Surge Pricing Moves Uber's Driver-Partners

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Agenda

Impact of Dynamic Pricing on relocation and revenue of Uber driver partners

What is Dynamic/Surge Pricing?

Pricing strategy in which businesses set flexible prices for products/services based on market demands.

Why Dynamic Pricing though?

- Reduces mismatch between drivers and riders
- Reduces waiting times
- Increases the number of trips
- Improves welfare of both riders and drivers

Uber’s Surge pricing system

Fare for a trip depends on 2 factors

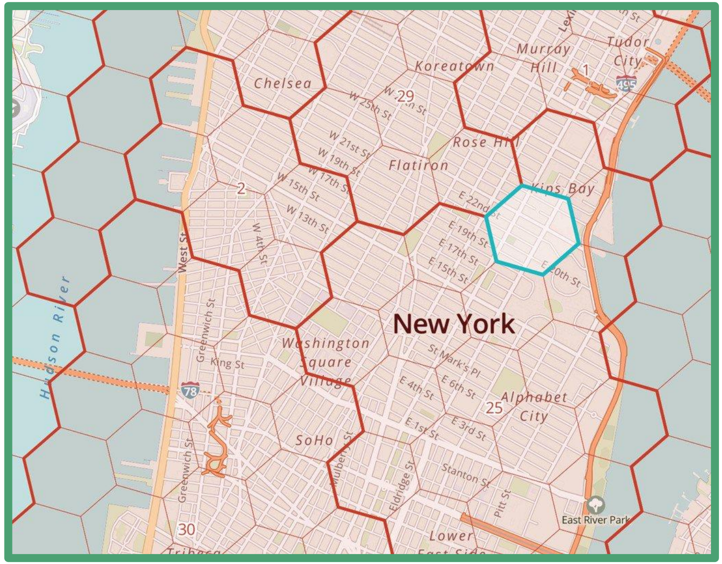
- Unsurged fare
- Surge multiplier

The price you pay the driver is Unsurged fare x Surge Multiplier

Driver’s earnings for a trip is Amount left after paying a fixed commision to Uber.

What is a Surge Multiplier?

- Cities are partitioned into non-overlapping hexagons with edge length 0.2 miles.
- Each hexagon has a surge multiplier.



How do we compute a surge multiplier?

➢ Number of riders using the app to book a cab.

➢ Number of drivers in/near that area.

Image credits : https://twitter.com/ubereng/status/951939541060874241

Surge heatmap

The drivers are shown a visualisation map called the surge heatmap which displays the current surge multiplier in each hexagon.

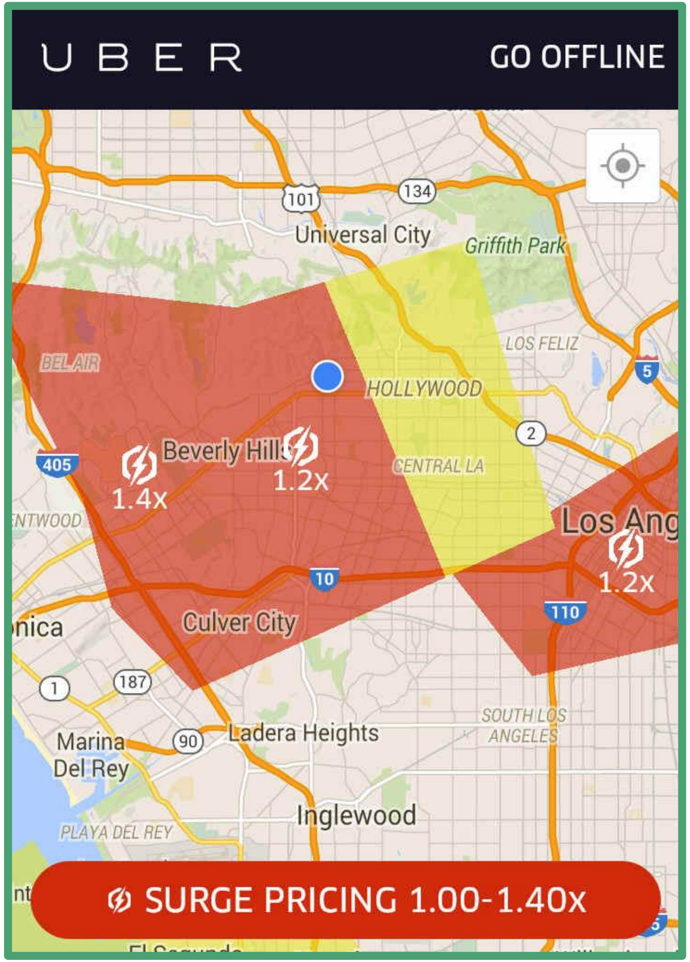


Image Credits : http://www.alvia.com/what-is-uber-surge-pricing/

Does Visibility of surge heatmap affect

- Driver’s relocation decisions?
- Driver’s Revenue?

