Pricing and Efficiency in a Decentralized Ride-Hailing Platform

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Research Question:
How does **decentralization in pricing** affect welfare of market participants on a ride-hailing platform?

Context: Platform - inDriver

- Launched in Yakutsk in 2013 map.
- Currently present in 45 countries, 145M app installs.
- Request always starts with the **passenger offering price**.
- Drivers can agree, make a counteroffer or ignore the request.

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Findings:

- Both sides can benefit from decentralized pricing.
- Driver welfare under optimal centralized regime is lower by 10%.
- Rider welfare under optimal centralized regime is lower by 4%.

Data and Mechanism

Dataset

Internal dataset: universe of transactions from a single city.

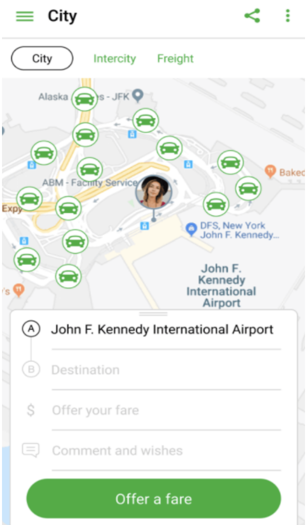
Unique feature: contains information about **unmatched** requests.

Current sample: November 1st, 2018 - April 3rd, 2019.

$\approx$ 64,000 unique passengers, $\approx$ 3,400 unique drivers, $\geq$ 1.7M requests.

Daily Stats Cleaning Hourly Distributions

Rider's Screen and Stylized Facts



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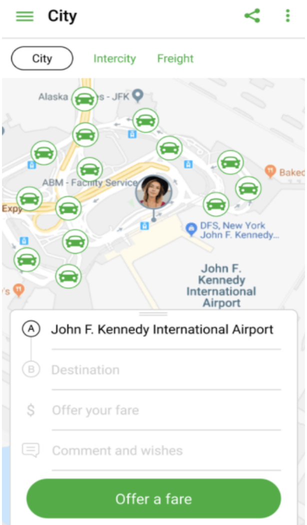

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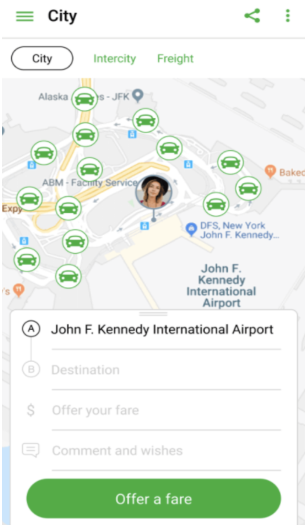

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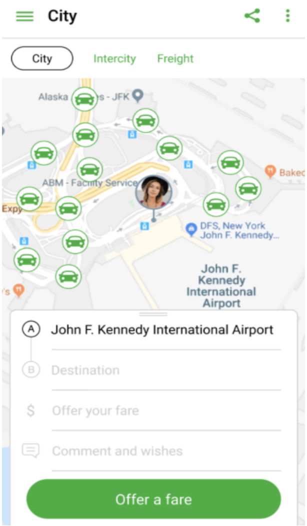

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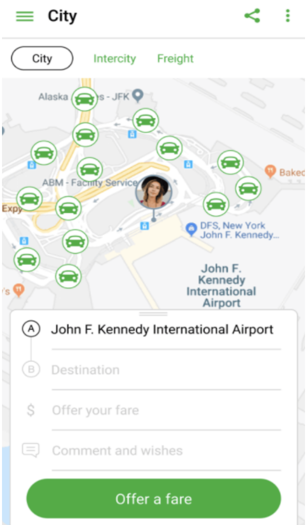
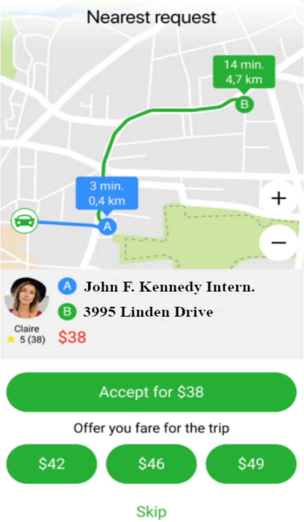


- Offered prices: 300, 350 and 400.
- Riders offer different prices for similar trips. Details
- High offer is associated with better chances to get matched quickly, all other things equal. Details
- Most riders make one attempt to get matched. Details

Driver's Screen and Stylized Facts



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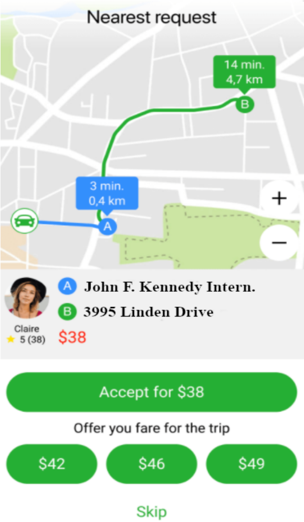

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Details

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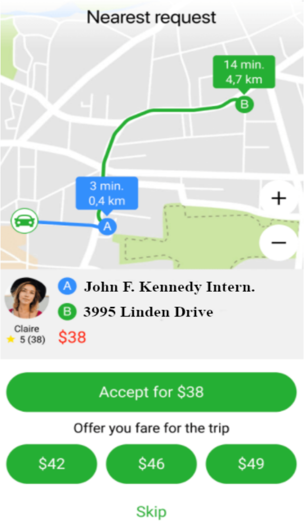

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- Drivers are strategic. Details

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- Platform breaks ties based on drivers' distances and rankings.

Example

Model

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- Time is discrete with an infinite horizon.
- Riders are short-lived and try to get matched only once.
- Drivers behave dynamically and have a discount factor β.
- There is a probability $(1 - \pi)$ that a period is the driver's last period at the platform: driver's measure of impatience: $\delta = \beta \times \pi$.

