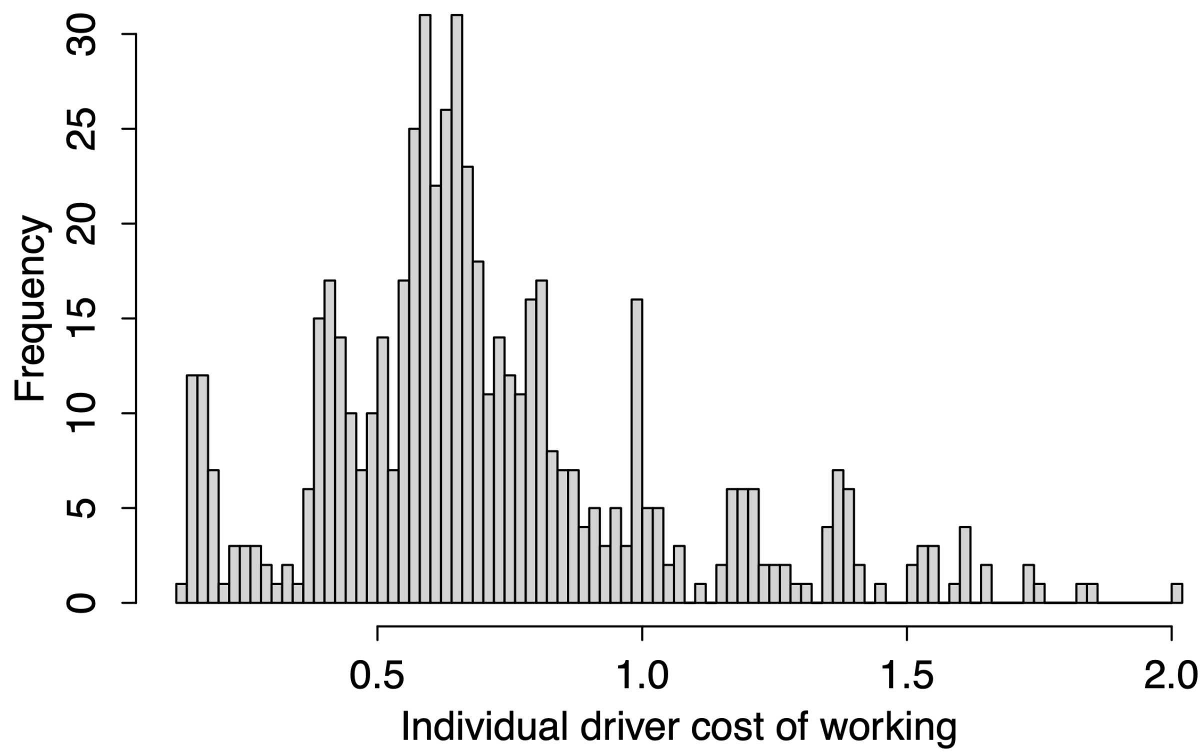

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Data	Simulated
Mean daily duration: 6.3 hours (median = 5.5)	Mean daily duration: 6.3 hours (median = 5.3)

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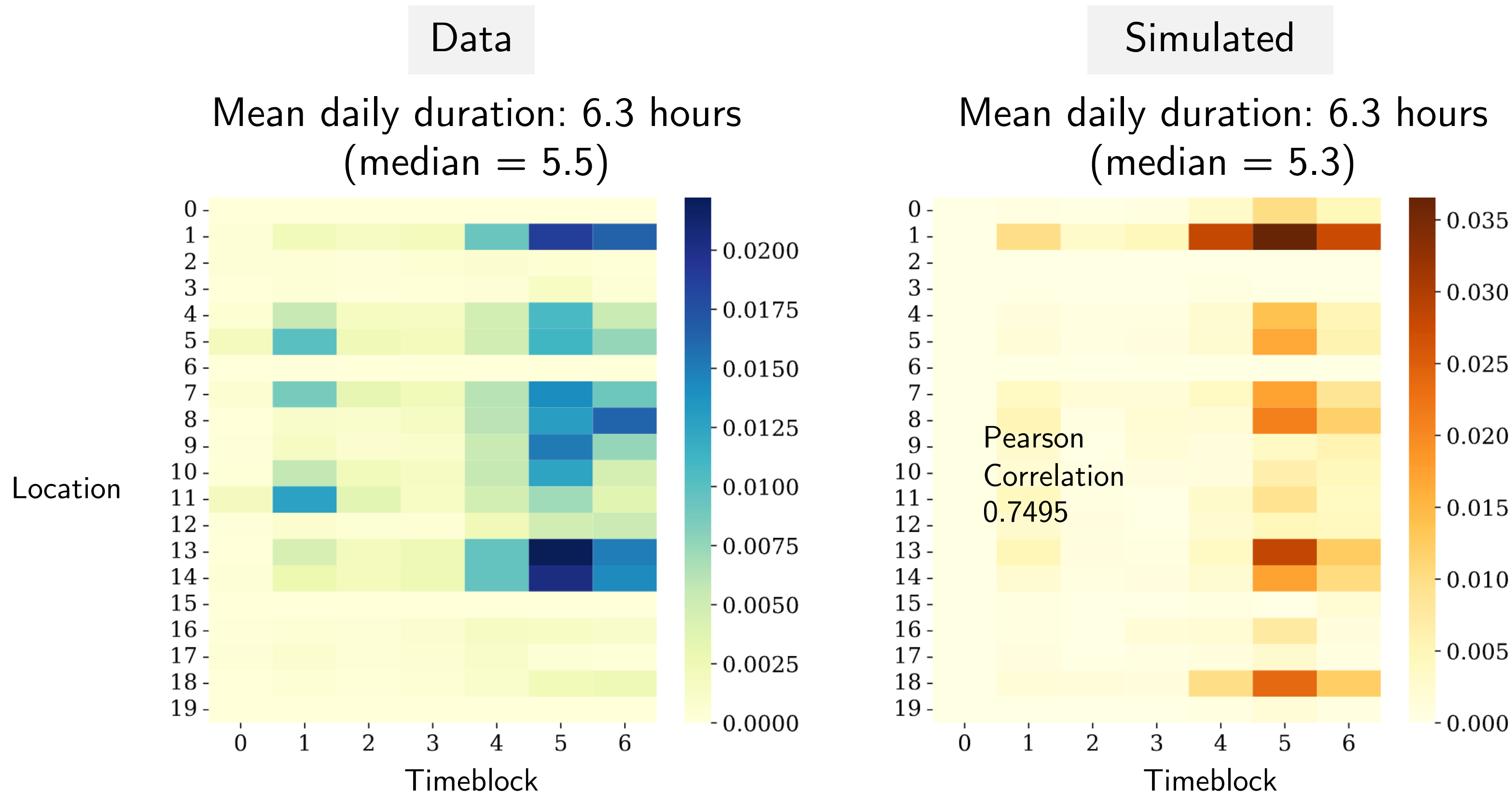

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66.59% most days

Fraction of workdays multihoming

Estimation Results

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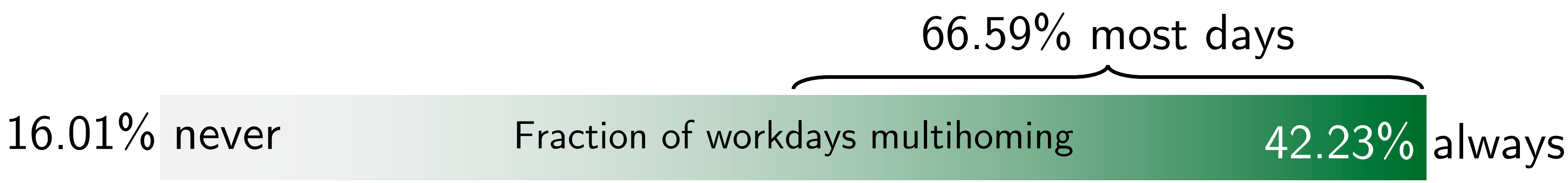

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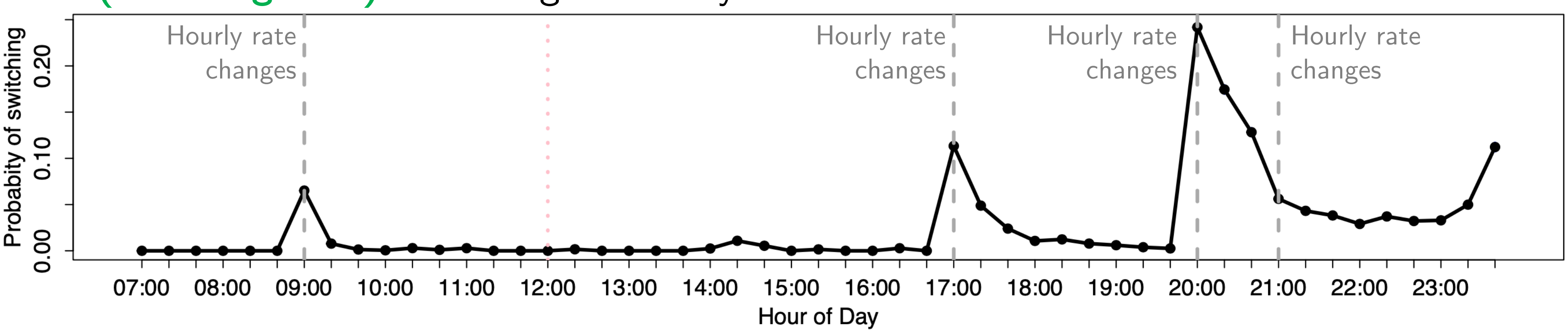
66.59% most days

16.01% never — Fraction of workdays multihoming — 42.23% always

P(switching to B) on average weekday



"Drivers strongly prioritize short-term earnings with
significant reaction to differences in short-run earnings across platforms."

How to Control Multihoming?

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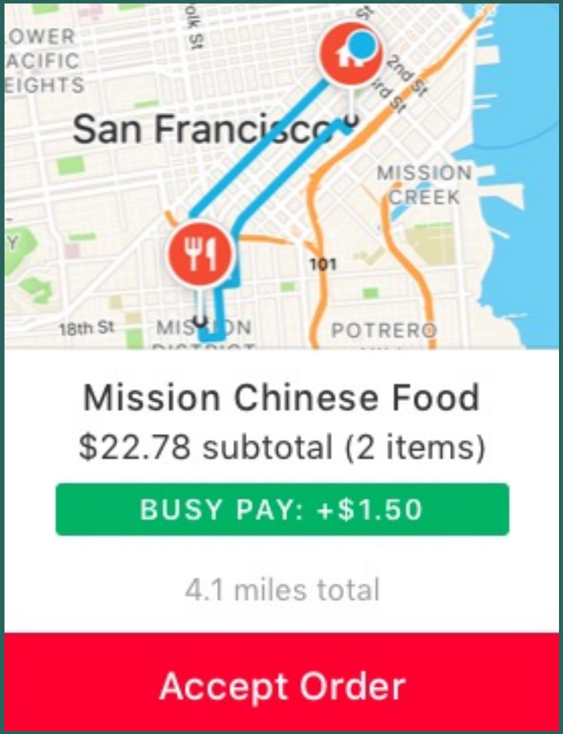
How to Control Multihoming?

dynamic pay per work?



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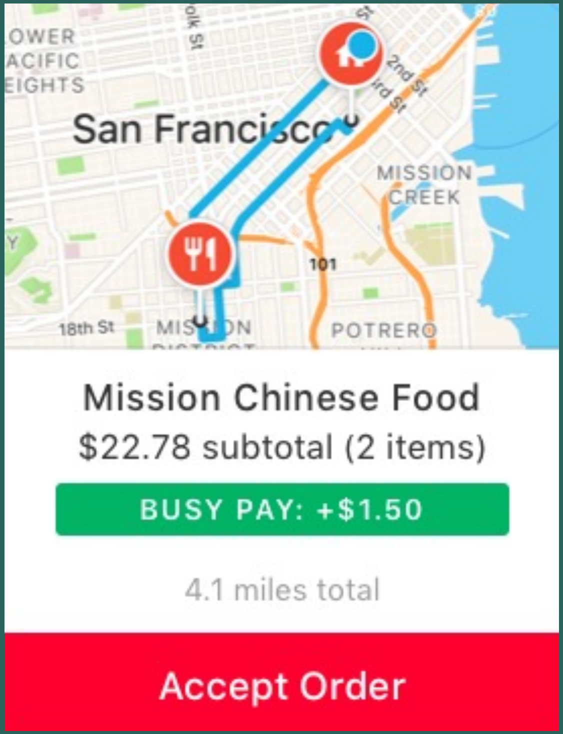
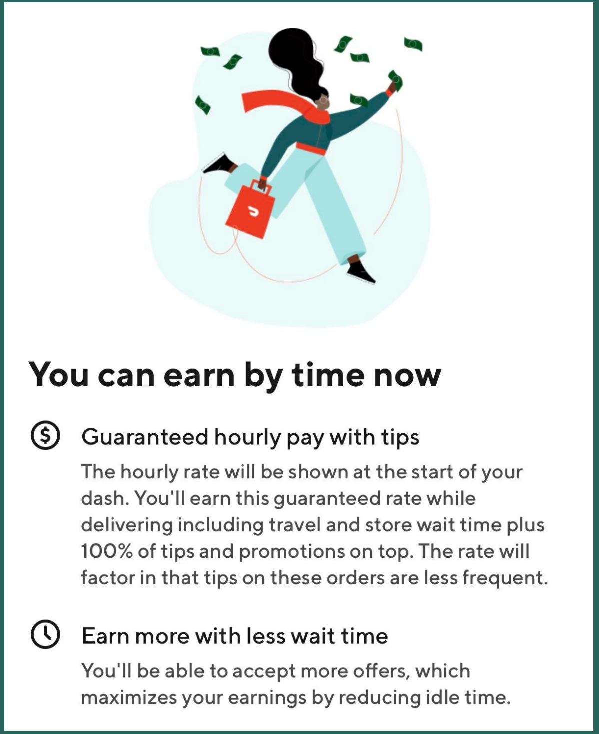


dynamic guaranteed pay?



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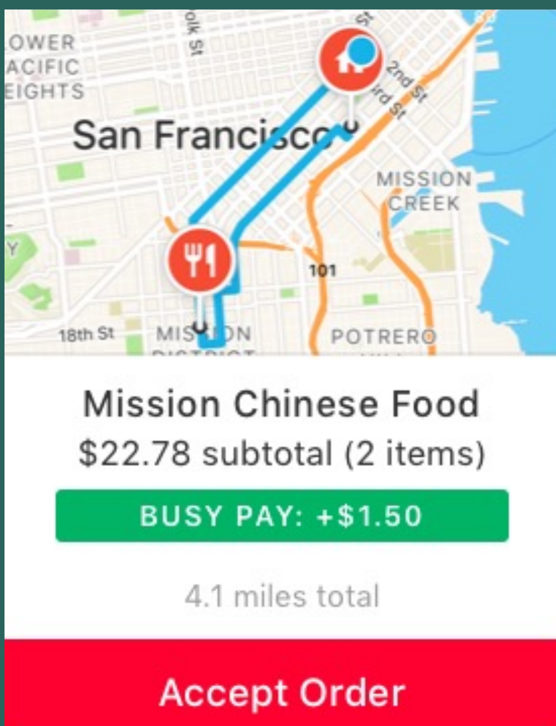
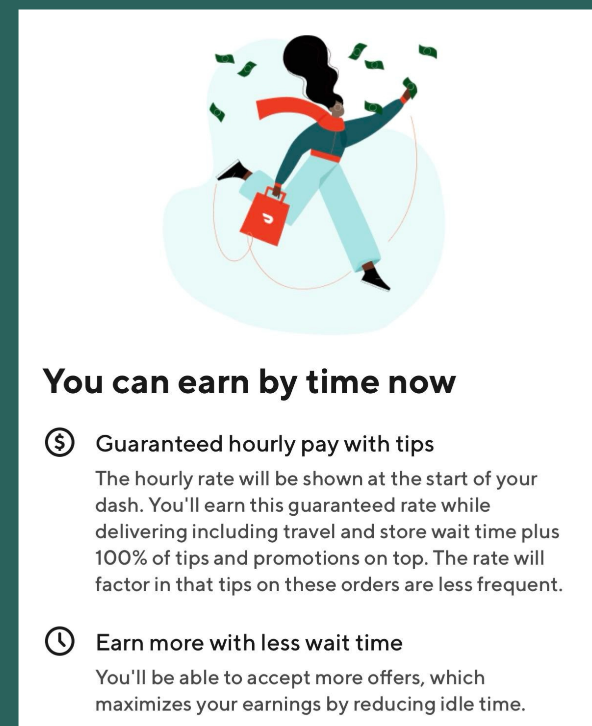


Counterfactual #1

which pay is better?
(long-term capacity)

dynamic guaranteed pay?



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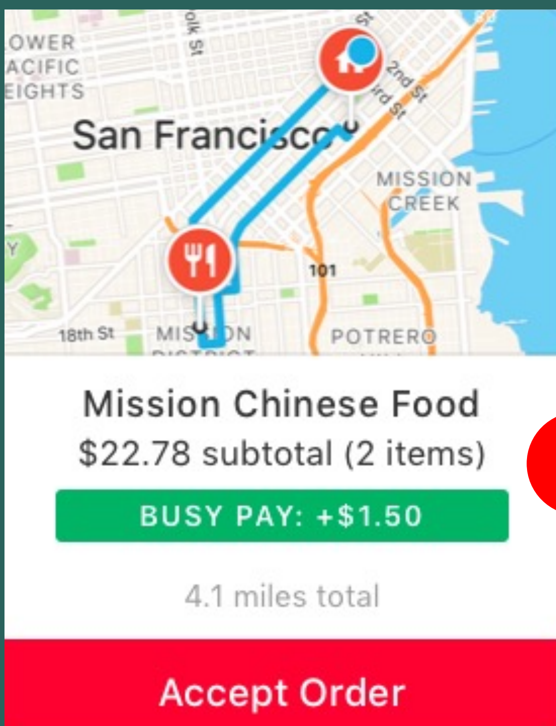
How to Control Multihoming?

dynamic pay per work?

dynamic guaranteed pay?

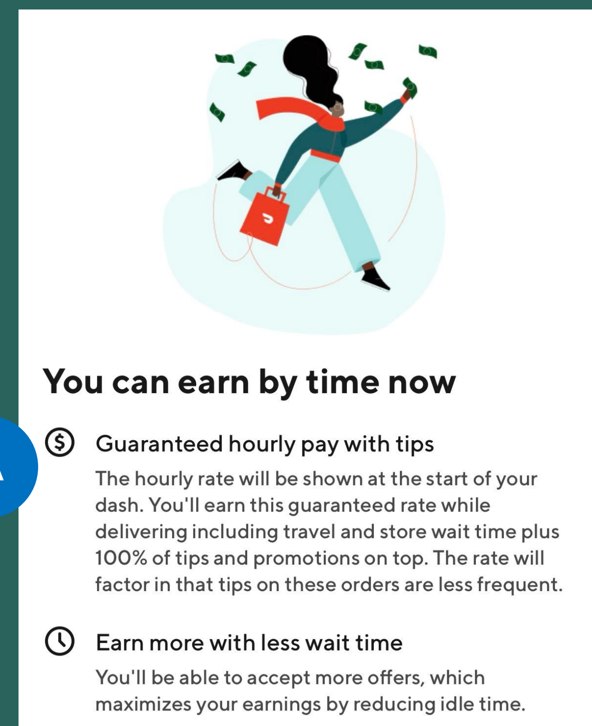


Counterfactual #1

which pay is better?
(long-term capacity)

B ← A

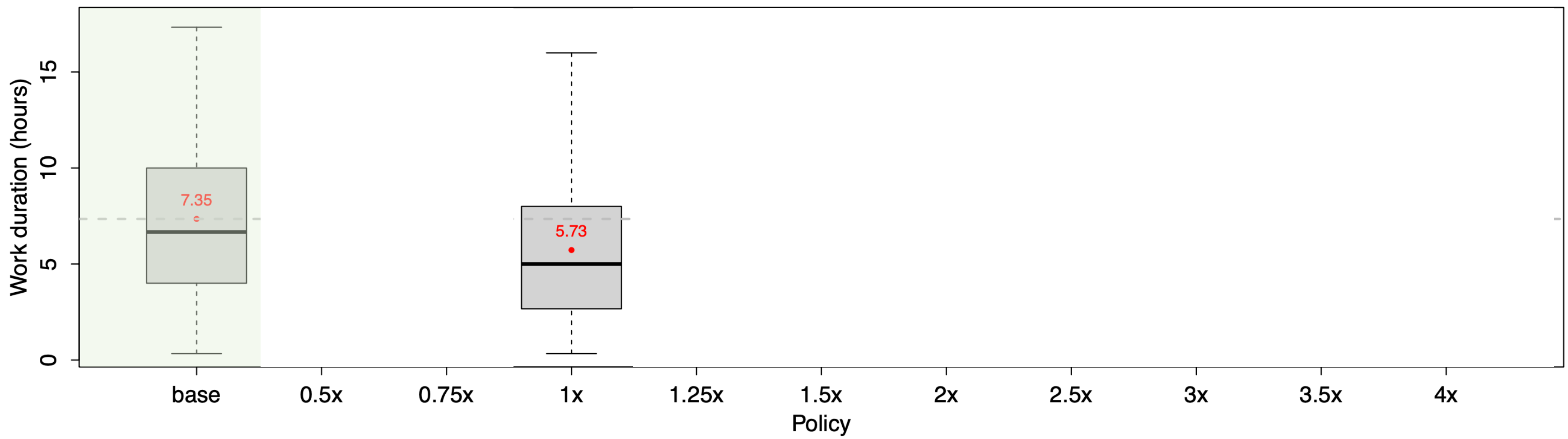
what happens when the focal firm switches to pay per work?



Counterfactual #1 Pay Scheme

Guaranteed Pay

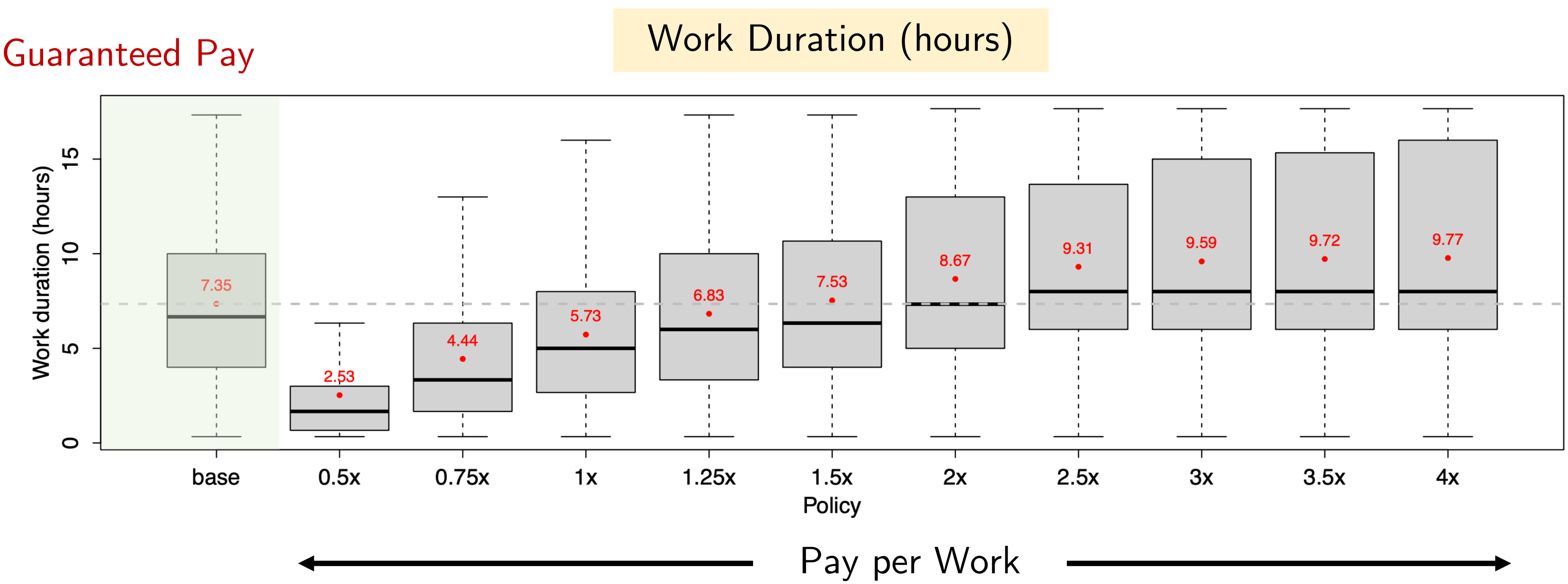
Work Duration (hours)



Pay per Work

Switching from guaranteed pay → pay per work of equivalent rate = reduces work duration

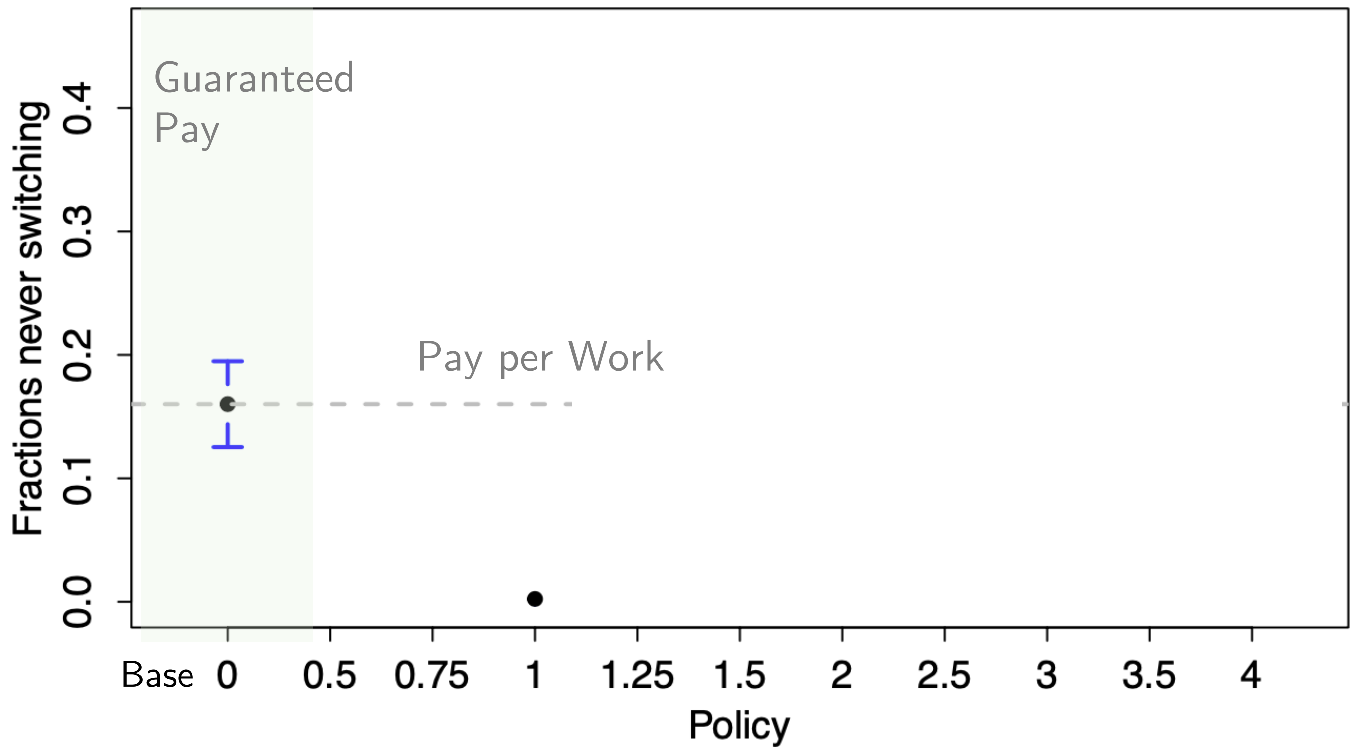
Counterfactual #1 Pay Scheme



Switching from guaranteed pay → pay per work,
need 1.25-1.5x rate to match prior work duration

Counterfactual #1 Pay Scheme

Fraction of workers who never switched



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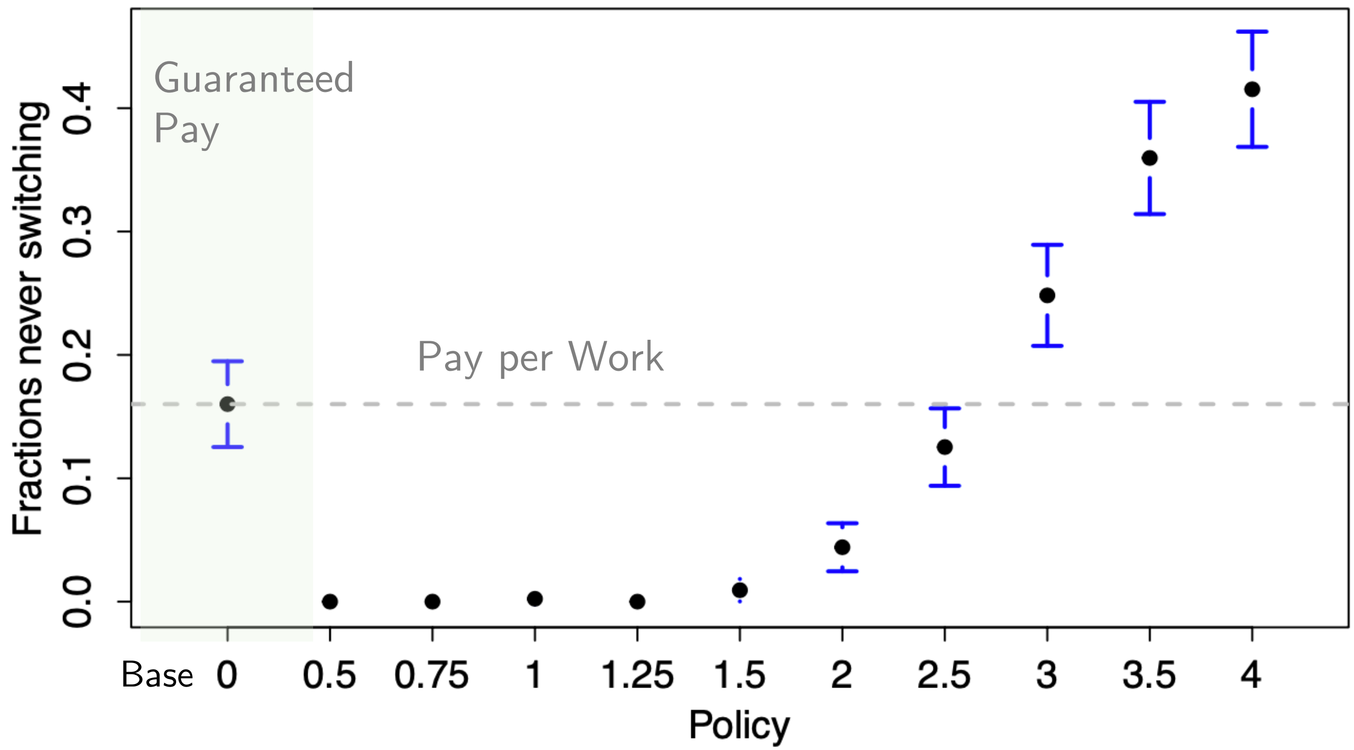


Need 2.5-3x rate to
keep the most dedicated workers

“Pay is not the only lever that platforms currently use to influence worker behavior”

How to Control Multihoming?

"Pay is not the only lever that platforms currently use to influence worker behavior"

How to Control Multihoming?

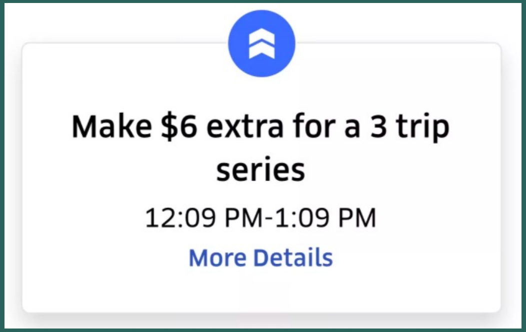
Counterfactual #2

impact of incentives
to stay longer?
(short-term capacity)

"Pay is not the only lever that platforms currently use to influence worker behavior"

How to Control Multihoming?

Streak Bonus



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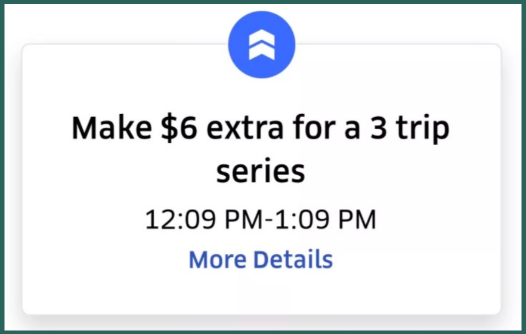
How to Control Multihoming?

