Estimating Demand Elasticities and Consumer Surplus: the Case of Uber

Jiaming Mao

Xiamen University

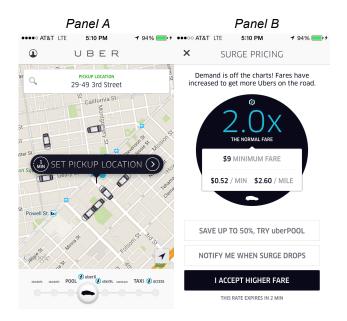
Copyright © 2014–2021, by Jiaming Mao This version: Fall 2021 Contact: jmao@xmu.edu.cn Course homepage: jiamingmao.github.io/principles-of-economics



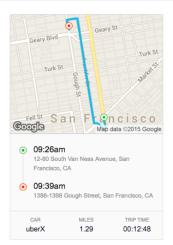
All materials are licensed under the Creative Commons Attribution-NonCommercial 4.0 International License.

Introduction

- Uber is an app-based service that algorithmically matches drivers to consumers seeking rides.
- Uber uses real-time pricing ("surge" pricing) to equilibrate local, short-term supply and demand.
- Consumers face prices ranging from the base price ("1.0x") to five or more times higher, depending on local market conditions.



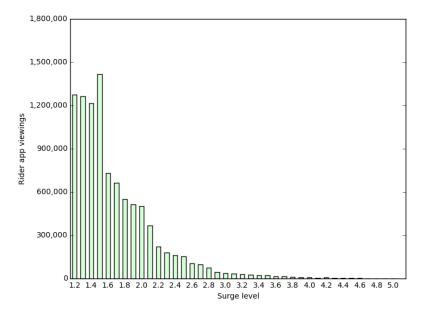
\$11.08 Ø



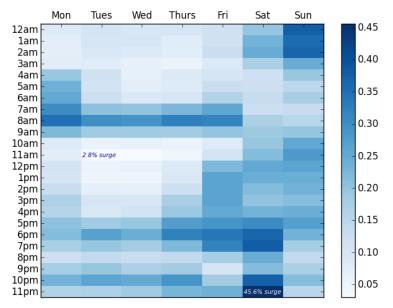
Thanks for choosing Uber, Peter

BREAKDOWN
2.20
1.67
3.33
\$7.20
2.88
\$10.08
ie Rides Fee (?) 1.00
\$11.08

Distribution of Surge Prices

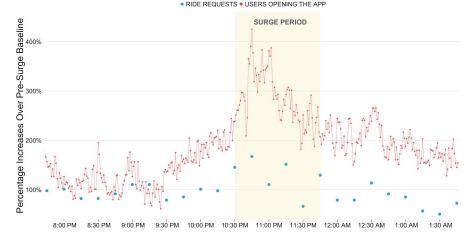


Distribution of Surge Sessions



Demand and Supply in Action

- On March 21, 2015, Ariana Grande played a sold out show at Madison Square Garden. Attendees attempting to get home after the concert caused a large spike in demand.
- The number of riders opening the Uber app after the concert spiked up to 4 times the normal number of app openings.



Uber demand around Madison Square Garden on March 21, 2015.

Demand and Supply in Action

- In response to the higher demand, Uber's surge pricing kicked in, fluctuating between 1x and 1.8x for over an hour after the concert (10:30PM 11:45PM).
- As a result, the number of active drivers in the area increased by up to 2 times during the surge period.



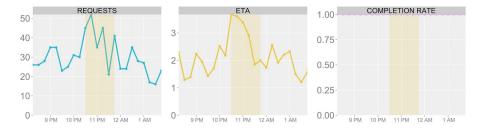


Active drivers around Madison Square Garden on March 21, 2015.

Effect of Surge Pricing

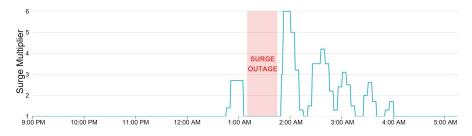
- Surge pricing worked to equilibriate supply with demand and clear the market:
 - Completion rate didn't drop during peak demand.
 - Wait times did not increase substantially.

