#### ORIE 5355

Lecture 11: Algorithmic pricing:
Pricing in Ride-hailing
+ Congestion pricing

Nikhil Garg

#### Announcements & reminders

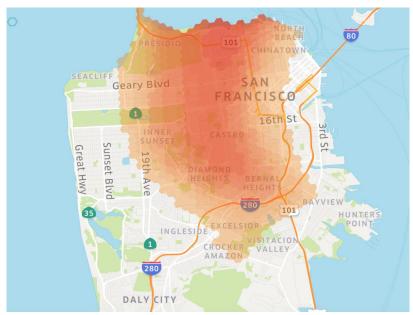
No class Monday (Fall break)

## Dynamic pricing in ride-hailing

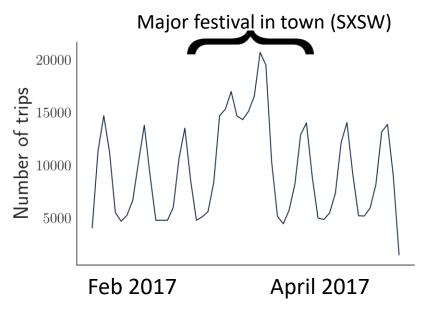
## Surge pricing

Demand fluctuates substantially
Surge matches demand with supply

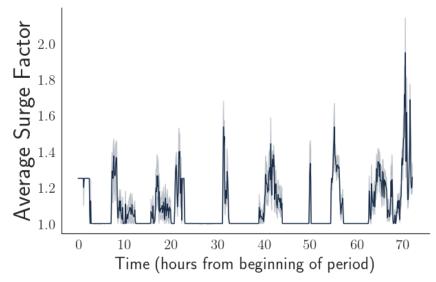
#### Spatially:



#### Within weeks:

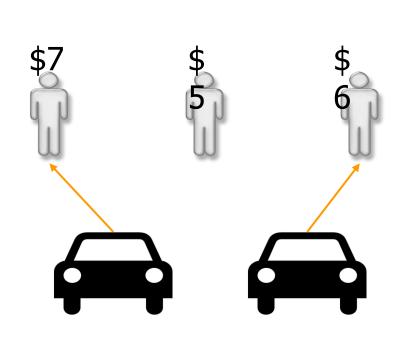


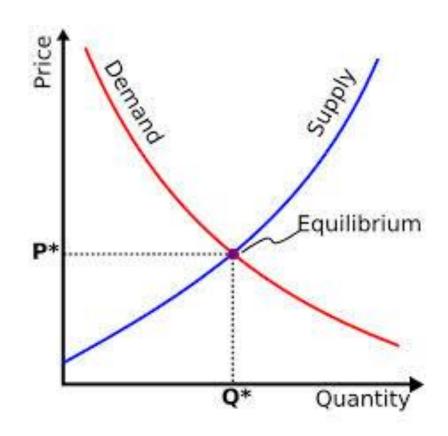
#### Within a day:



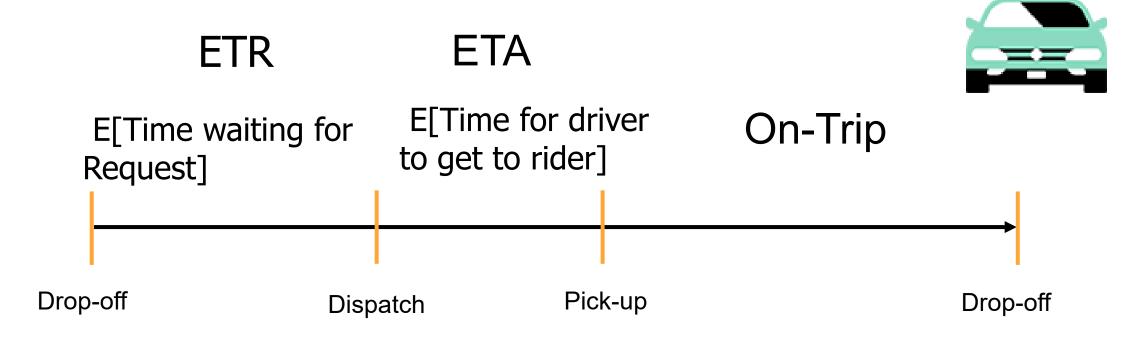
#### Surge Pricing Goal

Efficient and Reliable allocation of scarce resources via price increase



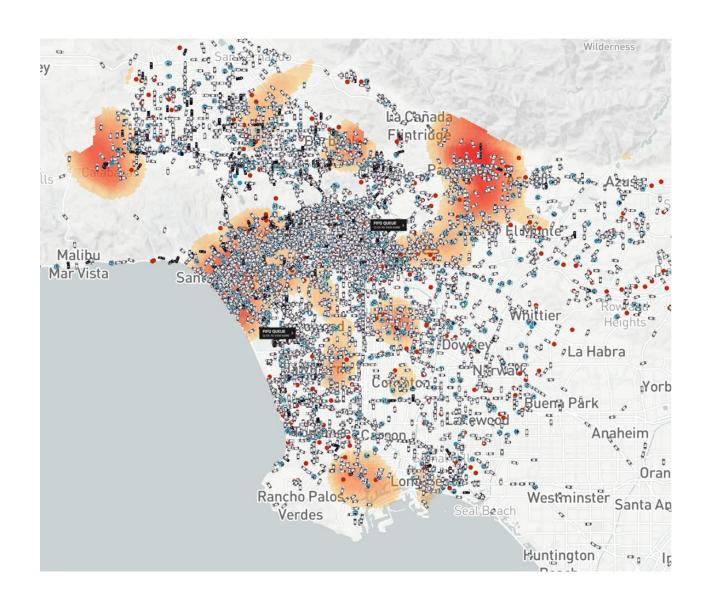


#### Dynamics for a Single Trip (a single driver's perspective)



Efficiency = Total On-Trip / (Total ETR + Total ETA + Total On-Trip)

Dynamic pricing regulates the level of Open Cars to maintain reliability and to increase efficiency.



Prices too low

⇒
Too many requests
⇒
Few open drivers
⇒
Takes longer to drive to
rider
⇒
Efficiency suffers

#### Surge makes the marketplace reliable.



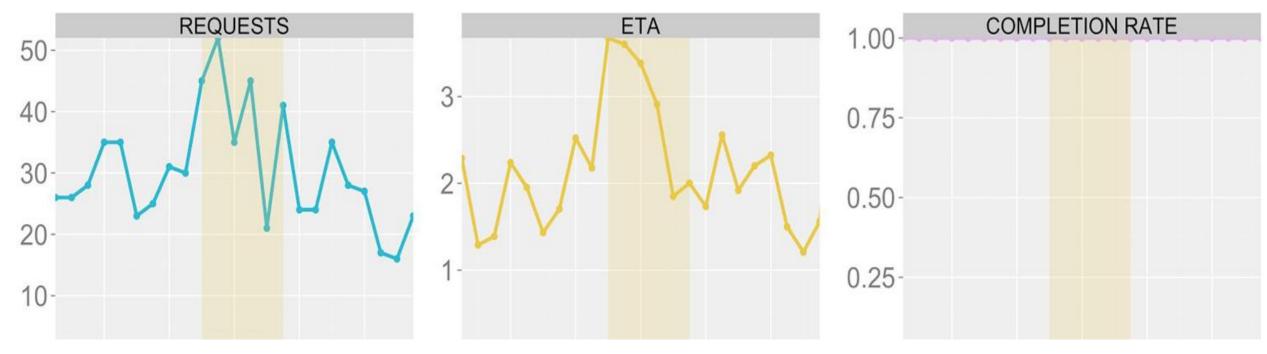
Sold Out Ariana Grande Concert, Madison Square Garden, New York March 21, 2015

#### Surge makes the marketplace reliable.



Surge multiplier and trip demand following Ariana Grande concert

#### Marketplace health indicators



Yellow band shows surge period.

Raising prices maintains a "healthy market" as measured by ETA and Completion Rate.