Time Delay

Streak Bonus



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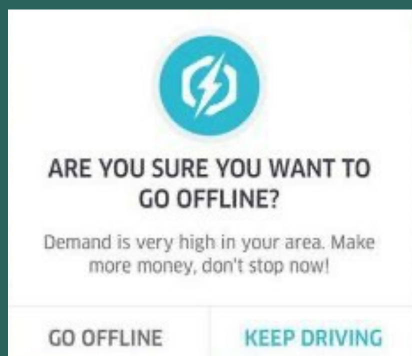
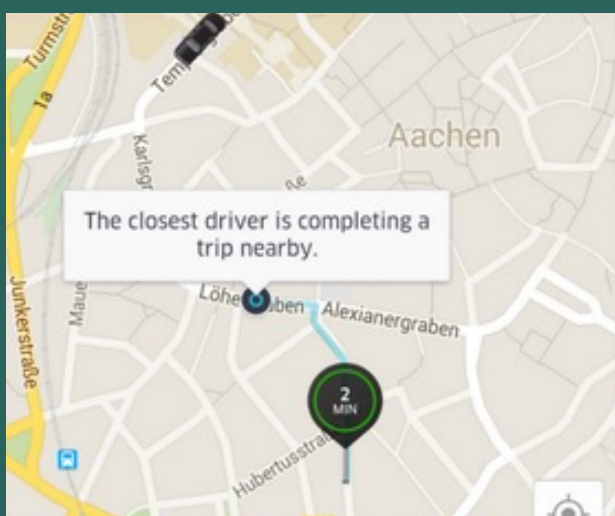
Time Delay





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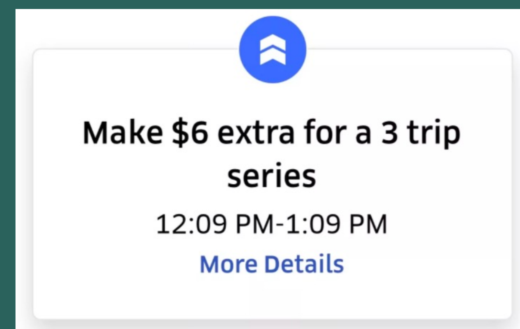


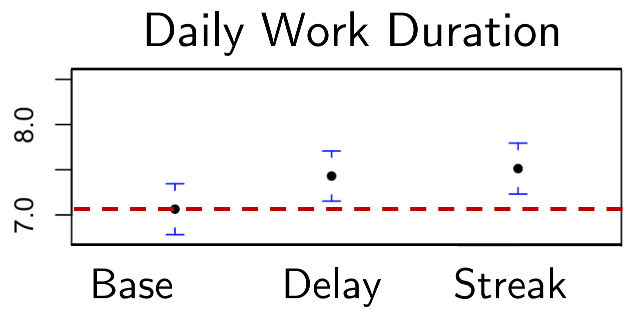
Counterfactual #2

impact of incentives to stay longer?

(short-term capacity)

Counterfactual #2 Short-Term

Time Delay



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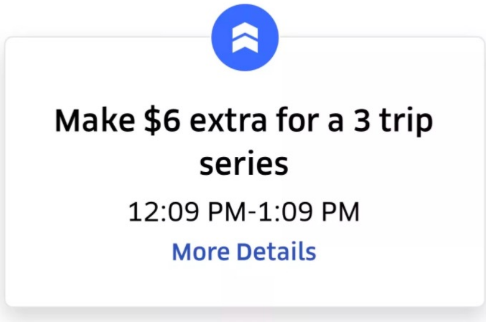
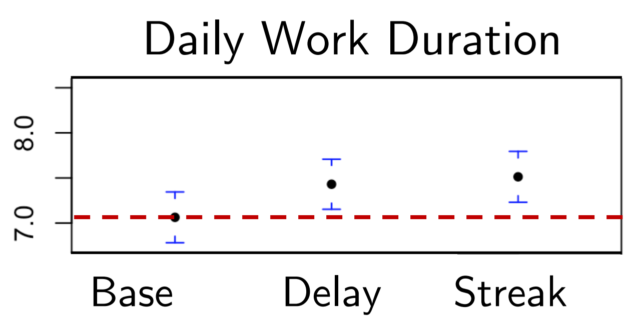


Counterfactual #2 Short-Term

Time Delay



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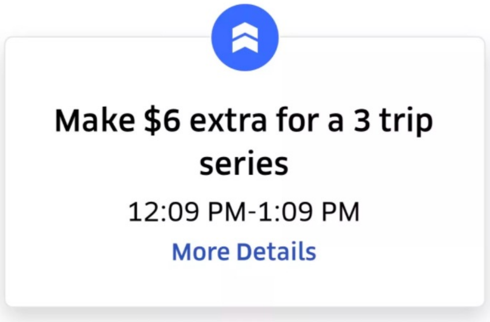
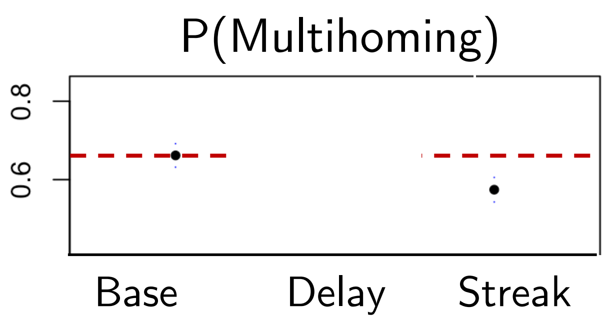
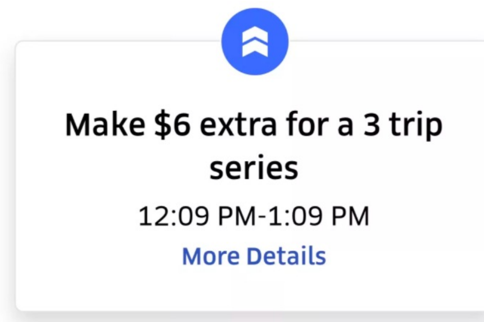




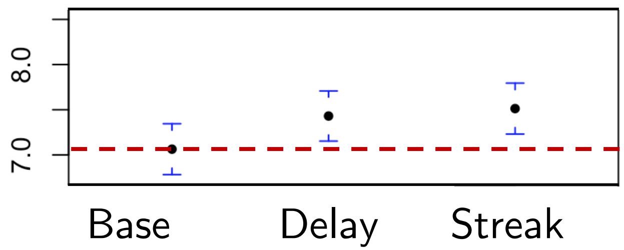
Counterfactual #2 Short-Term

Time Delay

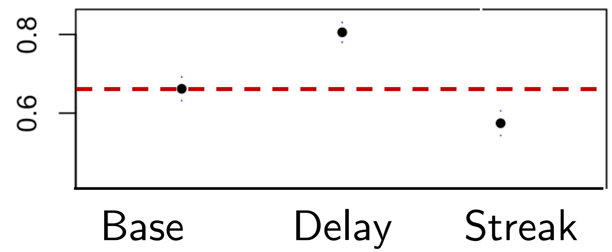
Streak Bonus



Daily Work Duration



P(Multihoming)

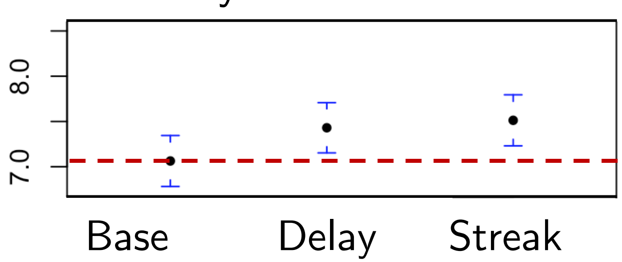


Counterfactual #2

Short-Term

Time Delay

Daily Work Duration



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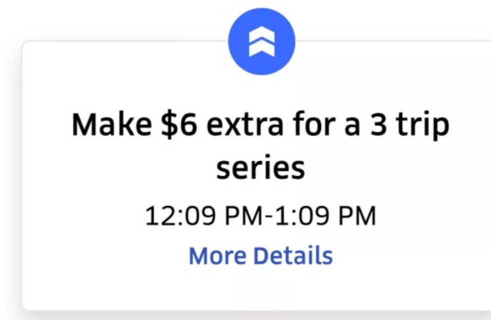

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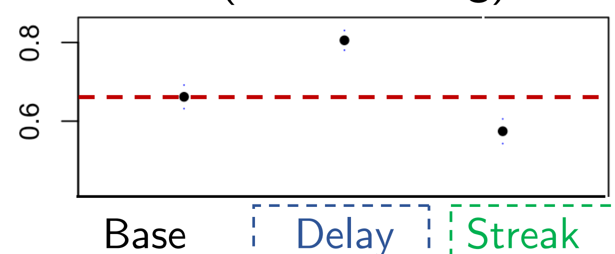

Good for low demand

Good for peak hours

POLITICS

New York City passes nation's first minimum pay rate for Uber and Lyft drivers

The new rule will likely give drivers an extra $5 an hour.

Vox

by **Alexia Fernández Campbell**

Dec 5, 2018, 11:10 AM PST

For 2019, only applied to
pay-per-work platforms

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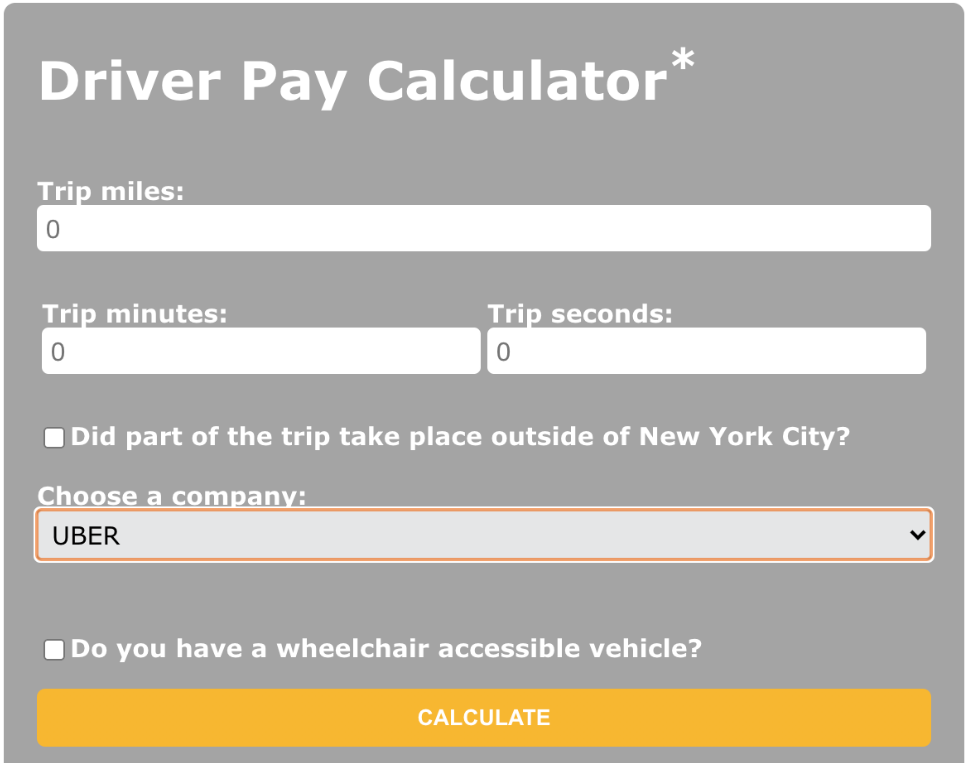

Counterfactual #3 Policy Analysis

POLITICS

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The new rule will likely give dr

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Dec 5, 2018, 11:10 AM PST

Driver Pay Calculator*

Trip miles:
0

Trip minutes:
0

Trip seconds:
0

Did part of the trip take place outside of New York City?

Choose a company:
UBER

Do you have a wheelchair accessible vehicle?

CALCULATE

Counterfactual #3 Policy Analysis

POLITICS

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Counterfactual #3 Policy Analysis

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Dec 5, 2018, 11:10 AM PST

Drivers: *"Not really. Too many drivers. Too much idle time."*

Fares not necessarily higher (3-5%)
(Parrott, Reich 2018)

Field Experiments (in progress)

Collaboration with LINE MAN, Thailand's leading food delivery platform (also runs restaurants' POS system)

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- Switchback experiments in July-August 2025
- 30 cities, each with one incentive type per week

Field Experiments (in progress)

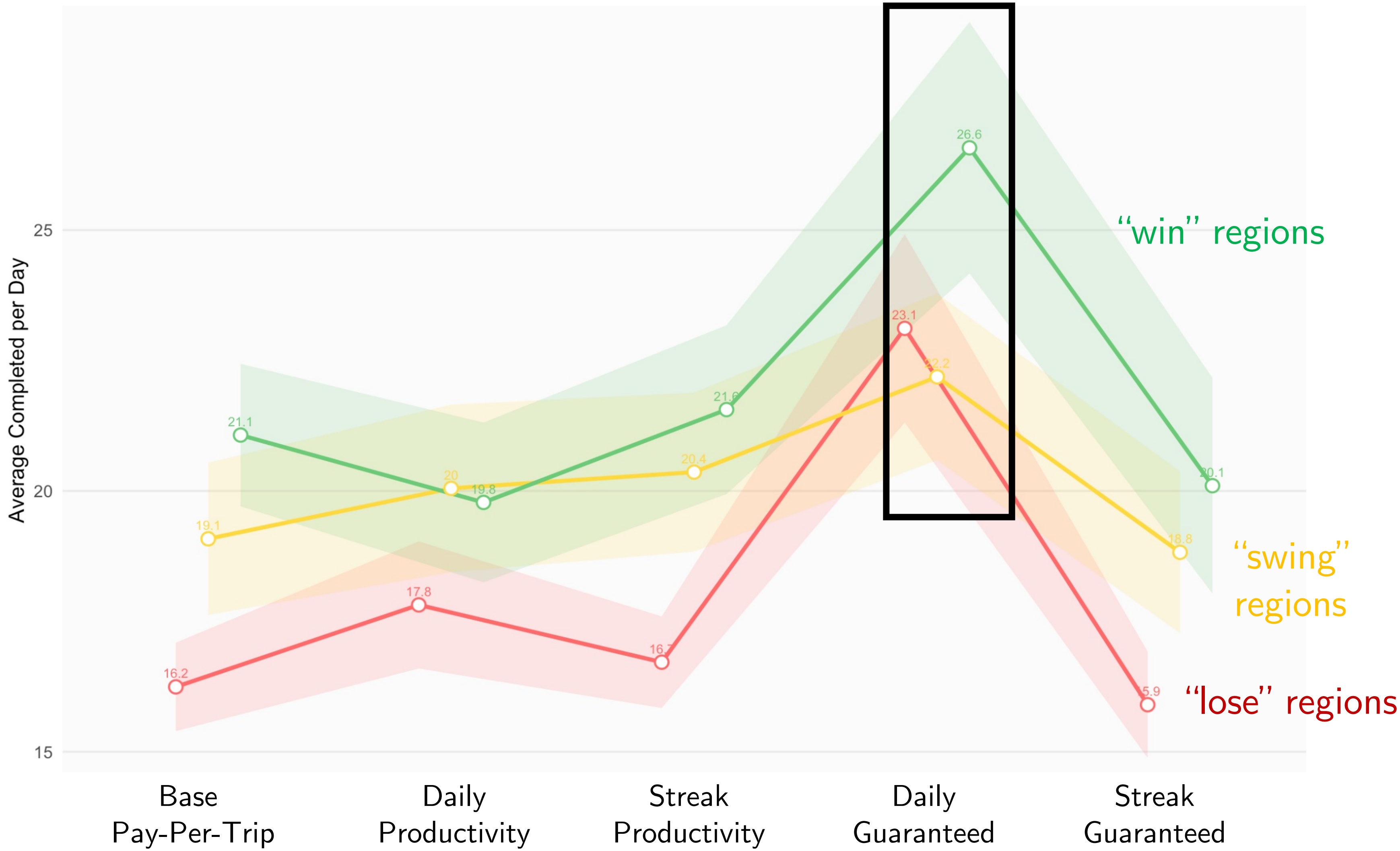
Collaboration with LINE MAN, Thailand's leading food delivery platform (also runs restaurants' POS system)

- Switchback experiments in July-August 2025
- 30 cities, each with one incentive type per week

- Control: per-trip base
- Daily productivity (X trips today)
- Streak productivity (X trips for Y days)
- Daily guaranteed (X hours today)
- Streak guaranteed (X hours a day for Y days)

Early Results

Daily guaranteed outperforms other incentives in terms of # completed orders / day and online hours.



Online Experiments (in progress)

Safeway for Charlotte

$ 20
Piedmont

4 - apple
3 - watermelon
3 - orange

Target for Jacob

$ 20
Emeryville

2 - pineapple
9 - watermelon
2 - grape
1 - apple
3 - banana

Safeway for James

$ 20
Piedmont

4 - orange
3 - apple
4 - watermelon

Target for William

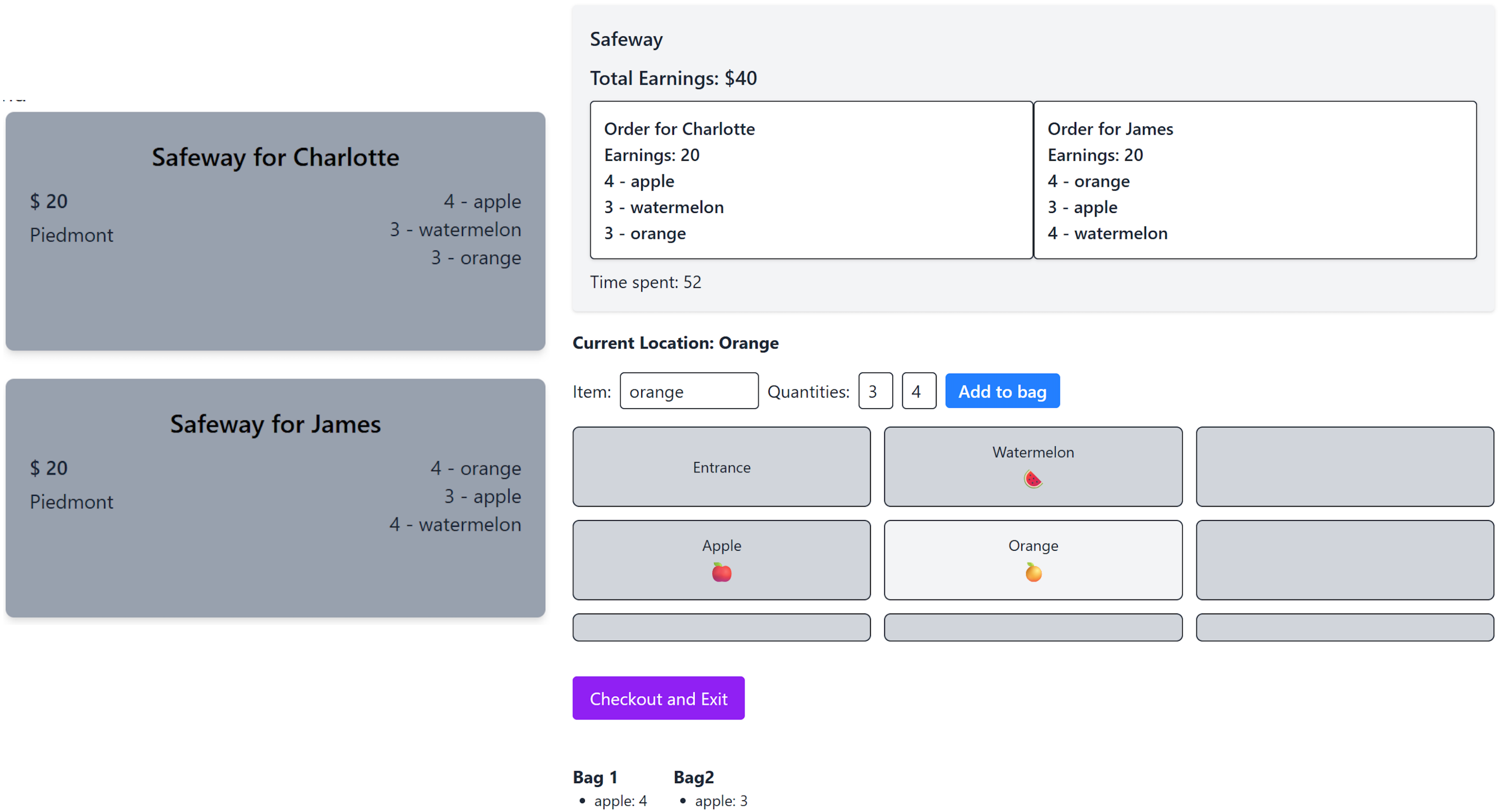
$ 20
Emeryville

1 - banana
1 - apple
1 - pineapple
1 - grape
1 - watermelon

Travel to Piedmont. Then go to store

Travel to Emeryville | Travel to Berkeley | Travel to Piedmont

Online Experiments (in progress)



Summary So Far…

Structural modeling of gig workers' multihoming decisions

Insights

- ML/GAN-based adversarial estimation (historically hard to trace)
- 42% of drivers always multihome, 2/3 on most days
- Drivers are strongly myopic; responding to short-term incentives

- Guaranteed pay: save 25-50% from pay-per-work
- Peak hours: streak bonus to retain drivers
- Low demand: time delay to nudge earlier departure
- Our model helps predict impact of policy




Read more: bit.ly/mmwpaper

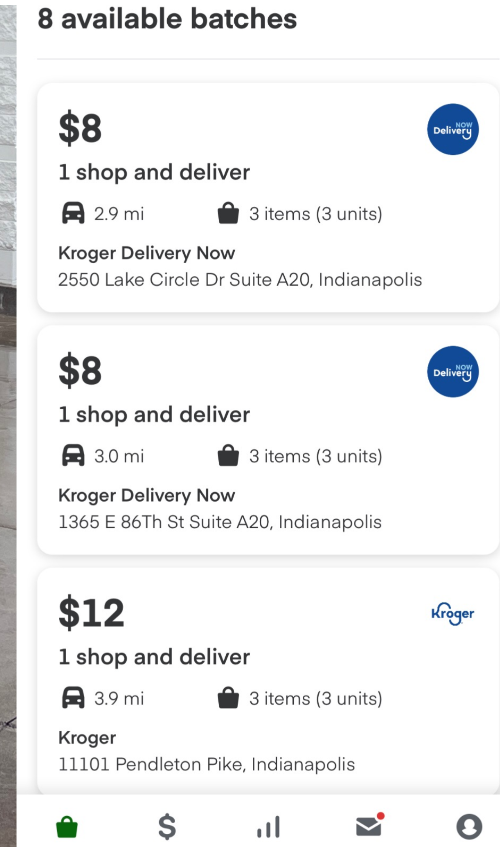
Gad Allon, Maxime Cohen, Ken Moon, **Park Sinchaisri** (parksinchaisri@berkeley.edu)

Back to...

...Struggling Gig Workers

Back to...

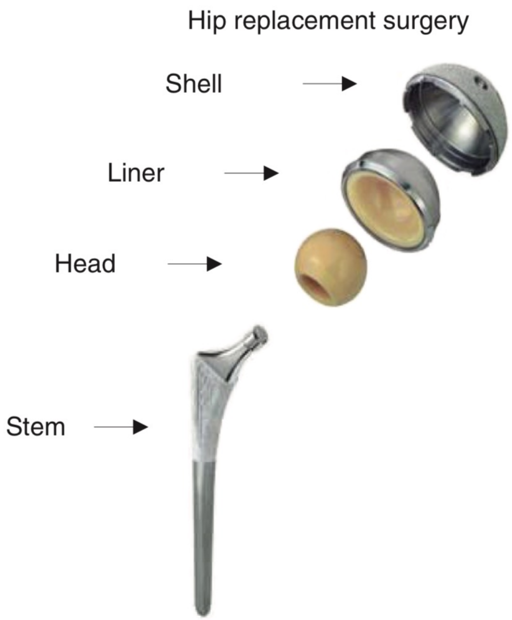
...Struggling Gig Workers



instacart

Learning is Hard & Costly

Learning is Hard & Costly



New device

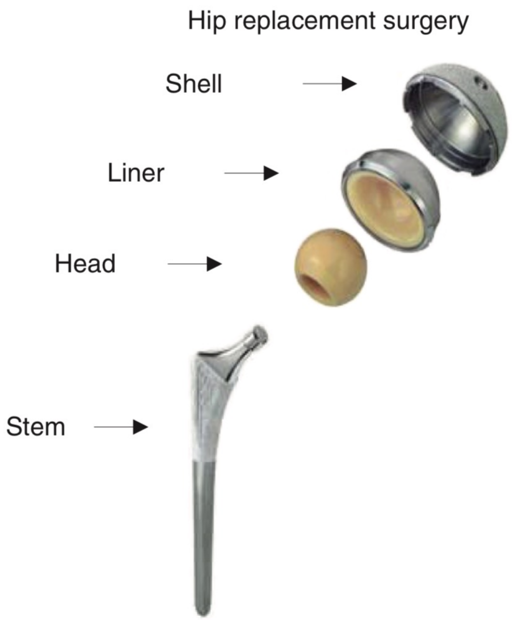
= **+32.4%**

surgery duration

- Ramdas et al. 2018

Also – Tucker et al 2002, Ibanez et al 2017, Gurvich et al 2019, Bloom et al 2020, Bavafa & Jonasson 2021, ...

Learning is Hard & Costly



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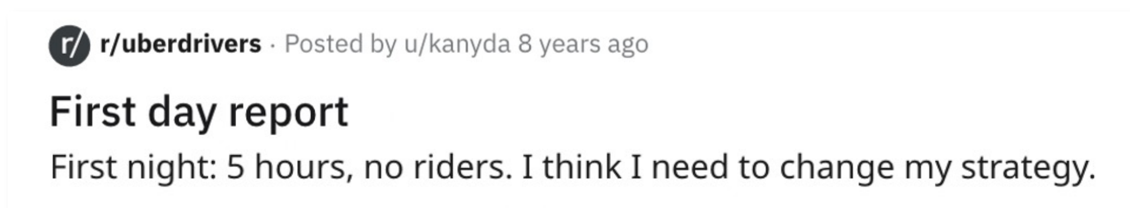
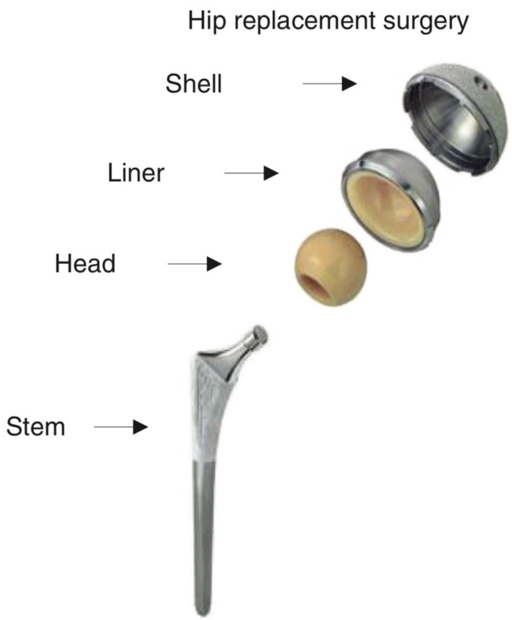

r/ r/uberdrivers · Posted by u/kanyda 8 years ago

First day report

First night: 5 hours, no riders. I think I need to change my strategy.

Also – Tucker et al 2002, Ibanez et al 2017, Gurvich et al 2019, Bloom et al 2020, Bavafa & Jonasson 2021, ...

Learning is Hard & Costly



New device

= **+32.4%**

surgery duration

- Ramdas et al. 2018

Tuesdays are the least profitable day of the week.

The early morning (7-10) is pretty good money.

r/uberdrivers · Posted by u/kanyda 8 years ago

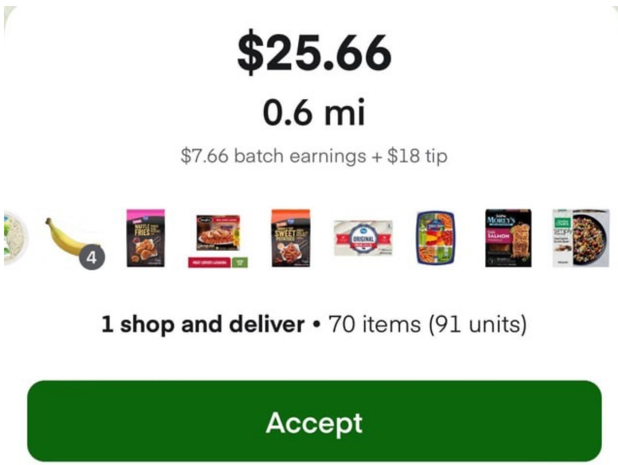
First day report

First night: 5 hours, no riders. I think I need to change my strategy.

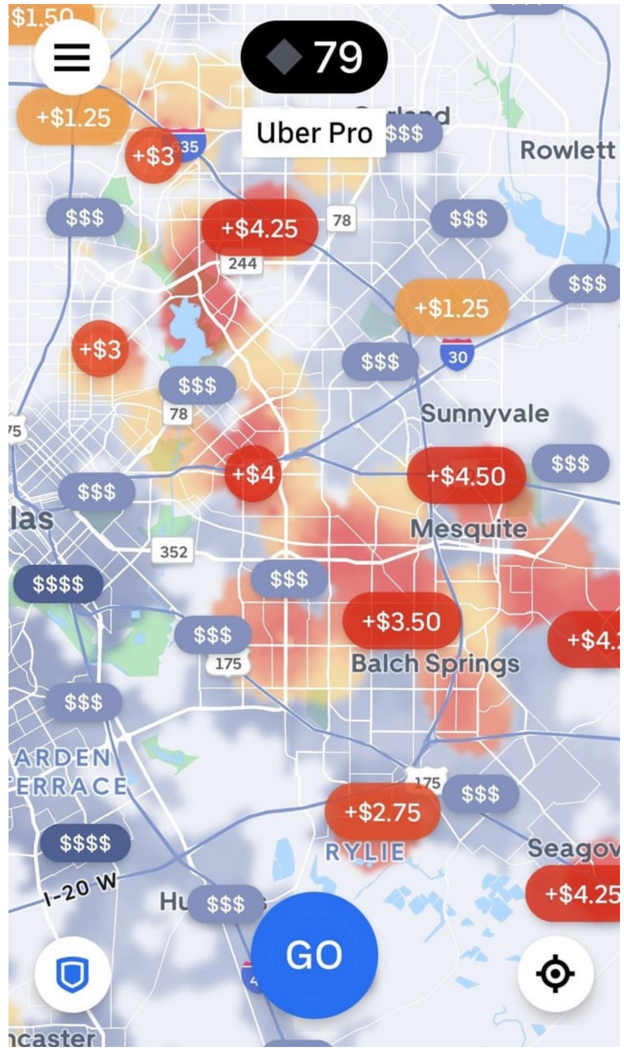
Also – Tucker et al 2002, Ibanez et al 2017, Gurvich et al 2019, Bloom et al 2020, Bavafa & Jonasson 2021, ...

Humans learn from experience
(Shafer et al 2001, Boh et al 2007, Argote 2012, Bavafa & Jónasson 2021)

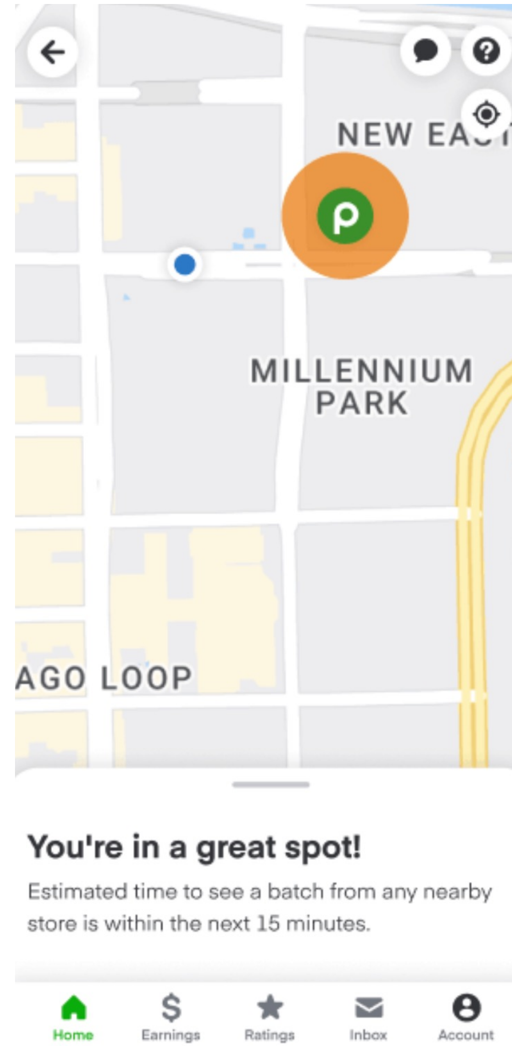
AI Can Help…



$25.66
0.6 mi
$7.66 batch earnings + $18 tip
1 shop and deliver • 70 items (91 units)
Accept

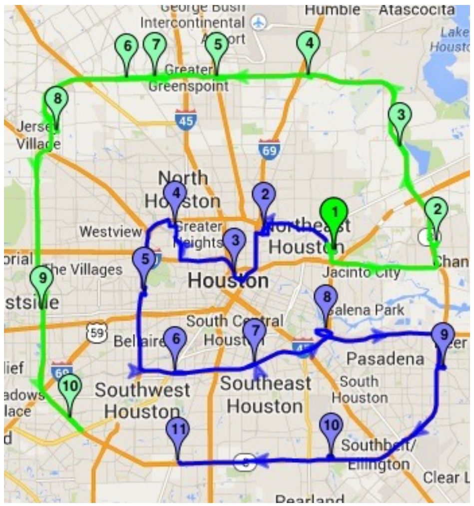


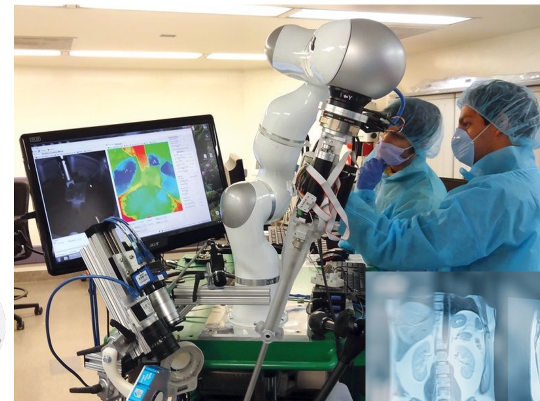
79
Uber Pro
+$1.25
+$3
+$4.25
+$1.25
+$3
+$4
+$4.50
+$3.50
+$2.75
+$4.25
$$$
$$$$
Rowlett
Sunnyvale
Mesquite
Balch Springs
GO



MILLENNIUM PARK
You're in a great spot!
Estimated time to see a batch from any nearby store is within the next 15 minutes.
Home
Earnings
Ratings
Inbox
Account

AI Can Help…


Humble
Atascocita
Intercontinental
Greater
Greenspoint
North
Westview
Houston
Jacinto City
Pasadena
South
Houston
Southwest
Houston
Southeast
Houston
Pearland



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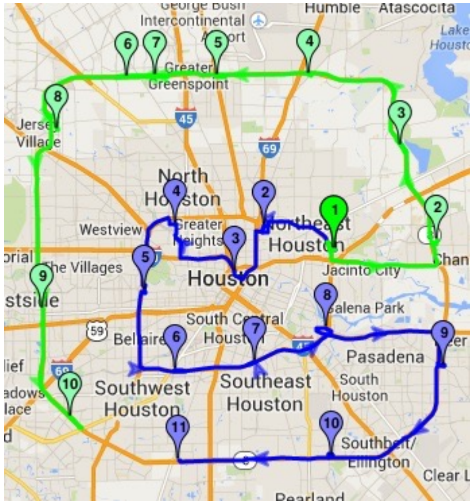

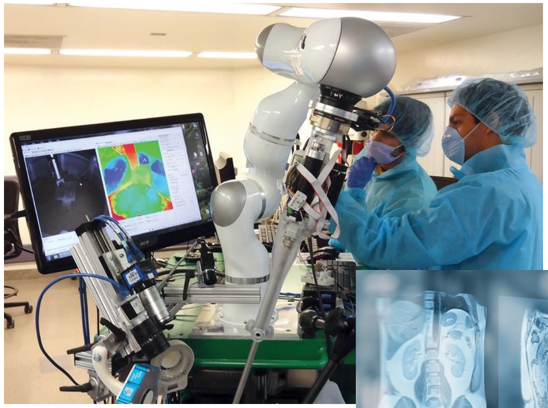

Usually, workers still have discretion over the actual action taken

Radiologists prioritize similar tasks and those they expect to complete faster. They exercise more discretion as they accumulate experience.