Effect of Surge Pricing



When Surge Pricing was not Available

- Because of a technical glitch, the surge pricing algorithm across New York City broke down for 26 minutes (1:24am to 1:50am) on New Year's Eve, December 31, 2014 to January 1, 2015.
- New Year's Eve represents one of the busiest days of the year for Uber and illustrates why surge pricing is often necessary to equilibriate supply with demand.
 - At the same time that demand is unusually high, drivers are simultaneously reluctant to work because the value of their leisure time (e.g., their own celebrations of New Year's Eve) is high. Put bluntly, people do not want to drive on NYE.
 - Without surge pricing, drivers are less attracted to the platform while riders are not forced to make the proper economic tradeoffs. This could lead to a significant shortage.

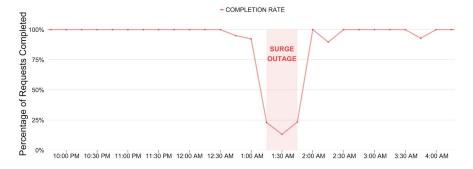


Twenty Minutes Without Surge on New Year's Eve (January 1, 2015)

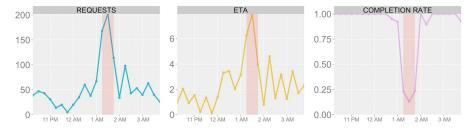
When Surge Pricing was not Available

• As a result of the glitch, completion rates fell dramatically and wait times increased, causing a failure of the system from an economic efficiency perspective¹.

¹The best evidence for the effectiveness of Uber's surge algorithm is the remarkable consistency of the expected wait time for a ride.



Twenty Minutes Without Surge on New Year's Eve (January 1, 2015)



Twenty Minutes Without Surge on New Year's Eve (January 1, 2015)

Estimating Demand Elasticities

- How to estimate the demand elasticities of Uber users?
- We observe the prices offered to Uber users and whether they ended up requesting a ride. Hence, we observe prices and purchase rates.
- Prices and purchase rates, however, are equilibrium data points. Variations in equilibrium across time and space can be driven by both demand and supply shifts.
- Therefore, simply looking at how purchase rates vary with prices would not inform us of the demand curve².

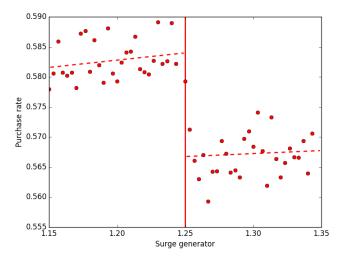
²To estimate a demand curve, one needs to hold everything else constant, other than price.

Estimating Demand Elasticities

- To estimate demand elasticities, we could exploit the discontinuities in Uber pricing: Uber calculates each surge price as a continuous number, but consumers are presented with discrete price increments (1.0x, 1.2x, 1.3x, ...).
 - The Uber algorithm (called "surge generator") value of 1.249x leads to a surge price of 1.2x whereas a value of 1.251 triggers a 1.3x surge. The market conditions, however, are nearly identical in these two cases.
- This provides the opportunity for **regression discontinuity** (**RD**) analysis, which allows us to estimate local elasticities of demand across the full range of surge prices³.

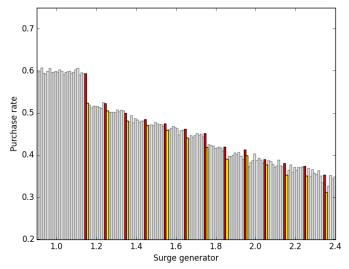
³Note that the simplest way for Uber to estimate the demand elasticities of its users is to employ the device of price randomization: randomly assign prices at random times to randomly chosen individuals and observe how their purchase rates vary with the prices they face. However, Uber did not conduct such randomization experiments.

Price Discontinuity



The purchase rate falls 3 percent at the discontinuity; price rises by 8.3 percent (from 1.2x and 1.3x), for an implied price elasticity of roughly -0.36.

Price Discontinuity



(red, yellow): observations within .01 units to the (left, right) of a price discontinuity; purchase rates fall consistently as price discontinuously jumps.

