

Change in Online Taxi Drivers' Labor Supply: Experience or Price Effect?

Peyman Shahidi

University of Chicago Booth School of Business

September 23, 2022

Outline

- 1 Introduction
- 2 Institutional Background and Data
- 3 Model
- 4 Simulation
- 5 Identification
- 6 Conclusion

Background: Ridesharing in Iran

- Uber, Lyft, and other well known ride-hailing platforms are not active in Iran.

Background: Ridesharing in Iran

- Uber, Lyft, and other well known ride-hailing platforms are not active in Iran.
- Similar domestic platforms exist: Snapp and Tapsi.

Background: Ridesharing in Iran

- Uber, Lyft, and other well known ride-hailing platforms are not active in Iran.
- Similar domestic platforms exist: Snapp and Tapsi.
- Snapp/Tapsi are different from Uber/Lyft in the way they operate.

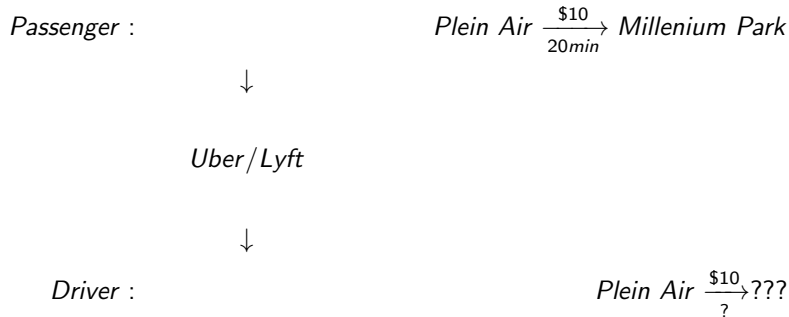
Background: Ridesharing in Iran

- Uber, Lyft, and other well known ride-hailing platforms are not active in Iran.
- Similar domestic platforms exist: Snapp and Tapsi.
- Snapp/Tapsi are different from Uber/Lyft in the way they operate.
- My focus → two unique features in supply side of matching in Tapsi

Background: Ride Dispatching in ROW

- Uber/Lyft:

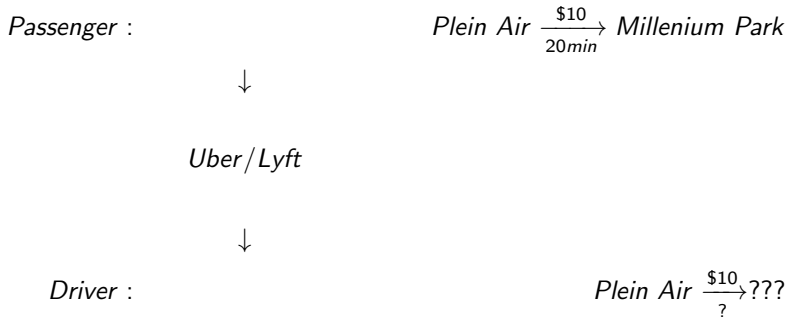
- ① ride information is not disclosed to driver prior to passenger pickup:



Background: Ride Dispatching in ROW

- Uber/Lyft:

- ① ride information is not disclosed to driver prior to passenger pickup:

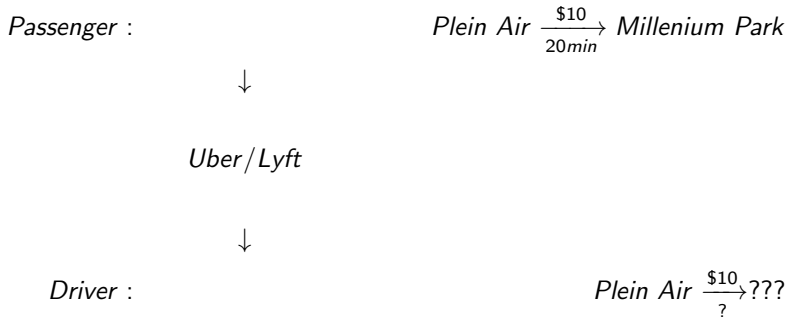


- ② driver incurs penalty if rejects the ride.