- Ibanez et al 2018

Dietvorst, Simmons & Massey 2015
Castelo, Bos & Lehmann 2019
Sun, Zhang, Hu & van Mieghem 2022
Balakrishnan, Ferreira & Tong 2022
Bastani, Bastani & Sinchaisri 2025

...But Humans Deviate

…Or Humans Get Worse

...Or Humans Get Worse

'Automation Addiction': Are Pilots Forgetting How to Fly?

Is auto-pilot weakening response time to emergency situations?

By ABC News
August 31, 2011, 3:39 AM

The Dangers of Overreliance on Automation

Safety Concerns and Mitigation Strategies for Pilots

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FAA Safety BRIEFING
The FAA Safety Policy Voice of Non-commercial General Aviation

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FAA Safety BRIEFING
The FAA Safety Policy Voice of Non-commercial General Aviation

One of the most significant risks of overreliance on automation is the erosion of manual flying proficiency. When pilots frequently engage autopilot systems, their hand-flying skills may deteriorate. This becomes critical in emergency situations where automation may fail, requiring immediate manual control. The crash of Air France Flight 447 in 2009 demonstrated how pilots who lacked hand-flying practice and relied on automation did not properly recover from a stall during an automation failure in a highly trained airline environment.

...Or Humans Get Worse

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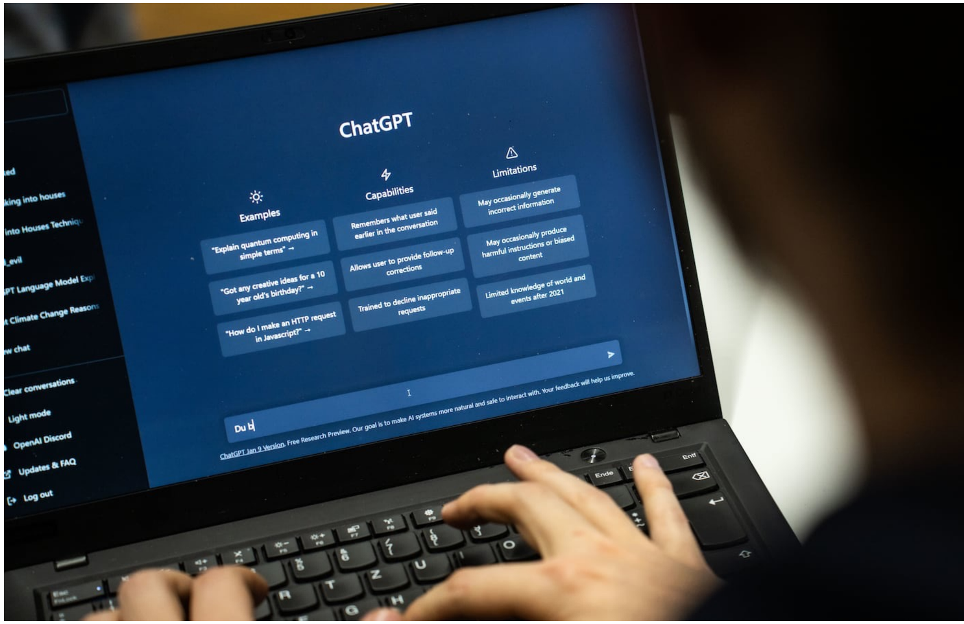

TIME

APR 17, 2025 7:05 AM ET

The Real Reason Why Students Are Using AI to Avoid Learning

IDEAS · AI

...Or Humans Get Worse

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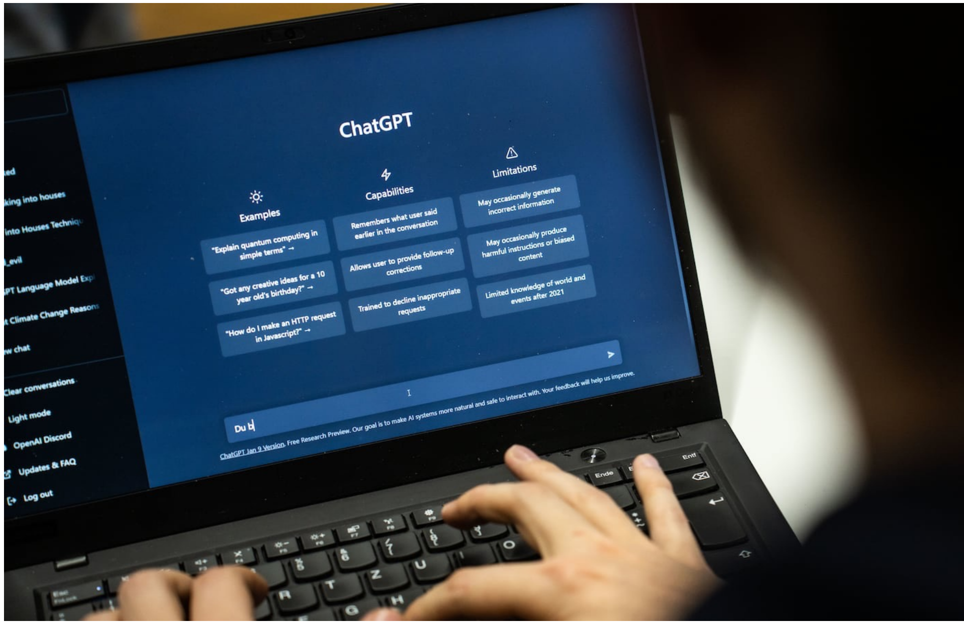

TIME
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The Real Reason Why Students Are Using AI to Avoid Learning

IDEAS AI

NEW YORK POST
BUSINESS

ChatGPT outage live updates: College students spiraling during finals

By Taylor Herzlich, Ariel Zilber, Kaydi Pelletier and Isabella Bernabeo
Updated June 10, 2025, 12:51 p.m. ET

10 Comments

Give Humans Advice, and You Feed Them for a Day

Balancing Efficiency & Learning in Algorithmic Recommendations

Park Sinchaisri

UC Berkeley Haas

with **Philippe Blaettchen** (SMU)

How to Help Humans Learn to **Make Better Sequential Decisions** Even After Advice is Gone?

How to Help Humans Learn to **Make Better Sequential Decisions** Even After Advice is Gone?

"Driving Game"

How Humans Make Sequential Decisions?

How to Help Humans Learn to Make Better Sequential Decisions Even After Advice is Gone?

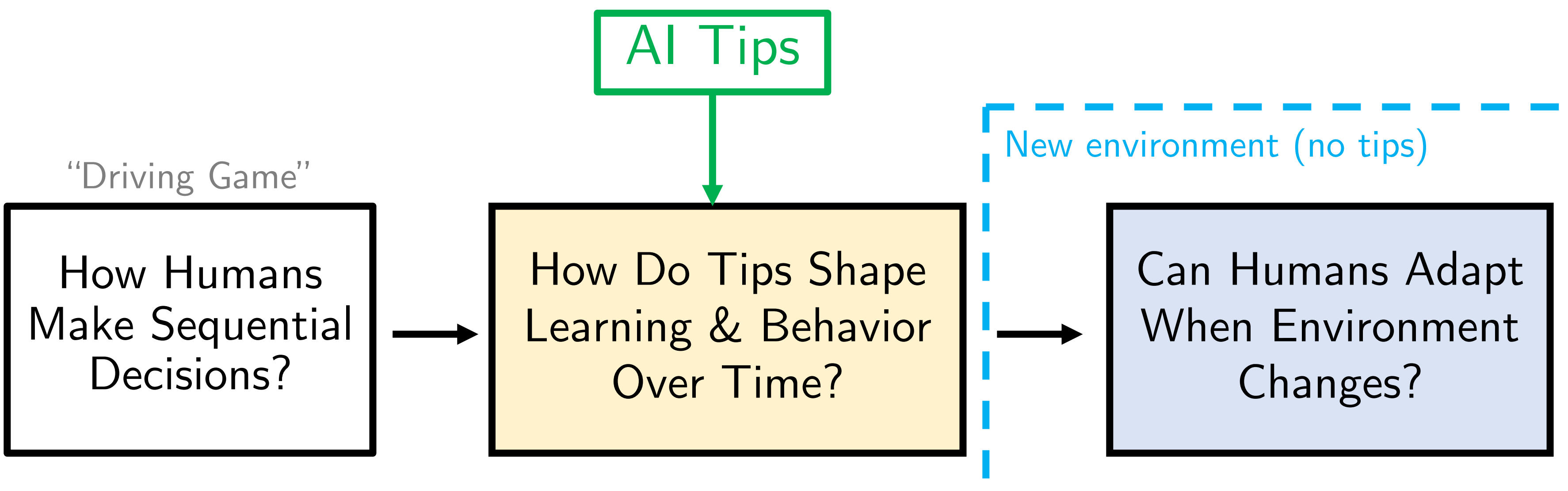
AI Tips

"Driving Game"

How Humans Make Sequential Decisions?

How Do Tips Shape Learning & Behavior Over Time?

How to Help Humans Learn to Make Better Sequential Decisions Even After Advice is Gone?



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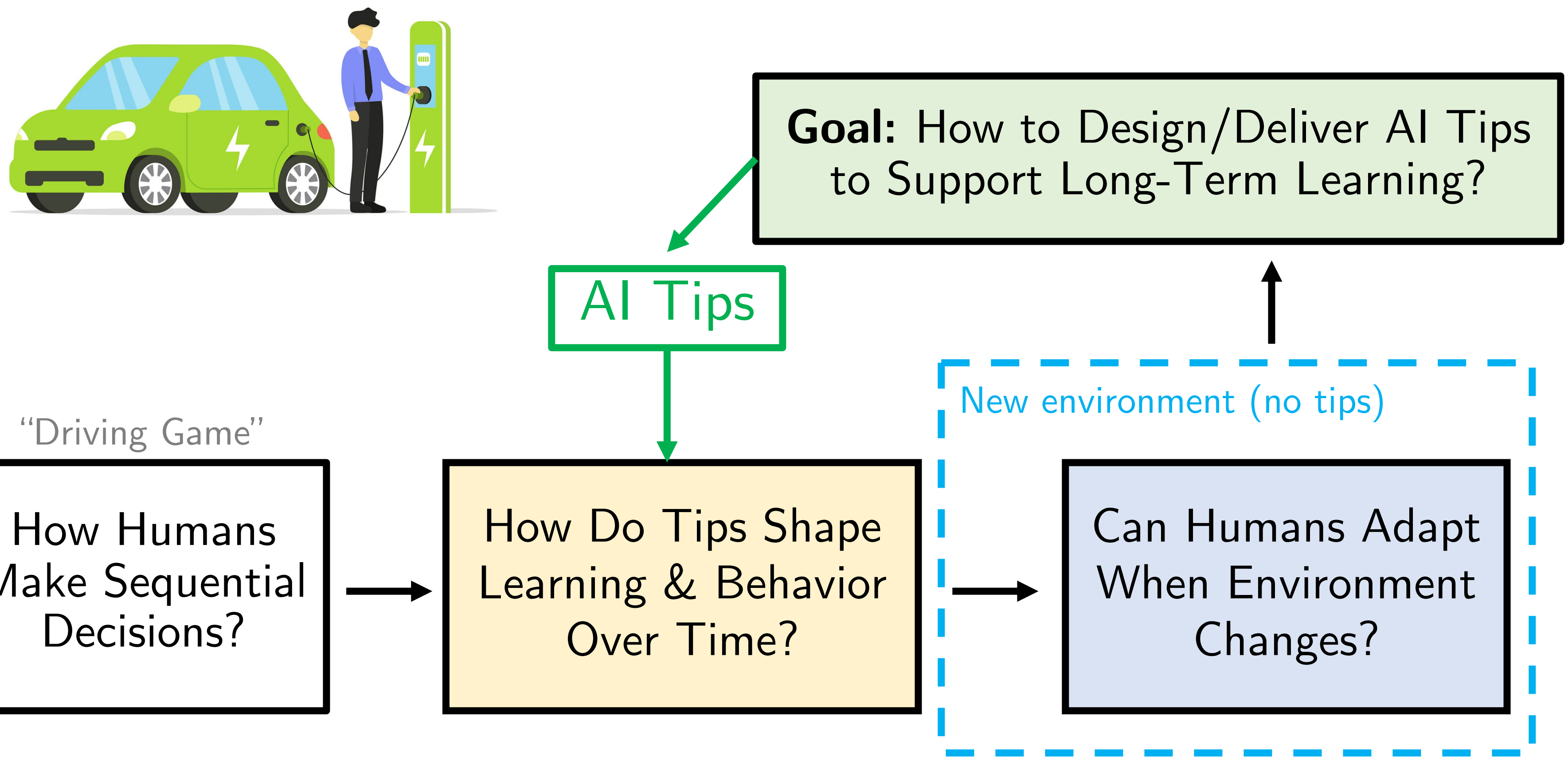
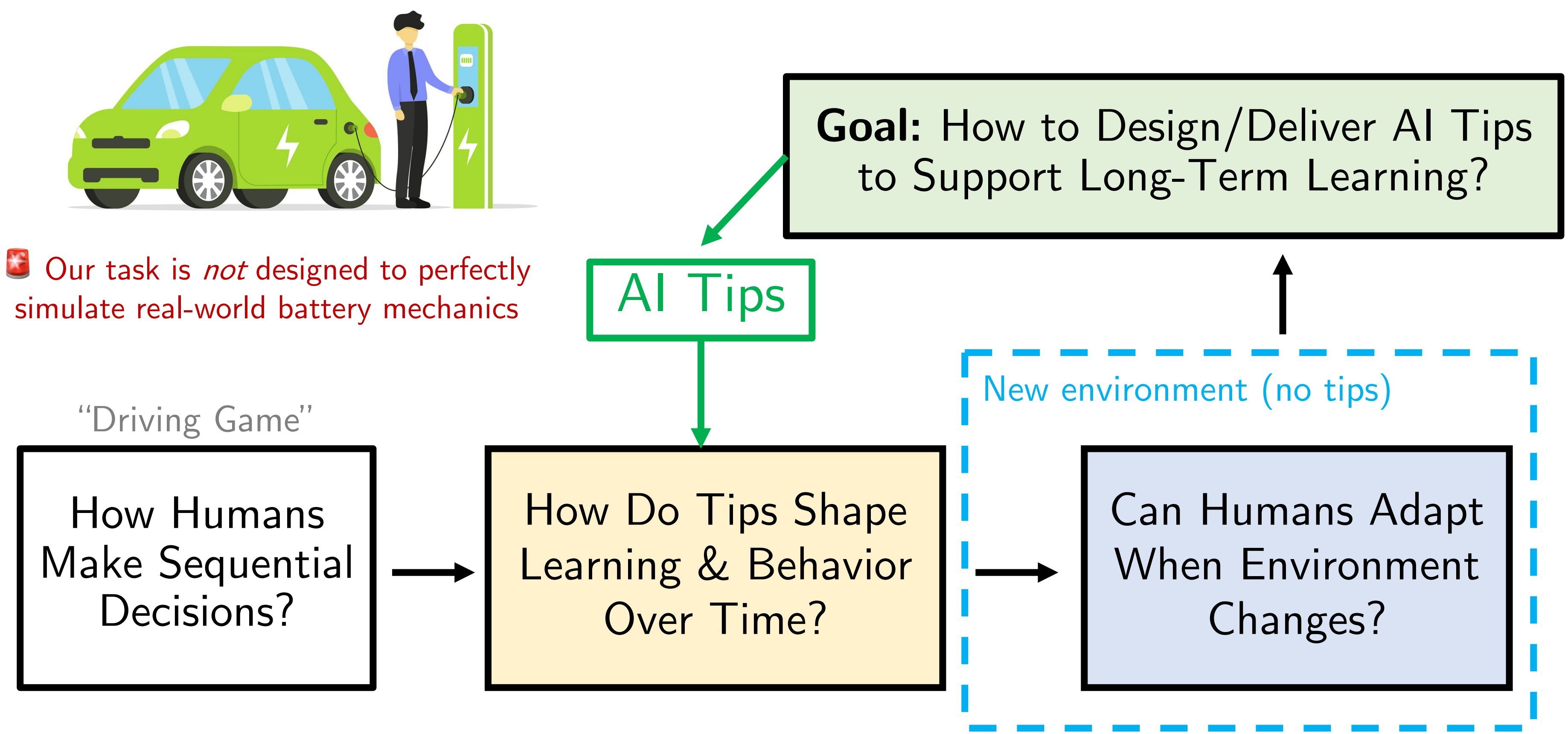
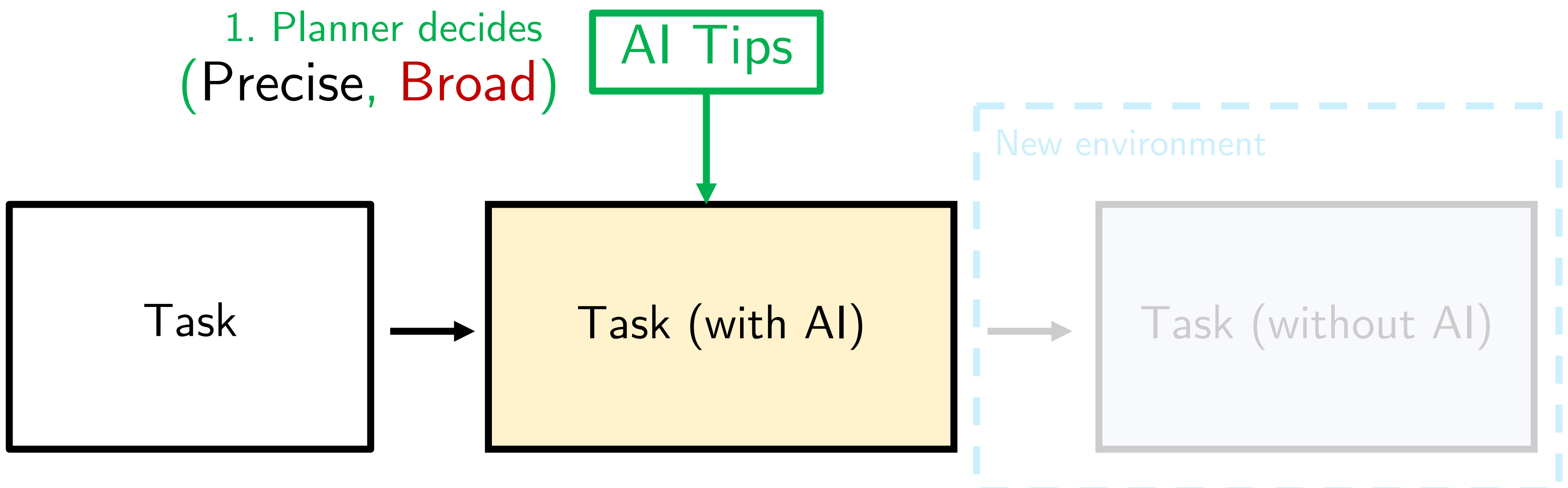


How to Help Humans Learn to **Make Better Sequential Decisions** Even After Advice is Gone?



Model Overview



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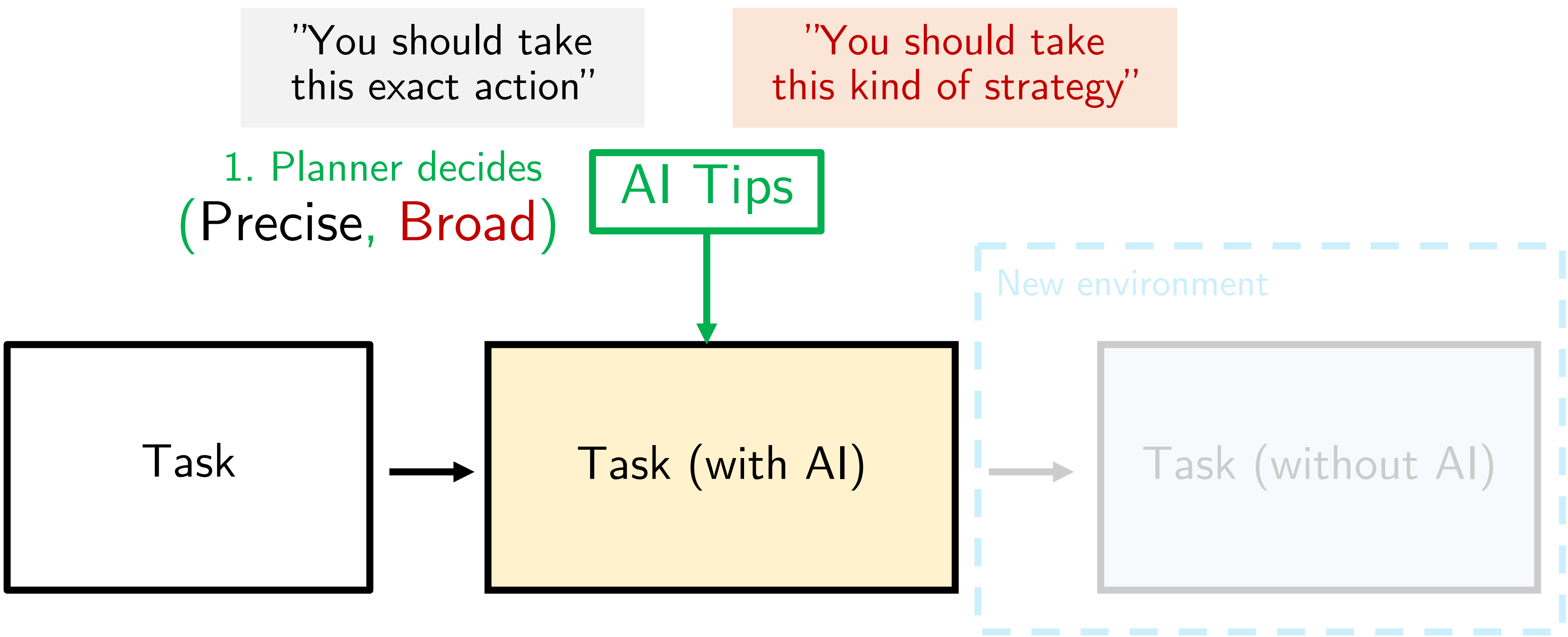
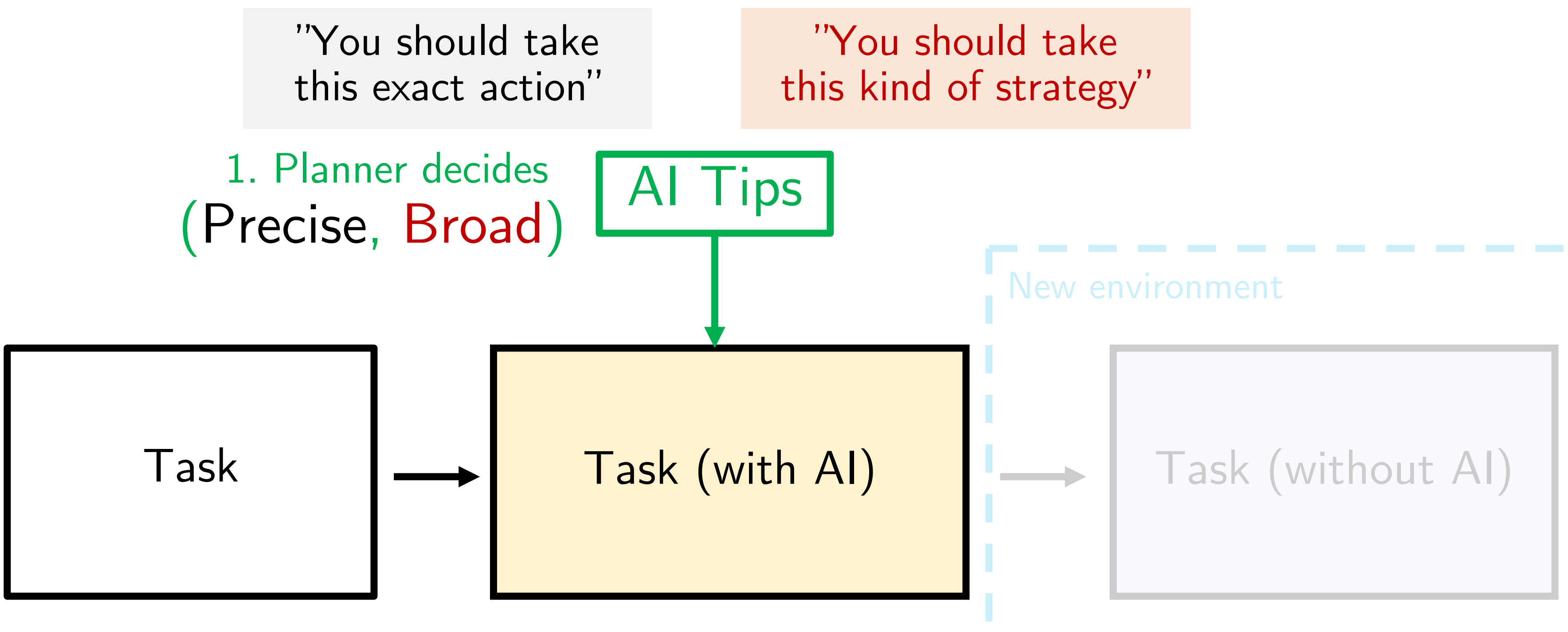


Model Overview

2. Worker decides effort $e_1 \in [0,1]$ with cost $c(e_1) = \frac{k}{2}e_1^2$ with $k > 0$.



Model Overview

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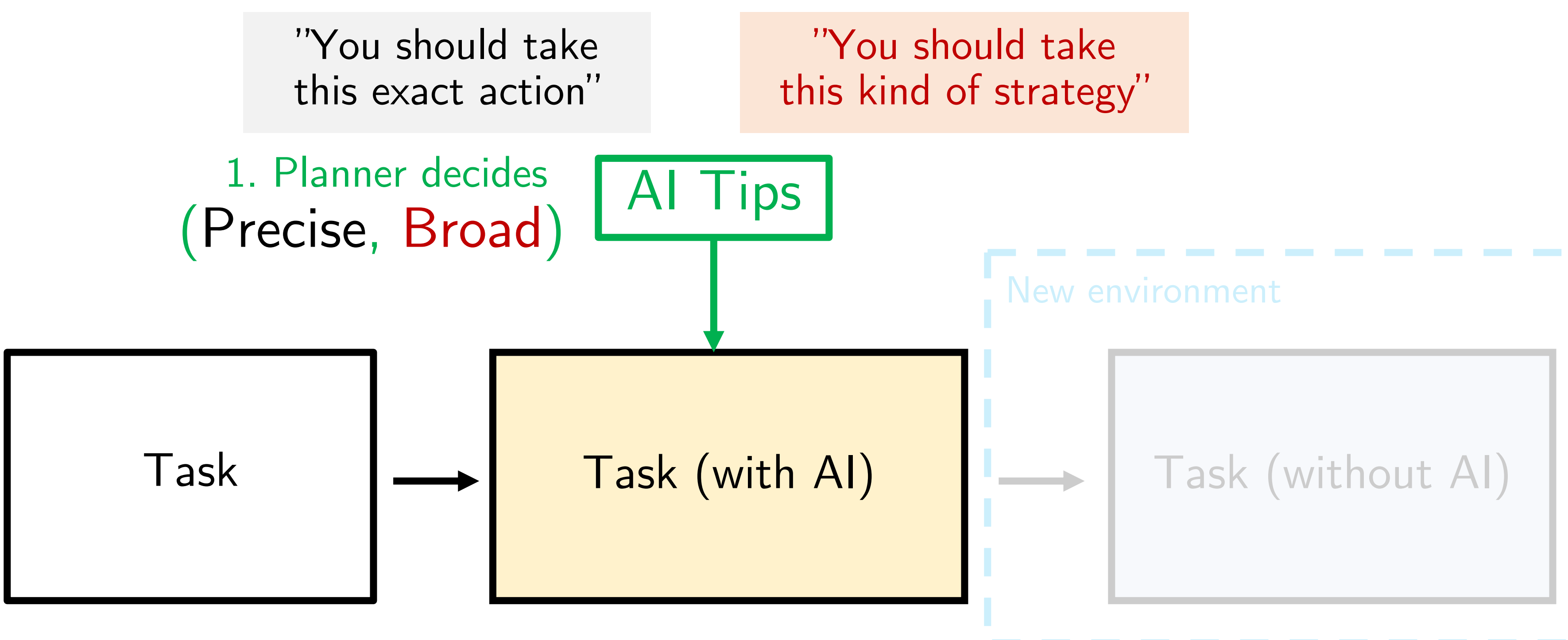
3. Worker follows the advice with probability: $\pi_a^1(e_1) = \alpha_a + \beta_a e_1$



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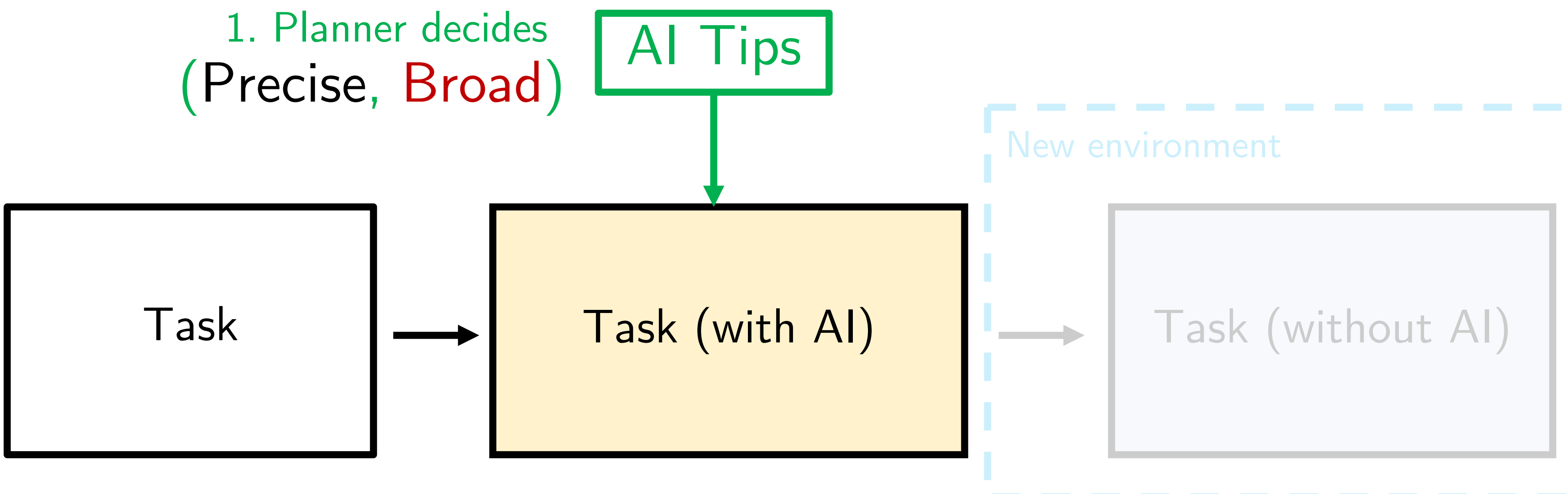
$$0 \leq \alpha_b < \alpha_p < 1$$

Precise tip is easier to follow



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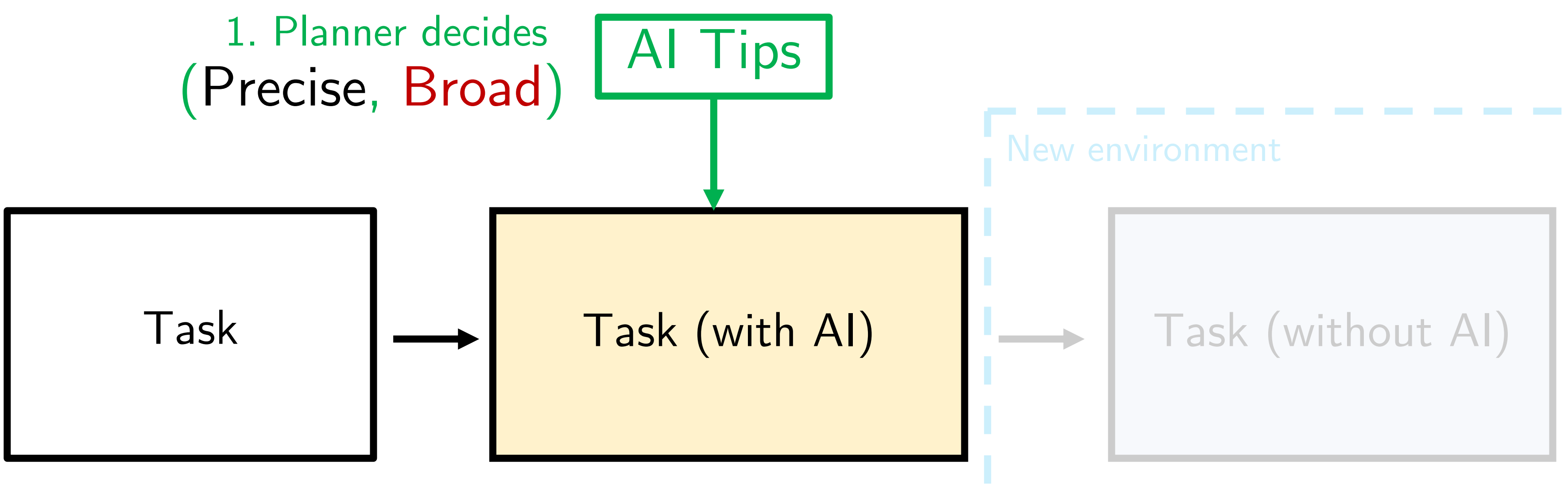
$$0 \leq \alpha_b < \alpha_p < 1$$