YES!

➢ Attracts drivers towards areas with higher surge prices
➢ Increases driver’s revenue upto 70%

Data Overview

Data was collected from four sources

1. **Surge heatmap data** : Surge multipliers for each hexagon are recorded for every minute.
2. **Driver location data** : GPS data of each driver is recorded for estimating their arrival times.
3. **Operating system** : The OS run by the driver’s phone is recorded.
4. **Driver’s Metadata** : Driver’s age, date of joining is also recorded

Example Dataset Used

Row	Driver	Time	OS	Current Hexagon	1-Ring Surge Values	Next Hexagon	Age	Tenure
0	Josie	9:00	iOS	a0	(1.0,1.0,1.2,1.2,1.3,1.0, 1.2)	a0	32	2.5
1	Josie	9:01	iOS	a0	(1.2,1.0,1.2,1.3,1.4,1.0, 1.2)	a1	32	2.5
2	Josie	9:02	iOS	a1	(1.2,1.0,1.2,1.3,1.4,1.0, 1.2)	a2	32	2.5
3	Josie	10:25	iOS	a10	(1.8,2.2,1.7,1.6,1.5,1.5, 1.6)	a12	32	2.5
4	Josie	10:26	iOS	a12	(1.8,2.2,1.7,1.6,1.5,1.5, 1.6)	a12	32	2.5
	...	...	...	...	...	...	...	...
5	Mark	10:25	iOS	b38	(1.0,1.0,1.0,1.0,1.0,1.0,1.0)	b39	41	1.2
6	Mark	10:26	iOS	b39	(1.0,1.2,1.0,1.0,1.0,1.0,1.0)	b40	41	1.2
	...	...	...	...	...	...	41	1.2

Table Credits: [Lu et al. 2018] Surge Pricing Moves Uber's Driver-Partners

Natural Experiment

- Cities served by one of Uber's data centers suffered from a technical outage in the surge pricing system during the weekend of November 4th to 6th in 2k16.
- NY, Boston, Chicago, Washington DC, and many other cities in the US
- The iOS drivers were not able to see the surge heatmap :(, while the android drivers were able to see it normally.
- However, the price was multiplied by the respective surge multiplier for all the users.

Can we infer something cool?

We can study the impact of lack of visibility of the surge heatmap on drivers by comparing:

- iOS and Android users on the outage week
- iOS drivers on the outage week and non-outage week

For the non-outage week, data was collected from the weekend of 22-24th October 2k16.

Methodology

Modelling Driver Behavior

- We model a driver’s perceived utility based on various factors including the Surge Difference
- We use that utility to analyze driver movements using a multinomial logit (MNL) model
- The MNL model gives a probability of a particular decision taken by driver
- We have the observed data for drivers’ movements. We estimate the model parameters by fitting to this data

Modelling Driver Behavior

- Driver ***d***, present in hexagon ***i***, at time ***t***
- Can move to ***j*** at time ***t+1***
- ***j*** can take values ***0,1,...,6***

- The utility of moving in direction **j** from hexagon ***i*** at minute ***t*** is given by
  $u(t, i, j, d)$

Modelling Driver Behavior

- We only consider states where driver is “Open”. Rest is “unobserved”.

- We normalize the utility of staying in same hexagon as 0

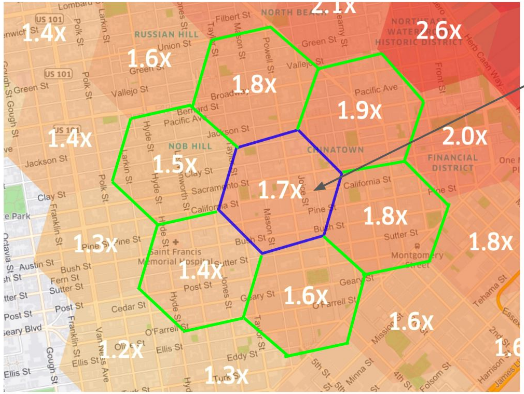
$$u(t, i, 0, d) = 0$$

Factors Affecting Utility

- **Surge Gradient** $\Delta p(t, i, j)$

  Difference in smoothed surge multiplier for each adjacent hexagon. Smoothing done for each hexagon by averaging the value in hexagons in three concentric rings