Demand Model

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3. Rider offers price $b \in \{b_L, b_H\}$.
4. Request can be accepted, counteroffered at $b + \Delta$ ($\Delta = b_H - b_L$) or ignored.

Demand Model: Rider's Choice

A rider with valuation v in state s solves optimization problem:

$$\max_{b \in \{b_L, b_H\}} \Big[\underbrace{\eta(A|b,s)}_{\text{Pr. req. is accepted}} \max(v-b,0) + \underbrace{\eta(C|b,s)}_{\text{Pr. req. is counteroffered}} \max(v-b-\Delta,0) \Big]$$

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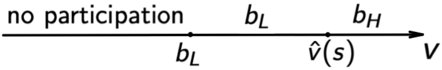

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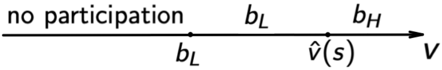

Threshold

Probability that a rider offers b_H:

$$\omega(b_H|s) = \int_{\hat{v}(s)}^{\infty} f(v)\,\mathrm{d}v$$

Take-away: b_H can signal rider's high valuation v or a rider's bad state s.

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4. The rider faces a match. If he accepts it, the match is formed. If not, the rider leaves the platform and the driver remains idle.

Supply Model: Types of Requests

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- Distance to a rider: $d_i \in \{d_1, ..., d_X\}$
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- It takes $g(d_i)$ seconds to complete a request of type (b, d_i, ϵ_i) if matched.

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- Drivers misses 20 seconds if $\{A, C\}$ and 5 seconds if I

Supply Model: Driver's Payoff

$$\tilde{U}(A, b, d_i, \epsilon_i) = \overbrace{\mu(A, b, d_i)}^{\text{Pr.to win if } A} \overbrace{[\bar{u}(b, d_i) + \epsilon_i + \delta^{g(d_i)} V]}^{\text{Payoff if } A \text{ and wins}} + \overbrace{(1 - \mu(A, b, d_i))}^{\text{Pr.to lose if } A} \overbrace{\delta^{20} V}^{\text{Cont.value}}$$

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$$\tilde{U}(I, b, d_i, \epsilon_i) = \overbrace{\delta^{5} V}^{\text{Cont.value}}$$

Supply Model: Solution

The driver's problem:

$$W(b, d_i, \epsilon_i) = \max_{D \in \{A,C,I\}} \tilde{U}(D, b, d_i, \epsilon_i)$$

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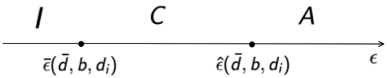

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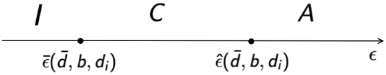

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$$\rho(A|b, d_i) = \int_{\hat{\epsilon}(b,d_i)}^{\infty} f(\epsilon|\sigma_\epsilon) d\epsilon$$

$$\rho(C|b, d_i) = \int_{\bar{\epsilon}(b,d_i)}^{\hat{\epsilon}(b,d_i)} f(\epsilon|\sigma_\epsilon) d\epsilon$$

Supply Model: Value of Being Idle

Ex-ante value of a request of type (b, d_i):

$$E_\epsilon[W(b, d_i, \epsilon_i)] = \int_{-\infty}^{\infty} W(b, d_i, \epsilon_i) f(\epsilon_i | \sigma_\epsilon) d\epsilon_i$$

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Value function of being idle:

$$V = \sum_{\substack{b \in \{b_L, b_H\} \times \\ d_i \in \{d_1, \ldots, d_X\}}} \alpha(b, d_i) \times E_\epsilon \Big[W(b, d_i, \epsilon_i) \Big] + \Big(1 - \sum_{\substack{b \in \{b_L, b_H\} \times \\ d_i \in \{d_1, \ldots, d_X\}}} \alpha(b, d_i) \Big) \times \delta V$$

Equilibrium

Beliefs Formation

- Riders' beliefs (η) depend on drivers' decisions.
- Drivers' beliefs about probabilities of requests arrival (α) and beliefs to win (μ) depend on riders' decisions.

Formulas for η Formulas for α Formulas for μ

Equilibrium

Definition: A rational-expectations equilibrium is a tuple: $\{\eta, \mu\}$, s.t.:

1. Riders maximize expected utilities given η and the state they face, s.
2. Riders' actions affect α.
3. Idle drivers maximize expected utilities by choosing $\{A, C, I\}$.
4. V is a fixed point of:

$$V = \sum_{\substack{b \in \{b_L, b_H\} \times \\ d_i \in \{d_1, \ldots, d_X\}}} \alpha(b, d_i) \times E_\epsilon\Big[W(b, d_i, \epsilon_i)\Big] + \Big(1 - \sum_{\substack{b \in \{b_L, b_H\} \times \\ d_i \in \{d_1, \ldots, d_X\}}} \alpha(b, d_i)\Big) \times \delta V$$

5. Market participants have rational expectations: beliefs $\{\eta, \mu\}$ are self-fulfilling given optimizing behavior.

Estimation and Results

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- Some primitives are estimated directly off the data.

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Supply-side primitives:

- **Static utilities:** $u_m(\bar{d}, b, d_i)$
- **Measure of impatience:** δ
- **Variance of ϵ-shocks:** σ_ϵ
- Number of idle drivers: $f_m(N)$
- Distribution of distances to the rider: $\mathbb{P}(d_x)$

Identification

Parametrization

Demand-side:

$$f(v|\psi_m(\bar{d})) \sim G[\quad \underbrace{k_m(\bar{d})}_{\text{Shape parameter}} \quad , \quad \underbrace{\theta_m(\bar{d})}_{\text{Scale parameter}} \quad , \quad \underbrace{b_L}_{\text{Lower limit}} \quad]$$

Supply-side:

$$\bar{u}_m(\bar{d}, b, d) = b - c \times d - \alpha_{0,m} - \alpha_1 \mathbb{1} \times (\bar{d} = L)$$

Demand-side Results

	Short Trips		Long Trips	
Market	$P(v < b_H)$	Median valuation	$P(v < b_H)$	Median valuation
8 a.m.	0.302	533.447	0.159	818.703
10 a.m.	0.094	1020.139	0.039	1357.894
noon	0.445	378.715	0.266	545.238
2 p.m.	0.406	403.776	0.265	539.723
4 p.m.	0.231	586.821	0.122	817.696
6 p.m.	0.466	367.862	0.288	566.807
8 p.m.	0.256	550.638	0.138	773.144

Notes: This table reports the (1) estimated shares of riders who would have been priced out of the market if b_H is charged for a trip and (2) the valuation of a median rider in the market. The left side of the table presents the results for the short trips and the right side presents the same statistics for the long trips.