Precise tip is easier to follow

$$0 \leq \beta_p < \beta_b < 1$$

Broad tip provides strategic insight, better converting efforts into results



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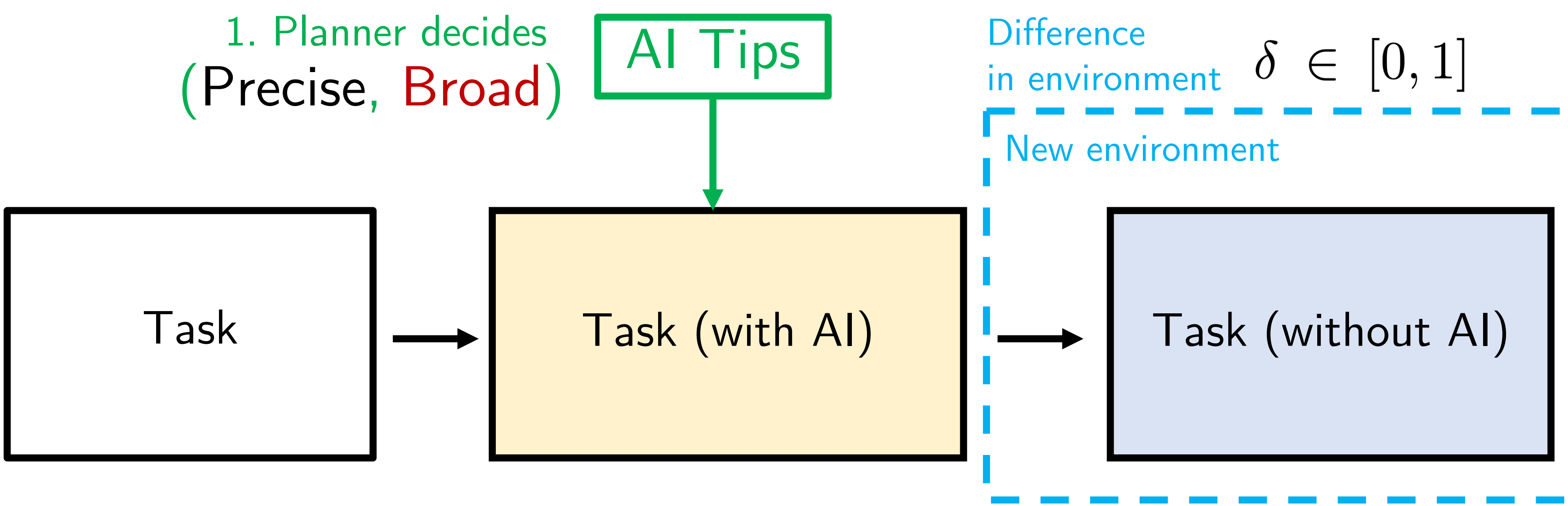
$$0 \leq \alpha_b < \alpha_p < 1$$

Precise tip is easier to follow

$$0 \leq \beta_p < \beta_b < 1$$

Broad tip provides strategic insight, better converting efforts into results



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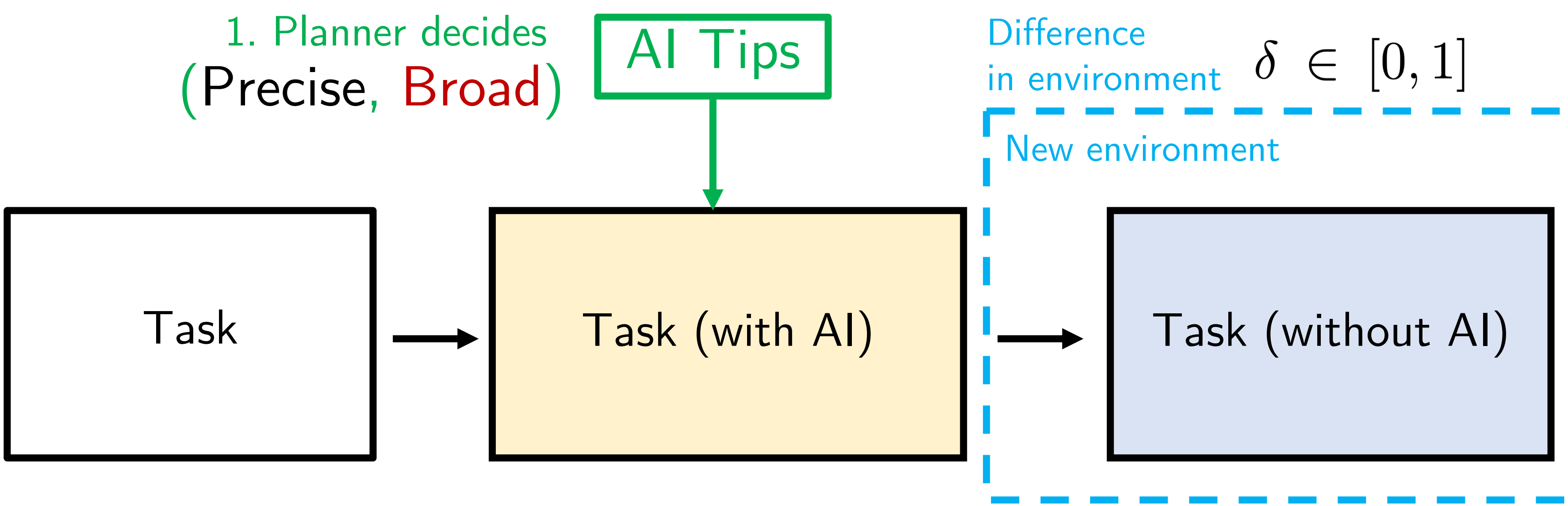
4. Workers decides effort $e_2 \in [0, 1]$ at cost $c(e_2) = \frac{k}{2}e_2^2$



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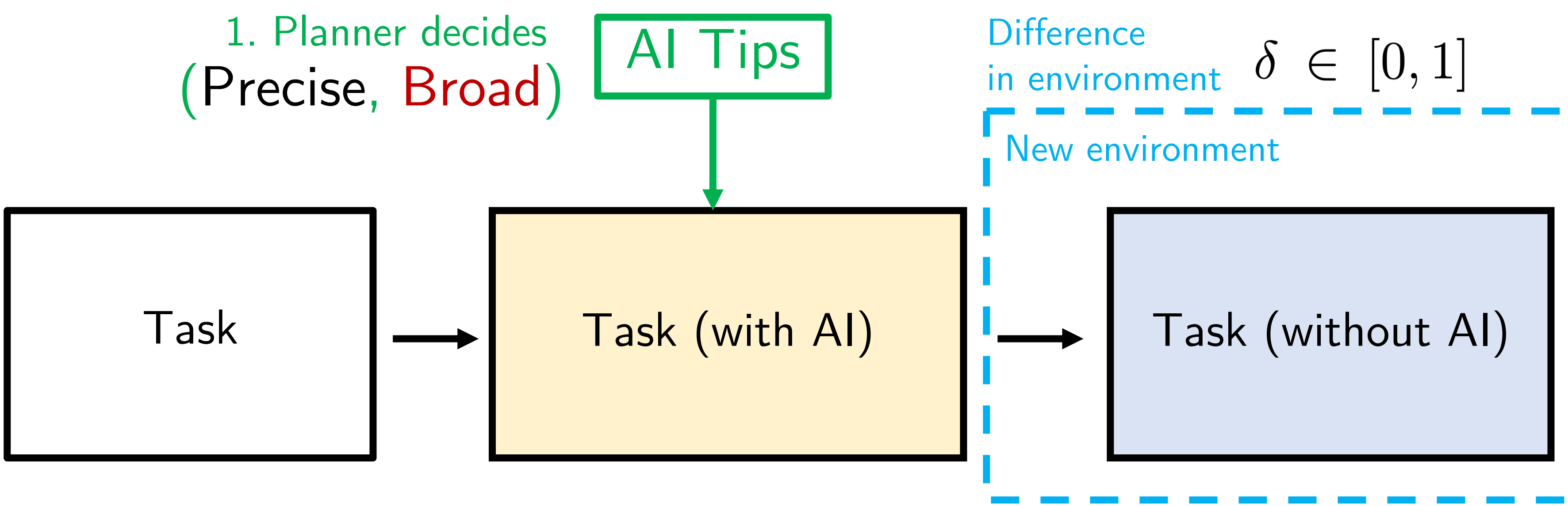
4. Workers decides effort $e_2 \in [0,1]$ at cost $c(e_2) = \frac{k}{2}e_2^2$

5. Worker selects best action with $\pi_a^2(e_1, e_2) = e_2\left[\lambda + (1-\delta)\,\omega_a e_1\right]$



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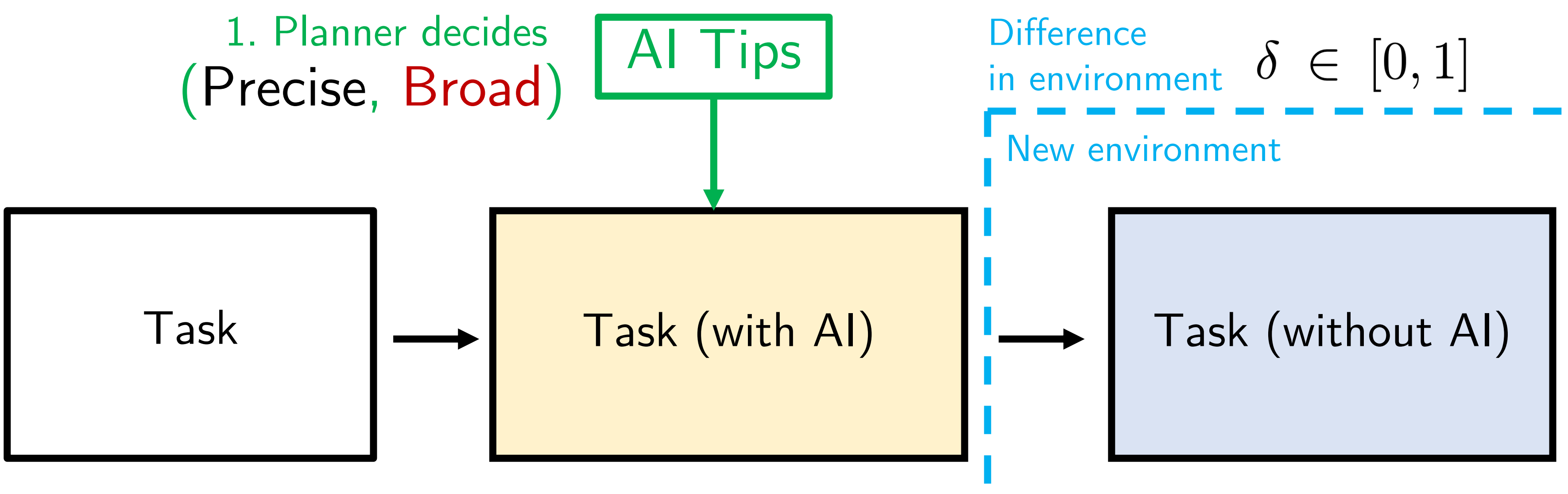
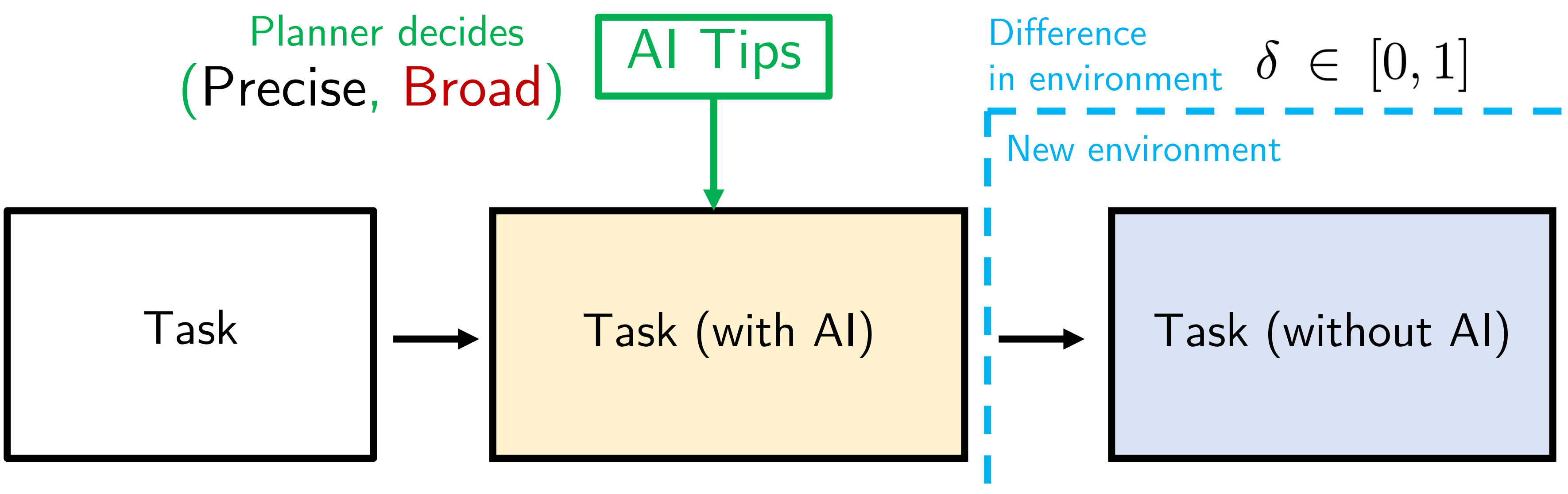
5. Worker selects best action with $\pi_a^2(e_1, e_2) = e_2\left[\lambda + (1-\delta)\,\omega_a e_1\right]$

Transferability of advice: $\omega_b > \omega_p$



Model Results

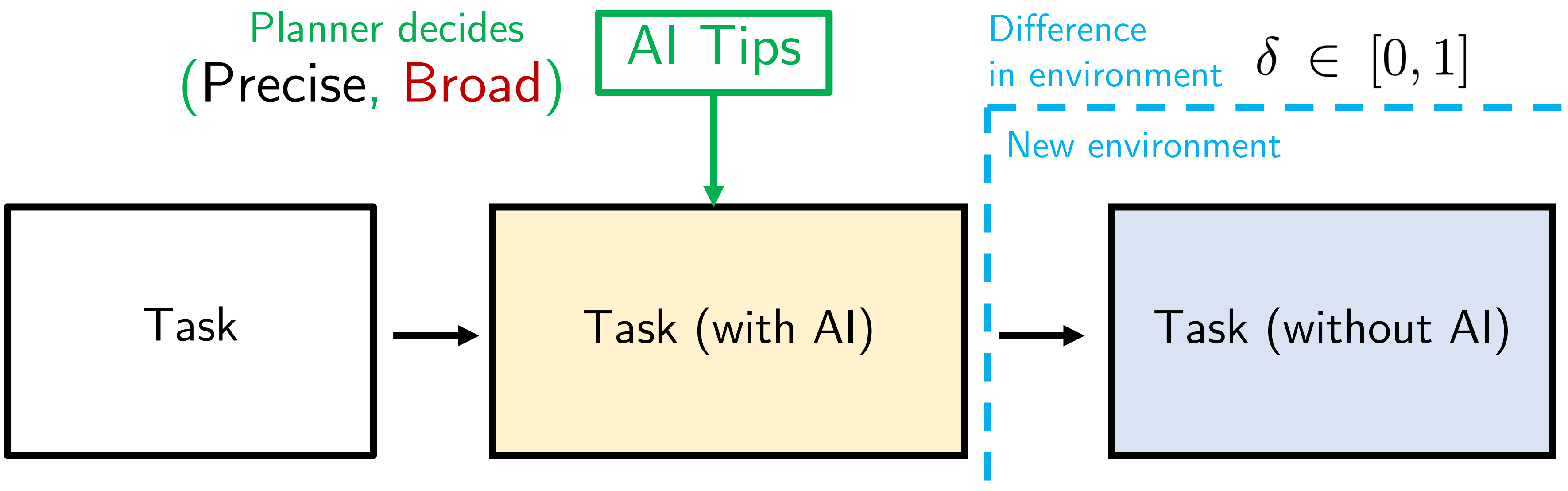
1. Broad tip is optimal for the planner if doing well in the new environment is more important than doing well in the current environment.
For high δ, the difference needs to be more pronounced.



Model Results

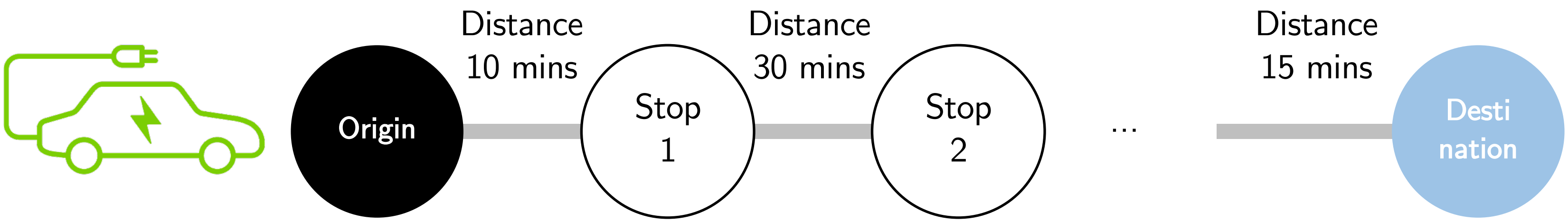
1. Broad tip is optimal for the planner if doing well in the new environment is more important than doing well in the current environment.
For high δ, the difference needs to be more pronounced.

2. When the task in the initial environment is a sequential task (MDP), learning benefits of broad over precise increase with time horizon.



Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game



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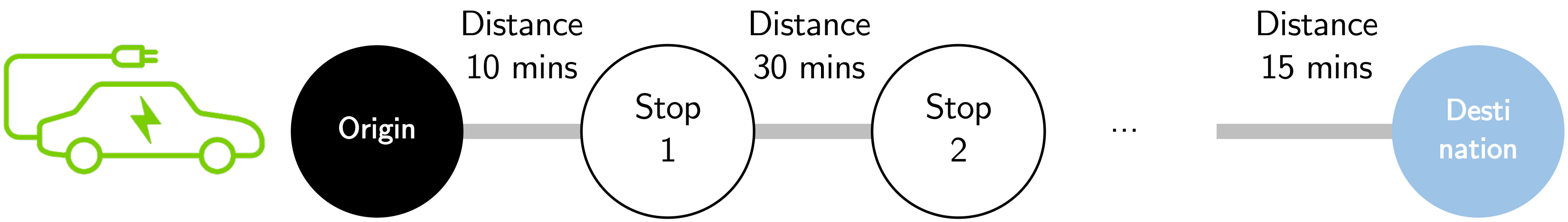
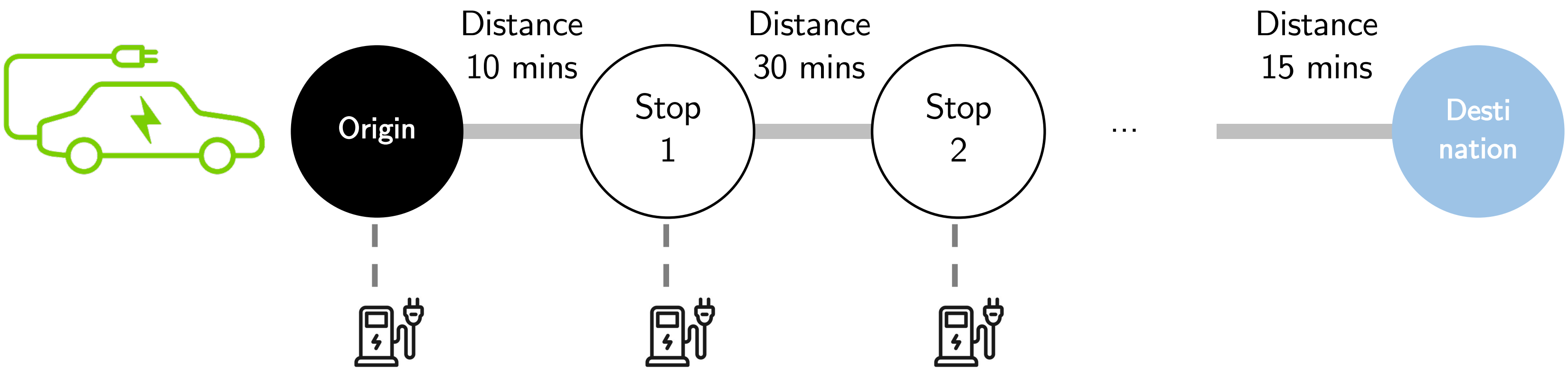


Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game

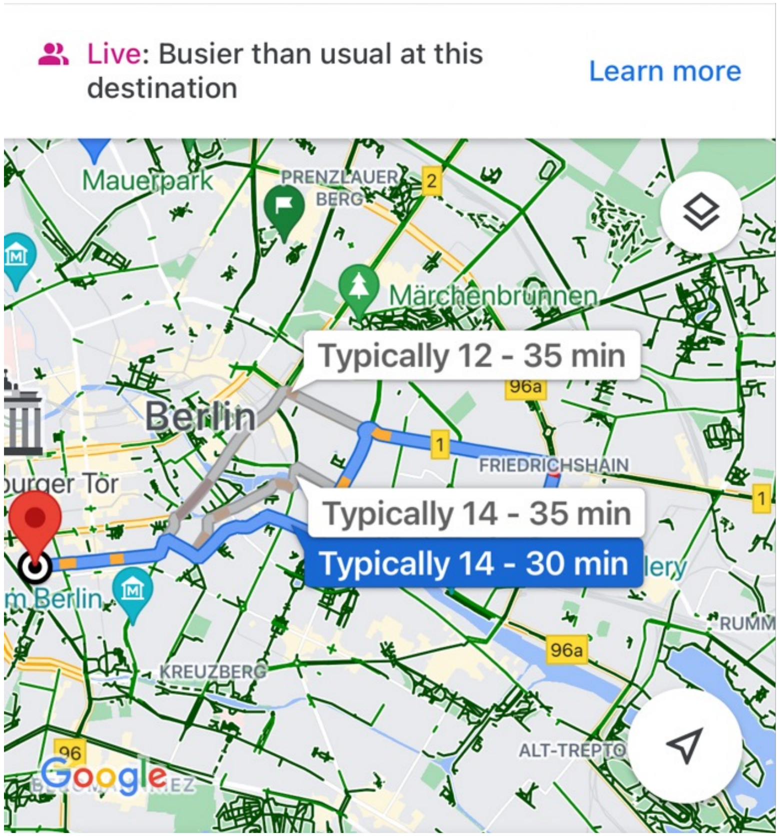


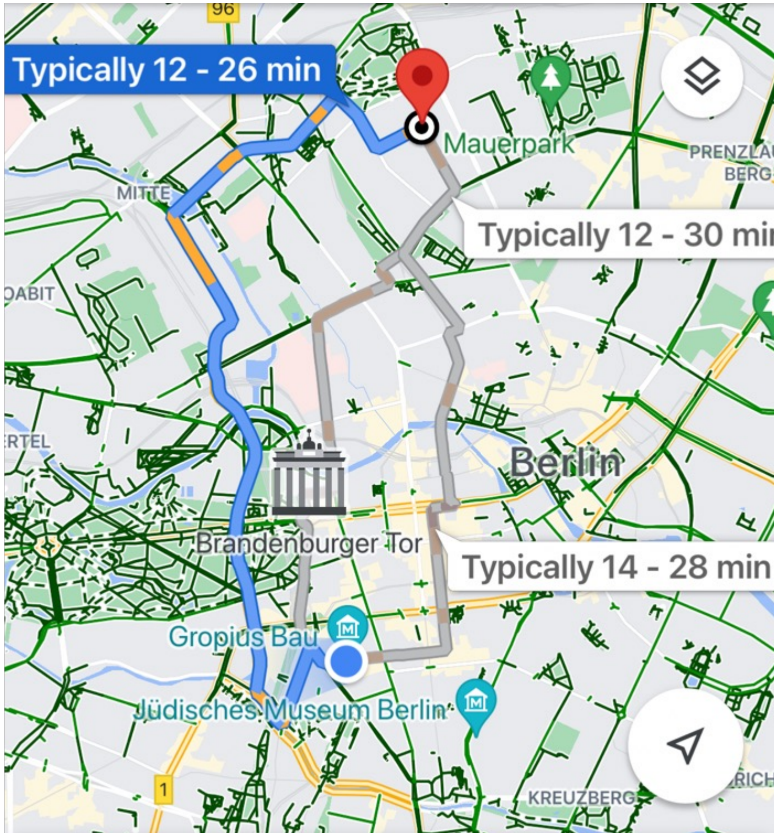
Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Challenges: Even without traffic, the amount of initial charge won't be enough

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game





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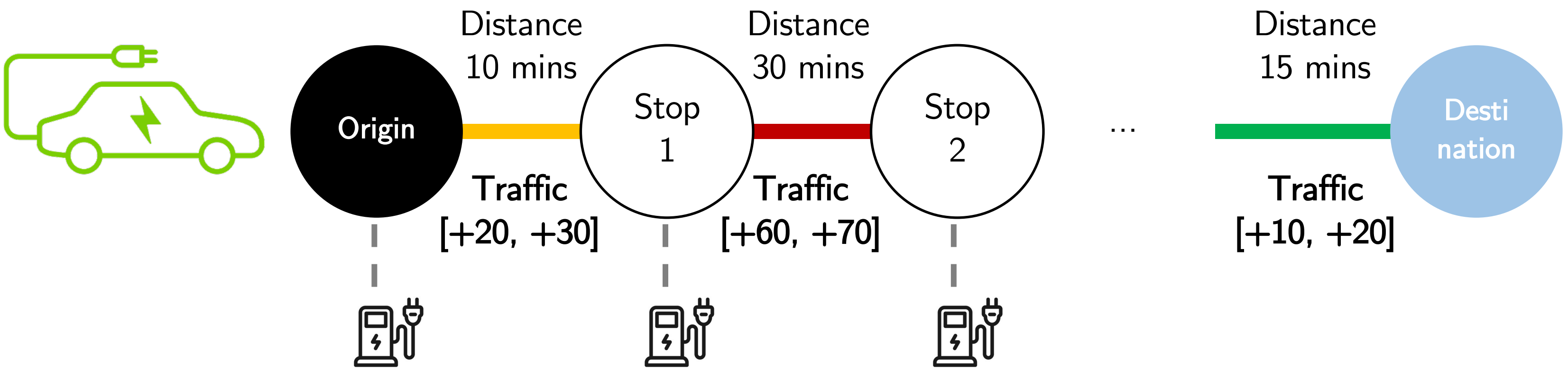
Driving Game



Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Challenges: Even without traffic, the amount of initial charge won't be enough
+ **Uncertain traffic**, uniformly distributed within the specified range

Pre-registered at https://aspredicted.org/7LP_J9G

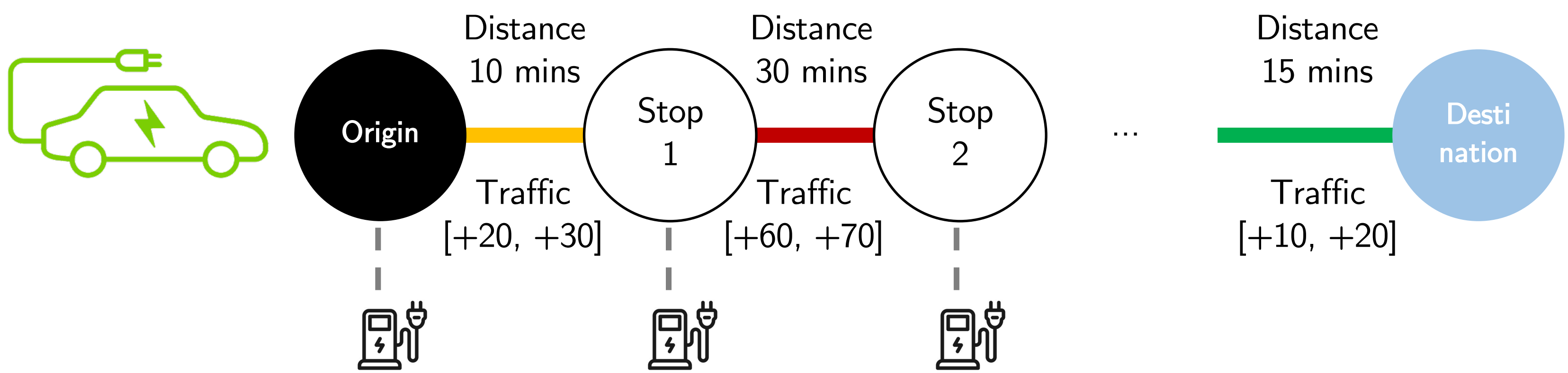
Driving Game

Electric Vehicle (EV) Charge Curves

For EV charging, power delivery is non-uniform over the duration of the session. Rather, it generally follows a curve: maximum power deliver happens when the battery level is relatively low, and power delivery tapers off as the battery becomes increasingly full. However, there is lots of differentiation in the shape of these curves - certain battery architectures have high speeds, then a significant dropoff, while others look to achieve a more stable rate throughout.

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game



Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

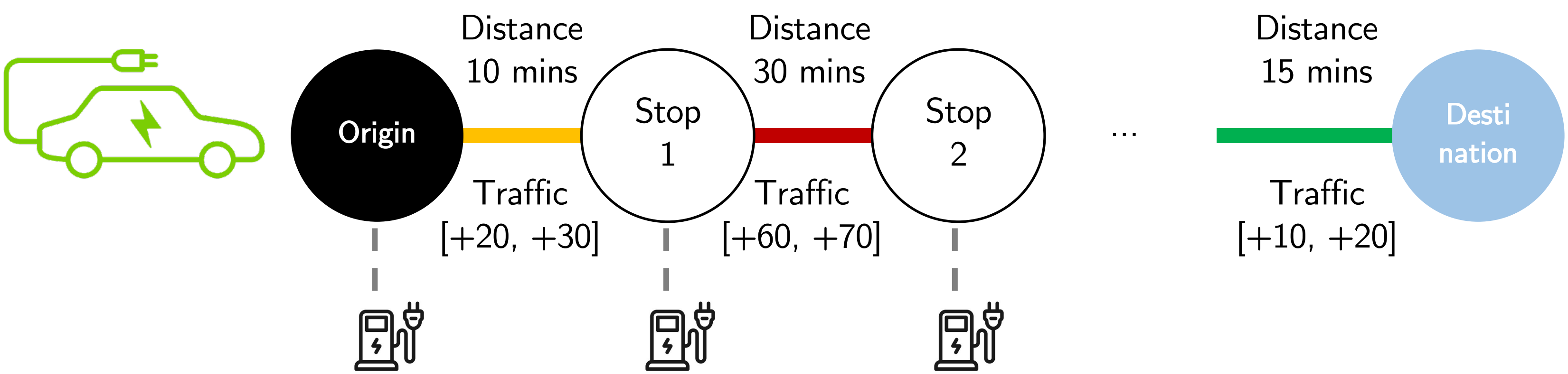
Challenges: Even without traffic, the amount of initial charge won't be enough

+ **Uncertain traffic**, uniformly distributed within the specified range

+ Cost to exit to charge **(+30 mins 🕑)** + **nonlinear charging time** 🕑

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game



Goal: Get to destination as fast as possible **(1% charge can travel 1 minute)**

Challenges: Even without traffic, the amount of initial charge won't be enough

+ **Uncertain traffic**, uniformly distributed within the specified range
+ Cost to exit to charge **(+30 mins 🕒)** + **nonlinear charging time** 🕒
+ Penalty if running out of charge in the middle **(+300 mins 💀)**

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game

Current Stop: 1

Elapsed Trip Time: 33 minutes

Current Charge Level: 67%

Pre-registered at https://aspredicted.org/7LP_J9G

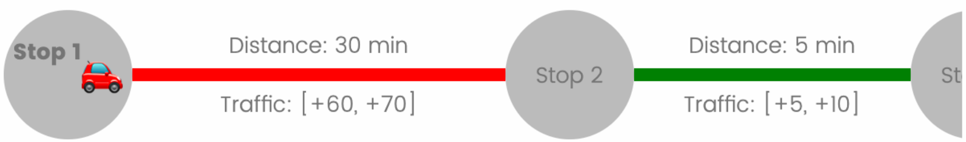
Driving Game

Current Stop: 1

Elapsed Trip Time: 33 minutes

Current Charge Level: 67%

Forward-looking behavior



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Driving Game

Current Stop: 1
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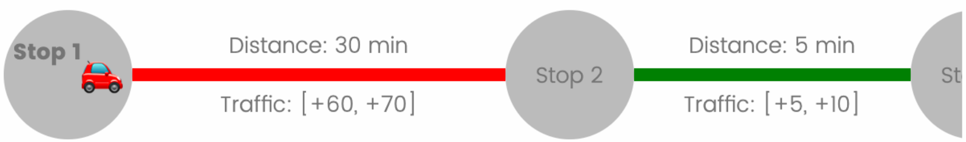


Would you like to make an exit at this stop to charge?

Yes	No
◉	○

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game

Current Stop: 1

Elapsed Trip Time: 33 minutes

Current Charge Level: 67%

Forward-looking behavior

Would you like to make an exit at this stop to charge?

Yes

No

Use this slider to help you determine how much time your recharging will cost.

0 10 20 30 40 50 60 70 80 90 100

Charge Addition Amount (+0% = +0 minutes)

Exploration of strategy

This is how much charge will be added. Your current charge + added charge will be capped at 100 min.

0

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game

Current Stop: 1

Elapsed Trip Time: 33 minutes

Current Charge Level: 67%

Forward-looking behavior

Would you like to make an exit at this stop to charge?