Background: Ride Dispatching in ROW

- Uber/Lyft:

- ① ride information is not disclosed to driver prior to passenger pickup:



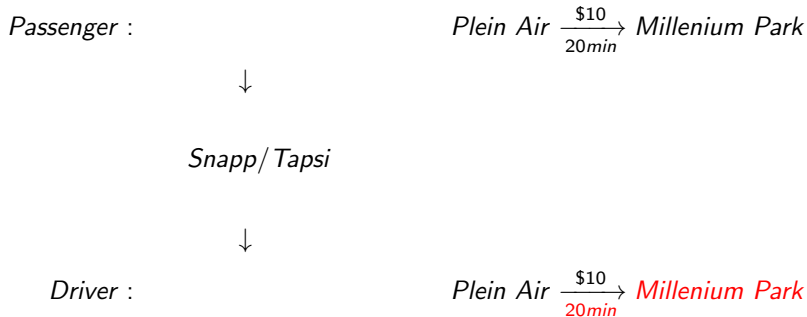
- ② driver incurs penalty if rejects the ride.

- Drivers are indifferent between rides with similar prices.

Background: Ride Dispatching in Iran

- Snapp/Tapsi:

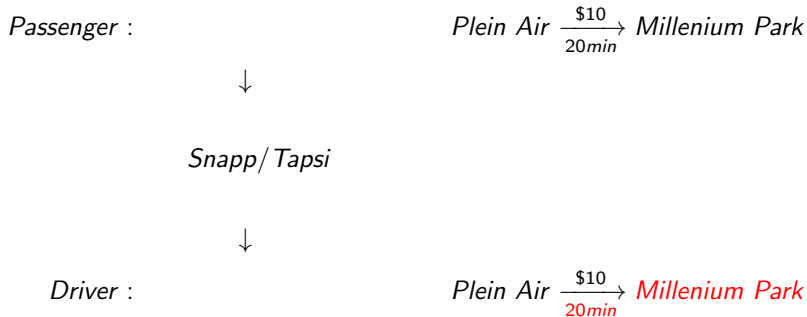
- ① ride information is disclosed to driver when offer is being proposed:



Background: Ride Dispatching in Iran

- Snapp/Tapsi:

- ① ride information is disclosed to driver when offer is being proposed:

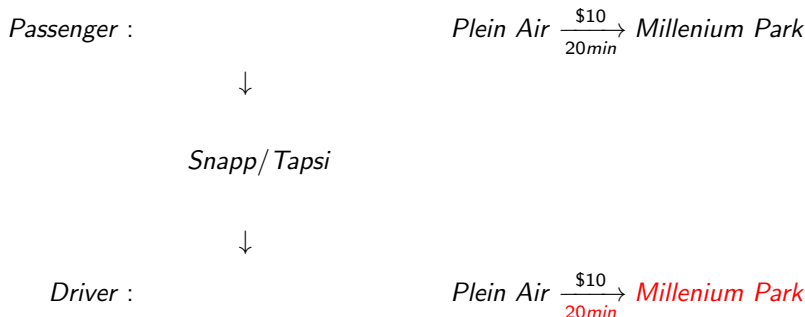


- ② driver incurs **no penalties** if rejects the ride.

Background: Ride Dispatching in Iran

- Snapp/Tapsi:

- ① ride information is disclosed to driver when offer is being proposed:



- ② driver incurs **no penalties** if rejects the ride.

- Drivers are **not** indifferent between rides with similar prices. Destinations also matter.

- I study strategic ride acceptance behavior of drivers in Iran using data from Tapsi.

- I study strategic ride acceptance behavior of drivers in Iran using data from Tapsi.
- Research question:
How much belief about “goodness” of prices contribute to driver’s labor supply?

- I study strategic ride acceptance behavior of drivers in Iran using data from Tapsi.
- Research question:
How much belief about “goodness” of prices contribute to driver’s labor supply?
- Contributions:
 - Introducing a new channel for labor supply at the *intensive margin* for taxi drivers.
(mechanism adopted by Uber just recently)
 - Decomposing effect of exogenous price shocks to labor supply into two components:
 - 1 pure price effect,
 - 2 experience effect.