Parameters

Supply-side Results

Parameter	Estimate	(S.E.)	Transformed (money terms)
γ	0.009	(0.000)	1.000
c (per-km)	3.288	(0.006)	365.333
$\alpha_{0,m}$: 8 a.m.	1.636	(0.011)	181.778
$\alpha_{0,m}$: 10 a.m.	1.458	(0.011)	162.000
$\alpha_{0,m}$: noon	1.287	(0.010)	143.000
$\alpha_{0,m}$: 2 p.m.	1.465	(0.010)	162.778
$\alpha_{0,m}$: 4 p.m.	1.527	(0.010)	169.667
$\alpha_{0,m}$: 6 p.m.	1.701	(0.010)	189.000
$\alpha_{0,m}$: 8 p.m.	1.634	(0.010)	181.556
α_1	0.105	(0.003)	11.667
δ	0.969	(0.001)	0.969
σ_ϵ	1.000	-	111.111
Num.obs.		1,346,804	
Log-likelihood		-707,348.476	

Notes: This table reports the results of the supply-side estimation. I use choices of drivers that are within 1 km of a rider. This exclusion is driven by the fact that drivers who are farther than 1 km from a rider do not often participate.

Welfare Analysis

Scenarios

→ **Decentralized pricing (DP)**

- Rider makes an offer (b_L or b_H)
- Driver accepts, counteroffers or ignores
- Platform proposes a match

Scenarios

→ **Decentralized pricing (DP)**

- Rider makes an offer (b_L or b_H)
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Rider's price reflects both his valuation (v) and market conditions (s).

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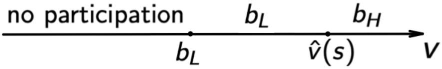
Need to inform a platform about market conditions (s).

Transformation of Multidimensional s into an Index

Recall demand model:



$\hat{v}(s)$ summarizes information about market state.

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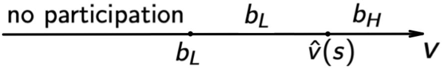
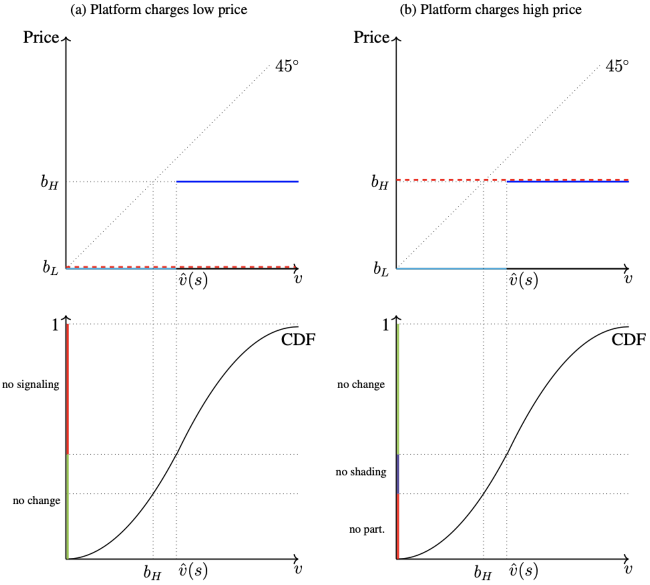


$\hat{v}(s)$ summarizes information about market state.

Rider's point of view:

- high $\hat{v}(s) \rightarrow$ "good market" from rider's point of view: b_L
- low $\hat{v}(s) \rightarrow$ "bad market" from rider's point of view: b_H

Platform's Trade-off: Quantity VS Prices



Surge Pricing Mechanism in CP

Counterfactual CP rule:

- $\hat{v}(s) < v_{CUTOFF} \rightarrow$ platform chooses b_H ("bad market")
- $\hat{v}(s) > v_{CUTOFF} \rightarrow$ platform chooses b_L ("good market")

Aim: Compute equilibrium for various v_{CUTOFF} and show how welfare changes relative to a decentralized system.

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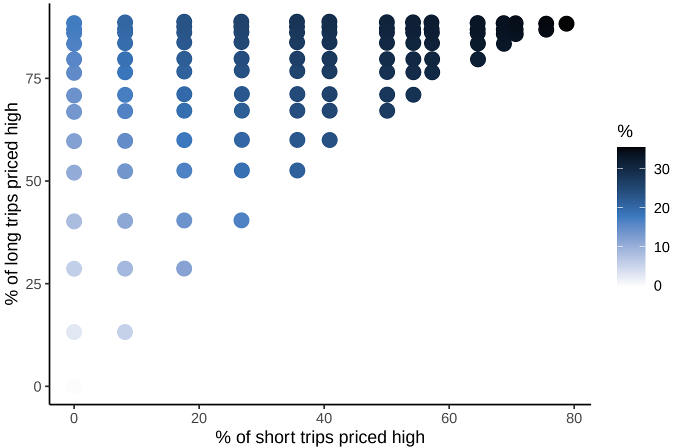
Aim: Compute equilibrium for various v_{CUTOFF} and show how welfare changes relative to a decentralized system.

Remark: various v_{CUTOFF} rules can be mapped into % of trips that are priced high on the platform.