Yes	No
◉	○

Use this slider to help you determine how much time your recharging will cost.

0 10 20 30 40 50 60 70 80 90 100

Charge Addition Amount (+15% = +80 minutes)

15

Exploration of strategy

This is how much charge will be added. Your current charge + added charge will be capped at 100 min.

15

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game

Current Stop: 1

Elapsed Trip Time: 33 minutes

Current Charge Level: 67%

Forward-looking behavior

Would you like to make an exit at this stop to charge?

Yes ◉ No ○

Use this slider to help you determine how much time your recharging will cost.

0 10 20 30 40 50 60 70 80 90 100

Charge Addition Amount (+33% = +147 minutes)

33

Exploration of strategy

This is how much charge will be added. Your current charge + added charge will be capped at 100 min.

33

Pre-registered at https://aspredicted.org/7LP_J9G

Driving Game

Feedback after each round

Previous Stop Summary

Distance: 10
Actual Traffic: 23 min (from expected [+20, +30] min)
Duration: 33 min

Current Stop: 1
Elapsed Trip Time: 33 minutes
Current Charge Level: 67%

Forward-looking behavior

Stop 1 — Distance: 30 min — Traffic: [+60, +70] — Stop 2 — Distance: 5 min — Traffic: [+5, +10]

Would you like to make an exit at this stop to charge?

Yes (selected) | No

Use this slider to help you determine how much time your recharging will cost.

0 10 20 30 40 50 60 70 80 90 100

Charge Addition Amount (+33% = +147 minutes)

33

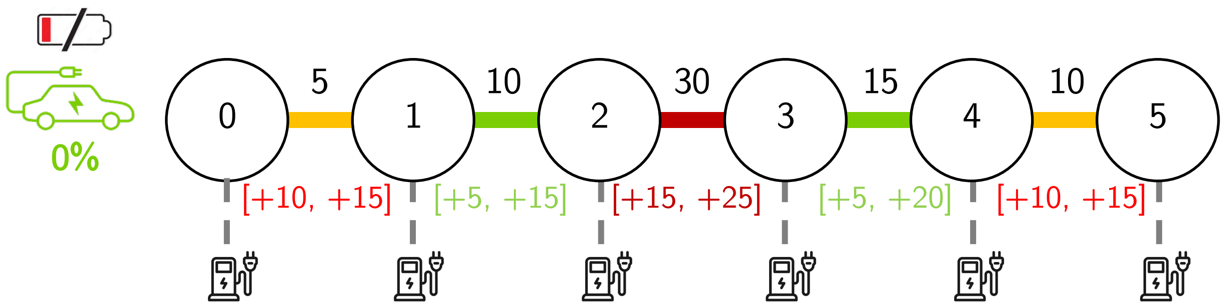
Exploration of strategy

This is how much charge will be added. Your current charge + added charge will be capped at 100 min.

33

Pre-registered at https://aspredicted.org/7LP_J9G

Design



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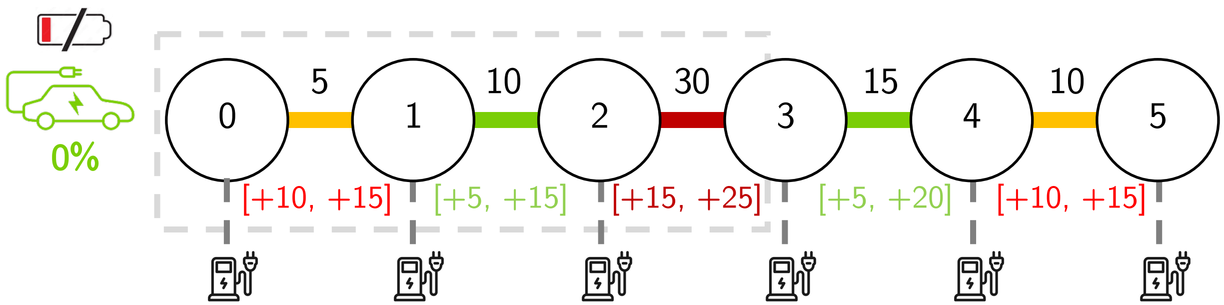
Design To Batch, or Not to Batch



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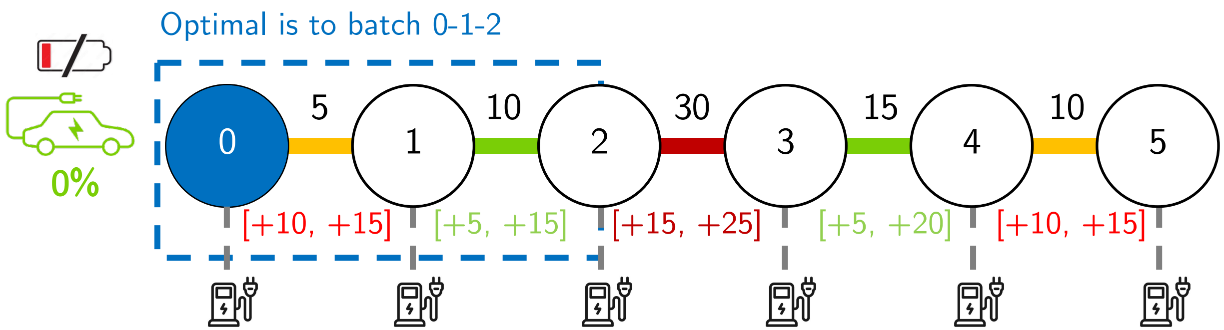

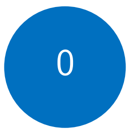

Optimal = "**batch**" required charges for the next two stops (0 → 2) rather than just 0 → 1 or further batch 0 → 3.

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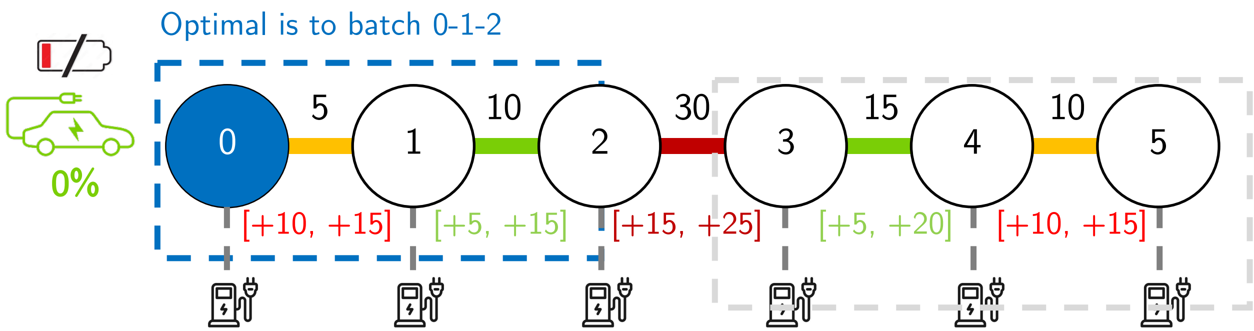

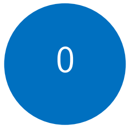

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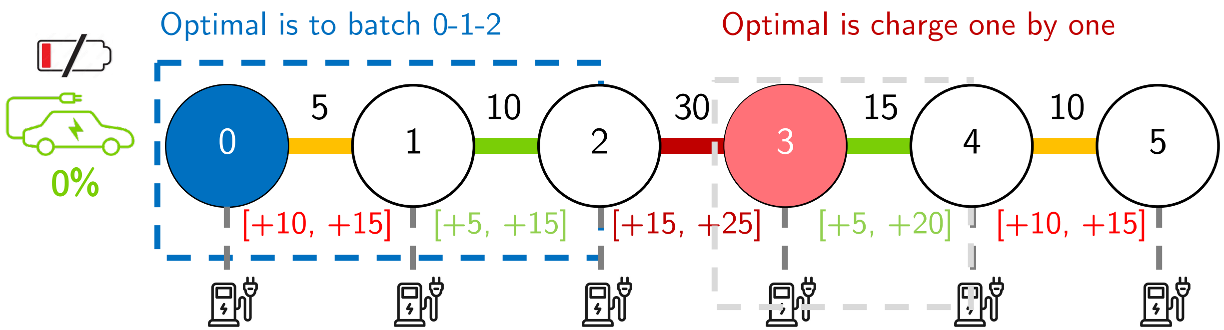
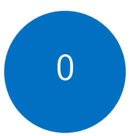


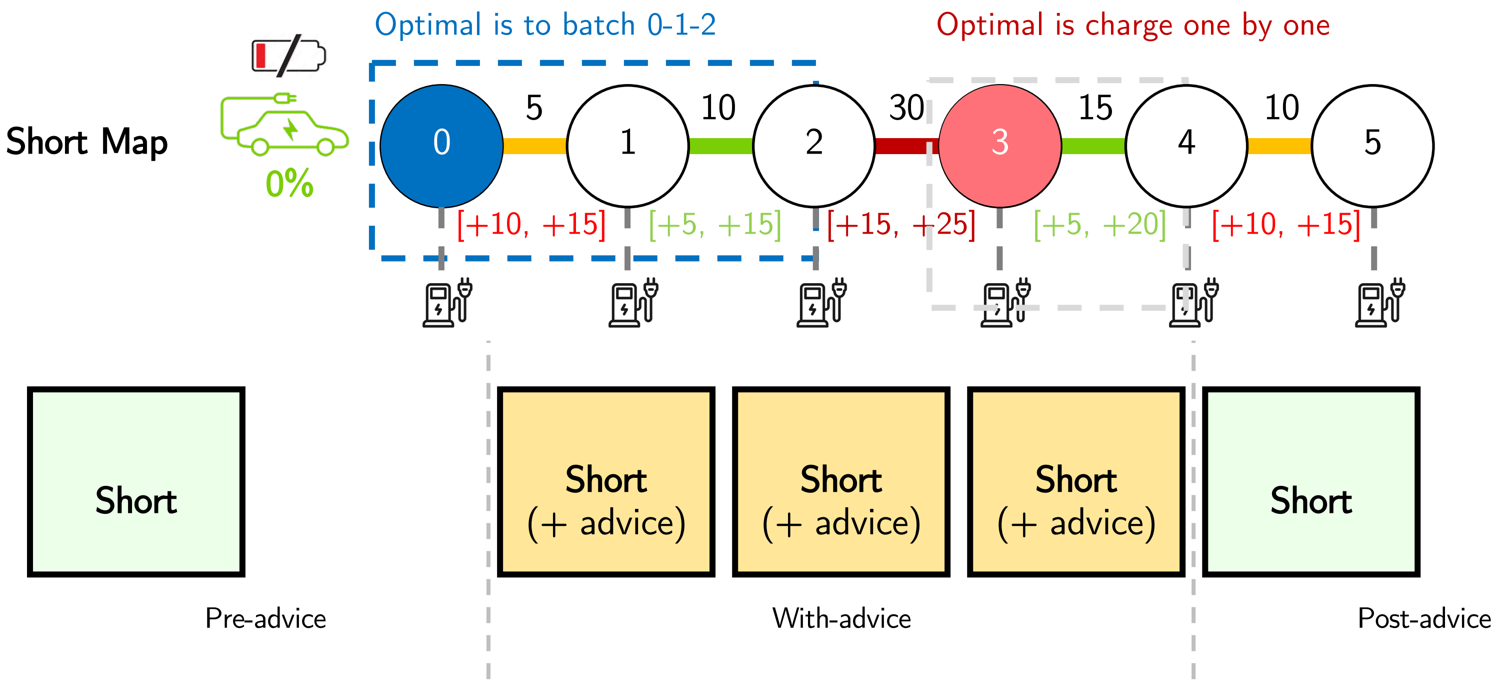


Optimal = **"batch"** required charges for the next two stops (0 → 2) rather than just 0 → 1 or further batch 0 → 3.

Optimal =**"split"** = only charge for the next stop (3 → 4) rather than batch 3 → 5.

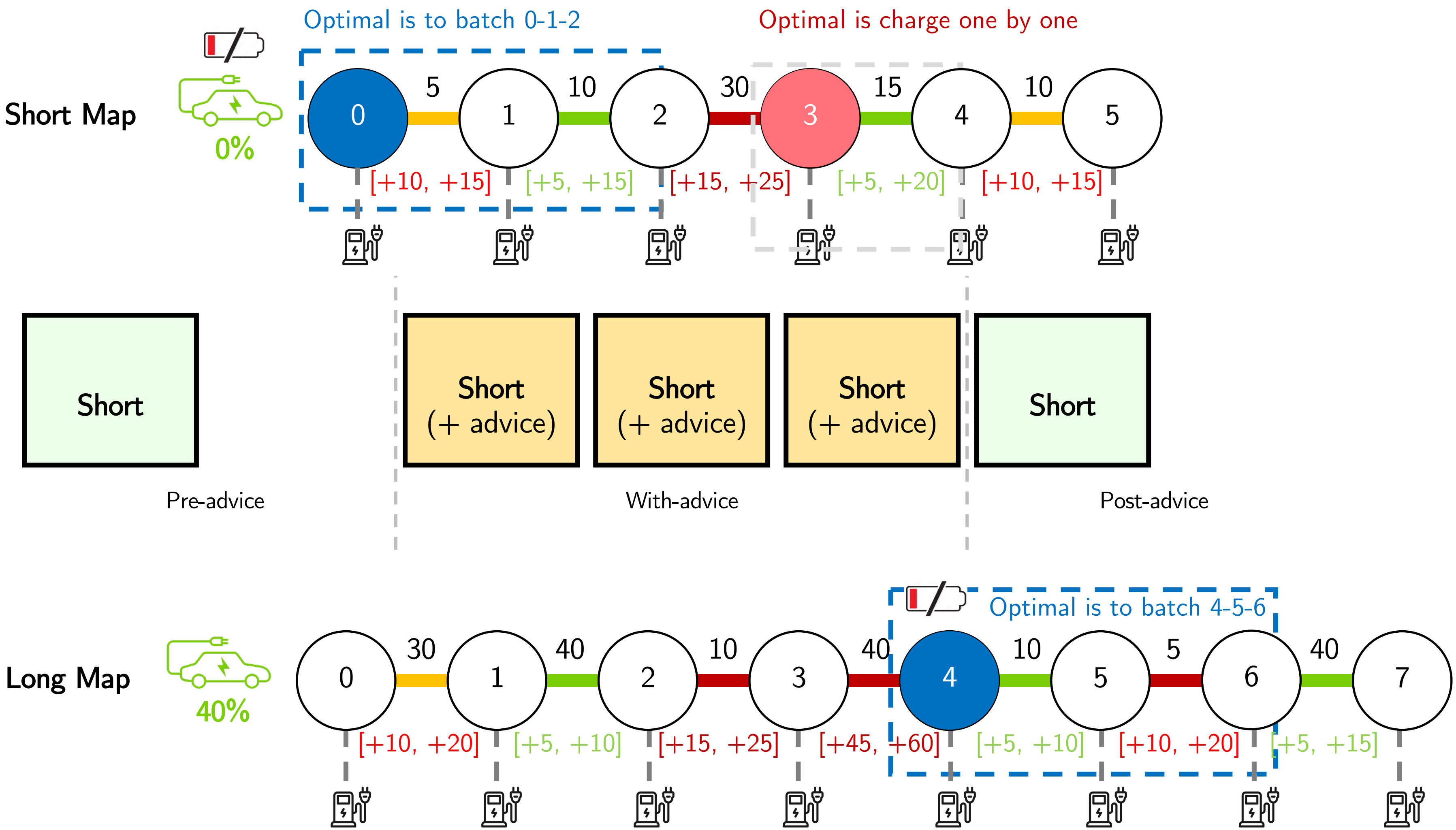
Pre-registered at https://aspredicted.org/7LP_J9G

Study 1 Learning in One Environment



Pre-registered at https://aspredicted.org/7LP_J9G

Study 1 + New Environment



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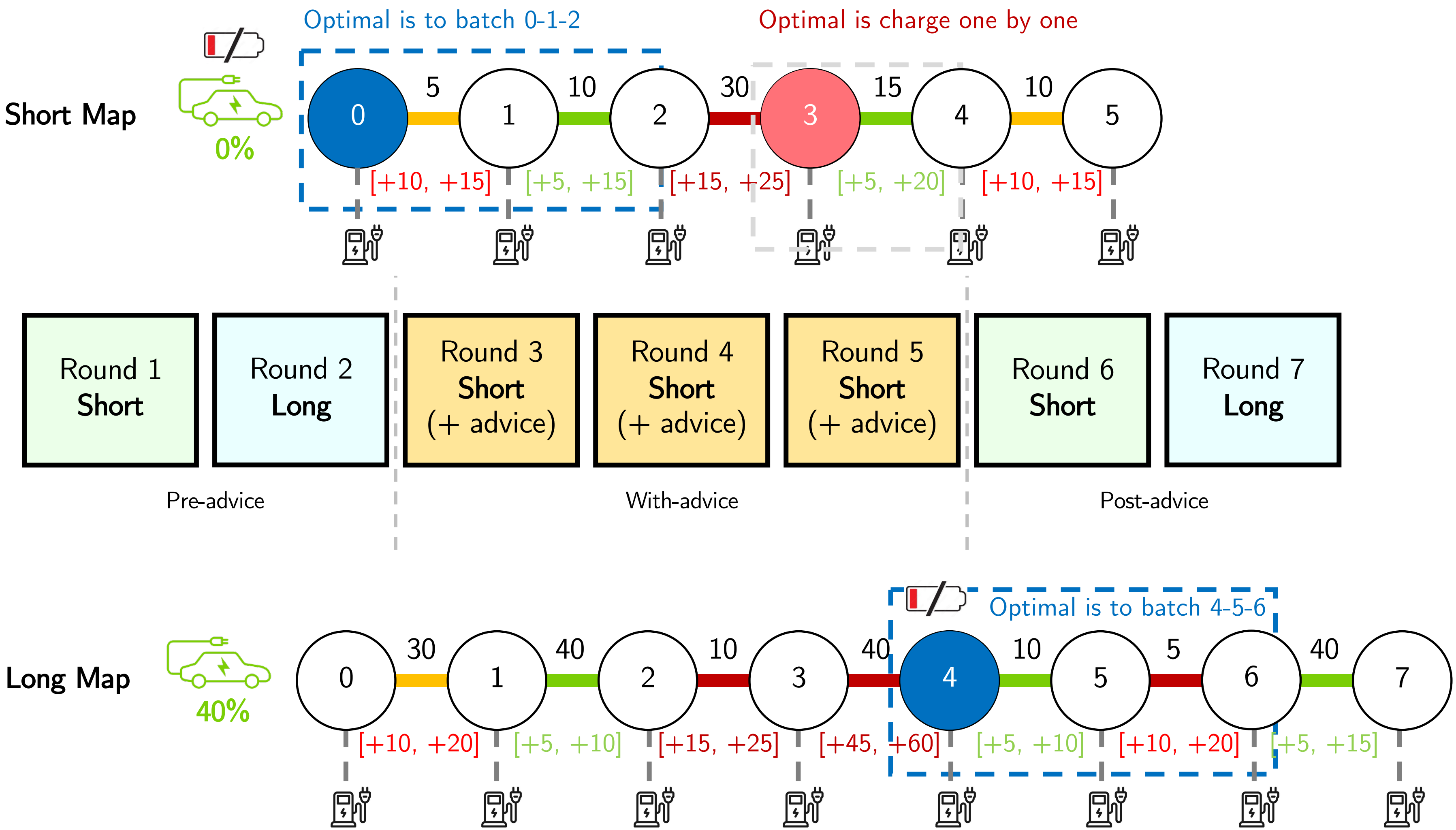
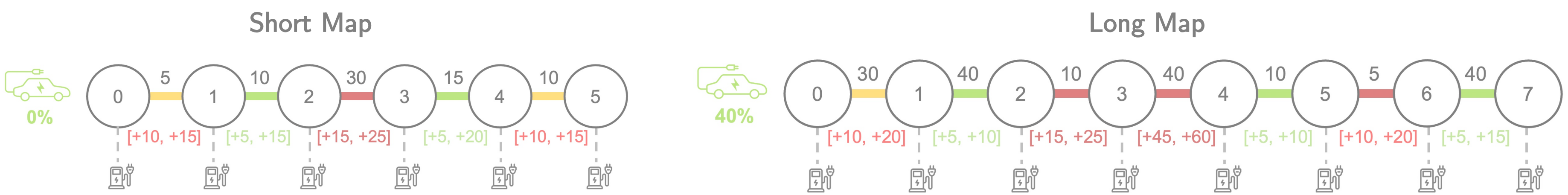
Study 1 + New Environment



Pre-registered at https://aspredicted.org/7LP_J9G

Study 1 Treatment Conditions



Round 1 Short	Round 2 Long	Round 3 Short (+ advice)	Round 4 Short (+ advice)	Round 5 Short (+ advice)	Round 6 Short	Round 7 Long

Pre-advice | With-advice | Post-advice

Pre-registered at https://aspredicted.org/7LP_J9G

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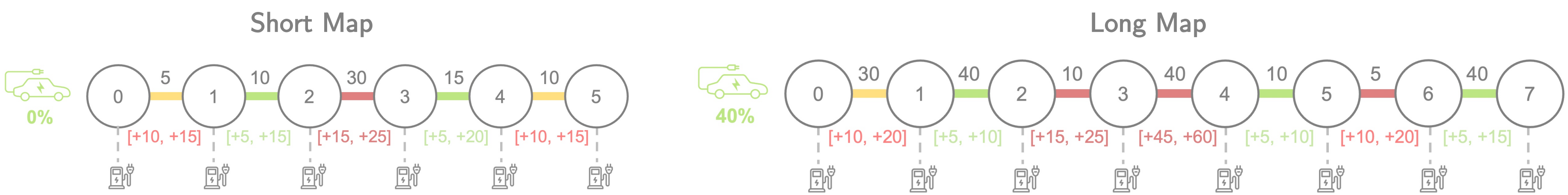

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Pre-advice | With-advice | Post-advice

You should **charge X%**

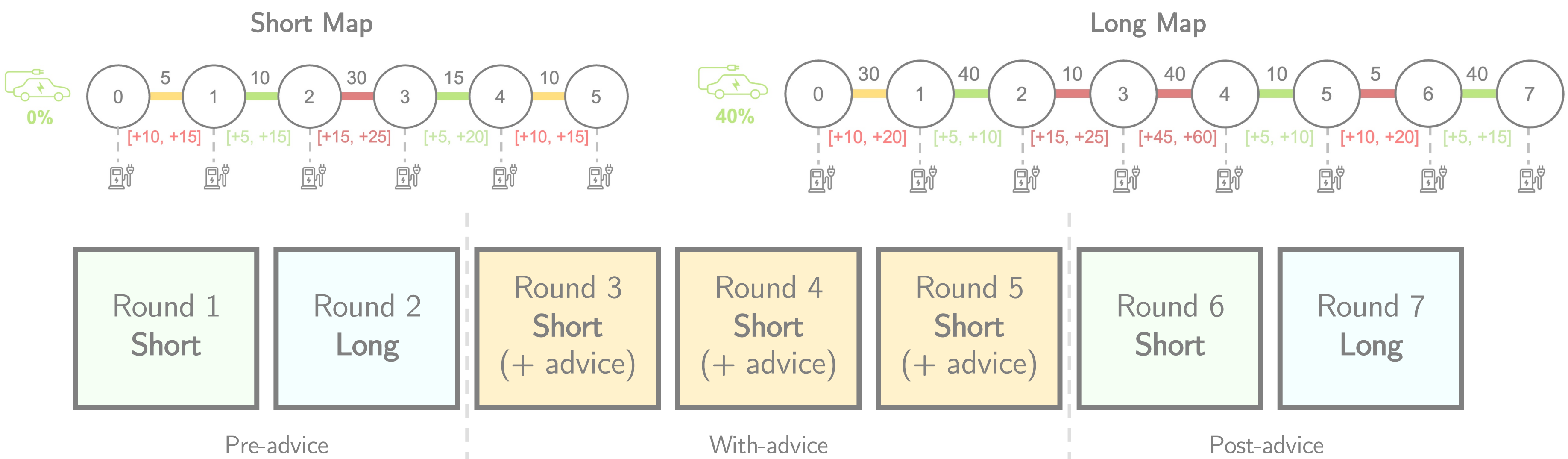
2

precise / **broad**
advice

You should **charge just enough for** this segment + the next one

Pre-registered at https://aspredicted.org/7LP_J9G

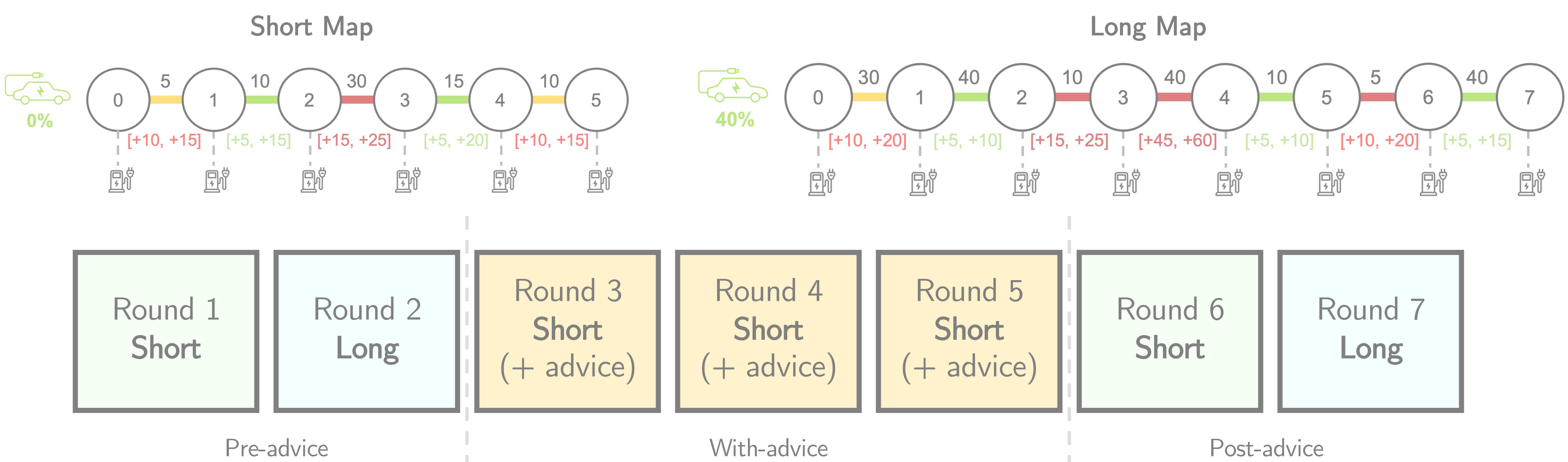
Study 1 Treatment Conditions



From operations, we know that **experiencing uncertainty impacts behaviors...**

Pre-registered at https://aspredicted.org/7LP_J9G

Study 1 Treatment Conditions



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- Workers facing uncertain workload: higher workload → use AI advice more (Snyder et al 2023)

Pre-registered at https://aspredicted.org/7LP_J9G

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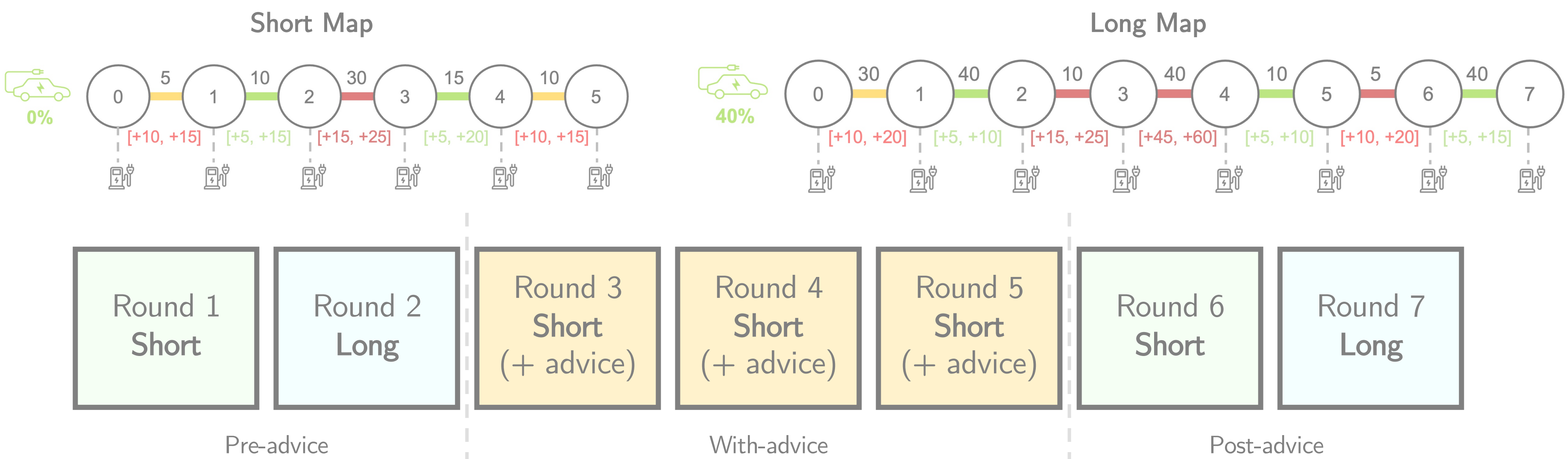

From operations, we know that **experiencing uncertainty impacts behaviors…**

- Workers facing uncertain workload: higher workload → use AI advice more (Snyder et al 2023)
- Paramedics experiencing one (two) prior critical incident(s) spend 2.6% (7.5%) more time completing their tasks (Bavafa & Jonasson 2020)

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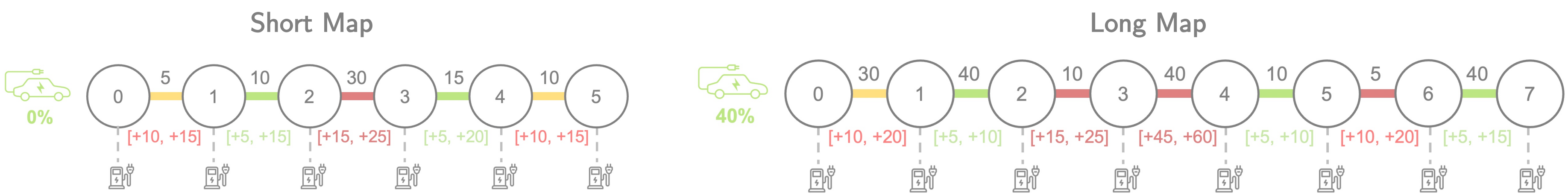
Study 1 Treatment Conditions



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You should **charge just enough for** this segment + the next one

2 x **2**

precise / **broad** advice

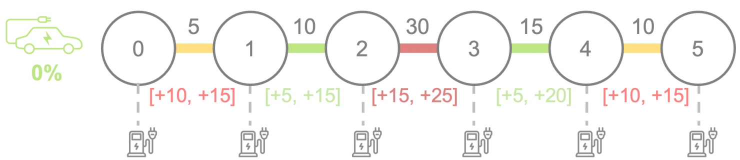
centered / **skewed** realized traffic

estimated traffic: [+10 ——— +20]

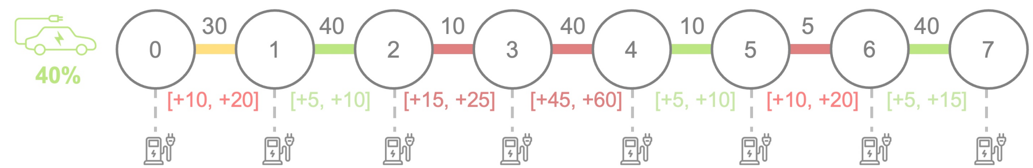
Pre-registered at https://aspredicted.org/7LP_J9G

Study 1 Treatment Conditions

Short Map



Long Map



Round 1 Short	Round 2 Long	Round 3 Short (+ advice)	Round 4 Short (+ advice)	Round 5 Short (+ advice)	Round 6 Short	Round 7 Long

Pre-advice — With-advice — Post-advice

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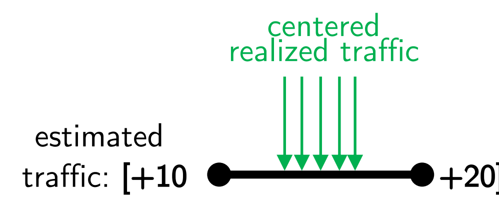

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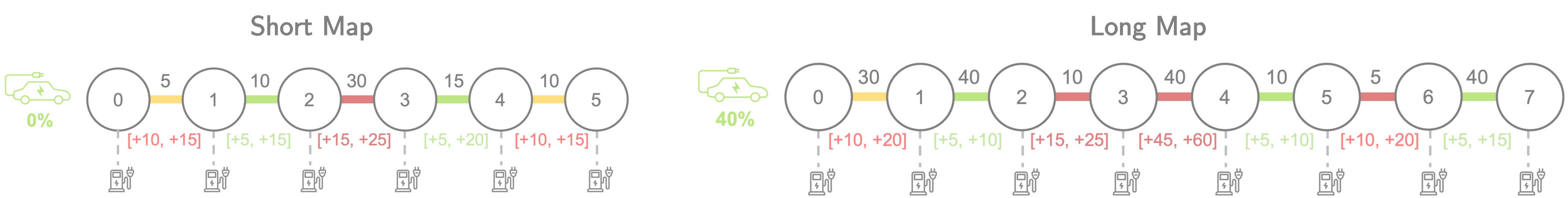
Study 1 Treatment Conditions