- **Visibility of Heat Map** $invisible(d, t)$



7 options with Prices

	Immediate	Smoothed
0	1.7x (+0.0x)	1.69x (+0.0x)
1	1.9x (+0.2x)	2.02x (+0.33x)
2	1.8x (+0.1x)	1.83x (+0.14x)
3	1.6x (-0.1x)	1.57x (-0.12x)
4	1.4x (-0.3x)	1.33x (-0.36x)
5	1.5x (-0.2x)	1.37x (-0.32x)
6	1.8x (+0.1x)	1.84x (+0.15x)

Image Credits: [Lu et al. 2018] Surge Pricing Moves Uber's Driver-Partners

Factors Affecting Utility

- **Driver Related Metrics: Age, Tenure, iOS/Android**

- **A Binary Indicator for identification of the weekend** $T(t)$
  The experiment is done over two weekends. The value is 0 for first week and 1 for second

Utility Function

$$
\begin{aligned}
u(t,i,j,d) = {} & \beta_0 + \beta_1 \cdot \Delta p(t,i,j) \\
& + T(t) \cdot [\beta_2 + \beta_3 \cdot \Delta p(t,i,j)] \\
& + \text{invisible}(d,t) \cdot [\beta_4 + \beta_5 \cdot \Delta p(t,i,j)] \\
& + \text{tenure}(d) \cdot [\beta_6 + \beta_7 \cdot \Delta p(t,i,j) + \beta_8 \cdot T(t) + \beta_9 \cdot \Delta p(t,i,j) \cdot T(t)] \\
& + \text{age}(d)[\beta_{10} + \beta_{11} \cdot \Delta p(t,i,j) + \beta_{12} \cdot T(t) + \beta_{13} \cdot \Delta p(t,i,j) \cdot T(t)] \\
& + \text{iOS}(d) \cdot [\beta_{14} + \beta_{15} \cdot \Delta p(t,i,j)]
\end{aligned}
$$

Analysis

- From the MNL assumption, The probability of observing a choice ***j***, is given by

$$P(j|t,i,d) = \frac{exp(u(t,i,j,d))}{\sum_{j'=0}^{6} exp(u(t,i,j',d))}$$

Analysis

- Parameters of the model estimated using Maximum Likelihood Estimation (MLE) where likelihood is calculated using the utility function and the corresponding probability of observing the choice that was actually observed

- We chose parameters that maximise the likelihood of observed data

Analysis : Difference-in-Differences Approach

- We are interested in the causal effect of visibility of heatmap towards driver relocation

- There is a natural difference in utility calculated over any two different time Periods