Quantity

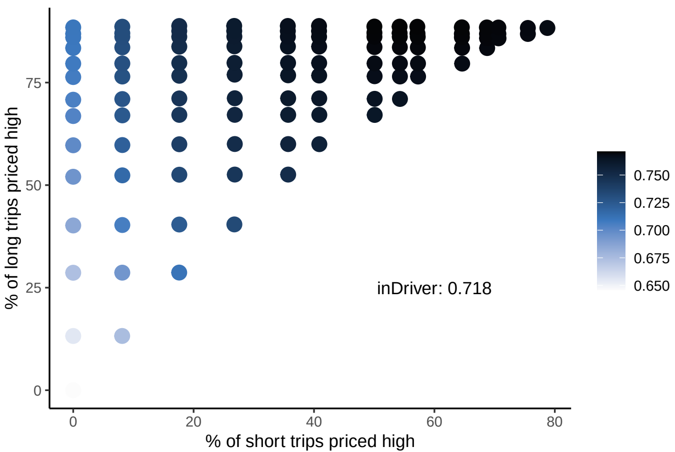
Figure: Percentage of Priced-Out Riders



Notes: This figure depicts the percentage of riders who would be priced out under various pricing rules implemented by the platform.

Matching Rates

Figure: Probability of Getting Matched



Notes: This figure shows the average probabilities of getting matched for a participating rider given a proposed price, under various pricing rules implemented by the platform.

Driver Welfare

$$\%\Delta V = 100\% \times \frac{V^{DP} - V^{CP}}{V^{DP}}$$

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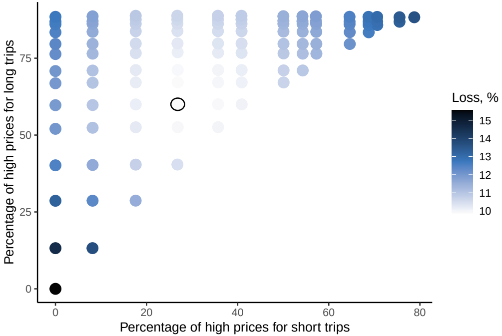
Figure: Loss in a Driver's Value Function Relative to a Decentralized Platform



Notes: This figure presents a loss in the driver's value function relative to a decentralized platform under various pricing rules implemented by the platform. The minimum loss is marked with a circle.

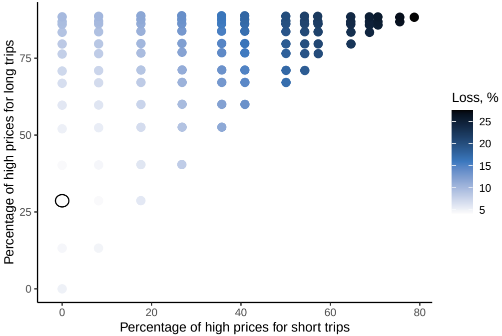
Rider Welfare

$$\%\Delta CS = \int_v \int_s \left[100\% \times \frac{CS^{DP}(v,s) - CS^{CP}(v,s)}{CS^{DP}(v,s)} \right] f(v) f(s) \, \mathrm{d}v \, \mathrm{d}s$$

Rider Welfare

$$\%\Delta CS = \int_v \int_s \left[100\% \times \frac{CS^{DP}(v,s) - CS^{CP}(v,s)}{CS^{DP}(v,s)}\right] f(v) f(s)\, \mathrm{d}v\, \mathrm{d}s$$

Figure: Loss in Rider Surplus Relative to a Decentralized Platform



Notes: This figure presents a loss in the rider's expected surplus relative to a decentralized platform under various pricing rules implemented by the platform. The minimum loss is marked with a circle.

Conclusion

- The results suggest that private information plays an important role for a two-sided market's efficiency.

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- Centralized platform that sets up the prices faces a trade-off between quantity and prices.
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Conclusion

- The results suggest that private information plays an important role for a two-sided market's efficiency.
- Centralized platform that sets up the prices faces a trade-off between quantity and prices.
- This trade-off is not present under a decentralized setting due to self price-discrimination.
- Both riders and drivers benefit from decentralized pricing in a studied market ("signaling" and "quantity" effects dominate "shading" effect).
- Ongoing research: results might vary with market density.

Thank You!

Comments welcome: rgaineddenova@hbs.edu

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Daily Statistics

	Days	10th %tile	Mean	90th %tile	SD
Monday–Friday					
— Number of requests	110	8,632.1	11,272.8	15,209.1	2,866.0
— Number of unique drivers	110	750.8	855.4	956.1	84.0
Saturday–Sunday					
— Number of requests	44	9,739.3	11,914.6	14,453.7	2,006.1
— Number of unique drivers	44	756.3	854.5	941.1	81.6

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Data Cleaning

	N
Unique requests	1,764,250
-Holidays	-96,121
-Extreme weather	-234,369
-Rare prices	-45,724
-Outliers in coordinates	-14,773
-Night Hours(9PM-6AM)	-443,854
-Not matched address	-166,404
Total requests	763,005

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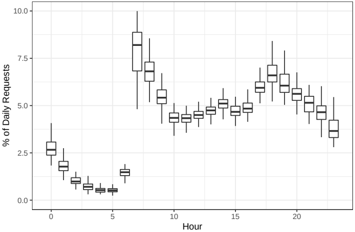
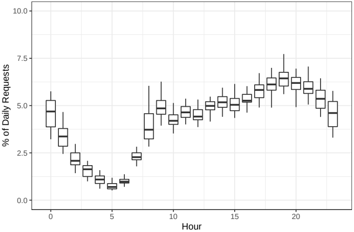
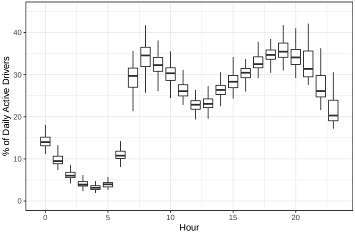
Hourly Distribution of Requests and Active Drivers



