Route-based Pirce Discrimination of a Ride-hailing Company: The Case of Uber

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Introduction

- Ride fares of Uber used to vary depending on a few sources: trip distance, duration and the level of local demand at origin.
- A discriminatory pricing scheme on UberX has been started, charging heterogeneous prices differing based on where they are travelling: "Route-based pricing."
- Consumer vs. Uber
  - Consumer: Uber targets rich passengers who are going from, or to a wealthy neighborhood.
  - Uber: A way to enhance the number of rides by only considering demand on each route, not customers' individual data or ride history.

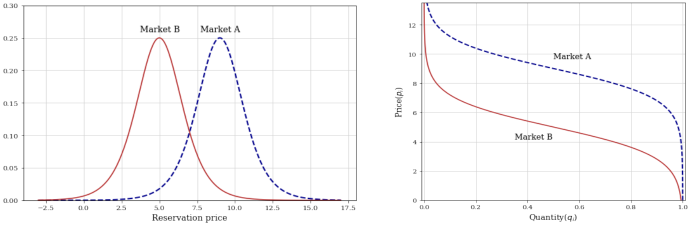
Introduction (cont.)

- I examine, in theory, when Uber realizes heterogeneous demand for each route:
  1. which pricing is more profitable (Discrimination vs. Uniform pricing) and,
  2. if a better pricing scheme is chosen, how it affects social welfare.
- I test if Uber does price discriminate using the OLS hedonic regressions
  - Narrow the scope of trip: Airport $\longrightarrow$ Hotel in LA, NY and SF
  - Assumption: passengers traveling to hotels with higher room-rate have higher reservation ride fare.
  - Hypothesis: the route-based pricing would set higher ride fares on the routes in which the passenger reservation price is comparatively higher.

The route-based price discrimination — Model

- Model setup
  - Travelers on two routes A and B have different distribution of reservation price of UberX, and Uber is aware of the distributions;
  - The distributions are derived from the logistic function with the differing means, $\theta_A > \theta_B$, but the common standard deviation, σ;
  - The utility function of a passenger is quasi-linear and strictly concave, and Uber's marginal cost is constant.

Figure 1: Reservation price and demand function



(a) Reservation price distributions (b) Inverse demand functions

The route-based price discrimination — Model

Proposition 1

If firm maximizes its profit for the segmented markets by consumers' reservation price derived from the logistic function, then there exist profit-maximizing discriminatory prices, p_A^* and p_B^*, such that the uniform price, $\overline{p}^*$, maximizing profit in the aggregate market is in between the discriminatory prices, p_A^* and p_B^* ($\overline{p}^* \in [p_A^*, p_B^*]$).

- Proposition 1 suggests that the third-degree price discrimination is the result of profit maximizing behavior of the firm being aware of the distribution of consumers' reservation price.

The route-based price discrimination — Model

Proposition 2

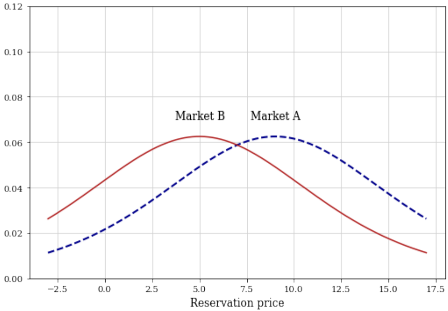
Given the logistic demand functions, social welfare with the route-based price discrimination is higher than that with uniform pricing.

- Proposition 2 implies that the third-degree price discrimination enhances social welfare when demand functions are derived from logistic distributions with different means and common standard deviation.

The route-based price discrimination — Model

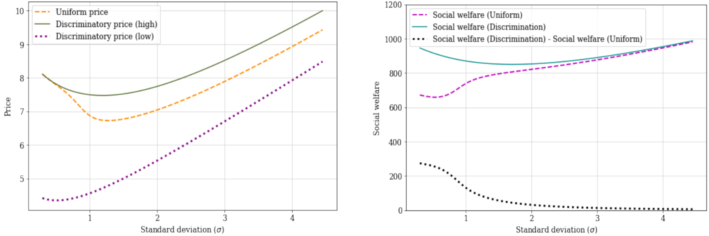
- What if the identical standard deviation is substantially high?