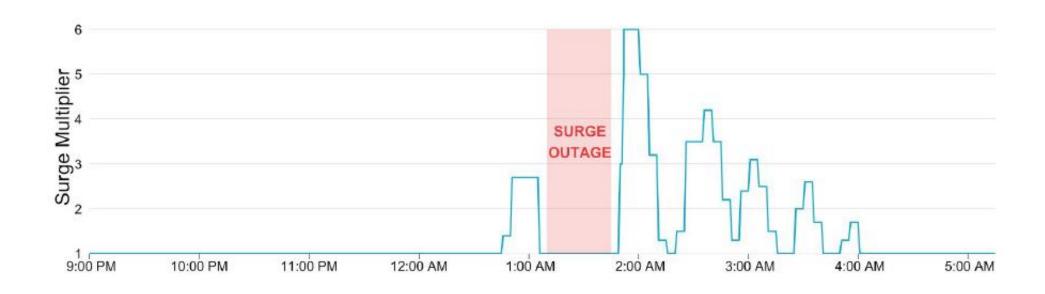
Slide credit: Hamid Nazerzadeh, Uber & USC

#### Surge Outage



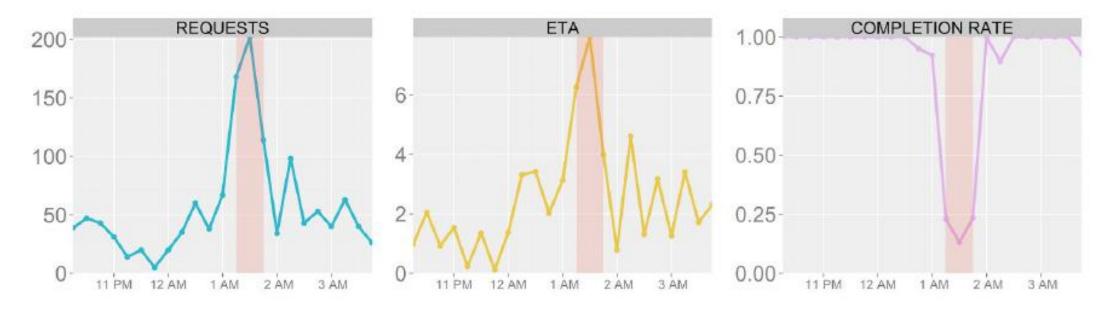
New York City, New Year's Eve 2014 20 Minute Long Surge Outage

#### What happens if the prices don't rise?



Due to a technical glitch, the surge multiplier was inoperable (stuck at 1) for 26 minutes (1:24 AM to 1:50 AM) on Jan 1, 2015 in NYC.

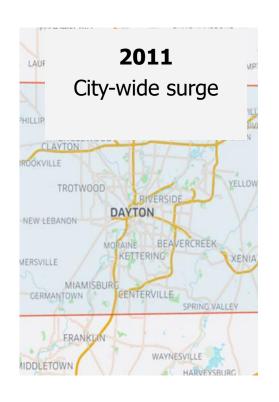
#### **Effects of Surge Outage**

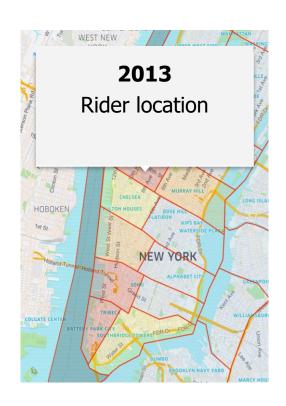


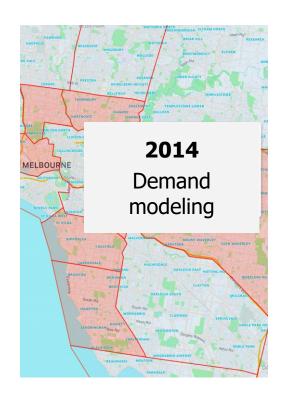
The pink band is the period of surge outage.

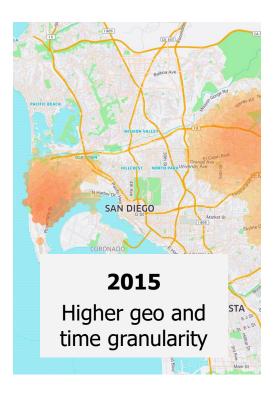
The outage resulted in a severe degradation in marketplace health. [Hall, Kendrick, Nosko 2015]