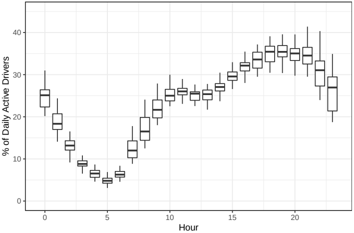
(a) Monday–Friday



(b) Saturday–Sunday



(c) Monday–Friday



(d) Saturday–Sunday

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Riders Offer Different Prices for Similar Trips

Dependent Variable:	$\mathbb{1}$(Rider offers high price)				
	(1)	(2)	(3)	(4)	(5)
Long trip	✓	✓	✓		
Hour FE	✓	✓	✓	✓	
Weekday/Weekend	✓				
Origin FE			✓	✓	
Destination FE				✓	✓
Origin-Hour FE					✓
Date FE		✓	✓	✓	✓
Controls for changing market conditions	✓	✓	✓	✓	✓
Number of observations	763,005	763,005	763,005	763,005	763,005
McKelvey and Zavoina's pseudo-R^2	0.078	0.089	0.107	0.095	0.099
Mean Absolute Error	0.443	0.439	0.432	0.436	0.435

Notes: This table reports the results of the logit regressions of the likelihood of a rider offering a high price (either 350 or 400) on various controls. The controls included in the model are marked. I use the city-district identifier for the origin and destination FE. The number of idle drivers within a 0.5-km radius is included as the control for changing market conditions. I calculate McKelvey and Zavoina's pseudo-R^2 to assess the proportion of explained variation under each model.

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Trade-off in Rider's Decision

	Total prob.	Acceptance prob.
High price	0.071***	0.183***
	(0.002)	(0.002)
N. of idle drivers within 500 meters	0.044***	0.046***
	(0.0003)	(0.0003)
High price × N. of idle drivers within 500 meters	−0.008***	−0.008***
	(0.0005)	(0.0005)
Short trip	0.027***	0.085***
	(0.001)	(0.001)
Constant	0.263***	0.072***
	(0.007)	(0.007)
Hour FE	✓	✓
Date FE	✓	✓
Observations	763,005	763,005
R^2	0.104	0.130

Notes: This table presents the results for the analysis of a trade-off that a rider faces while making a pricing decision. The left column corresponds to the regression analysis results, where the dependent variable is the total probability that a rider faces a match (either agreement or counteroffer). The right column shows the regression analysis results where the dependent variable is the probability that a rider faces an agreement. Standard errors are in parentheses; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Most Riders Try to Get Matched Only Once

	N	% of Total	% of Unmatched (within 20 seconds)
Total Observations:	763,005		
· Matched within 20 seconds	581,191	76.17	
· Not matched (within 20 seconds):	181,814		
Matched after 20 seconds at requested price	74,164	9.72	40.79
Cancelled at requested price	30,950	4.06	17.02
Canceled at higher price	13,205	1.73	7.26
Matched at higher price (rider increased)	49,358	6.47	27.15
Matched at higher price (driver increased)	13,793	1.81	7.59
Others	265	0.03	0.15

Notes: This table presents final matching outcomes for all requests in the sample. More than 75% of riders were matched within 20 seconds. The remainder did not increase their offered price often.

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Drivers are Selective

	Prob. to agree	Prob. to counter
Pickup distance (in km)	-1.020^{***}	-0.326^{***}
	(0.005)	(0.003)
High price	0.255^{***}	-0.218^{***}
	(0.003)	(0.002)
Short trip	0.190^{***}	-0.130^{***}
	(0.002)	(0.001)
Distance to a rider (in km) × High price	-0.204^{***}	0.285^{***}
	(0.009)	(0.005)
High price × Short trip	-0.128^{***}	0.108^{***}
	(0.005)	(0.003)
Short trip × Pickup distane (in km)	-0.301^{***}	0.178^{***}
	(0.007)	(0.004)
High price × Short trip × Pickup distance (in km)	0.174^{***}	-0.156^{***}
	(0.014)	(0.008)
Constant	0.542^{***}	0.327^{***}
	(0.003)	(0.002)
Hour FE	✓	✓
Weekday/Weekend FE	✓	✓
Observations	1,429,437	1,429,437
R^2	0.130	0.051

Notes: I include only responses of drivers located at a distance lower than 500 meters from a rider. A driver whose distance exceeded this threshold rarely entered the matching stage (less than 2% of all drivers located at a longer distance did in my sample). Standard errors in parentheses; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Drivers are Strategic

	Prob. to agree	Prob. to participate
Low price	-0.103^{***}	-0.032^{***}
	(0.004)	(0.004)
Pickup distance (in km)	-1.206^{***}	-1.327^{***}
	(0.011)	(0.011)
Short trip	0.066^{***}	0.020^{***}
	(0.003)	(0.003)
Rush hour	-0.074^{***}	-0.029^{***}
	(0.005)	(0.005)
Low price × Rush hour	-0.108^{***}	-0.065^{***}
	(0.006)	(0.006)
Constant	0.916^{***}	0.976^{***}
	(0.005)	(0.005)
Observations	118,805	118,805
R^2	0.138	0.127

Notes: Only requests that appeared weekdays between 7 a.m. and 8 a.m. (rush hour) and 10 a.m. and 11 a.m. (non–rush hour) are included in the regression. I include only observations for which the pickup distance does not exceed 0.5 km. Standard errors in parentheses; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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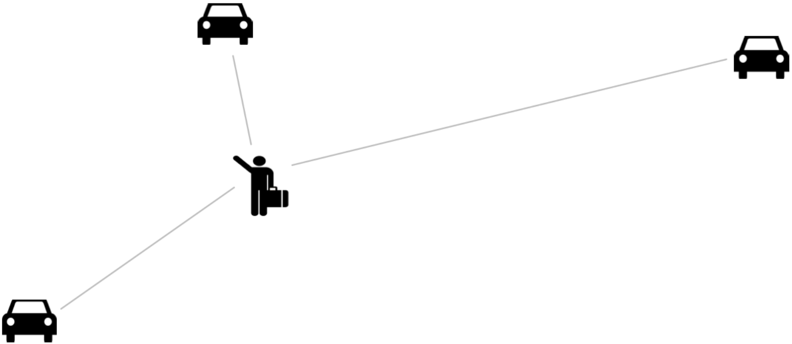
Allocation Algorithm



