Chapter 14

Pricing Concepts For Establishing Value (Part II)
Today’s concepts

• Describe the difference between an everyday low price strategy (EDLP) and a high/low strategy
• Describe the pricing strategies used when introducing a new product
• Describe dynamic pricing
• Describe price discrimination
• **Everyday Low Pricing (EDLP)**
  – Promises to consumers a low price without the need to wait for **sale price** events or **comparison shopping**

  ![Walmart Everyday Low Price](image)

- Consumers: reduces search costs → adds value
- Firms: saves effort and expense needed to mark down prices
Pricing strategies

• **High/low pricing**
  – Relies on promotion of *sales*
  – Attracts two different segments
    • Price insensitive customers (when price is high)
    • Price sensitive customers (when price is low)

  **Amazon case**

  – Big discounts can attract new users (whom would not have purchased the product otherwise!!)
    • E.g., [Groupon case](#)
The Groupon Effect on Yelp Ratings
[Byers et al. 2012]

A review on Yelp.com consists of a star rating, and some free text. The star rating takes on a value from \(\{1, 2, 3, 4, 5\}\). For each Groupon business, we associate an offer date that corresponds to the date they initiate a Groupon offer. Then, for every review of a Groupon business, we associate an integer offset with that review reflecting how many days after (or before) the offer date the review was posted. For example, a review posted on March 7th for a business that subsequently initiates a Groupon offer on March 13th would have an offset of -6.

4. REVIEW OF THE GROUPON EFFECT

We begin by reviewing evidence and providing new evidence for the finding that Groupon offers coincide with substantially lower ratings for Groupon businesses than other reviews, and that this is caused by Groupon users. The most telling evidence comes from comparing mean ratings from Groupon reviews and non-Groupon reviews for our seed set: Groupon reviews have a mean score of 3.27 stars, while non-Groupon reviews have a mean of 3.73 stars. This discrepancy is somewhat larger than what we initially reported in [Byers et al. 2012] on a smaller data set. We can gain more insight into the effects of Groupon offers via some simple visualizations.

Discontinuities at the Groupon offer date:
In Figure 1a, the top scatterplot and trend line capture the relationship between the average Yelp rating and the offset for reviews of Groupon businesses. Each point records the average rating of all reviews with a given offset across all Groupon businesses, using the Yelp star rating as depicted on the left side of the y-axis. The discontinuities seen at offset zero coincide with the Groupon offer date. The trend lines are computed as a 30-day moving average across offsets, with the average resetting at offset zero to highlight the different behavior at the Groupon date. (From offset 0, only \(k+1\) days are averaged at offset \(k\), and similarly at the left end of the plot.) The histograms at bottom reflect the daily review volume for each given offset, using the scale on the right side of the y-axis for the number of reviews. The smaller histograms with darker shading reflect the volume of Groupon reviews (i.e. those mentioning Groupon specifically). Again, there are striking discontinuities at offset zero as review volumes surge subsequent to the Groupon offer. Note that Groupon reviews account for only about half of the increase, suggesting there exist Groupon users who do not mention Groupon in their review. Finally, observe the gradual increase in review volume prior to offset zero: this is consistent with the rapid ACMA Journal Name, Vol. X, No. X, Article X, Publication date: February 2012. More customers!
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Why do ratings decrease?
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– Groupon Businesses are More Likely to be “Bad” Businesses
  • Limited evidence

– Groupon users are often engaging in experimentation

– Groupon reviews are less likely to be artificially inflated (fake)
New Product Pricing Strategies

Two strategies:

1. Penetration pricing
2. Price skimming
Penetration pricing

• Set initial price low to build sales, market share, profits

• Good if cost of production decreases with quantity produced (economy of scale)
Penetration pricing

• Pros
  – Creates customer base quickly
  – Builds market share
  – Quick profits
  – Discourages competitors from entering the market

• Cons
  – Sacrifices higher profits (low margins)
  – Firm has to keep up with high demand
  – Signaling problem: Low price → low quality
  – May not create loyal customer base
Penetration pricing example

- Cable, Internet companies, streaming services
Price Skimming

• At first high prices
  – Target consumers willing to pay premium to have innovation first

• When market saturates
  – Lower (skim) price
    • Target most price-sensitive segment

• Popular with technology products
Price Skimming

• Pros
  – Increased Quality Perception
  – Benefits from Early Adopters
    • Brand ambassadors
  – Fast costs recovery

• Cons
  – Cannot last long
    • Competitors soon launch rival products
  – Consumer Dissatisfaction
    • Negative feedback from early adopters as the firm lowers its prices
Apple

– New IPhone enters the market at a very high price
  • Reduced when or just before new version hit the markets
Dynamic pricing: The Case of Uber
How does Uber set prices?
How does Uber set prices?