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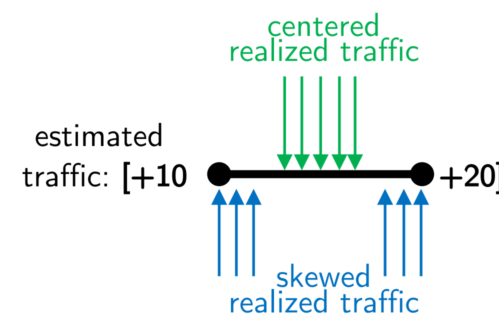
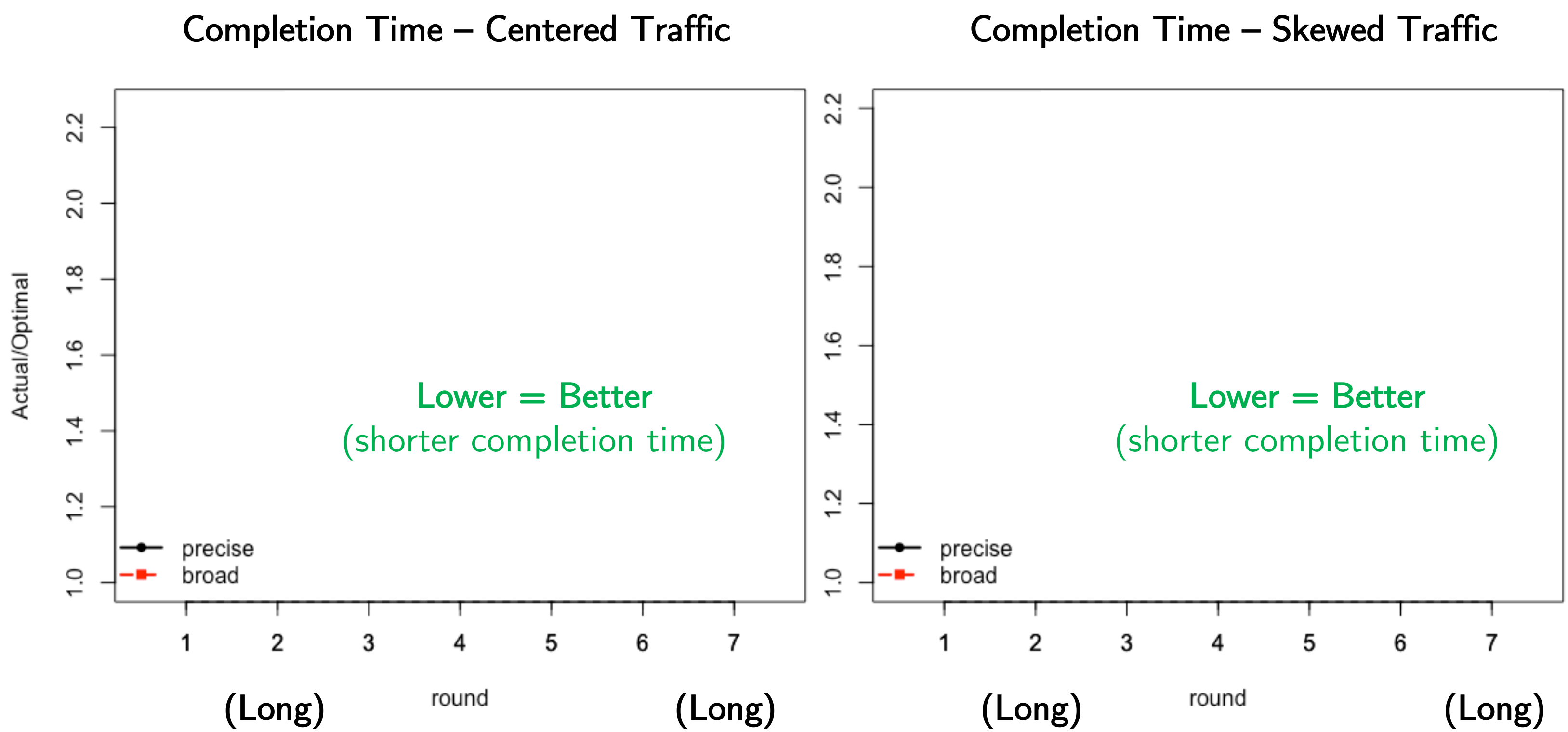


Study 1:

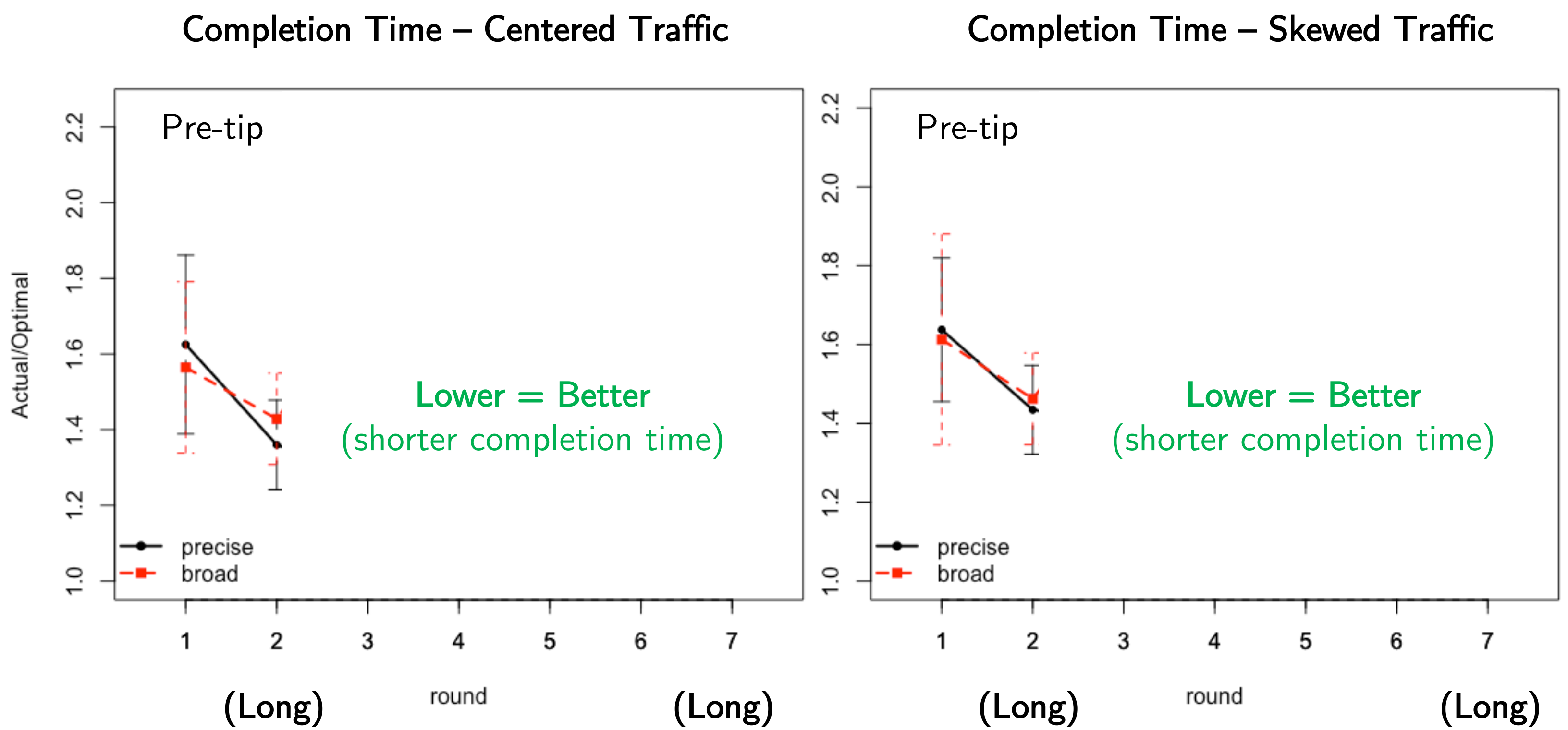
Results Performance Across Rounds



Amazon Mechanical Turk, N = 102, 3,978 decision points

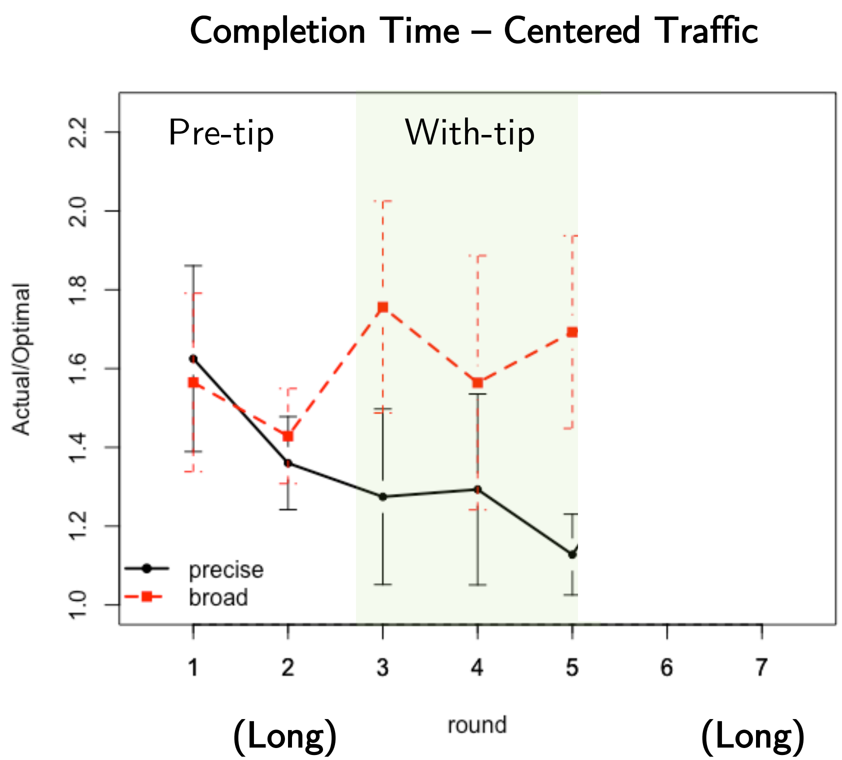
3 R³ S

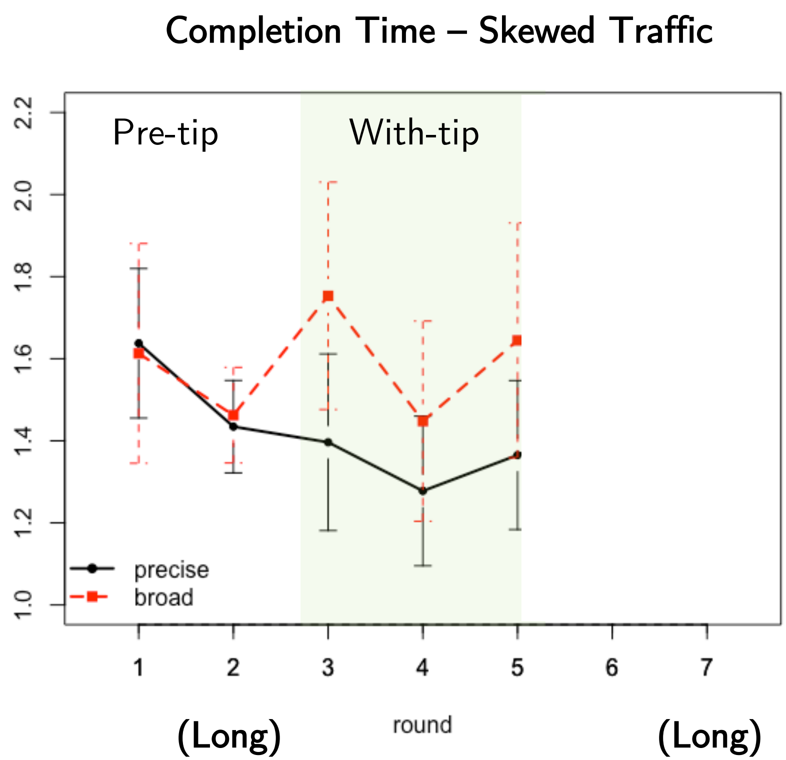
Study 1:
Results



Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 1:
Results

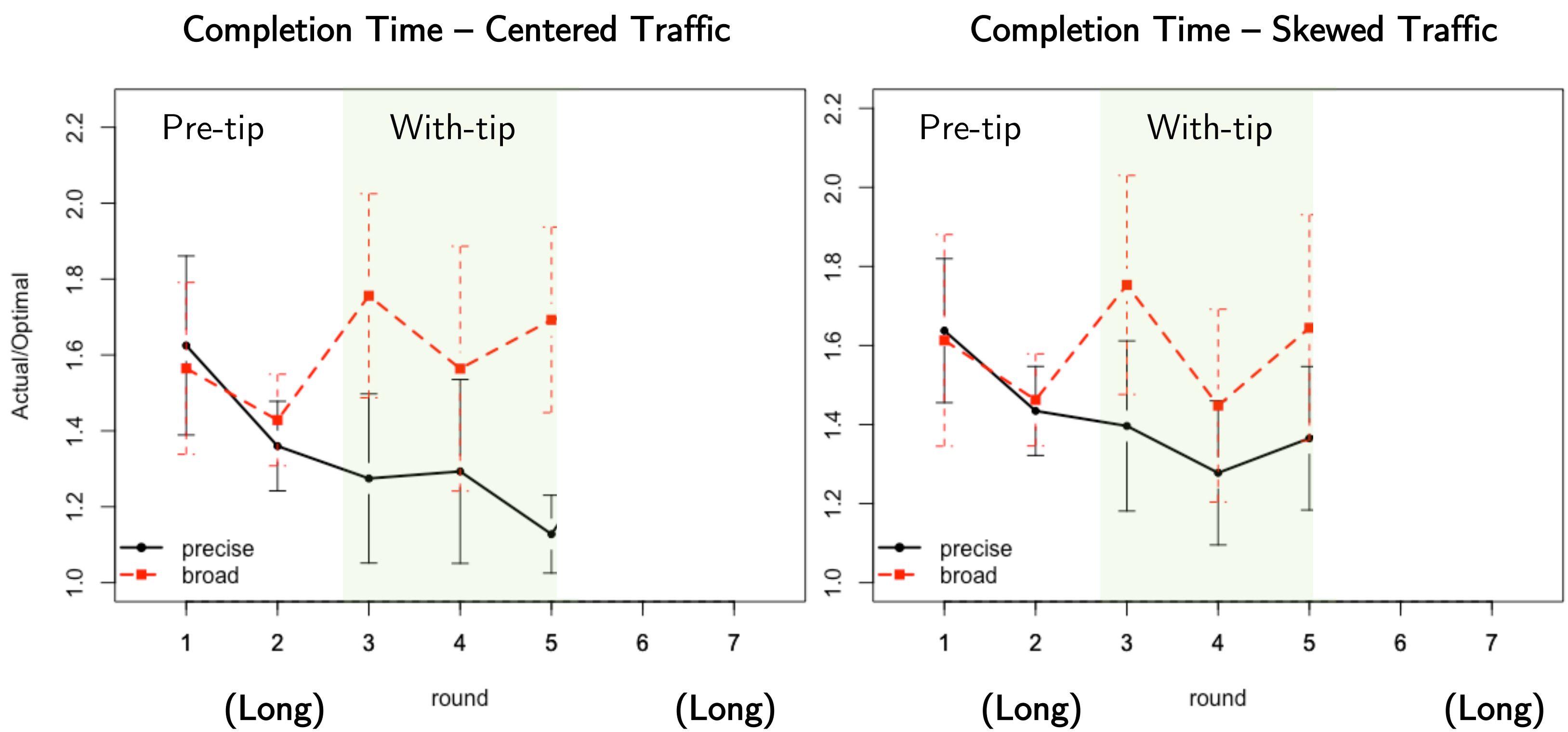




Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 1:

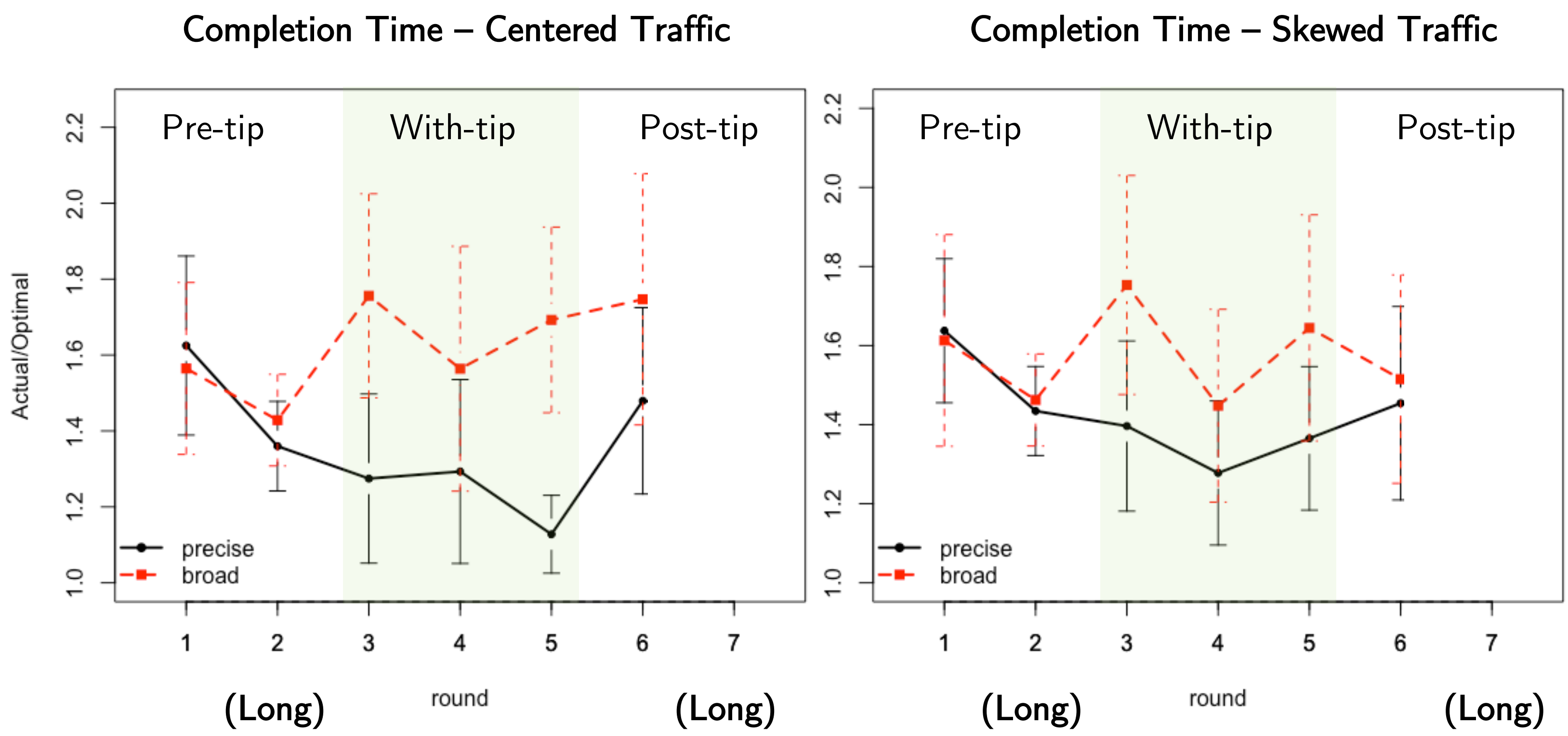
Results Precise Tip Works Instantly



Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 1:

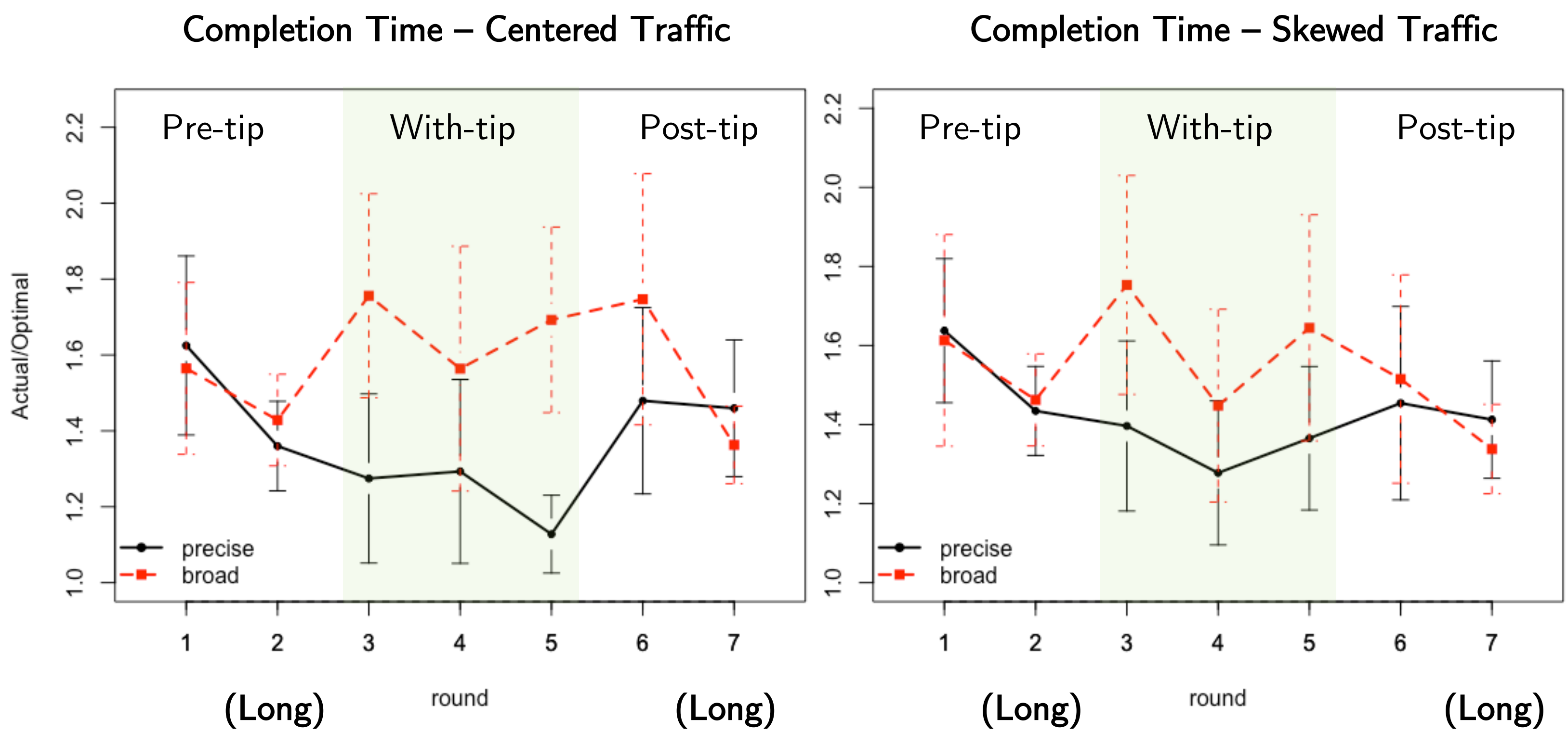
Results Performance Dips Post-Tip



Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 1: Results

Broad Tip Seems to Help with New Environment



Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 1:

Results Broad Tip Seems to Help with New Environment

AI Meets the Classroom:
When Does ChatGPT Harm Learning?

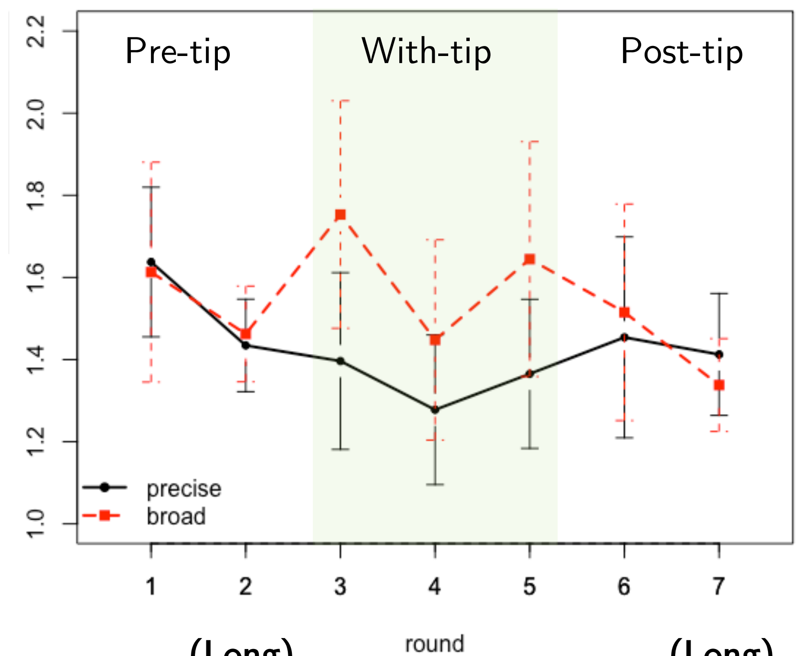
Matthias Lehmann,[1] Philipp B. Cornelius,[2] Fabian J. Sting[1,2]
[1]University of Cologne, [2]Rotterdam School of Management, Erasmus University

Generative AI Can Harm Learning

Hamsa Bastani,[1*] Osbert Bastani,[2*] Alp Sungu,[1*†]
Haosen Ge,[3] Özge Kabakcı,[4] Rei Mariman

[1]Operations, Information and Decisions, University of Pennsylvania
[2]Computer and Information Science, University of Pennsylvania
[3]Wharton AI & Analytics, University of Pennsylvania
[4]Budapest British International School

Completion Time – Skewed Traffic

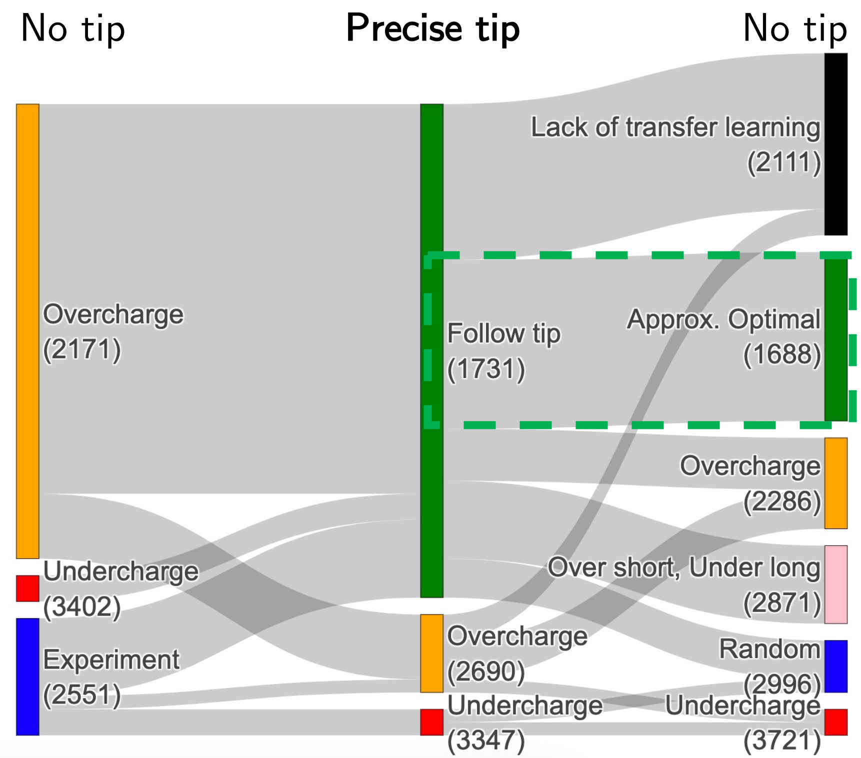


(Long) (Long)

Amazon Mechanical Turk, N = 102, 3,978 decision points

Study 1:

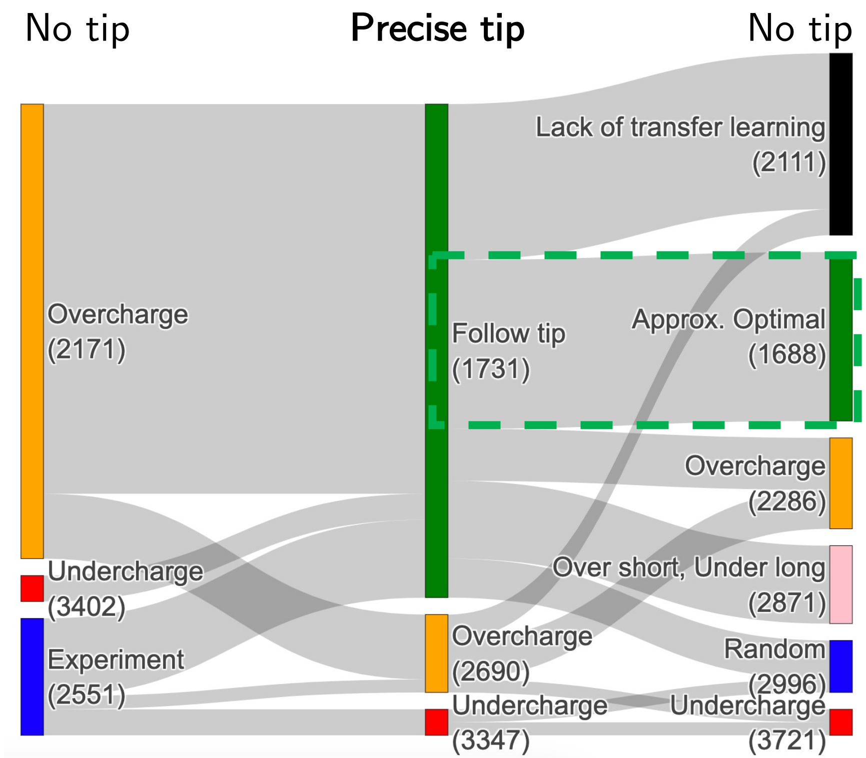
Results Long-Term Learning from Tip



34% stay with
optimal strategy afterwards

Study 1:

Results Long-Term Learning from Tip



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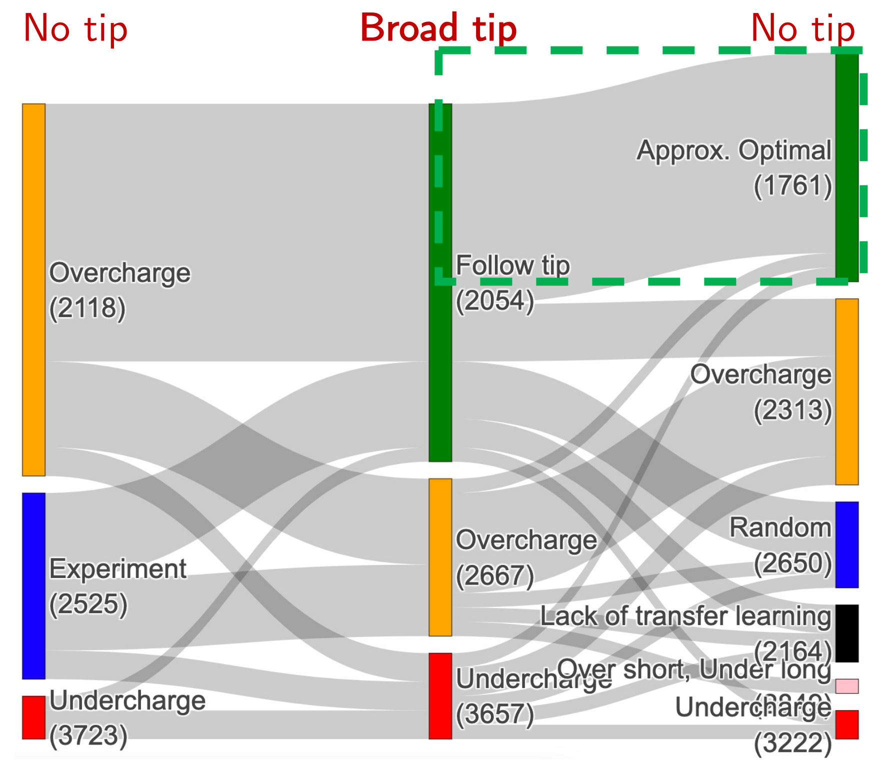
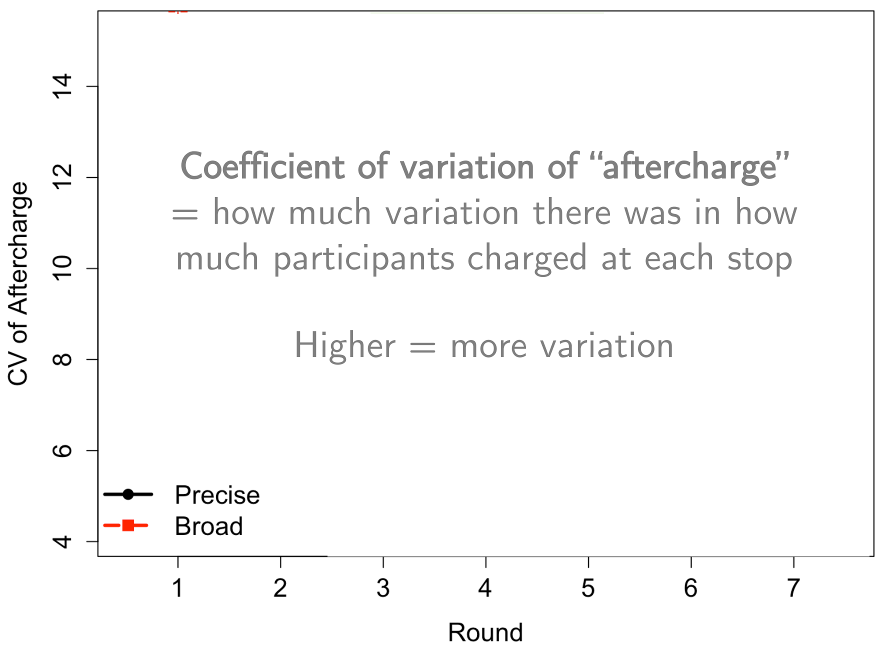


56% stay with
optimal strategy afterwards

Study 1:

Mechanism

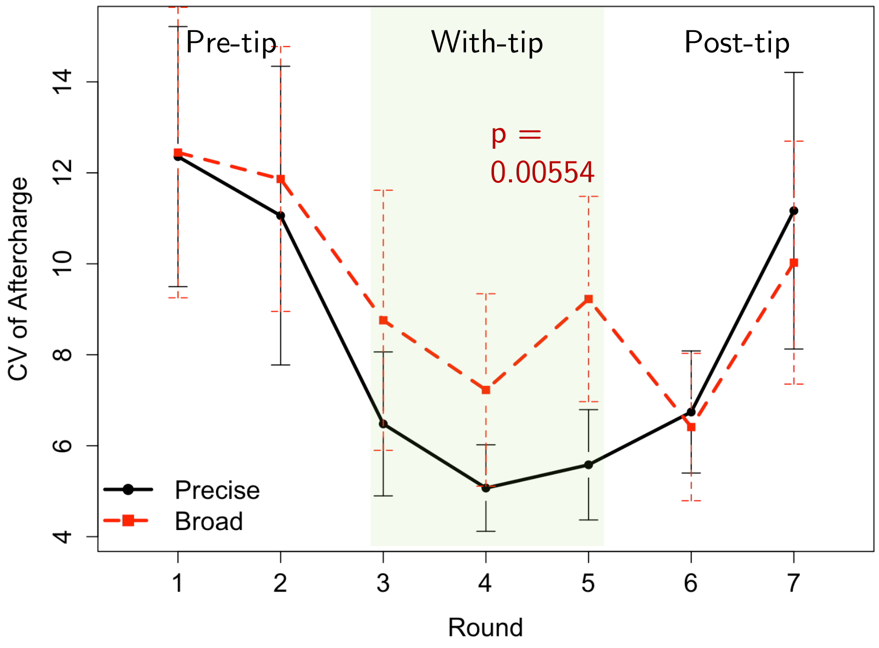
Strategy Exploration



Study 1:

Mechanism

Strategy Exploration



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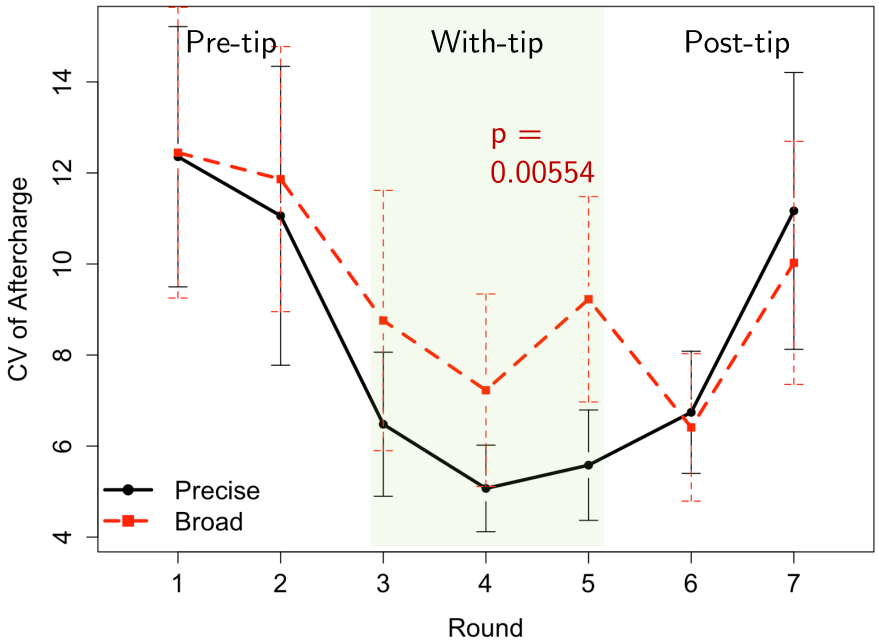
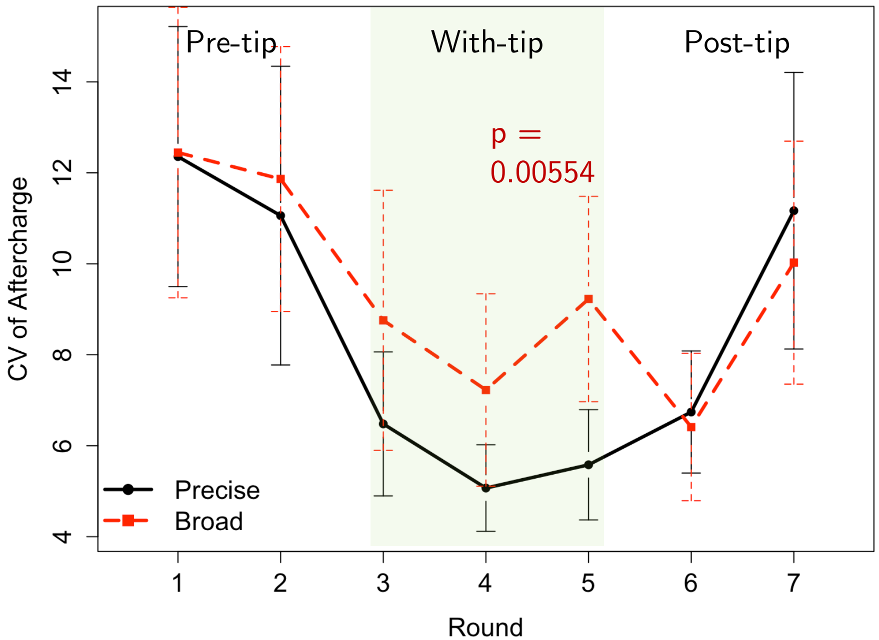


Broad tip: Greater variation in charging decisions

Study 1:

Mechanism

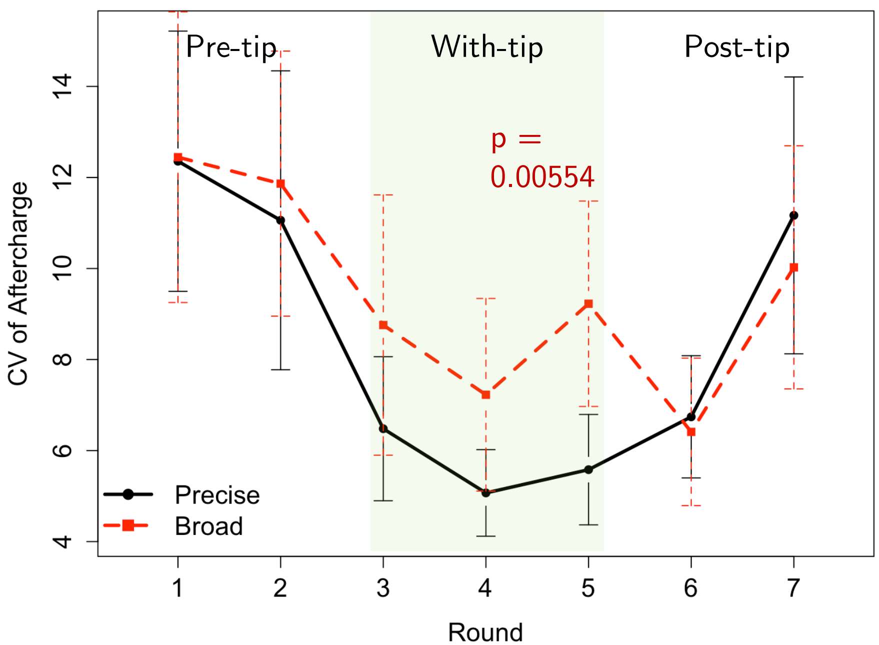
Strategy Exploration

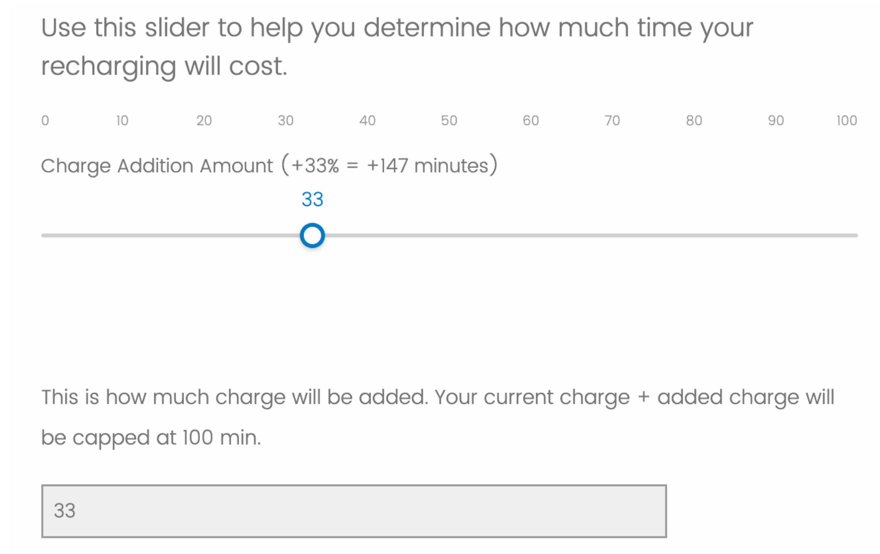


Broad tip: Greater variation in charging decisions
→ continued experimentation and flexible adjustment

Study 1:

Mechanism Strategy Exploration





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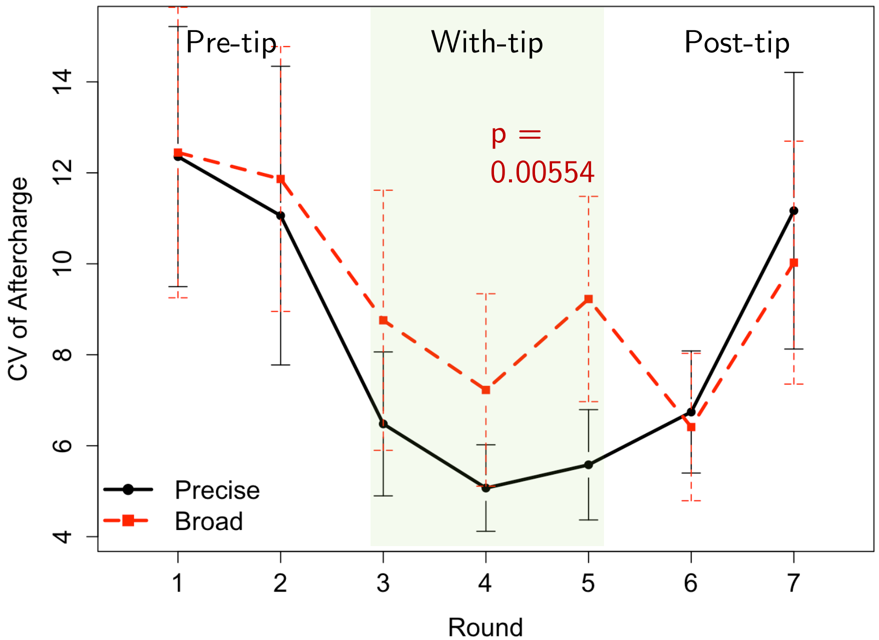
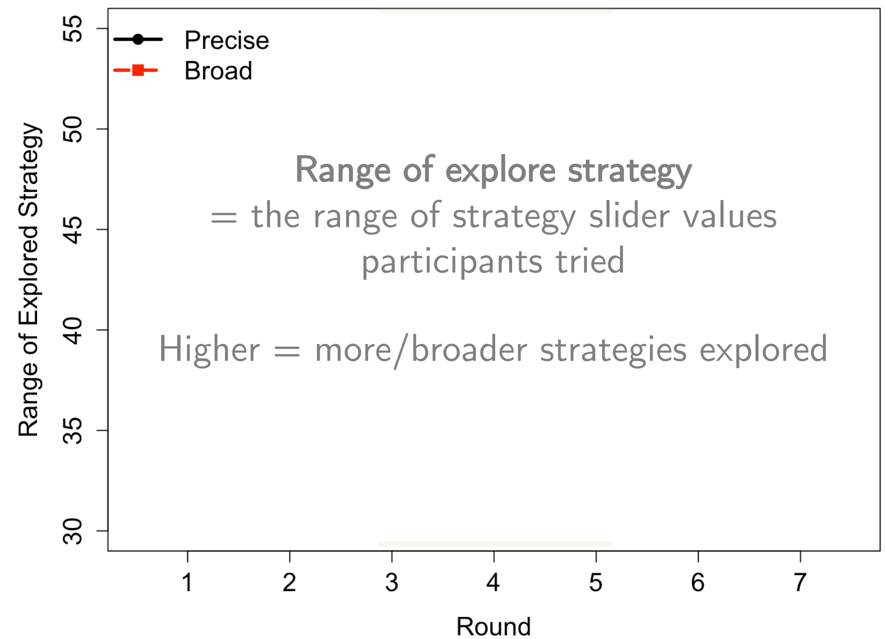
Mechanism Strategy Exploration





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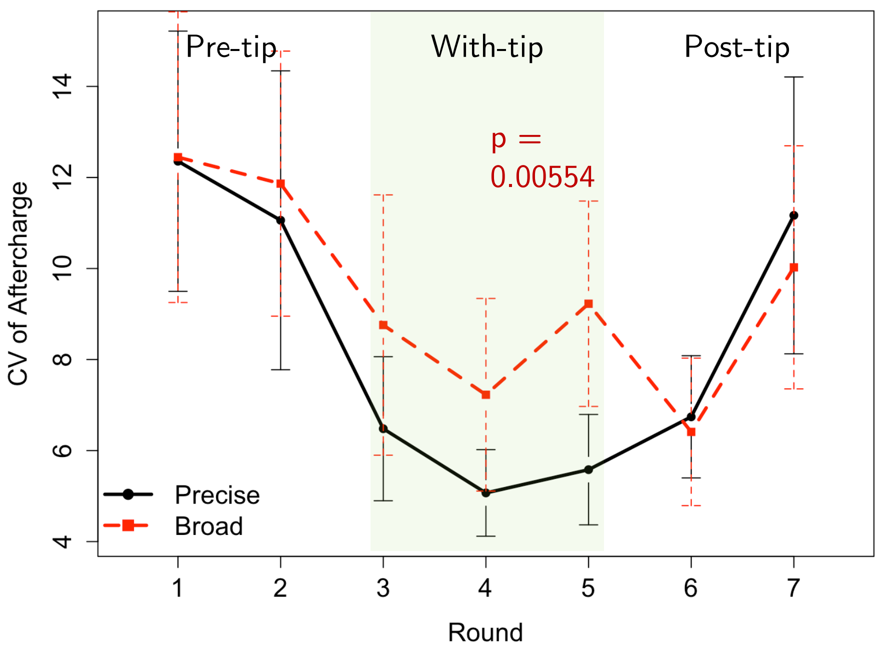
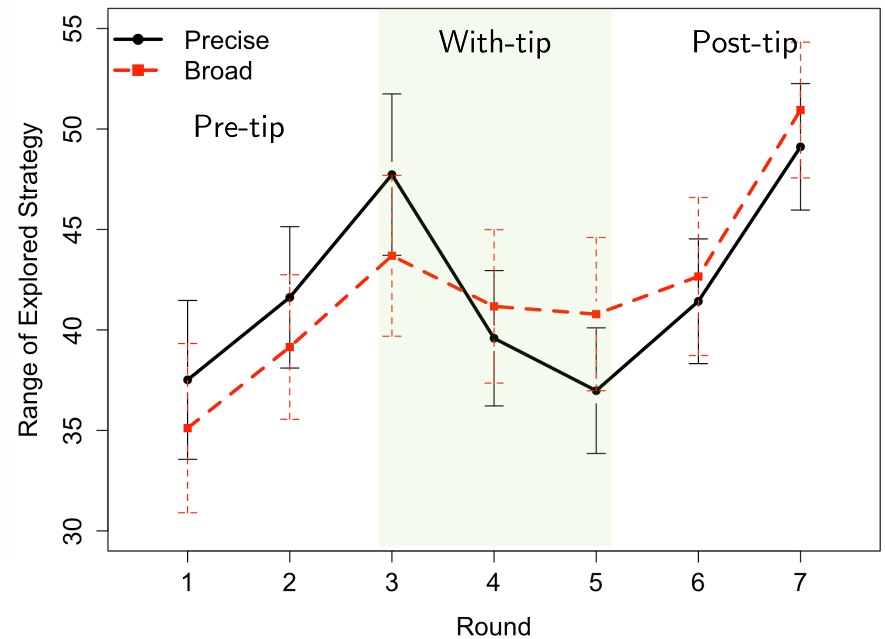
Mechanism Strategy Exploration





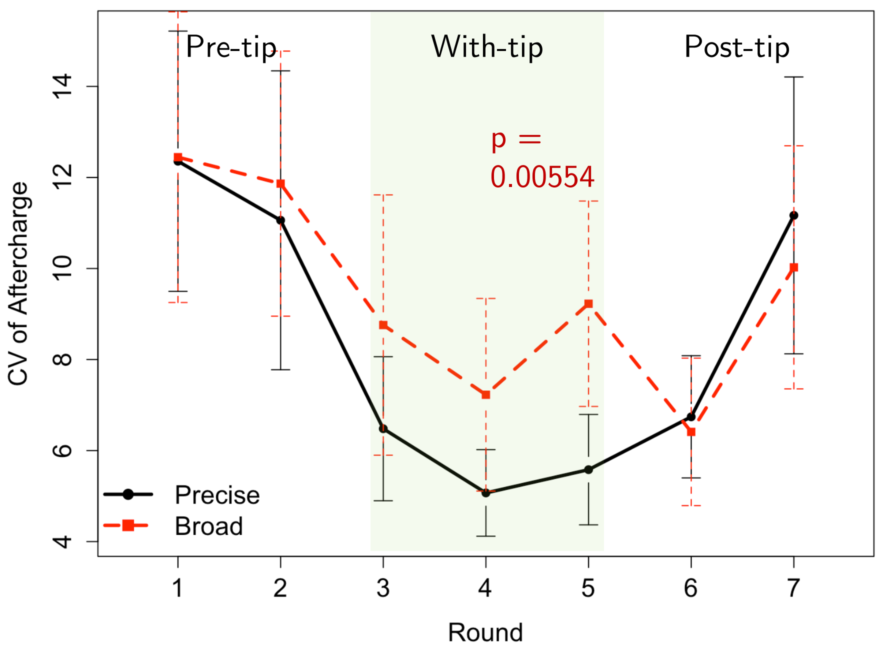
Broad tip: Greater variation in charging decisions
→ continued experimentation and flexible adjustment

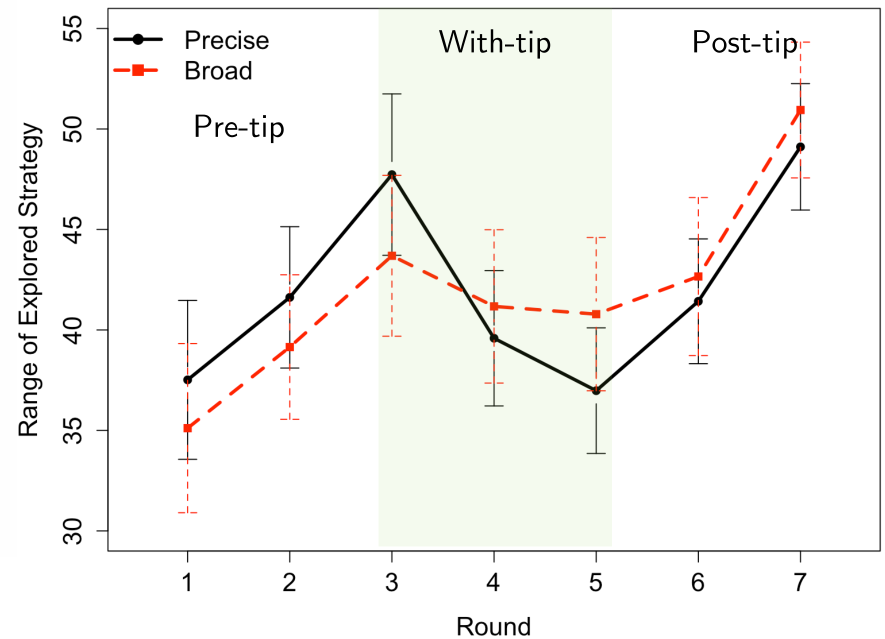
Broad tip: Explore a wider range of charging strategies

Study 1:

Mechanism

Strategy Exploration





Broad tip: Greater variation in charging decisions
→ continued experimentation and flexible adjustment

Broad tip: Explore a wider range of charging strategies
→ deeper engagement with the task, not blind compliance

Humans follow an MDP (S, A, P, r_s, s_1) over a finite horizon T

Quantifying Human Strategy

Inverse Reinforcement Learning (IRL)

- V^ψ = expected sum of rewards when following policy ψ
- Then, we assume that actions are taken according to a (possibly randomized) policy $\psi^* \in \arg\sup V^\psi$ to infer the reward function r_s **(→ the human strategy!)**

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...applied to our case

- Suppose μ^* is the policy maximizing V^{ψ} under the reward function r_s^h of the human decision-maker. We assume that $r_{s_t}^h(a_t) = \sum_{j=1}^{k} \boldsymbol{\theta_j} \phi_j(s_t, a_t)$

various reward components

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various reward components

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- Meanwhile, ν^* is the policy maximizing V^ψ under the reward function r_s^d intended by the designer.

- Without tips, the decision-maker follows μ^*.
- With tips, the decision-maker follows:

$$\psi^* = \begin{cases} \nu^*, & \text{with prob. } \pi \\ \mu^*, & \text{with prob. } 1 - \pi \end{cases}$$

Quantifying Human Strategy

- Human reward function: $r_{s_t}^{h}(a_t) = \sum_{j=1}^{k} \theta_j \phi_j(s_t, a_t)$

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  - $\phi_t =$ **Time taken at current stop** (including charging & emergency)

"Take the **total amount of time needed** to get to the next point after including worst traffic scenario..."

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“Take the **total amount of time needed** to get to the next point after including worst traffic scenario…”

  - ϕ_s = **Simplicity of action** (e.g., high for 0, max, following tip)

“I first just tried to **make sure my charge was 100%.** I then tried to make sure I had just enough charge for the next stop.”

Quantifying Human Strategy

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  "I first just tried to **make sure my charge was 100%.** I then tried to make sure I had just enough charge for the next stop."

  - ϕ_r = **Risk exposure** (decreasing with likelihood of reaching next stop)

  "Play it safe!"

Quantifying Human Strategy

- Human reward function: $r^h_{s_t}(a_t) = \sum_{j=1}^{k} \theta_j \phi_j(s_t, a_t)$
- Based on topic modeling of participant's textual feedback, we derive several components of the reward function, e.g.,

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Others: Risk exposure after penalty (*rp*), margin over worst-case traffic (*m*), split (*sp*)

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Challenge: Each subject has their own weights and compliance probabilities, but we only observe a few rounds per subject/condition.

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Estimation: We use Stochastic Variational Inference (a Bayesian approach)

This enables us to efficiently estimate posterior distributions, rather than point estimates only

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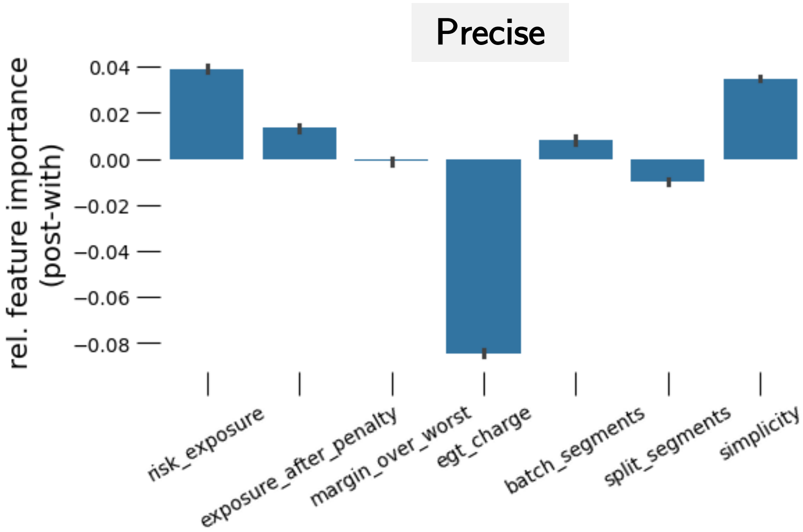

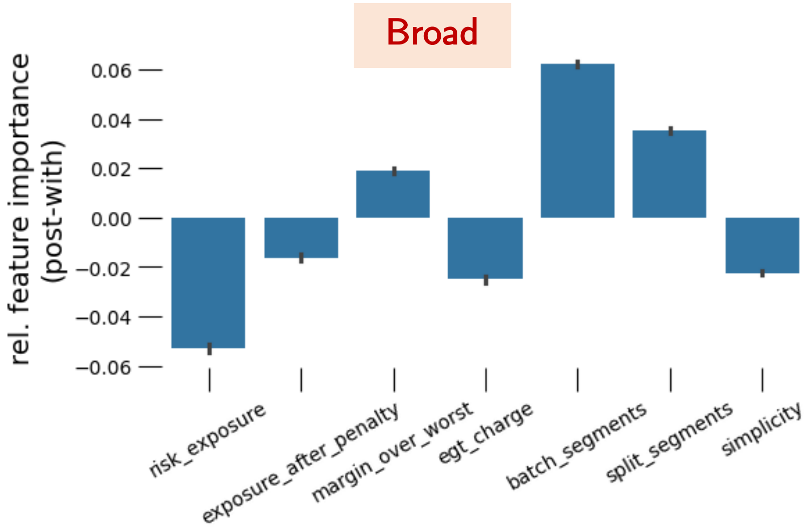

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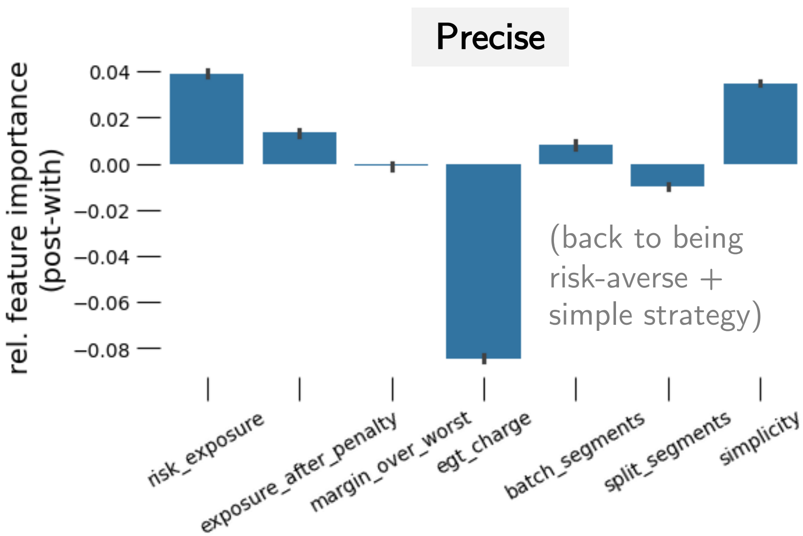

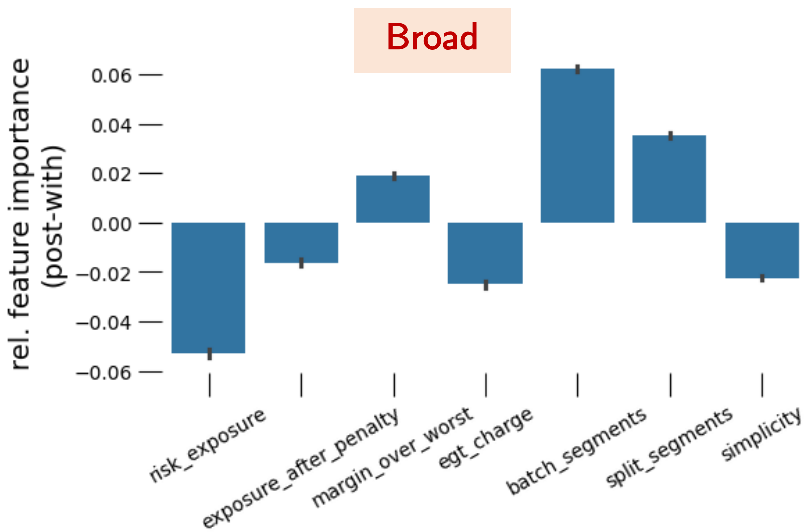

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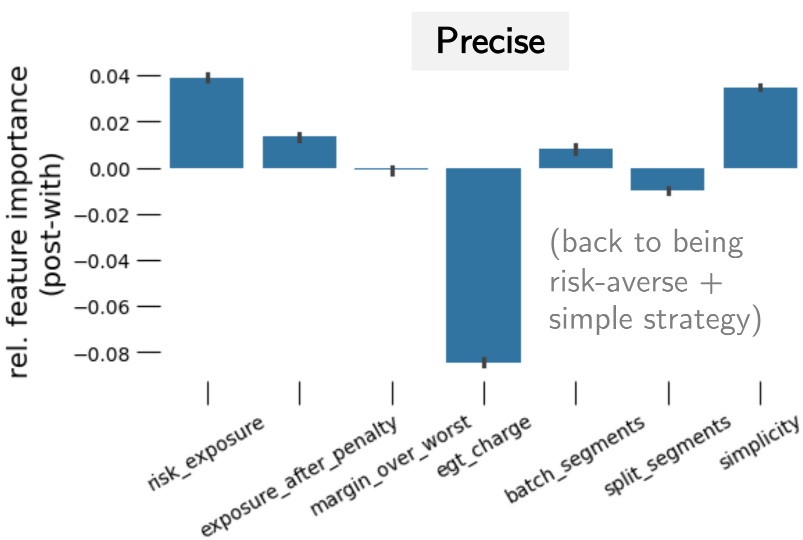

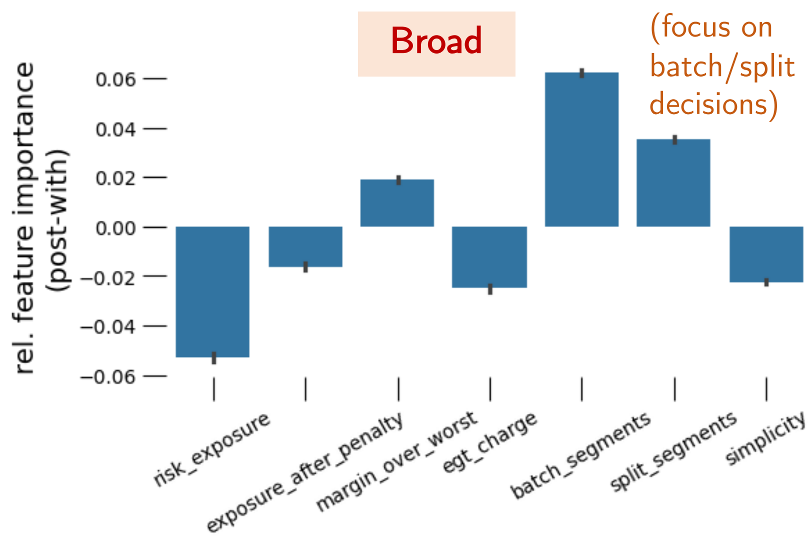

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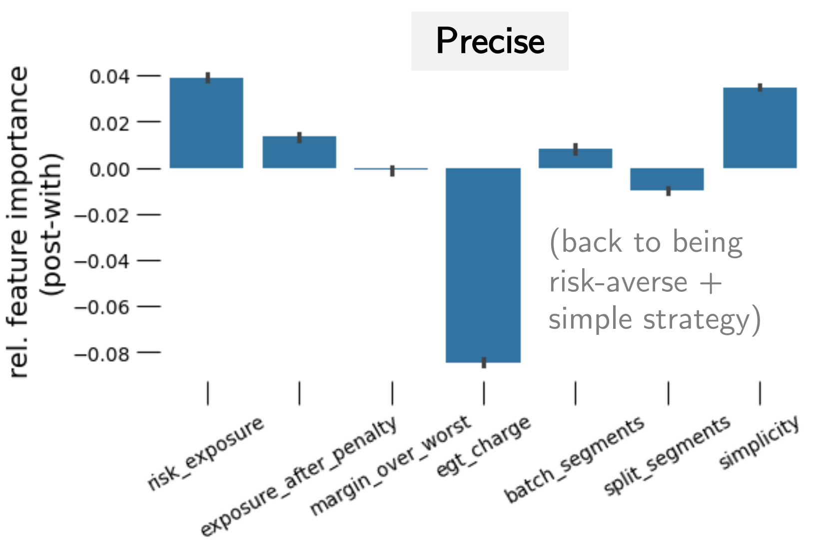

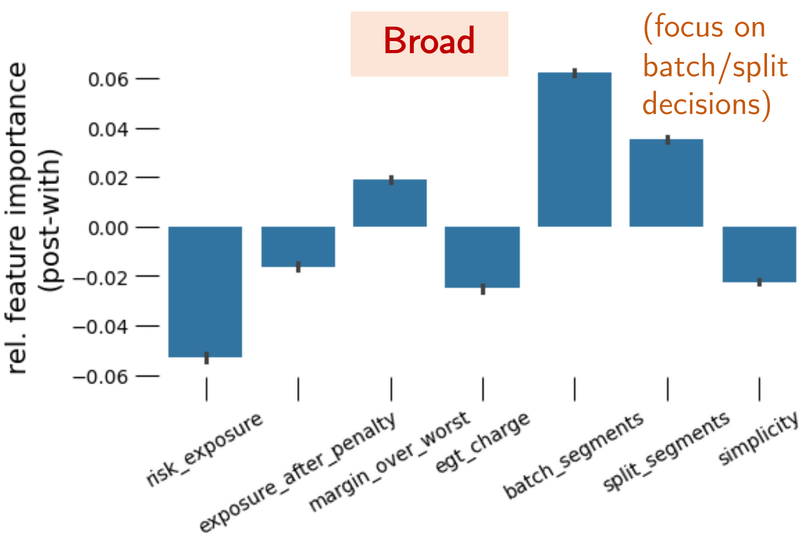

Broad tip nudges humans to internalize the nonlinearity of charging costs: helping them move beyond default preferences for simplicity and safety, and toward more reward-optimal strategies.

Summary

Goal: How to Design/Deliver AI Tips to Support Long-Term Learning?

AI Tips

New environment (no tips)

"Driving Game"

How Humans Make Sequential Decisions? → How Do Tips Shape Learning & Behavior Over Time? → Can Humans Adapt When Environment Changes?

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Precise tips improve short-run efficiency, but without explanation, they can limit learning and adaptability.

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Feedback (+ tips) very welcome!