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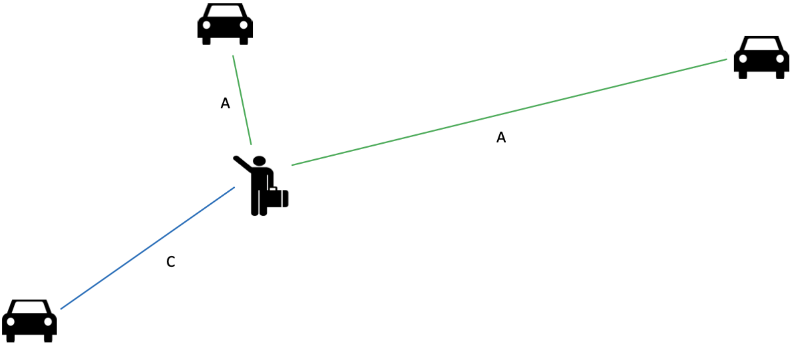

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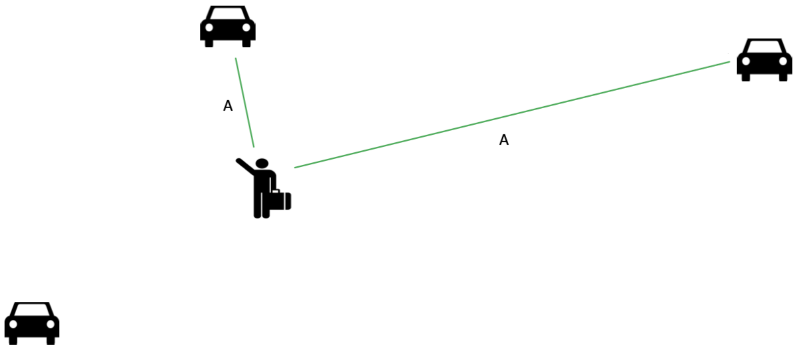

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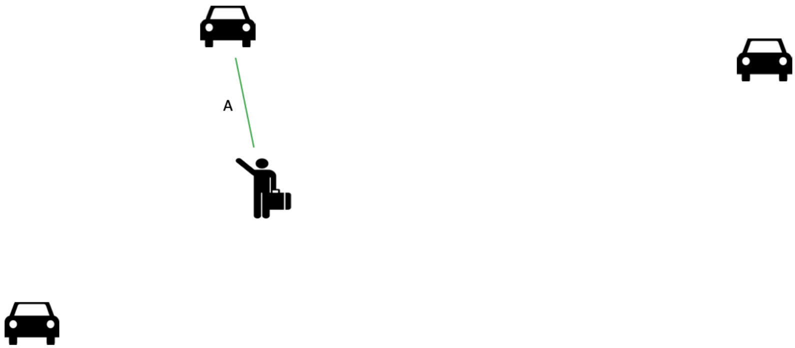

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Demand Model: Threshold

$\rightarrow$ 1) If $2\eta(A|b_L, s) + 2\eta(C|b_L, s) < \eta(A|b_H, s)$:

$$\hat{v}(s) = \frac{\overbrace{[\eta(A|b_L, s)b_L + \eta(C|b_L, s)(b_L + \Delta)]}^{\text{expected payoff if } b_L \text{ is offered}} - \overbrace{[\eta(A|b_H, s)b_H]}^{\text{expected payoff if } b_H \text{ is offered}}}{\underbrace{[\eta(A|b_L, s) + \eta(C|b_L, s)]}_{\text{Pr.to get matched if } b_L \text{ is offered}} - \underbrace{[\eta(A|b_H, s)]}_{\text{Pr.to get matched if } b_H \text{ is offered}}}$$

$\rightarrow$ 2) If $2\eta(A|b_L, s) + 2\eta(C|b_L, s) > \eta(A|b_H, s)$:

$$\hat{v}(s) = \frac{\overbrace{[\eta(A|b_L, s)b_L + \eta(C|b_L, s)(b_L + \Delta)]}^{\text{expected payoff if } b_L \text{ is offered}} - \overbrace{[\eta(A|b_H, s)b_H + \eta(C|b_H, s)(b_H + \Delta)]}^{\text{expected payoff if } b_H \text{ is offered}}}{\underbrace{[\eta(A|b_L, s) + \eta(C|b_L, s)]}_{\text{Pr.to get matched if } b_L \text{ is offered}} - \underbrace{[\eta(C|b_H, s) + \eta(C|b_H, s)]}_{\text{Pr.to get matched if } b_H \text{ is offered}}}$$

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Supply Model: Thresholds

$$\bar{\epsilon}(b, d_i) = \frac{\delta^5 V - \delta^{20} V}{\mu(C, b, d_i)} - \bar{u}(b + \Delta, d_i) + \delta^{20} V - \delta^{g(d_i)} V$$

$$\hat{\epsilon}(b, d_i) = \frac{\mu(C, b, d_i) \times \bar{u}(b + \Delta, d) - \mu(A, b, d_i) \times \bar{u}(b, d)}{\mu(A, b, d_i) - \mu(C, b, d_i)} + \delta^{20} V - \delta^{g(d_i)} V$$

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Riders' Beliefs: η

The rider forms the beliefs based on the state he observes s.

Full state s can be expressed as a vector: $[(d_1, k_1), ..., (d_X, k_X)]$, where k_i represents the number of drivers in a distance bin.