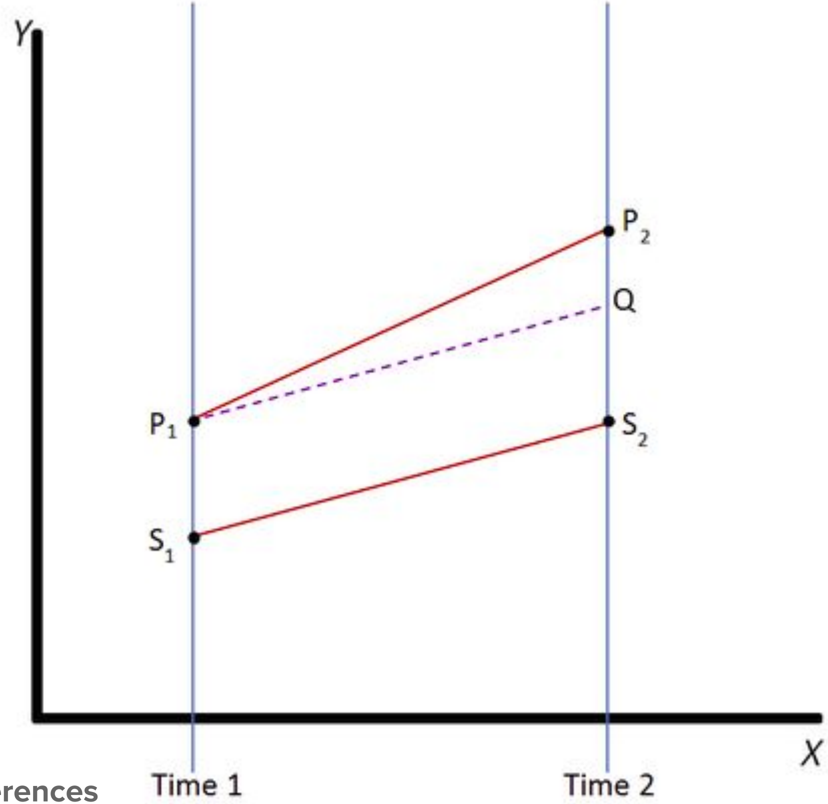


Image Credits: https://en.wikipedia.org/wiki/Difference_in_differences

Analysis : Difference-in-Differences Approach

- Naive Approach: P2 - P1

  Does not account for the difference in Market conditions for the two periods

- Solution: Q - P2

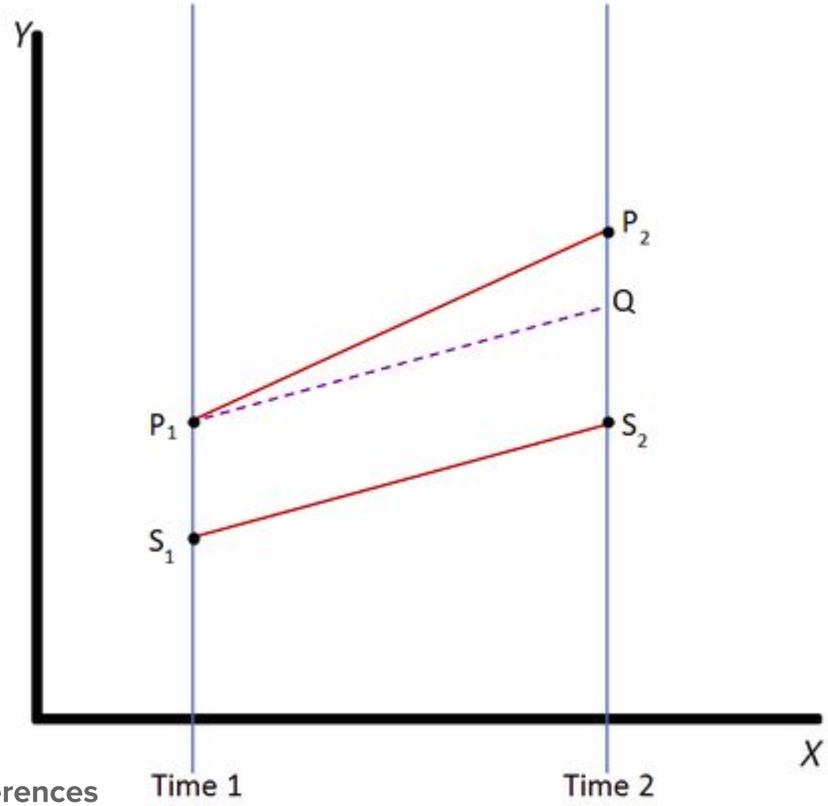


Image Credits: https://en.wikipedia.org/wiki/Difference_in_differences

Analysis : Difference-in-Differences Approach

- We assume that the difference would have remained constant in second week **Parallel Trend Assumption**