- Classic utilities Vs. reference-dependence utilities [Camerer et al. (1997)]
- Flexibility in work hours / Value of time [Buchholz et al. (2020), Chen et al. (2020)]
- Information disclosure (?)

Outline

- 1 Introduction
- 2 Institutional Background and Data
- 3 Model
- 4 Simulation
- 5 Identification
- 6 Conclusion

Institutional Background: Ride Dispatching

- Tapsi is the second largest ride-hailing company in Iran behind Snapp.

Institutional Background: Ride Dispatching

- Tapsi is the second largest ride-hailing company in Iran behind Snapp.
- I have 3 months of data for Tehran in 2018: > 60 million observations.

Institutional Background: Ride Dispatching

- Tapsi is the second largest ride-hailing company in Iran behind Snapp.
- I have 3 months of data for Tehran in 2018: > 60 million observations.
- Two unique features in ride dispatching:
 - ① disclosure of ride information prior to acceptance,
 - ② no penalty for rejection (pecuniary or otherwise).

Institutional Background: Ride Dispatching

- Tapsi is the second largest ride-hailing company in Iran behind Snapp.
- I have 3 months of data for Tehran in 2018: > 60 million observations.
- Two unique features in ride dispatching:
 - ① disclosure of ride information prior to acceptance,
 - ② no penalty for rejection (pecuniary or otherwise).
- Drivers behave strategically.

Institutional Background: Ride Dispatching

- Tapsi is the second largest ride-hailing company in Iran behind Snapp.
- I have 3 months of data for Tehran in 2018: > 60 million observations.
- Two unique features in ride dispatching:
 - ① disclosure of ride information prior to acceptance,
 - ② no penalty for rejection (pecuniary or otherwise).
- Drivers behave strategically.
- Result: low acceptance rates, high waiting times

Institutional Background: Surge Pricing

- Tapsi uses *Surge Pricing Mechanism*:
 - *baseline* price: function of ride characteristics
 - *surge* price: multiplies baseline price by a factor greater(smaller) than 1 depending on magnitude of excess demand(supply) in region

Institutional Background: Surge Pricing

- Tapsi uses *Surge Pricing Mechanism*:
 - *baseline* price: function of ride characteristics
 - *surge* price: multiplies baseline price by a factor greater(smaller) than 1 depending on magnitude of excess demand(supply) in region
- If demand \gg supply, ride prices \uparrow :
 - 1 some passengers leave
 - 2 drivers come to the region

Institutional Background: Surge Pricing

- Tapsi uses *Surge Pricing Mechanism*:
 - *baseline* price: function of ride characteristics
 - *surge* price: multiplies baseline price by a factor greater(smaller) than 1 depending on magnitude of excess demand(supply) in region
- If demand \gg supply, ride prices \uparrow :
 - 1 some passengers leave
 - 2 drivers come to the region
- Drivers know if surge is applied, but don't know its magnitude.

Institutional Background: Surge Pricing

- Tapsi uses *Surge Pricing Mechanism*:
 - *baseline* price: function of ride characteristics
 - *surge* price: multiplies baseline price by a factor greater(smaller) than 1 depending on magnitude of excess demand(supply) in region
- If demand \gg supply, ride prices \uparrow :
 - 1 some passengers leave
 - 2 drivers come to the region
- Drivers know if surge is applied, but don't know its magnitude.
- About 2/3 of rides have surge multiplier $\neq 1$.

