Competition-Based Dynamic Pricing In Online Retailing

Research Collaboration with Yihaodian

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Gang Yu • Yihaodian, Co-Founder and Chairman
Dynamic Pricing

Retailers are adjusting prices on everyday items several times a day. Here is a look at prices for a GE microwave on Aug. 12 at three Web retailers:

Note: All times are in Pacific Daylight Time

Source: Decide.com
Graphic by Alberto Cervantes/The Wall Street Journal
Respond?
To Whom?
By How Much?
– $ – ％
Competition-Based Dynamic Pricing

How elastic is demand?
Who do I really compete with?
Do customers shop prices across retailers?
Our Partner

Founded in 2008
Sales reach $3 billion in 2014
Walmart's online arm in China
Top 10 fastest growing tech company in Asia
Challenges

Endogenous Price
Challenge I – Endogenous Price

- retail price
- sales unit

Price (¥)

Units

Challenges

Endogenous Price
Limited Price Variation
Challenge II: Limited Price Variation

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- Retail price
- Lowest competitor price

Stock out
Choice of Category

303 SKUs
Top 29 SKUs
Sales > 1 per day
80.1% total revenue
Price range ¥13 ~ ¥165
### Randomized Price Experiment

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6 June 2015
When Randomization Isn’t Good Enough
Consumer Choice Set
Model

Demand for SKU j on day t

$$D_{jt} = \frac{z_{jt} \exp \left( \frac{\alpha_j + \beta_j \log p_{jt}}{1 - \lambda} \right) \left( \sum_r z_{jrt} \exp \left( \frac{\alpha_j + \alpha_r + \beta_j \log p_{jrt}}{1 - \lambda} \right) \right)^{-\lambda} \exp(X_{ot}Y) + \sum_r \sum_k z_{krt} \exp \left( \frac{\alpha_j + \alpha_r + \beta_j \log p_{krt}}{1 - \lambda} \right) \left( \sum_r z_{krt} \exp \left( \frac{\alpha_k + \alpha_r + \beta_j \log p_{krt}}{1 - \lambda} \right) \right)^{-\lambda} M_j}{\sum_{all SKUs over all major retailers} \sum_{all SKUs over all major retailers}}$$

SKU specific price elasticity

Price of SKU j on day t

Degree of price shopping (0~1)

Market size

No purchase (day of week effects included)

Competitor in-stock indicator

Competitor price

Consumer preference of SKU k

Consumer preference of retailer r
Model

\[ D_{jt} = \frac{z_{jt} \exp\left(\frac{\alpha_j + \beta_j \log p_{jt}}{1 - \lambda}\right) \left(\sum_r z_{jrt} \exp\left(\frac{\alpha_j + \alpha_r + \beta_j \log p_{jrt}}{1 - \lambda}\right)\right)^{-\lambda} M_j}{\exp(X_0^t \gamma) + \sum_r \sum_k z_{krt} \exp\left(\frac{\alpha_j + \alpha_r + \beta_j \log p_{krt}}{1 - \lambda}\right) \left(\sum_r z_{krt} \exp\left(\frac{\alpha_k + \alpha_r + \beta_j \log p_{krt}}{1 - \lambda}\right)\right)^{-\lambda}} \]

Demand for SKU \( j \) on day \( t \)

SKU specific price elasticity

Price of SKU \( j \) on day \( t \)

Degree of price shopping (0~1)

Market size

No purchase (day of week effects included)

Competitor in-stock indicator

Competitor price

Consumer preference of SKU \( k \)

Consumer preference of retailer \( r \)

Sum over all SKUs over all major retailers
Challenges

Endogenous Price
Limited Price Variation
Lack of Competitor Sales Data
Challenge III: Lack of Competitor Sales Data

Sales?  Sales?  Sales?

Sales?  Sales?  Sales?