Figure 2: The distribution of reservation prices with high standard deviation



The route-based price discrimination — Model

Figure 3: Uniform and discrimination pricing and social welfare varying with σ



(a) Uniform and discriminatory prices

(b) Social welfare under uniform and discriminatory pricing

- It suggests that the price discrimination guarantees to enhance the social welfare, but achieving a significant difference in welfare requires the sufficiently low level of standard deviation of the reservation price.

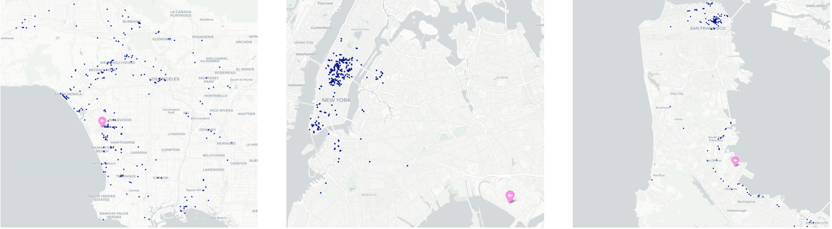
Empirical Analysis — Overview

- Steps to empirically observe the route-based discriminatory pricing:
  1. Specify the routes: the trips from airport (the identical origin) to hotels (heterogeneity in room rate and location);
  2. Collect the ride fare and trip characteristics data of UberX and the room rates and geographic information of the sampled hotels;
  3. Estimate the relationship between ride fare and hotel room rate, controlling for the other factors affecting the ride fare.
- The underlying assumption: passengers involving hotels with higher room rate are more likely to have higher reservation price for a ride of UberX.

Empirical analysis — Data

- Ride fare and trip characteristics of UberX for about 700 routes between airports, LAX, JFK and SFO, and hotels located within 20 miles radius of each airport over Sep 1st – Nov 30th, 2018.
- Hotel rates and location information culled from the American Automobile Association (AAA).

Figure 4: Airports and the locations of sampled hotels



(a) LAX (b) JFK (c) SFO

Empirical analysis — Data

Table 1: Summary statistics: Price and ride characteristics of UberX and hotel rate by region

	City		
	Los Angeles (1)	New York (2)	San Francisco (3)
A. Ride fare and characteristics			
Ride fare ($)	31.6148	64.5569	31.4588
	(15.5792)	(9.1397)	(10.0791)
Distance (mile)	15.3378	18.5562	11.9960
	(8.4065)	(2.5256)	(5.0215)
Duration (per trip, min)	31.6214	45.6975	21.4908
	(14.8913)	(12.0035)	(10.0240)
Duration (per mile, min)	2.4300	2.4871	1.8576
	(0.9562)	(0.6784)	(0.4686)
ETA (min)	4.5007	3.1998	2.5846
	(2.3189)	(1.2405)	(1.4009)
Observations	1582694	1510151	928785
B. Hotel room rate			
Room rate ($)	218.4514	344.6823	336.1518
	(119.8042)	(169.8863)	(191.1609)
Observations	261	267	152

Empirical analysis — Model (Baseline)

- The route-based price discrimination model — Baseline

$$P_{jt} = \beta HP_j + \gamma_0 + \gamma_1 Distance_{jt} + \gamma_2 Duration_{jt} + \sum_{t=1}^{T} \Psi_t Time_t + \epsilon_{jt} \quad (1)$$

- Variable description
  - P_{jt}: ride fare of UberX charged for route j at time t;
  - HP_j: the average room price of hotel as an endpoint of route j;
  - $Distance_{jt}$ and $Duration_{jt}$: trip distance and duration per mile respectively;
  - $Time_t$: time fixed effects capturing changes in prices over time.

Empirical analysis — Result (Baseline)

Table 2: Estimation result — Baseline

Dep. Var. P_{jt}	Los Angeles		New York		San Francisco	
	(1)	(2)	(3)	(4)	(5)	(6)
$HighHP$	1.0296***		0.848***		0.6311***	
	(0.0141)		(0.0086)		(0.0122)	
HP		0.0054***		0.0016***		0.001***
		(0.0001)		(0.0000)		(0.0000)
$Distance$	1.6029***	1.6069***	2.602***	2.6133***	1.8196***	1.8386***
	(0.0015)	(0.0015)	(0.0023)	(0.0023)	(0.0013)	(0.0012)
$Duration$	1.7806***	1.7888***	7.8456***	7.8553***	2.4870***	2.5079***
	(0.0118)	(0.0118)	(0.0121)	(0.0121)	(0.0116)	(0.0115)
Constant	5.7304***	4.9801***	-4.3292***	-4.6928***	7.0925***	6.8309***
	(0.0591)	(0.0596)	(0.0558)	(0.0565)	(0.049)	(0.0487)
Observations	1582694	1582694	1510151	1510151	928785	928785