### **Evolution of Surge**





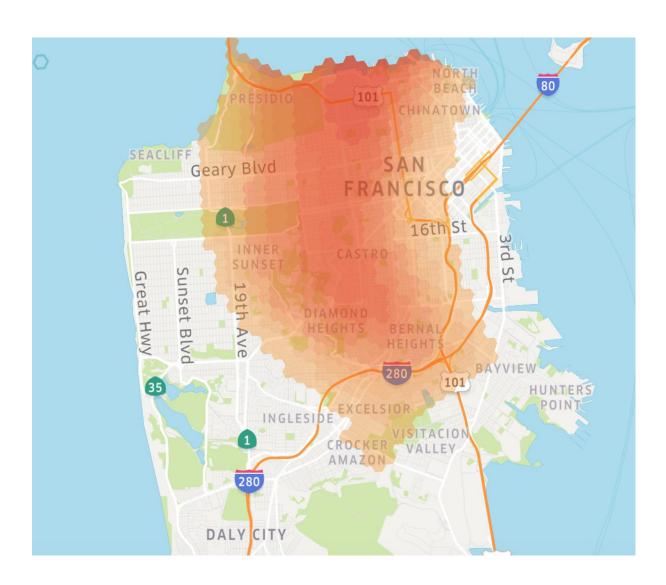




#### Fine-grained Dynamic Spatial-Temporal Pricing

- Fine spatial grid
- Updated every two minutes





Slide credit: Hamid Nazerzadeh, Uber & USC

## Other (potential) aspects of rider pricing

#### • Pickup times:

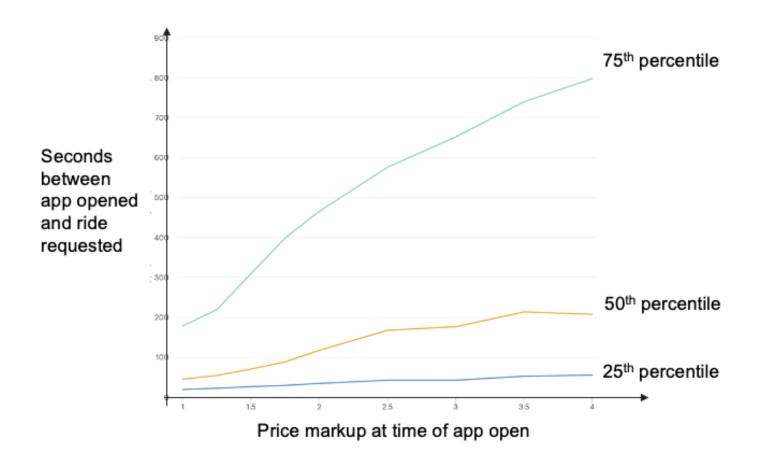
Do you charge just for the time the rider is in the car, or also the time it takes to pick them up?

#### Personalized pricing:

These platforms send coupons to individual riders – easy way to personalize Goal of personalization? Convince riders who otherwise wouldn't ride, to ride Customers who haven't ridden in a while; new customers

 Open question: predictable surge, or purely stochastic (random) surge?

# Rider waiting behavior: paying higher price or waiting?



=> Lyft "Wait and Save," in which you're offered a cheaper price if you can wait 5-15 minutes for a ride

[Slide Credit: Daniel Freund, MIT and Lyft]

## Question for survey in homework

On Uber/Lyft, drivers have to drive longer to pick up the passengers in certain suburbs or neighborhoods, because they tend to be farther away. Is it acceptable for them to charge more to passengers from these neighborhoods?

## Question for survey in homework

On Uber/Lyft, drivers have to drive longer to pick up the passengers in certain suburbs or neighborhoods, because they tend to be farther away. Is it acceptable for them to charge more to passengers from these neighborhoods, if these neighborhoods tend to be socioeconomically disadvantaged historically?