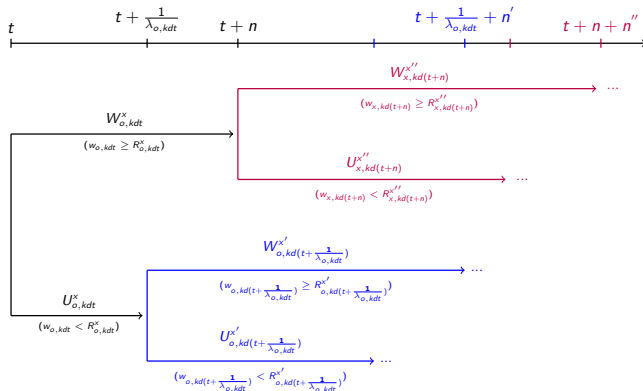
Outline

- 1 Introduction
- 2 Institutional Background and Data
- 3 Model**
- 4 Simulation
- 5 Identification
- 6 Conclusion

Timing of Driver's Problem

- Drivers face a tradeoff when responding to ride offers.

Figure 1: Timeline of decision making for driver



Typical Job Search Model

- Typical job search model:
 - Employment state: worker accepts wage drawn from a distribution:

$$W(w) = w + \delta w + \delta^2 w + \dots = \frac{w}{1 - \delta}$$

Typical Job Search Model

- Typical job search model:
 - Employment state: worker accepts wage drawn from a distribution:

$$W(w) = w + \delta w + \delta^2 w + \dots = \frac{w}{1 - \delta}$$

- Unemployment state: worker rejects offer and waits for next proposals to arrive

$$U = c + \delta \left(\lambda \mathbb{E}_w [\max\{W(w), U\}] + (1 - \lambda)U \right)$$

Typical Job Search Model

- Typical job search model:
 - Employment state: worker accepts wage drawn from a distribution:

$$W(w) = w + \delta w + \delta^2 w + \dots = \frac{w}{1 - \delta}$$

- Unemployment state: worker rejects offer and waits for next proposals to arrive

$$U = c + \delta \left(\lambda \mathbb{E}_w [\max\{W(w), U\}] + (1 - \lambda)U \right)$$

- Reservation wage R , a cutoff strategy solving $W(R) = U$:
 - $w > R$: accept
 - $w < R$: reject

Departure from Typical Job Search

In context of Tapsi drivers:

- ① Working shift continues: drivers receive offers after arriving at current offer's destination

Departure from Typical Job Search

In context of Tapsi drivers:

- 1 Working shift continues: drivers receive offers after arriving at current offer's destination
- 2 Locations matter: distribution of offers is location-dependent

Departure from Typical Job Search

In context of Tapsi drivers:

- 1 Working shift continues: drivers receive offers after arriving at current offer's destination
- 2 Locations matter: distribution of offers is location-dependent
- 3 Drivers don't know the *actual* distribution: "learn" it as they receive offers

Model: Ride Proposals

- Offers in location o , week k , day d , and time t :
 - arrive with Poisson rate $\lambda_{o,kdt}$,

Model: Ride Proposals

- Offers in location o , week k , day d , and time t :
 - arrive with Poisson rate $\lambda_{o,kdt}$,
 - are randomly assigned a trip duration $n \in N \subset \mathbb{N}$,

Model: Ride Proposals

- Offers in location o , week k , day d , and time t :
 - arrive with Poisson rate $\lambda_{o,kdt}$,
 - are randomly assigned a trip duration $n \in N \subset \mathbb{N}$,
 - are randomly assigned a destination $x \in Y$, where Y is set of all regions available in the city,

Model: Ride Proposals

- Offers in location o , week k , day d , and time t :
 - arrive with Poisson rate $\lambda_{o,kdt}$,
 - are randomly assigned a trip duration $n \in N \subset \mathbb{N}$,
 - are randomly assigned a destination $x \in Y$, where Y is set of all regions available in the city,
 - are randomly assigned an actual ride price drawn from lognormal price/wage distribution:

$$w_{o,kdt} \sim N(\mu_{o,kdt}, \sigma^2)$$

where $\mu_{o,kdt} = \mu_{o,kd}(1 + \alpha_{o,kdt})$.

Model: Ride Proposals

- Offers in location o , week k , day d , and time t :
 - arrive with Poisson rate $\lambda_{o,kdt}$,
 - are randomly assigned a trip duration $n \in N \subset \mathbb{N}$,
 - are randomly assigned a destination $x \in Y$, where Y is set of all regions available in the city,
 - are randomly assigned an actual ride price drawn from lognormal price/wage distribution:

$$w_{o,kdt} \sim N(\mu_{o,kdt}, \sigma^2)$$

where $\mu_{o,kdt} = \mu_{o,kd}(1 + \alpha_{o,kdt})$.