Dynamic pricing:
The Case of Uber
How does Uber set prices?

Rates automatically increase, when the demand for drivers is higher than drivers around you.
• Surge price in action [Nosko et al. 2015]

Figure 1: Demand for Uber Spikes Following Sold-Out Concert on March 21, 2015

Note: Figure reports the number of users opening the Uber app each minute over the course of March 21, 2015 (in red), as well as the sum of total requests for Uber rides in 15-minute intervals over the same time period (blue circles). Data is for a restricted geospatial bounding box containing Madison Square Garden in New York City, roughly 5 avenues long and 15 streets wide, for uberX vehicles only. Pure volume counts have been normalized to a pre-surge baseline, defined as the average of values between 9:00 and 9:30 PM that evening, before surge turned on. “Surge period” (yellow box) is the time over which the surge multiplier increased beyond 1.0x.
Dynamic pricing: The Case of Uber

- Surge price in action [Nosko et al. 2015]

**Figure 2:** Uber Driver-Partner Supply Increases to Match Spike in Demand

Note: Figure reports the number of “active” UberX driver-partners within the same geospatial box (noted above) each minute over the course of March 21, 2015 (in green). In this case, “active” means they were either open and ready to accept a trip, en route to pick up a passenger, or on trip with a passenger. Pure volume counts have been normalized to a pre-surge baseline, defined as the average of values between 9:00 and 9:30 PM that evening, before surge turned on. The “surge period” (yellow box) is the time over which the surge multiplier increased beyond 1.0x.
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**Figure 4:** Vital Signs of Surge Pricing in Action on March 21, 2015

*Note: All data above is for uberX vehicles from within the geospatial bounding box mentioned earlier, aggregated into 15 minute intervals over the course of the evening of March 21, 2015. “Requests” is the count of Uber trips requested during the 15 minute interval. “ETA” is the average wait time for a driver-partner to arrive, in minutes, over the 15 minute interval. “Completion rate” is the percentage of requests that are fulfilled (calculated as the number of completed trips within the 15 minute interval, divided by the sum of completed trips and unfulfilled trips). The yellow box indicates the same “surge period” highlighted in Figures 1-3.*
What is the goal (or goals) Uber is trying to achieve with the surge price algorithm?

1. Match demand with supply
2. Reducing waiting time
• We have seen:
  – Pricing strategies
    • EDLP
    • High/Low pricing
  – New products pricing strategies
    • Market penetration
    • Skimming
  – Dynamic pricing (Uber)
When a firm sets a very low price for one or more of its products with the intent to drive its competition out of business, it is using **predatory pricing**

– Illegal under both the Sherman Antitrust Act and the Federal Trade Commission Act
• Identical goods or services are sold at different prices by the same provider in different markets

• It requires
  – Market segmentation, e.g.,
    • Student vs non-students

  – No arbitrage
    • Lower-priced users cannot resell to high-priced users!
Example fro NYT

To discriminate you need to separate
1. Personalized pricing (or first-degree price discrimination)
2. Product versioning (or second-degree price discrimination)
3. Group pricing (or third-degree price discrimination)
First-Degree Price Discrimination

- **Information**: The firm is able to identify each consumer type
- **Arbitrage**: Not possible
- **Prices**: Will be different to each consumer and each unit
First-Degree Price Discrimination
• **Information**: The firm cannot differentiate consumers ex-ante, but it must know the aggregate characteristics of the market
  – Can still segment!
• **Arbitrage**: Not possible
• **Prices**: Will change according to the quantity (or quality) the consumer buys
  – Electricity providers
  – Airlines (first class, economy, etc.)
Second-Degree Price Discrimination

Source: energy prices
Third-Degree Price Discrimination

• Most common
• **Information**: can distinguish consumer groups through a signal (location, age, gender, etc.)
• **Arbitrage**: Not possible
• **Prices**: Will change according according to consumer groups (student, senior)
Third-Degree Price Discrimination
• Some internet retailers use personal information that users leave (involuntarily) online to price discriminate
  – Type of browser used
  – Location
  – Age, gender, etc.

• In the [news](#)
• Price discrimination
  – First-degree: “personalization”
  – Second-degree: quantity/version
  – Third-degree: groups

• Internet and big data are facilitating first degree price discrimination