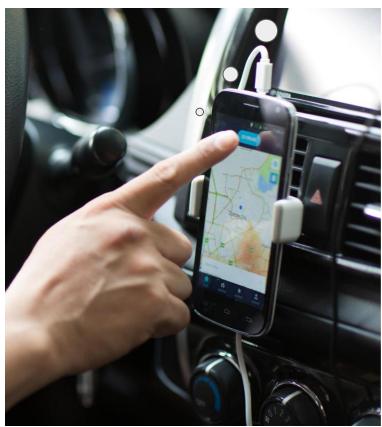
## Driver-side (dynamic) payments

## Surge and payments from driver perspective

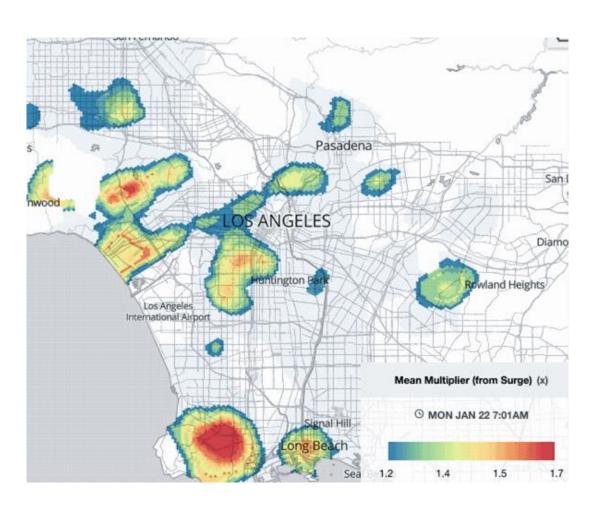
- In ride-hailing (like taxis), drivers are paid per-trip
  - Historically, earn a fixed % of what the rider paid
- Generally, do not earn money while online and waiting for a trip
- Historically, do not earn money while driving to the customer
- Justification: want to align driver incentives, so that they earn more money when the platform earns money
  - Incentivized to drive when and where there are more riders
- Two ways drivers can respond to prices:
  - What times of day, and where in the city, do they begin driving
  - During their shift, do they *relocate* from one part of the city to another Heatmap influenced driver movement toward surge. [Frazier and Lu, 2018]

#### Challenge 1: Fast vs Slow

Will it still be surging by the time I get there?



Slide credit: Hamid Nazerzadeh, Uber & USC

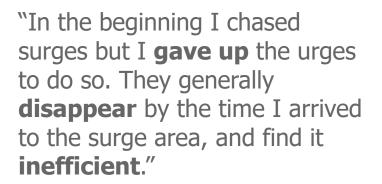


#### Drivers did not "trust" surge as a reliable relocation signal.











"The surge when it appears on the map is **fake a lot of times** to encourage drivers to go to a certain area. Then get no surge rides. I have pictures of this happening multiple times."

#### How to improve drivers' experience with Surge?

#### Fundamental challenge:

- Riders respond to prices quickly
- Drivers respond to prices slowly

#### Solution: **Decoupled Pricing**

(Surge updates differently for riders and drivers)

## Challenge 2: Destination spatial pricing

- Earlier: higher prices in pick-up locations that were busy
- For the driver, destination also matters – their next trip will probably be close to where they dropped off the previous rider!
- Do you compensate the driver for being taken to a location that hurts their future earnings?
- Do you charge the rider more?
   Potentially illegal, depending on destination

#### **Driver Location Value**



Average Earnings-Per-Hour

## Other aspects of driver-side pricing

- Gender wage gap: There is a 7% earnings gap between men and women drivers! [Cook et al. 2020]
  - How? Presumably, Uber isn't actually paying drivers based on gender Experience on the platform, preferences and constraints over where to work, and driving speed
- Can Uber increase average overall earnings per hour, without limiting how many drivers are on the road?
  - Of course, right? Just increase driver's pay per trip
  - Issue: If more drivers join platform as a result, then drivers spend more of their time waiting for a trip, lowering average earnings
  - [Hall et al 2021]
- New NYC regulation: average minimum wage over time

## Congestion pricing

#### Congestion Pricing: The Challenges of Data-driven Solutions

- Traffic negatively impacts quality of life: hours/money lost, freight delays, environment, etc.
- Cities are turning to congestion pricing.
- Technology has enabled data-driven solutions.
- Challenges: (i) multiple objectives and (ii) unpredictable user behavior; among others.



[MTA website]

#### Congestion Pricing: The Challenges of Data-driven Solutions

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[WSJ, 2024]

## Studying congestion pricing is hard

- Can't experiment with prices as easily
- Have to calculate *equilibrium* 
  - Prices affect traffic and people's decisions
  - Traffic affects people's decisions
  - ...which affects traffic