[1] Coefficients of time fixed effects are omitted.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Empirical analysis — Model (Geographic matching)

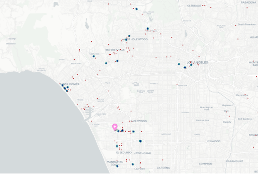
- The route-based price discrimination model — Geographic matching

$$\begin{aligned} P_{jt} = & \alpha + \beta_0 LocHP_j + \beta_1 DLocHP_j + \gamma_0 + \gamma_1 Distance_{jt} \\ & + \gamma_2 Duration_{jt} + \sum_{t=1}^{T} \Psi_t Time_t + \epsilon_{jt} \end{aligned} \tag{2}$$

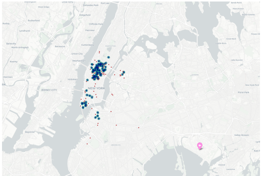
- Variable description (cont.)
    - $LocHP_j$: the mean of HP_js within 0.1 mile radius of hotel on route j;
    - $DLocHP_j$: the average room rate of neighboring hotels within 0.1 mile radius of hotel j subtracted from HP_j.

Empirical analysis — Data (Geographic matching)

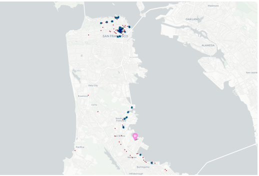
Figure 5: Locations of geographically matched hotels



(a) Los Angeles



(b) New York



(c) San Francisco

Table 3: Summary statistics: Geographically matched hotels

	Los Angeles (1)	New York (2)	San Francisco (3)
The number of neighboring hotels within each group	2.3455 (0.6727)	4.0396 (2.201)	3.8462 (2.38)
Average room rate of grouped neighboring hotels ($LocHP$, \$)	244.8801 (86.6316)	349.1422 (121.982)	338.622 (103.073)
Difference between hotel j's rate and average room rate of neighboring hotels ($DLocHP$, \$)	0.4264 (63.6216)	-3.7529 (156.7537)	7.0686 (134.3905)
The number of hotels chosen as neighbor	55	202	78

[1] Hotel j is chosen as a neighbor of hotel k if hotel j is within 0.1mile radius of hotel k.

Empirical analysis — Result (Geographic matching)

Table 4: Estimation result — Geographic matching

Dep. Var. P_{jt}	Los Angeles		New York		San Francisco	
	(1)	(2)	(3)	(4)	(5)	(6)
LocHP	0.009***	0.0089***	0.0019***	0.0019***	0.0053***	0.0053***
	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
DLocHP		0.0005***		0.0002***		0.0002***
		(0.0002)		(0.0000)		(0.0001)
Distance	1.5724***	1.5724***	2.4585***	2.4585***	1.8471***	1.8471***
	(0.0034)	(0.0034)	(0.0028)	(0.0028)	(0.0016)	(0.0016)
Duration	1.4187***	1.4173***	7.3972	7.3978***	2.4459***	2.4460***
	(0.0221)	(0.0221)	(0.014)	(0.0140)	(0.0172)	(0.0172)
Constant	4.6825***	4.6857***	-0.752***	-0.7684***	5.5206***	5.5187***
	(0.1159)	(0.1160)	(0.0689)	(0.0690)	(0.0694)	(0.0694)
Observations	333522	333522	1164502	1164502	476627	476627

[1] Coefficients of time fixed effects are omitted.
[2] Robust standard errors are in parentheses.
[3] *** Significant at the 1% level.

Concluding remarks

- When demand functions for each route are derived from logistic distribution of reservation price with differing means and a common standard deviation, if Uber is well-informed as for the distributions,
    1. in theory, the third-degree price discrimination is more profitable pricing strategy than uniform pricing;
    2. the discriminatory pricing leads to greater social welfare than non-discriminatory pricing unless the standard deviation of reserve price is extremely low.
- As what theory predicts, it is empirically observed that Uber does price discriminate by charging higher ride fare to the route in which riders have higher reservation price.
    - When routes are confined to ‘airport to hotels’, evidence is found suggesting that the route-based pricing sets higher ride fare on the route where the room rate is higher.

Q & A

Thank you!

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