- Need to make sure the Assumption Holds, for our analysis to be valid

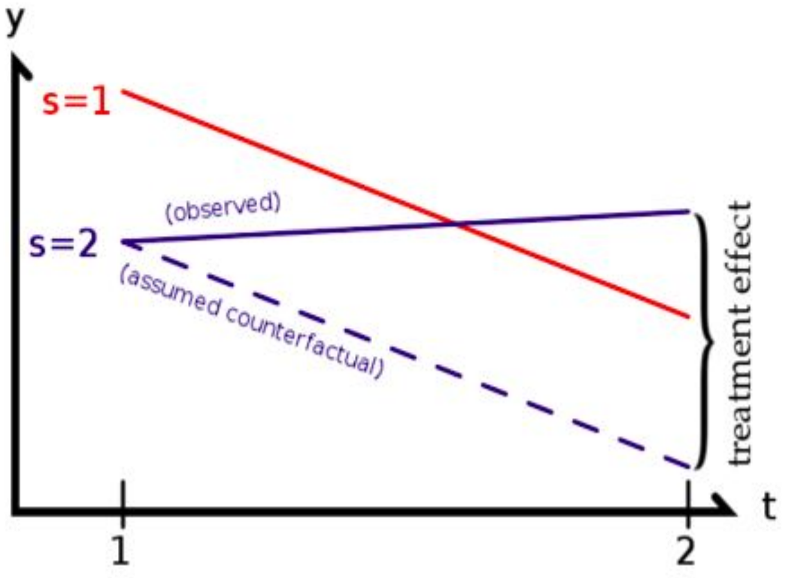


Illustration of the Parallel Trend Assumption

Image Credits: https://en.wikipedia.org/wiki/Difference_in_differences

Utility Function

$$
\begin{aligned}
u(t,i,j,d) = \beta_0 &+ \beta_1 \cdot \Delta p(t,i,j) \\
&+ T(t) \cdot [\beta_2 + \beta_3 \cdot \Delta p(t,i,j)] \\
&+ \text{invisible}(d,t) \cdot [\beta_4 + \beta_5 \cdot \Delta p(t,i,j)] \\
&+ \text{tenure}(d) \cdot [\beta_6 + \beta_7 \cdot \Delta p(t,i,j) + \beta_8 \cdot T(t) + \beta_9 \cdot \Delta p(t,i,j) \cdot T(t)] \\
&+ \text{age}(d)[\beta_{10} + \beta_{11} \cdot \Delta p(t,i,j) + \beta_{12} \cdot T(t) + \beta_{13} \cdot \Delta p(t,i,j) \cdot T(t)] \\
&+ \text{iOS}(d) \cdot [\beta_{14} + \beta_{15} \cdot \Delta p(t,i,j)]
\end{aligned}
$$

DiD Parallel Trend Assumption:

Coefficient of interaction terms

$iOS(d).T(t)$

$iOS(d).T(t).\Delta p(t,i,j)$

Must be Zero.

Significance of Various Coefficients

Sensitivity to Surge Gradient

$$\beta_1 + \beta_3 \cdot T(t) + \beta_5 \cdot \text{invisible}(d, t) + \beta_7 \cdot \text{tenure}(d) + \beta_9 \cdot \text{tenure}(d) \cdot T(t) + \beta_{11} \cdot \text{age}(d) + \beta_{13} \cdot \text{age}(d) \cdot T(t) + \beta_{15} \cdot \text{iOS}(d). \quad (1)$$

Hypotheses

- (1) is positive
- β_5 is negative

Significance of Various Coefficients

Coefficient Associated With Moving when surge gradient = 0

$$\begin{aligned}\beta_0 + \beta_2 \cdot T(t) + \beta_4 \cdot \text{invisible}(d,t) + \beta_6 \cdot \text{tenure}(d) + \beta_8 \cdot \text{tenure}(d) \cdot T(t) + \\ \beta_{10} \cdot \text{age}(d) + \beta_{12} \cdot \text{age}(d) \cdot T(t) + \beta_{14} \cdot \text{iOS}(d)\end{aligned} \quad (2)$$

Hypotheses

- (2) is negative

Results And Other Experiments

Analysis of Model Assumptions

- Analysis relies on the Assumption that $iOS(d)*T(t)$ and $iOS(d)*T(t)*\Delta p(t,i,j)$ have zero coefficients
- To study this assumption further we study the following items
    - Difference between the two weekends
    - Difference between iOS and Android Drivers

Difference Across Time

- No guarantee that Market Condition were similar across the two weekends
- Market Conditions are determined by the Imbalance between demand and supply
- Demand and Supply patterns were different over the two weekends but the surge pricing algorithm made adjustment accordingly

Difference Across Operating System

- Might reflect difference in demographics which are co-related with driver's driving habit
- As per the data driver's using iOS OS have younger average as compared to Android OS users in all the cities
- But their average tenure are different in different cities
- In order to address these differences we include driver's tenure and age as covariates in our factor model

Composition of Drivers

- Invisibility of surge heatmap may cause some iOS drivers to not drive thus changing composition of online drivers.
- These drivers who are offline are also more likely to stay in place or move away from the surging area,then this change in composition could make prominent impact of heatmap invisibility on driver movement towards surge.

Impact of surge on Driver’s Movement

β5 is significantly negative for most of the cities as the lack of surge heatmap visibility causes drivers to be less sensitive to surge differences

Experienced drives are less likely to move out from their current hexagon

- ❖ Imbalance in surge might dissipate by the time they relocate
- ❖ Afraid of being dispatched out of a low-surge hexagon they go offline and then drive towards high-surge hexagon and become open upon arrival

In big cities experienced drives are less attracted by surge while in small cities the effect was reversed

Impact of Surge on Driver's Revenue

- Indeed the iOS drivers earned less in most of the cities
  - On average the absence of surge information reduces driver revenue by 20 to 80 cents per hour
  - Absence of heatmap reduces driver's revenue in small cities as drivers in these cities possibly had less experience and they relied more heavily on the heatmap to make self-positioning decisions

Conclusion

- Experienced drivers in big cities less affected as compared to less experienced drivers in small cities.
- Surge Information helps in identify earning opportunities and can improve revenue upto 70%
  - ➢ Hence dynamic pricing is useful as a real-time signaling tool for better self-positioning decision to be made by drivers.

Thank You.