The rider then forms the beliefs η for each b:

$$\eta(A|b, \underbrace{(d_1, k_1), ..., (d_X, k_X)}_{s}) = 1 - \prod_{j=1}^{X} \left(1 - \rho(A|b, d_j)\right)^{k_j}$$

$$\eta(C|b, \underbrace{(d_1, k_1), ..., (d_X, k_X)}_{s}) = \prod_{j=1}^{X} \left(1 - \rho(A|b, d_j)\right)^{k_j} - \prod_{j=1}^{X} \rho(I|b, d_j)^{k_j}$$

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Drivers' Beliefs: $\alpha(b, d_j)$

- Driver i observes d_i, but not $\boldsymbol{d_{-i}}$.
- $\boldsymbol{d_{-i}}$ is a vector that contains distances of K competitors.
- Drivers know long-run probabilities for each $\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}} : \mathbb{P}(\boldsymbol{d_{-i}})$.

Probability that request of type $(\bar{d}, b, d_i)$ appears:

$$
\begin{aligned}
\alpha(b, d_i) &= \lambda \times \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \mathbb{P}(b, d_i, \boldsymbol{d_{-i}}) \\
&= \lambda \times \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \mathbb{P}(b|d_i, \boldsymbol{d_{-i}})\mathbb{P}(d_i, \boldsymbol{d_{-i}}) \\
&= \lambda \times \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \mathbb{P}(b|d_i, \boldsymbol{d_{-i}})\mathbb{P}(d_i)\mathbb{P}(\boldsymbol{d_{-i}}) \\
&= \lambda \times \mathbb{P}(d_i) \times \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \mathbb{P}(b|d_i, \boldsymbol{d_{-i}})\mathbb{P}(\boldsymbol{d_{-i}}) \\
&= \lambda \times \mathbb{P}(d_i) \times \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \omega(b|\underbrace{d_i, \boldsymbol{d_{-i}}}_{s})\mathbb{P}(\boldsymbol{d_{-i}})
\end{aligned}
$$

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Driver's Beliefs: μ

$$\mu(A, b, d_i) = \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \mathbb{P}(\boldsymbol{d_{-i}} | b, d_i) \mathbb{P}(WM | A, b, d_i, \boldsymbol{d_{-i}})$$

$$\mu(C, b, d_i) = \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \mathbb{P}(\boldsymbol{d_{-i}} | b, d_i) \mathbb{P}(WM | C, b, d_i, \boldsymbol{d_{-i}}) \mathbb{P}(v > b + \Delta \mid b)$$

Alternatively:

$$\mu(A, b, d_i) = \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \frac{\omega(b | d_i, \boldsymbol{d_{-i}}) \mathbb{P}(\boldsymbol{d_{-i}})}{\sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \omega(b | d_i, \boldsymbol{d_{-i}}) \mathbb{P}(\boldsymbol{d_{-i}})} \mathbb{P}(WM | A, b, d_i, \boldsymbol{d_{-i}})$$

$$\mu(C, b, d_i) = \sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \frac{\omega_m(b | d_i, \boldsymbol{d_{-i}}) \mathbb{P}(\boldsymbol{d_{-i}})}{\sum_{\boldsymbol{d_{-i}} \in \boldsymbol{D_{-i}}} \omega(b | d_i, \boldsymbol{d_{-i}}) \mathbb{P}(\boldsymbol{d_{-i}})} \mathbb{P}(WM | C, b, d_i, \boldsymbol{d_{-i}}) \mathbb{P}(v > b + \Delta \mid b)$$

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Drivers' beliefs: μ (cont.)

$$\mathbb{P}(WM|A, b, d_i, \boldsymbol{d_{-i}}) = \mathbb{P}(WM|A, b, d_i, \underbrace{[(d_1, n_1),}_{n_1 \text{ competitors with distance } d_1} \quad ... \quad \underbrace{, (d_X, n_X)]}_{n_X \text{ competitors with distance } d_X}$$

$$= \prod_{j=1}^{X} [\rho(A|b, d_j) \times \mathbb{P}(win|d_i, d_j) + (1 - \rho(A|b, d_j)) \times 1]^{n_j}$$

$$\mathbb{P}(WM|C, b, d_i, \boldsymbol{d_{-i}}) = \mathbb{P}(WM|C, b, d_i, \underbrace{[(d_1, n_1),}_{n_1 \text{ competitors with distance } d_1} \quad ... \quad \underbrace{, (d_X, n_X)]}_{n_X \text{ competitors with distance } d_X}$$

$$= \prod_{j=1}^{X} [\rho(C|b, d_j) \times \mathbb{P}(win|d_i, d_j) + (1 - \rho(A|b, d_j) - \rho(C|b, d_j)) \times 1]^{n_j}$$

$\mathbb{P}(win|d_j, d_i)$ - tie-breaking rule.

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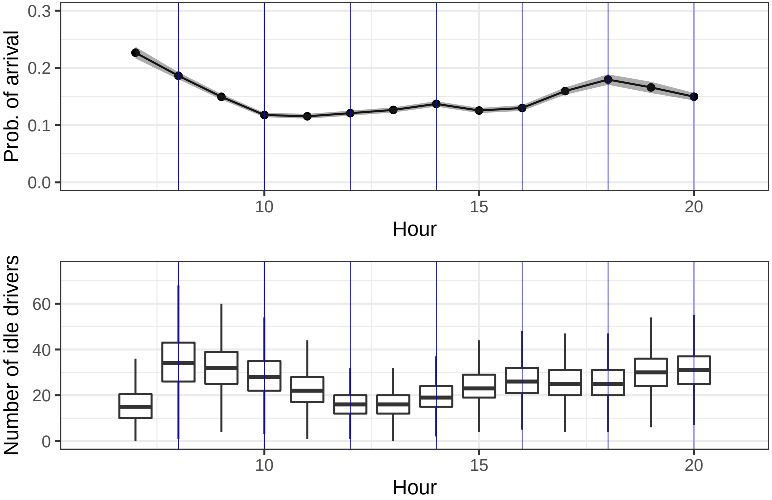
Market Definition: Arrival Rates and Idle Drivers