- Tuple $(w_{o,kdt}, n, x)$ is a ride proposal.

Model: Belief Construction

Assumptions. Driver:

- Knows σ^2 .

Model: Belief Construction

Assumptions. Driver:

- Knows σ^2 .
- Knows the general mean parameter $\mu_{o,kd}$.

Model: Belief Construction

Assumptions. Driver:

- Knows σ^2 .
- Knows the general mean parameter $\mu_{o,kd}$.
- Does not know the surge multiplier. Has prior belief

$$\hat{\mu}_{o,kdt} = \mu_{o,kd}(1 + \hat{\alpha}_{o,kdt}),$$

and updates it after every ride offer price $w_{o,kdt}$.

Model: Belief Construction

Assumptions. Driver:

- Knows σ^2 .
- Knows the general mean parameter $\mu_{o,kd}$.
- Does not know the surge multiplier. Has prior belief

$$\hat{\mu}_{o,kdt} = \mu_{o,kd}(1 + \hat{\alpha}_{o,kdt}),$$

and updates it after every ride offer price $w_{o,kdt}$.

- Thus, learning is only limited to surge multiplier.

Model: Ride Acceptance

- Flow value of ride rejection:

$$\delta U(\hat{\mu}_{o,kdt}) = \underbrace{c}_{\text{cost of waiting/resting benefit}} + \lambda_{o,kdt} \times \underbrace{\mathbb{E}_y \left[\int_{R_{o,kdt}^y}^{\infty} (1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}) d\tilde{w}) \right]}_{\text{driver's expected value of next offer in current location}},$$

where $y \in Y$ is destination of next offer.

Model: Ride Acceptance

- Flow value of ride rejection:

$$\delta U(\hat{\mu}_{o,kdt}) = \underbrace{c}_{\text{cost of waiting/resting benefit}} + \lambda_{o,kdt} \times \underbrace{\mathbb{E}_y \left[\int_{R_{o,kdt}^y}^{\infty} (1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}) d\tilde{w}) \right]}_{\text{driver's expected value of next offer in current location}},$$

where $y \in Y$ is destination of next offer.

- Flow value of ride acceptance for ride proposal $(w_{o,kdt}, n, x)$:

$$\delta W(w_{o,kdt}, n, \hat{\mu}_{x,kd(t+n)}) = \underbrace{\delta n w_{o,kdt}}_{\text{instantaneous earning from ride completion}} + \underbrace{c + \lambda_{x,kd(t+n)} \times \mathbb{E}_y \left[\int_{R_{x,kd(t+n)}^y}^{\infty} (1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}) d\tilde{w}) \right]}_{\text{expected value of receiving offer in current offer's destination at time of arrival}}.$$

Model: Reservation Wage

- $R_{o,kdt}^x$ reservation wage of driver at o, kdt for proposal with duration n and destination x :

$$R_{o,kdt}^x = \frac{1}{\delta n} \left[\underbrace{\lambda_{o,kdt} \mathbb{E}_y \left[\int_{R_{o,kdt}^y}^{\infty} (1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}) d\tilde{w}) \right]}_{\text{expected earning opportunities in origin}} - \underbrace{\lambda_{x,kd(t+n)} \mathbb{E}_y \left[\int_{R_{x,kd(t+n)}^y}^{\infty} (1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}) d\tilde{w}) \right]}_{\text{expected earning opportunities in destination of current offer}} \right].$$