## Bogotá: Data and Setup Description

#### Bogotá Stratification

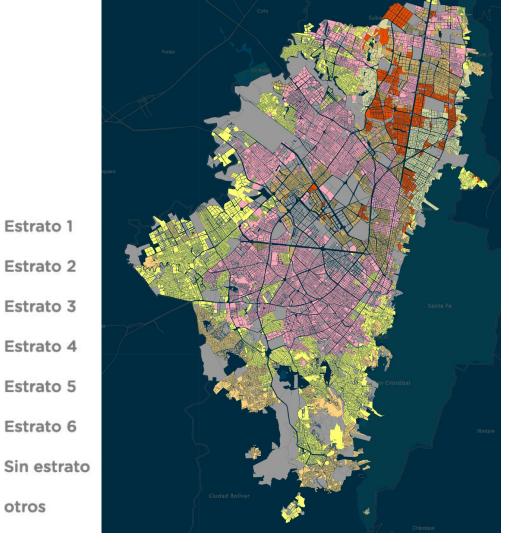
Since 1990's, blocks in Bogotá's disctricts are socioeconomically classified from 1 to 6, where 1 is the poorest and 6 is the wealthiest.

We consider a set of strata S composed by:

Low-income: Strata 1-2

Mid-income: Stratum 3

High-income: Strata 4-6

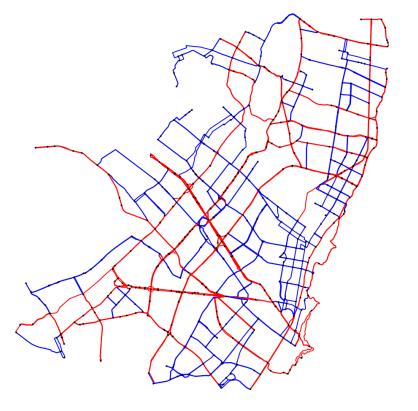


#### **Network Data**

We used the Open Street Maps Networkx library (Python) to extract the road network.

Network was reduced to make the problem sufficiently tractable.

Center Coordinates	4.67172, -74.11290
City Radius	10  km.
Nodes	543
Roads (Arcs)	1213
Primary Roads	592
High-income Demand	1462  trips  (1004)
Mid-income Demand	5146 trips (3836)
Low-income Demand	2762  trips  (2134)



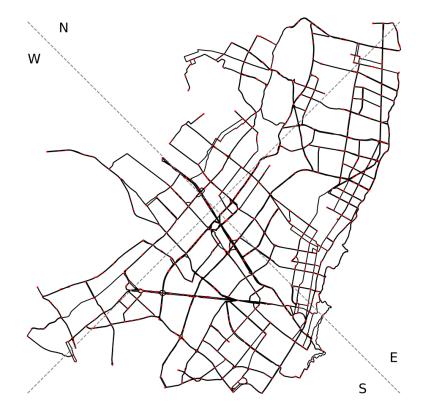
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Area split. N, S, W and E



#### Demand Data: ClearRoad

Collected over 139 days on 204 users.

Data. More than 38,000 trips. Each trip: Sequence of GPS points and user's information

Demand matrices. For each trip that crosses the network (10km instance)

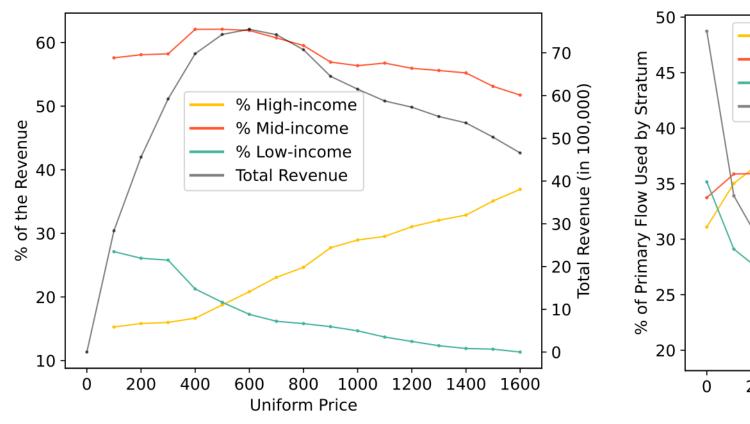
- We trimmed the GPS points that lie in that zone.
- Updated starting and ending GPS points were projected to the graph.