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Riders' Beliefs Estimation

	8 a.m.	10 a.m.	noon	2 p.m.	4 p.m.	6 p.m.	8 p.m.
High price	-0.434	-0.346	-0.519	-0.580	-0.539	-0.612	-0.597
	(0.026)	(0.040)	(0.029)	(0.028)	(0.033)	(0.022)	(0.027)
Number of visible drivers	-0.359	-0.213	-0.304	-0.232	-0.177	-0.262	-0.224
	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.006)	(0.007)
Short trip	-0.408	-0.342	-0.315	-0.451	-0.338	-0.319	-0.355
	(0.025)	(0.037)	(0.026)	(0.025)	(0.030)	(0.021)	(0.026)
Ordered probit thresholds							
Limit 1	0.301	1.067	-0.029	0.024	0.706	-0.290	0.328
	(0.021)	(0.032)	(0.023)	(0.022)	(0.027)	(0.020)	(0.024)
Limit 2	0.692	1.463	0.351	0.509	1.180	0.190	0.863
	(0.019)	(0.029)	(0.021)	(0.018)	(0.022)	(0.015)	(0.018)
Number of observations	42,656	26,881	28,664	31,707	30,388	43,711	37,263
Log-likelihood	-26,925.284	-13,012.190	-22,705.330	-25,076.019	-18,424.472	-36,443.109	-25,418.540

Notes: This table reports the results for the riders' beliefs estimation using an ordered probit model. Beliefs are estimated separately for each market. The dependent variable can take three values: 1 (Request is accepted), 2 (Request is counteroffered), and 3 (Request is ignored). The independent variables are (1) the indicator for a high price offered for a request, (2) the number of drivers within R-meter radius, and (3) an indicator for a short trip.

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Drivers' Beliefs Estimation

	$\mathbb{1}$(Driver wins)
Agree	2.523 (0.039)
Pickup distance (d)	−0.647 (0.018)
Long trip × Low price	0.433 (0.027)
Long trip × High price	0.173 (0.028)
Short trip × Low price	0.133 (0.026)
10 a.m.	0.132 (0.076)
noon	0.331 (0.074)
2 p.m.	0.231 (0.068)
4 p.m.	0.156 (0.069)
6 p.m.	0.307 (0.063)
8 p.m.	0.156 (0.064)
Constant	−2.793 (0.046)
Interaction terms	✓
Number of observations	415,308
Log-likelihood	-252,394.400

Notes: This table reports the results for the drivers' beliefs estimation using a logit model. All interaction terms between market indicators and indicators for trip types, pickup distance, and a chosen action are omitted from the table for brevity.

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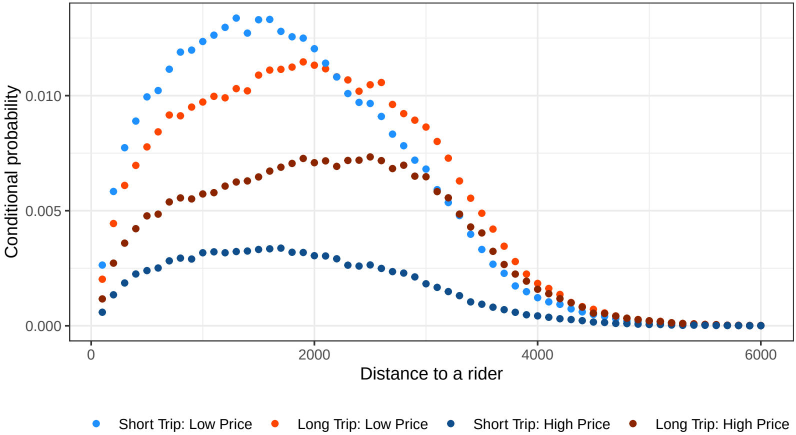
Drivers' Beliefs Estimation

Figure: Conditional Probability of Request Arrivals



Note: This figure presents the conditional distribution of the requests of different types for a single market.

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Identification

Demand-side:

Assumption: Variation in state that a rider observes is exogenous.

- This variation traces parts of the distribution $f(v|\psi_m(\bar{d}))$

Identification

Demand-side:

Assumption: Variation in state that a rider observes is exogenous.

- This variation traces parts of the distribution $f(v|\psi_m(\bar{d}))$

Supply-side:

Assumption: Type of observed requests is exogenous.

- Counteroffering pins down participation costs ($\beta^5 V_m - \beta^{20} V_m$) and variance of shocks (σ_ϵ).
- Static utilities $u_m(\bar{d}, b, d_j)$ are identified through drivers' choice probabilities.
- δ is identified through the probabilities to see counteroffers for different markets.

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Full Demand Estimates

	Short Trip				Long Trip			
	Num. obs.	Shape (k_m)	Scale (θ_m)	Log-likelihood	Num. obs.	Shape(k_m)	Scale (θ_m)	Log-likelihood
8 a.m.	18,520	0.340	2323.226	-10,463	24,136	0.521	2111.673	-17,154
		(0.008)	(58.871)			(0.009)	(49.614)	
10 a.m.	12,435	0.680	1851.909	-6,843	14,446	0.926	1700.558	-10,127
		(0.023)	(58.024)			(0.023)	(50.984)	
noon	13,205	0.268	1474.325	-7,070	15,459	0.419	1528.473	-10,484
		(0.013)	(99.470)			(0.016)	(97.734)	
2 p.m.	14,226	0.295	1485.884	-7,707	17,481	0.431	1411.844	-11,808
		(0.016)	(104.020)			(0.020)	(108.124)	
4 p.m.	13,684	0.471	1413.321	-7,382	16,704	0.655	1413.504	-11,353
		(0.026)	(85.382)			(0.028)	(83.803)	
6 p.m.	18,671	0.237	1834.072	-10,610	25,040	0.343	2615.305	-17,249
		(0.012)	(153.526)			(0.014)	(229.934)	
8 p.m.	15,041	0.440	1413.002	-8,777	22,222	0.622	1411.199	-15,472
		(0.019)	(74.633)			(0.018)	(62.576)	

Notes: This table reports the estimates for the parameters of truncated gamma distribution obtained via maximum likelihood. The estimation is performed separately for long and short trips on each market.

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