Model: Reservation Wage

- $R_{o,kdt}^x$ reservation wage of driver at o, kdt for proposal with duration n and destination x :

$$R_{o,kdt}^x = \frac{1}{\delta n} \left[\underbrace{\lambda_{o,kdt} \mathbb{E}_y \left[\int_{R_{o,kdt}^y}^{\infty} (1 - F_{\hat{\mu}_{o,kdt}}(\tilde{w}) d\tilde{w}) \right]}_{\text{expected earning opportunities in origin}} - \underbrace{\lambda_{x,kd(t+n)} \mathbb{E}_y \left[\int_{R_{x,kd(t+n)}^y}^{\infty} (1 - F_{\hat{\mu}_{x,kd(t+n)}}(\tilde{w}) d\tilde{w}) \right]}_{\text{expected earning opportunities in destination of current offer}} \right].$$

Proposition

We have: $\frac{\partial R_{o,kdt}^x}{\partial \hat{\mu}_{o,kdt}} > 0$ and $\frac{\partial R_{o,kdt}^x}{\partial \hat{\mu}_{x,kd(t+n)}} < 0$.

Implications of Model

Implications:

- Driver's expectation of earning opportunities in origin $\uparrow \rightarrow R \uparrow \rightarrow$ acceptance rate \downarrow ,

Implications of Model

Implications:

- Driver's expectation of earning opportunities in origin $\uparrow \rightarrow R \uparrow \rightarrow$ acceptance rate \downarrow ,
- Driver's expectation of earning opportunities in destination $\uparrow \rightarrow R \downarrow \rightarrow$ acceptance rate \uparrow ,

Implications of Model

Implications:

- Driver's expectation of earning opportunities in origin $\uparrow \rightarrow R \uparrow \rightarrow$ acceptance rate \downarrow ,
- Driver's expectation of earning opportunities in destination $\uparrow \rightarrow R \downarrow \rightarrow$ acceptance rate \uparrow ,
- Heterogenous responses to same ride offer due to different ride fulfillment experiences,

Implications of Model

Implications:

- Driver's expectation of earning opportunities in origin $\uparrow \rightarrow R \uparrow \rightarrow$ acceptance rate \downarrow ,
- Driver's expectation of earning opportunities in destination $\uparrow \rightarrow R \downarrow \rightarrow$ acceptance rate \uparrow ,
- Heterogenous responses to same ride offer due to different ride fulfillment experiences,
- Different responses to same ride proposal by the *same* driver at different times!

Implications of Model

Implications:

- Driver's expectation of earning opportunities in origin $\uparrow \rightarrow R \uparrow \rightarrow$ acceptance rate \downarrow ,
- Driver's expectation of earning opportunities in destination $\uparrow \rightarrow R \downarrow \rightarrow$ acceptance rate \uparrow ,
- Heterogenous responses to same ride offer due to different ride fulfillment experiences,
- Different responses to same ride proposal by the *same* driver at different times!

Main takeaway: Beliefs must be accounted for. Model captures this. Data allows to quantify it.

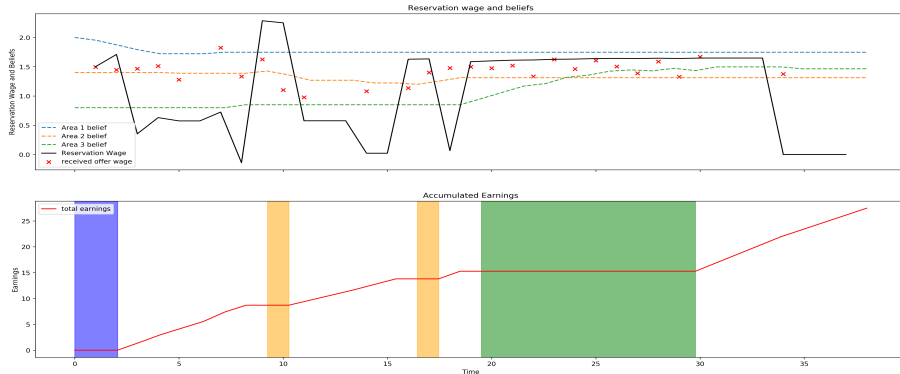
Outline

- 1 Introduction
- 2 Institutional Background and Data
- 3 Model
- 4 Simulation**
- 5 Identification
- 6 Conclusion

Simulation of Reservation Wage

- Three regions with same *actual* distribution, driver has different belief about each region.
- Prices randomly drawn and assigned to random destinations.