Sales?  Sales?  Sales?
Stock-out as a Source of Identification
A Sketch of Identification

Suppose there are two products 1 and 2, and two retailers, Yihao and competitor.

\[
\begin{align*}
    u_{11} &= \alpha_1 + \beta_1 Price_{1Y} + \varepsilon_{11}
    \\
    u_{12} &= \alpha_2 + \beta_2 Price_{2Y} + \varepsilon_{12}
    \\
    u_{1C} &= \alpha_1 + \beta_1 Price_{1C} + \alpha_c + \varepsilon_{1C}
    \\
    u_{2C} &= \alpha_2 + \beta_2 Price_{2C} + \alpha_c + \varepsilon_{2C}
    \\
    u_{i0} &= \varepsilon_{i0}
\end{align*}
\]

Product specific intercepts
Retailer preference

We observe market share \(s_{1Y}, s_{2Y}\). Conditional on purchasing from Yihao,

**Moment condition 1**

\[
\log \left( \frac{s_{1Y}}{s_{2Y}} \right) = \alpha_1 - \alpha_2 + \beta_1 Price_{1Y} - \beta_2 Price_{2Y}
\]

**Moment condition 2**

\[
\frac{s_{1Y}}{1 - s_{1Y} - s_{2Y}} = \frac{\exp(\alpha_1 + \beta_1 Price_{1C} + \alpha_c)}{1 + \exp(\alpha_1 + \beta_1 Price_{1C} + \alpha_c) + \exp(\alpha_2 + \beta_2 Price_{2C} + \alpha_c)}
\]

**Moment condition 3**

Bottle 1 stocks out at competitor

\[
\frac{s'_{1Y}}{1 - s'_{1Y} - s'_{2Y}} = \frac{\exp(\alpha_1 + \beta_1 Price_{1Y})}{1 + \exp(\alpha_2 + \beta_2 Price_{2C} + \alpha_c)}
\]
How Does It Work?
How Does It Work?
Estimation Results

\[ D_{jt} = \frac{\exp(X_{0t}\gamma)}{\exp(X_{0t}\gamma)} \left( \frac{\alpha_j + \beta_j \log p_{jt}}{1 - \lambda} \right) \left( \sum_r z_{jrt} \exp \left( \frac{\alpha_j + \alpha_r + \beta_j \log p_{jrt}}{1 - \lambda} \right) \right)^{-\lambda} M_j \]

SKU specific price elasticity

-1.6747***
-0.3667***
-6.7734***
-0.0036
-0.9532
-1.0537***
-0.5404***
-1.1644***
-1.1176***
-4.1492***
-0.5038***
-2.1872***
-11.281***
-0.9216***
-1.1421***

Degree of price shopping (0~1)

0.7911***

Consumer preference of retailer r

Yihaodian Reference
Competitor 1 0.2172
Competitor 2 0.0169
Competitor 3 -1.8363***
Competitor 4 -2.4642**
Goodness of Fit

Average MAD 37.7%
Goodness of Fit

Fast Moving SKU 26.1%
## Own and Cross Price Elasticity

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<tr>
<th>PRODUCT</th>
<th>Own</th>
<th>Competitor 1</th>
<th>Competitor 2</th>
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Algorithm for Best Response Pricing

\[
\max_{\{p_1, p_2, \ldots, p_J\}} \sum_{j=1}^{J} p_j s_j (p_j; z_j; p_{-j}, z_{-j}; \alpha, \beta, \gamma, \lambda)
\]

\[
s.t. \quad \frac{(p_j - c_j)s_j}{p_j s_j} \leq \text{margin target}
\]

\[
LB \leq \frac{(p_j - c_j)}{p_j} \leq UB, \forall j
\]

\[
LB_M \leq p_j \leq UB_M, \forall j \in J_M
\]

Competitor Prices and Product Availability

Consumer Choice Parameters

Margin constraints
Manufacturer Price Restrictions
Pilot Test with Controlled Experiment

![Comparison of Treatment and Control Groups](image)

- **Treatment**
  - $\$\$

- **Control**
  - $\$$\$$
Pilot Test with Controlled Experiment

0-6 months

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Above 7 months

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Performance Evaluation

Difference in Differences

Before | After
--- | ---
Treatment | Control

Before | After
--- | ---
Region A

Before | After
--- | ---
Region B

Triple Difference Estimator
Revenue Up by 11%+, while Margin Unchanged

Sales up by 11%
Margin unchanged

Sales up by 19%
Margin unchanged
# Executive Summary

**Intellectual Merit**
- Design and estimate a choice model that accounts for choices among substitutable products from multiple retailers.
- Introduce price variation through a randomized price experiment, while addressing endogeneity concerns.
- Deploy a novel identification strategy through stock-outs in the absence of competitor sales data.

**Practical Impacts**
- Accurate competitive response driven by deep understanding of competitors and consumers.
- Documented 11%+ revenue increase.
- Integrated with Yihaodian’s IT system, and being rolled out to other categories.
- Further collaboration: EDLP and Lo/Hi pricing for FMCG products.