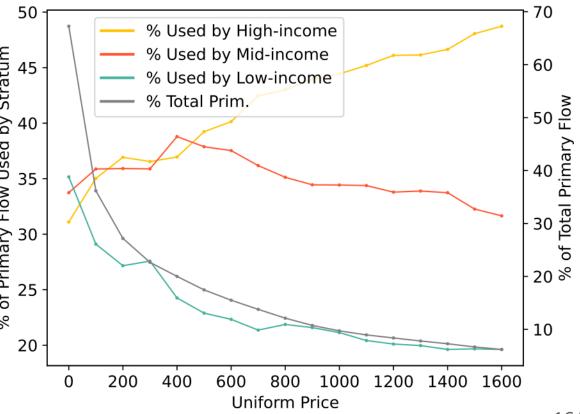
Result. 1462 trips for high-income, 5146 trips for mid-income and 2762 trips for low-income.

#### Uniform Pricing is Highly Inequitable

#### Uniform Pricing.

- Negatively impacts low-income: primary road usage, prop. trips started, welfare, speed, etc.
- Produces the least revenue.
- At revenue optimal price, most of trips are started (not effective for congestion).



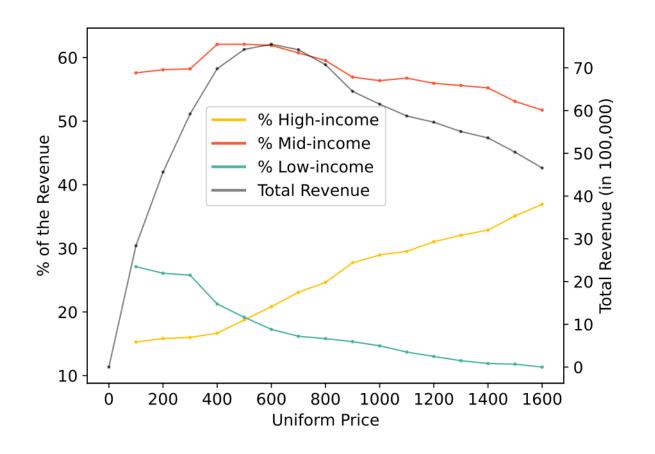


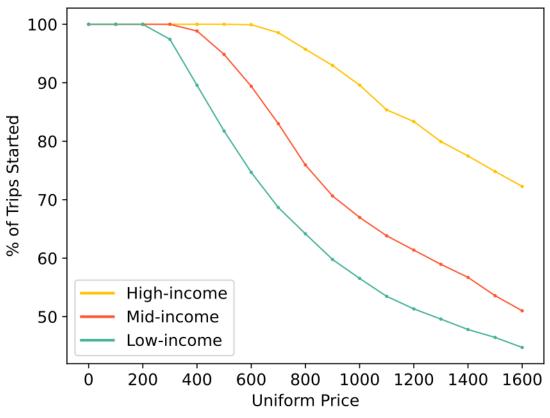
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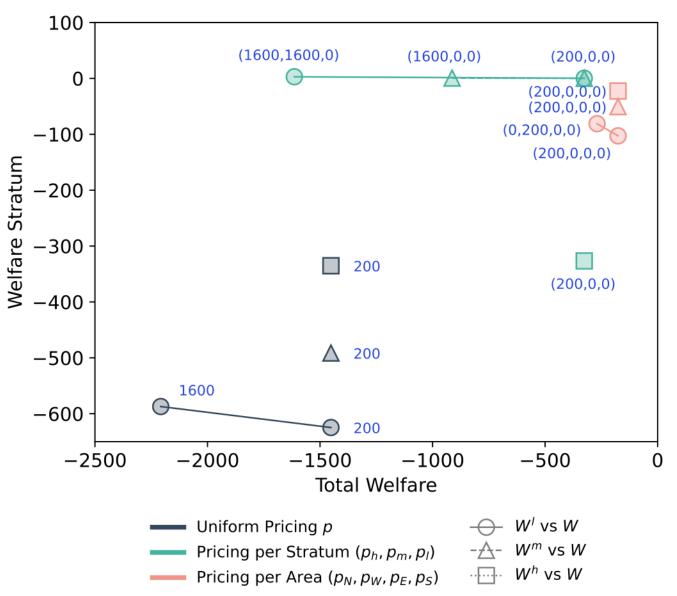
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#### Area Pricing Interpolates Per-stratum and Uniform Pricing



## Pricing module summary

## Things we covered

- Revenue maximization when selling a single item (no capacity constraints)
- Demand estimation
- Personalized pricing with personalized demand estimates
- Pricing over time with capacity constraints
- Pricing 2 items jointly
- Pricing ethics [In future lecture]

Some of these will be used in the class project!