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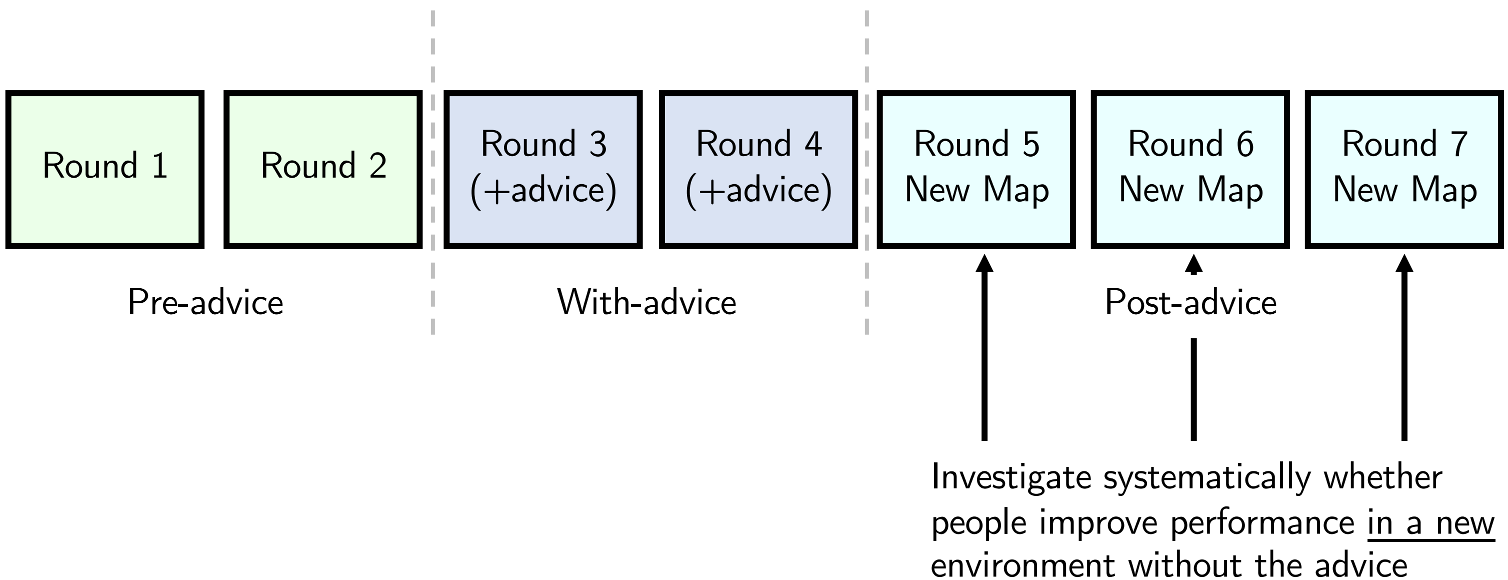
R3 S

Study 3



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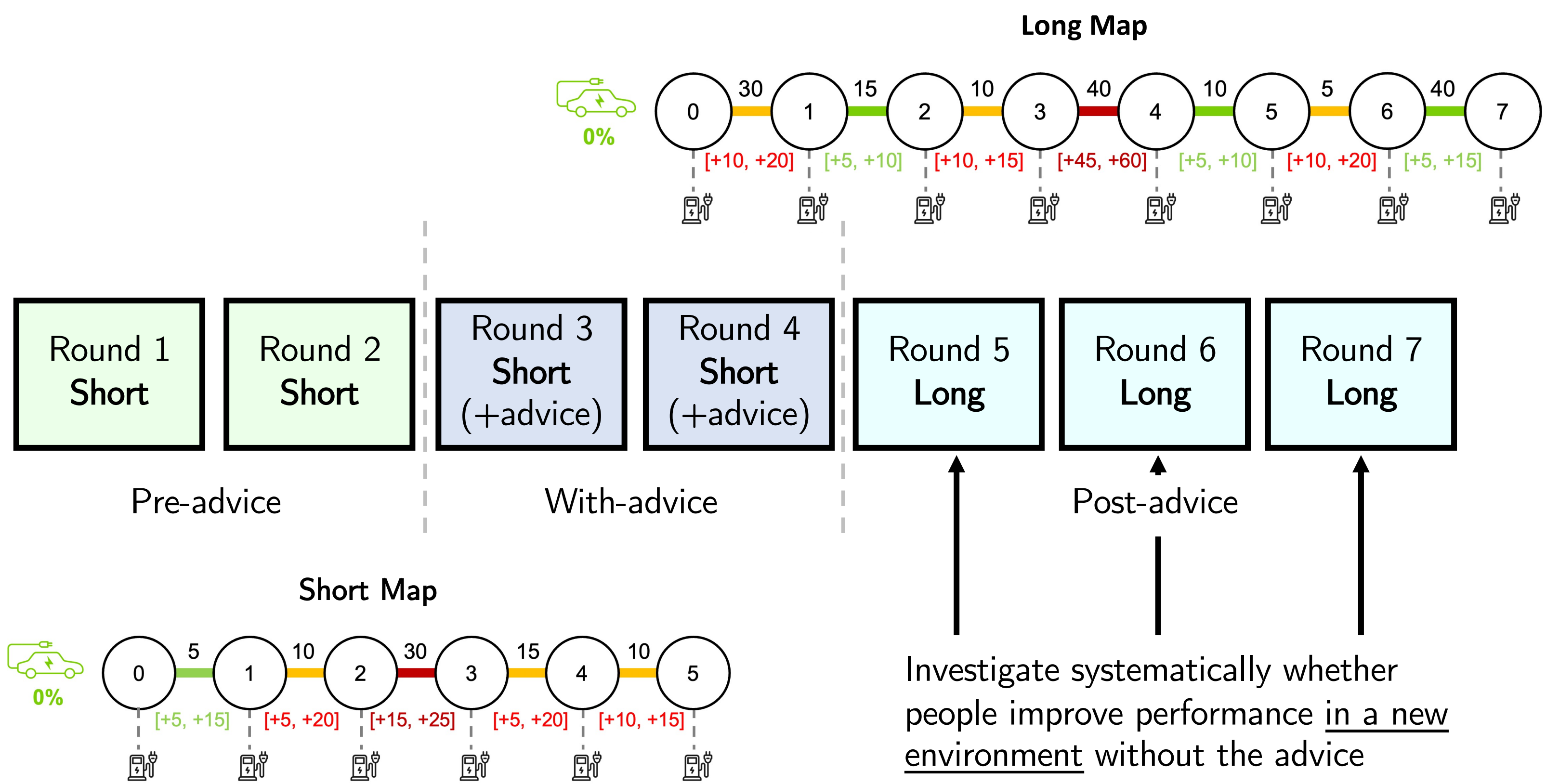

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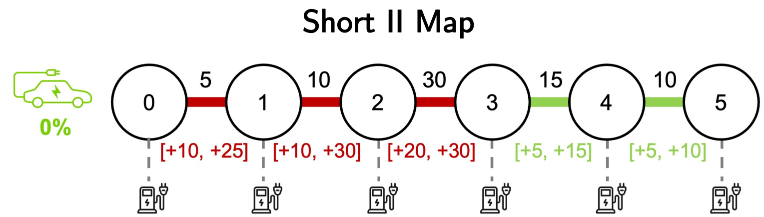
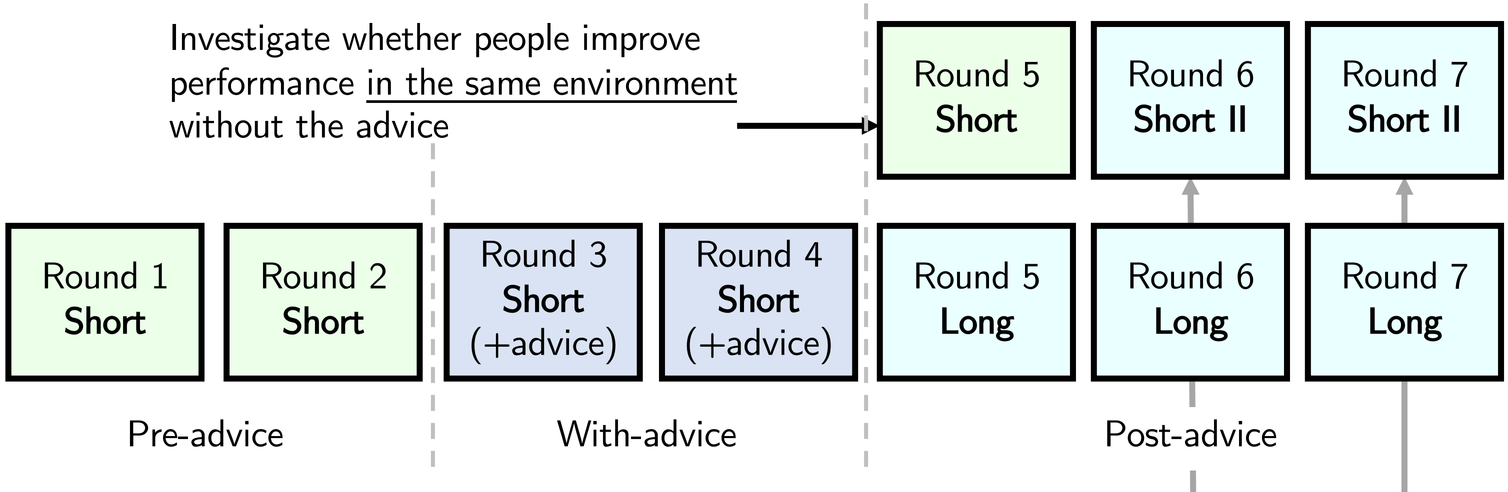
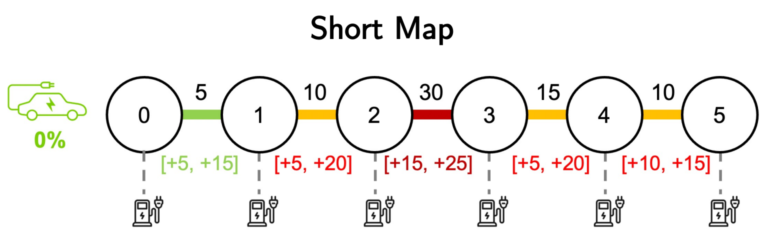
Study 3

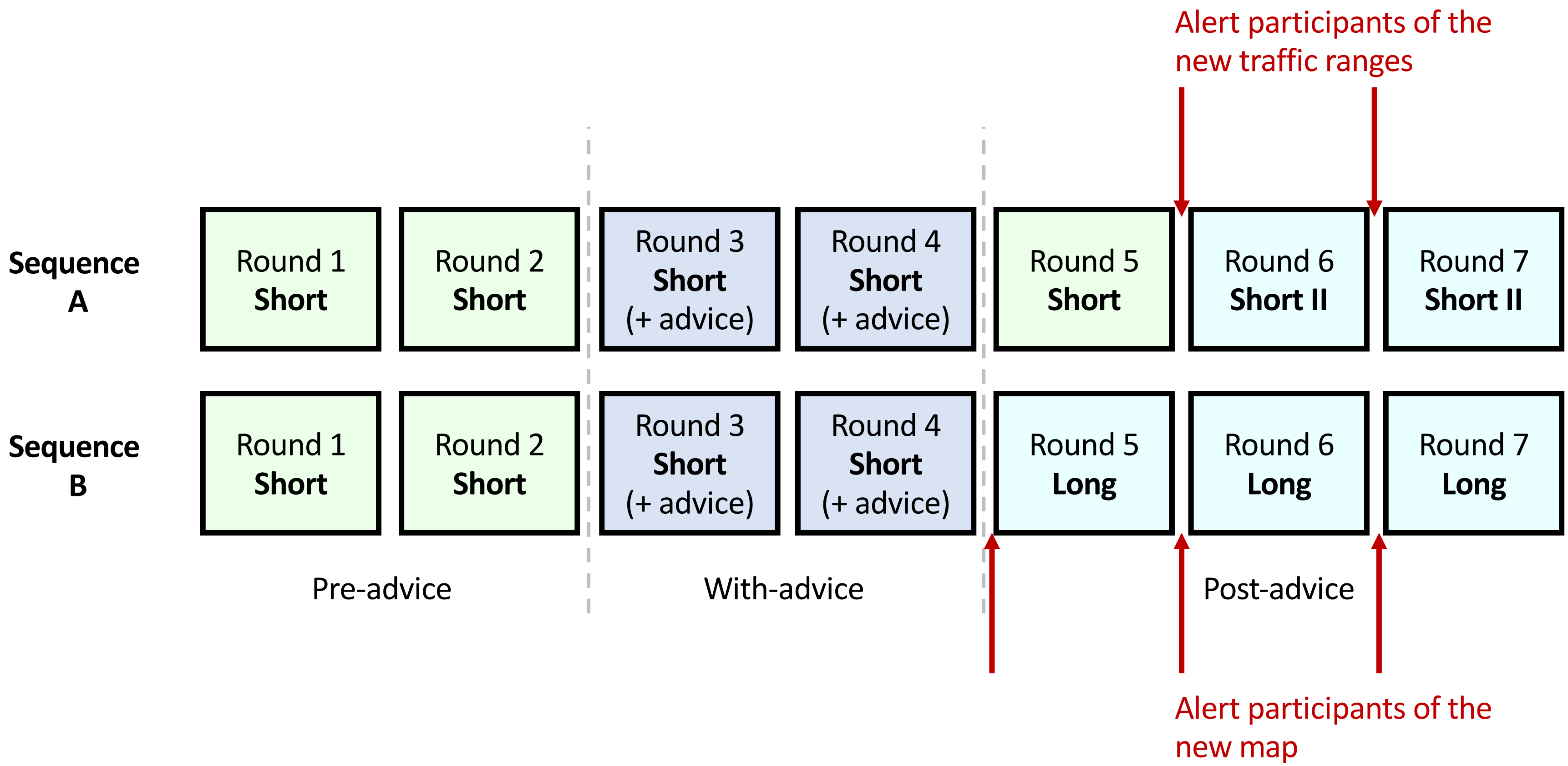
Same segments as Short
but with different traffic estimates
→ optimal batching is different!







Investigate systematically whether
people improve performance in a new
environment without the advice


Alert participants of the new traffic ranges
Sequence A
Round 1 Short
Round 2 Short
Round 3 Short (+ advice)
Round 4 Short (+ advice)
Round 5 Short
Round 6 Short II
Round 7 Short II
Sequence B
Round 1 Short
Round 2 Short
Round 3 Short (+ advice)
Round 4 Short (+ advice)
Round 5 Long
Round 6 Long
Round 7 Long
Pre-advice
With-advice
Post-advice
Alert participants of the new map

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Study 3

	Pre-advice		With-advice		Post-advice		
Sequence A	Round 1 **Short**	Round 2 **Short**	Round 3 **Short** (+advice)	Round 4 **Short** (+advice)	Round 5 **Short**	Round 6 **Short II**	Round 7 **Short II**
Sequence B	Round 1 **Short**	Round 2 **Short**	Round 3 **Short** (+advice)	Round 4 **Short** (+advice)	Round 5 **Long**	Round 6 **Long**	Round 7 **Long**

Experimental conditions

2

map sequences

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Study 3

	Pre-advice		With-advice		Post-advice		
Sequence A	Round 1 Short	Round 2 Short	Round 3 **Short** (+advice)	Round 4 **Short** (+advice)	Round 5 Short	Round 6 Short II	Round 7 Short II
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Experimental conditions

2 map sequences x **3** advice precision

Precise Numerical: You should charge X%

Precise Qualitative: You should charge enough for this segment and the next, **assuming worst case traffic**

Broad Qualitative: You should charge enough for this segment and the next

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Experimental conditions

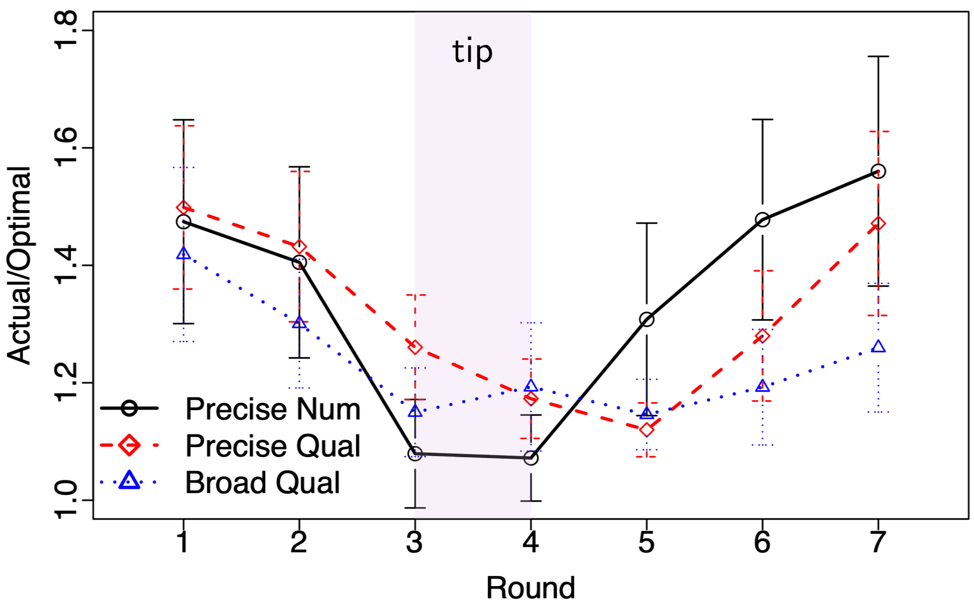
2 map sequences x 3 advice precision x 2 rationale?

Rationale:
"Looking ahead, if you need to charge but the sum of charges required for next segments <50%, charging is fast, so you should charge enough for these segments in one stop."

Study 3:

Results Broad's Success Replicated! 😊

😊 Familiar new map, no rationale



Prolific, N = 400

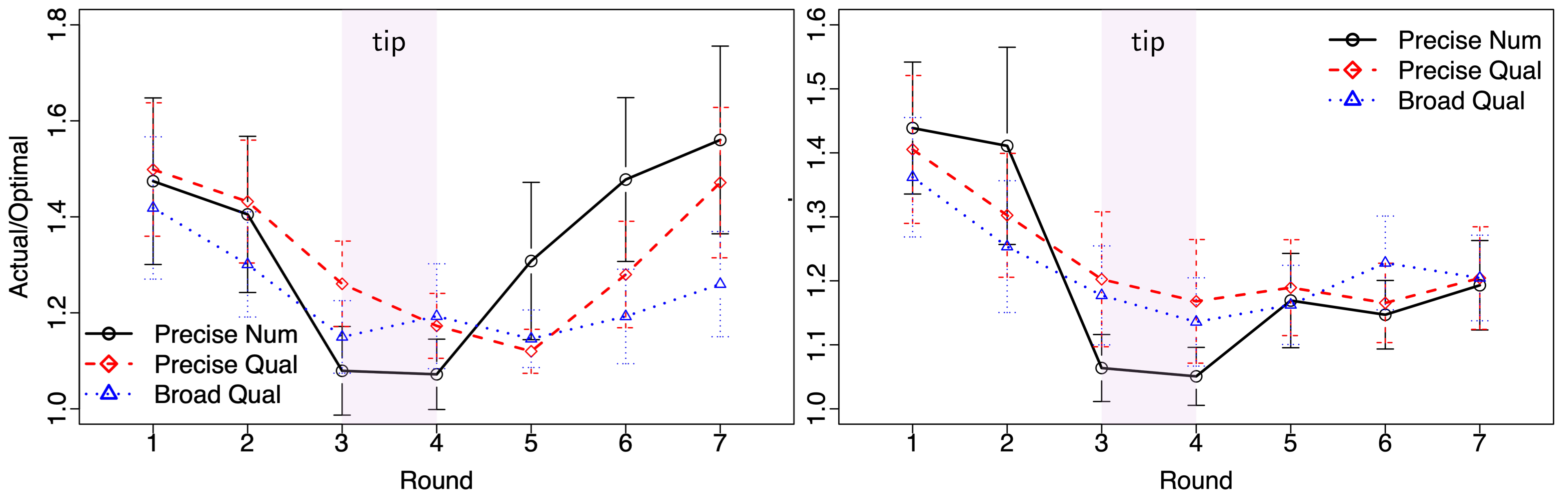
Study 3:

Results

Broad's Success Replicated! 😊
…Not When Things Change A Lot 🥺

😊 Familiar new map, no rationale

Unfamiliar new map, no rationale 🥺



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Results Rationale Helps with Precise Tip 😲

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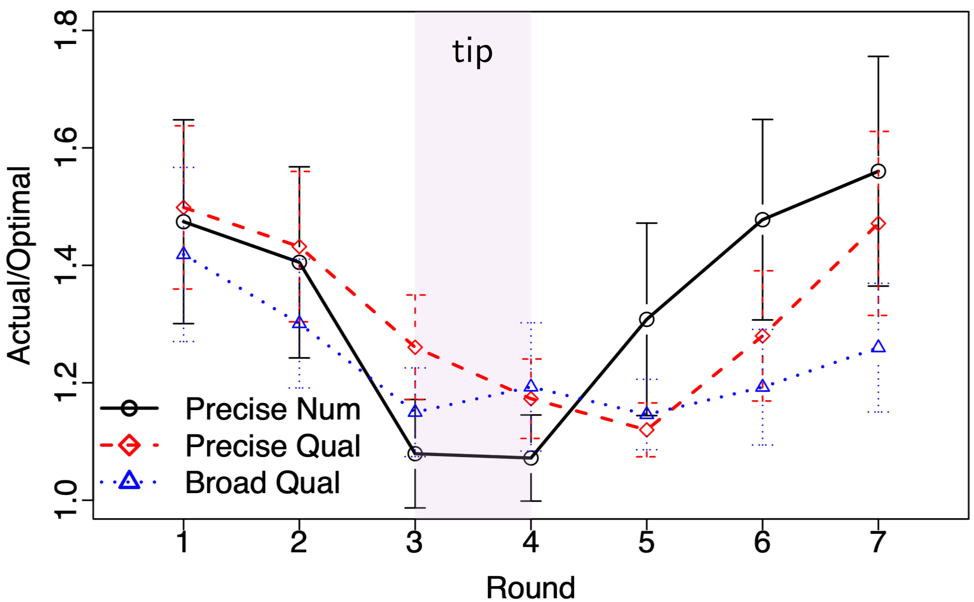
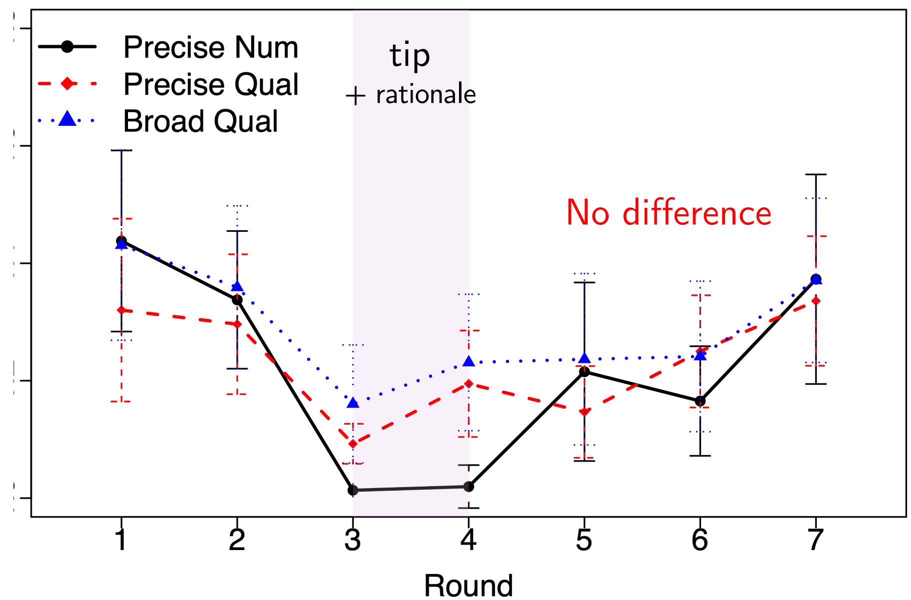


Familiar new map + rationale 😲



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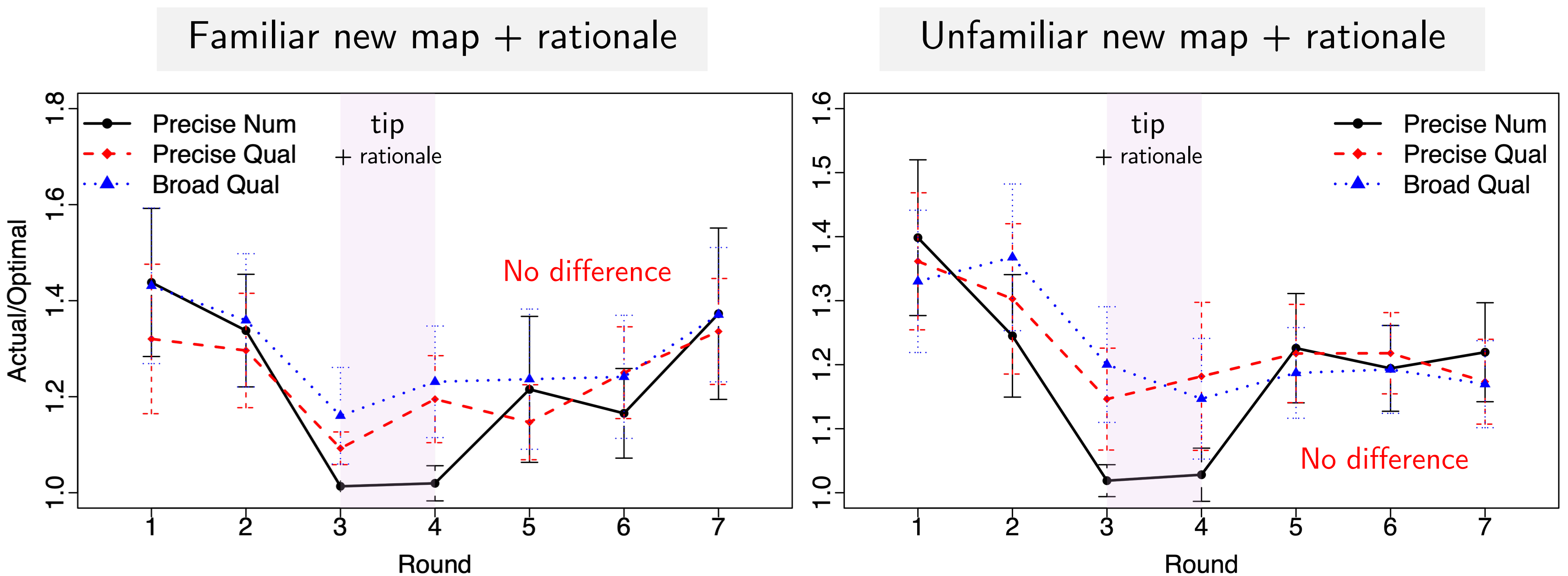


Prolific, N = 400

R³ S

Study 3:

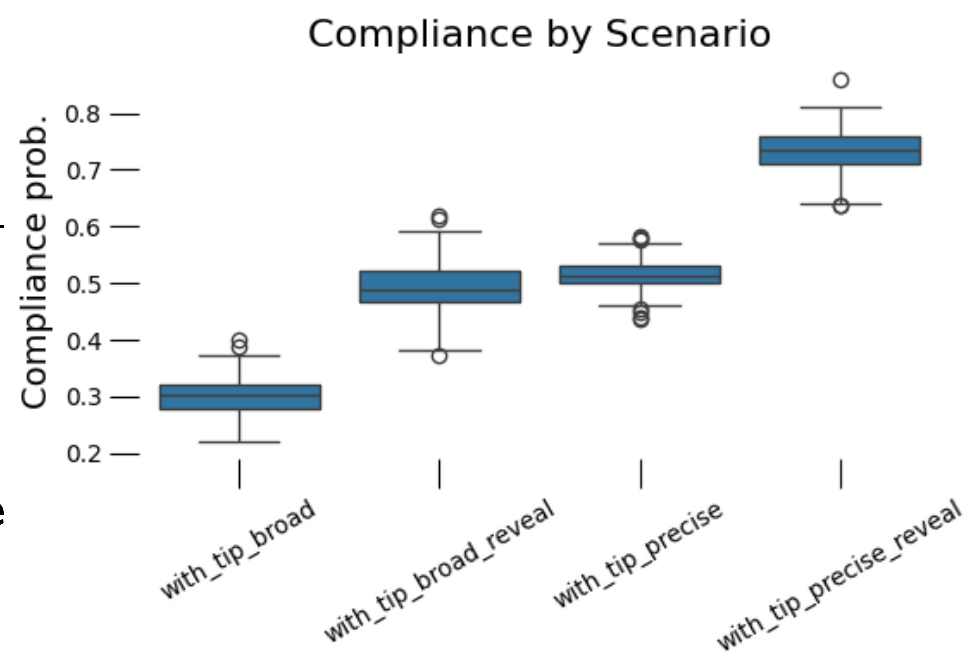
Mechanism How Tips Affect Strategy

Recall that in our IRL approach, we use a scenario-specific shift: $\boldsymbol{\Delta}_s$, respectively η_s

Here, we adjust $\boldsymbol{\Delta}_s$ and η_s, to take into consideration explanations: $s \in$ {pre, with(*type,reveal*), post(*type,reveal*)}:

- Broad+reveal leads to similar compliance as precise
- Feature-changes (with-tip → post-tip) are "in-between" what we observe from broad alone and precise alone

→ Useful in capturing the **immediate benefits of precise tips** and some of the **long-term benefits of broad tips**



Mechanism

Interlude: Validating the Approach

1. Synthetic data:
   - We **randomly generate** model **parameters**
   - Then, in the **existing trajectories**, we **replace the actions** taken by actions drawn from the policy suggested by our model
   - This shows that our estimation procedure can **identify parameters accurately**

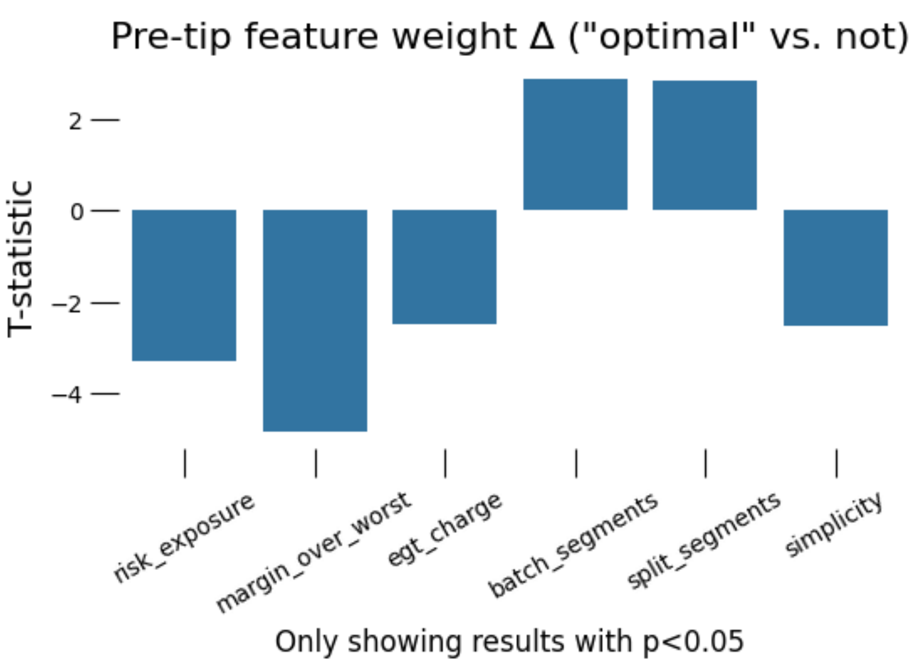
	$corr(\Delta_s, \widehat{\Delta}_s)$	$corr(\Delta_i, \widehat{\Delta}_i)$	$corr(\pi_s, \pi_s)$	$corr(\pi_i, \pi_i)$
Avg.	0.96	0.88	0.99	0.94
Std.	0.03	0.06	/	/

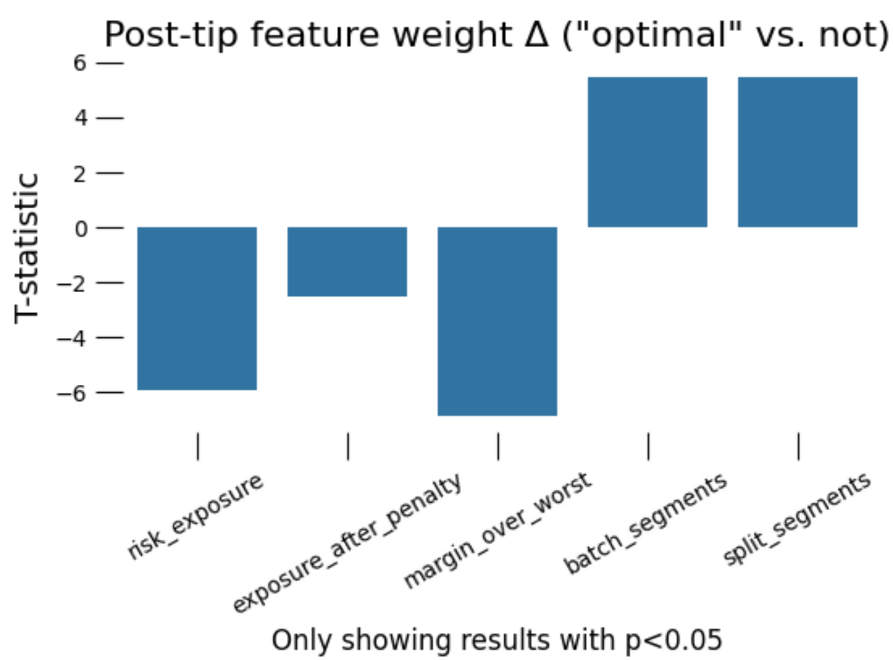
2. Real data, standard checks:
   - **Log-likelihoods**: Test set LL on real data (-13.41) in line with training LL on real data (-13.03) and test set LL on synthetic data (-11.81)
   - **Posterior-predictive checks**: Actual action is "as far" from estimated probabilities as action generated from model (Brier score of observations = 36.60, Avg. Brier score of simulations = 38.35, p = 0.93)

Mechanism

Interlude: Validating the Approach

3. Real data, consistency with qualitative insights:
   - We estimate our model on the actual data, then **compare the participant-specific shifts** based on the qualitatively assigned groups (sequence clusters)
   - We compare the individuals in the **"Optimal"/"learning" clusters to others**





Compliance (logit) of "Optimal" vs. other clusters: T-stat=11.47 (p-value < 0.01)