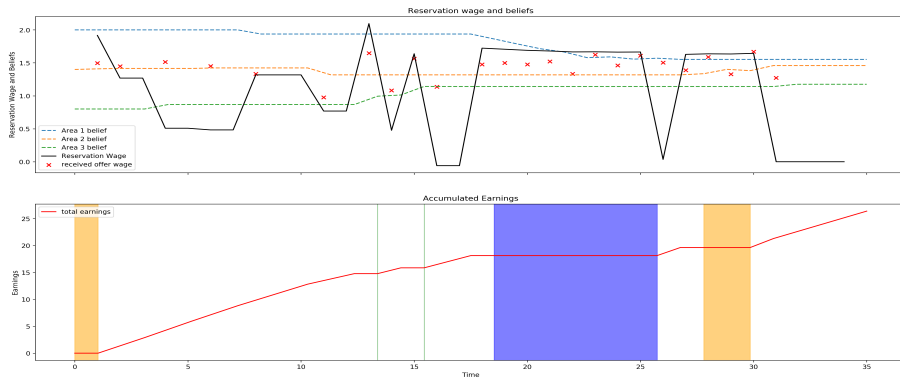
Figure 2: Reservation wage process - driver initially at region 1



Simulation of Reservation Wage

- Now, suppose driver starts from region 2.
- Same beliefs + prices but different destinations \rightarrow different reservation wage!

Figure 3: Reservation wage process - driver initially at region 2



Outline

- 1 Introduction
- 2 Institutional Background and Data
- 3 Model
- 4 Simulation
- 5 Identification**
- 6 Conclusion

Identification Discussion

Question:

Answer:

Question:

- 1 Drivers simultaneously operating on multiple platforms?

Answer:

Question:

- 1 Drivers simultaneously operating on multiple platforms?

Answer:

- 1 Before Nov 2018, drivers w/o a Tehran plate number could only work for Tapsi

Identification Discussion

Question:

- 1 Drivers simultaneously operating on multiple platforms?
- 2 Source of exogenous variation?

Answer:

- 1 Before Nov 2018, drivers w/o a Tehran plate number could only work for Tapsi

Identification Discussion

Question:

- 1 Drivers simultaneously operating on multiple platforms?
- 2 Source of exogenous variation?

Answer:

- 1 Before Nov 2018, drivers w/o a Tehran plate number could only work for Tapsi
- 2 Different surge multipliers at the borders of surge regions \rightarrow RD

Identification Discussion

Question:

- 1 Drivers simultaneously operating on multiple platforms?
- 2 Source of exogenous variation?
- 3 But belief is subjective component...?!

Answer:

- 1 Before Nov 2018, drivers w/o a Tehran plate number could only work for Tapsi
- 2 Different surge multipliers at the borders of surge regions → RD

Identification Discussion

Question:

- 1 Drivers simultaneously operating on multiple platforms?
- 2 Source of exogenous variation?
- 3 But belief is subjective component...?!

Answer:

- 1 Before Nov 2018, drivers w/o a Tehran plate number could only work for Tapsi
- 2 Different surge multipliers at the borders of surge regions → RD
- 3 Exploit accidents as exogenous shocks to driver's belief!

Outline

- 1 Introduction
- 2 Institutional Background and Data
- 3 Model
- 4 Simulation
- 5 Identification
- 6 Conclusion**

Conclusion and Future Work

- Introduced a channel in ride acceptance decision making of drivers.

Conclusion and Future Work

- Introduced a channel in ride acceptance decision making of drivers.
- Argued how it affects measurement of labor supply.

Conclusion and Future Work

- Introduced a channel in ride acceptance decision making of drivers.
- Argued how it affects measurement of labor supply.
- Next steps:
 - Take the model to data.
 - Simulation → compare acceptance rate and earnings against a benchmark of no learning
 - With minor changes also answer:
 - how fast do drivers adjust their beliefs over time?
 - how would drivers react if Tapsi's rejection policy changes? (counterfactual analysis)
 - design a pricing policy that prevents drivers to extract rent from experience.