Summary Statistics

	Full Data	Surge = 1	$1 < {\rm Surge} \leq 2.0$	$\mathrm{Surge} > 2.0$
Surge	1.141	1.000	1.509	2.531
Expected wait time	4.118	4.205	3.731	4.046
Purchase rate	59%	62%	53%	39%
City				
Chicago	22%	20%	29%	32%
Los Angeles	25%	26%	20%	24%
New York	29%	31%	21%	19%
San Francisco	24%	22%	30%	25%
Time of Day				
Evening rush	8%	8%	10%	13%
Morning rush	6%	6%	7%	14%
Slow nighttime	12%	13%	10%	8%
Weekday day	23%	25%	15%	12%
Weekday evening	14%	15%	13%	10%
Weekend day	15%	14%	18%	17%
Weekend evening	6%	6%	7%	6%
Weekend event	15%	14%	20%	20%
Rides in Period				
1 ride in period	6%	6%	4%	4%
$1 < rides$ in period ≤ 3	9%	10%	8%	7%
$3 < \text{rides in period} \leq 8$	14%	15%	13%	13%
> 8 rides in period	71%	70%	75%	75%
Sessions	47469440	37667052	8135793	1666595

Estimation: Elasticity

Surge Threshold	(1)	(2)	(3)	(4)	(5)
1.2	-0.26	-0.43	-0.52	-0.52	-0.52
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
1.3	-0.32	-0.31	-0.35	-0.36	-0.34
	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
1.4	-0.42	-0.47	-0.53	-0.53	-0.58
	(0.01)	(0.05)	(0.05)	(0.05)	(0.05)
1.5	-0.42	-0.47	-0.50	-0.50	-0.49
	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)
1.6	-0.33	-0.33	-0.43	-0.45	-0.50
	(0.02)	(0.06)	(0.06)	(0.06)	(0.06)
1.7	-0.62	-0.60	-0.66	-0.68	-0.68
	(0.03)	(0.08)	(0.08)	(0.08)	(0.08)
1.8	-0.73	-0.80	-0.85	-0.88	-0.89
	(0.03)	(0.10)	(0.10)	(0.10)	(0.10)
1.9 - 2.3	-0.77	-0.99	-1.02	-1.06	-1.01
	(0.02)	(0.07)	(0.07)	(0.07)	(0.07)
2.4 - 3.0	-0.37	-0.34	-0.38	-0.39	-0.25
	(0.05)	(0.17)	(0.17)	(0.17)	(0.17)
3.1 - 5.0	-0.72	-0.61	-0.75	-0.78	-0.65
	(0.14)	(0.46)	(0.46)	(0.46)	(0.46)
Source of identification	All variation	RD only	RD only	RD only	RD only
Control for wait time	No	No	Yes	Yes	Yes
Instrument for wait time	No	No	No	Yes	Yes
Additional controls	No	No	No	No	Yes

Estimation: Elasticity

Elasticity
-0.5463
(0.0209)
. ,
-0.6618
(0.0367)
-0.3270
(0.0458)
-0.6084
(0.0514)
-0.5244
(0.0378)

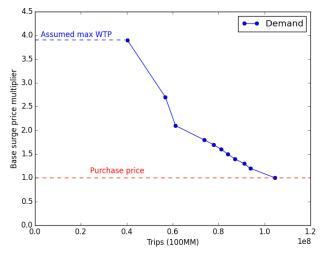
Estimating Demand Elasticities

- Result: demand is consistently inelastic along the length of the demand curve.
- The average price elasticity of demand is 0.55.

Estimating Consumer Surplus

- Using the estimated elasticities at each price discontinuity, we could map out the entire demand curve for consumers who requested rides at each surge price.
- We can then calculate the total consumer surplus associated with transactions at each surge price.

Estimated Demand Curve for Transactions at 1.0×



Piecewise linear demand curve with jumps at each price discontinuity. This curve is generated from the underlying elasticities estimated for each price discontinuity and for consumers facing transactions at 1.0x.

Estimating Consumer Surplus

- Result: in 2015 the UberX service generated about \$2.9 billion in consumer surplus in four U.S. cities (NYC, San Francisco, Chicago, LA).
- Extrapolating to the entire U.S., the overall consumer surplus generated by the UberX service in the U.S. in 2015 was estimated to be \$6.8 billion.

Limitations

- The set of sessions with high surge prices may differ systematically from those who see low surge.
- The estimated elasticities are very short-run elasticities⁴.

⁴The price variations exploited in the RD analysis is highly transient. The appropriate interpretation of the welfare estimate is: if Uber's system malfunctioned and Uber were unavailable for a day, how much would consumers suffer?

Reference

- Cohen P., R. Hahn, J. Hall, S. Levitt, and R. Metcalfe. 2016. "Using Big Data to Estimate Consumer Surplus: The Case of Uber," NBER Working Paper.
- Hall, J., C. Kendrick, and C. Nosko. 2015. "The Effects of Uber's Surge Pricing: A Case Study," NBER Working Paper.