Price Discrimination and Online Sales in the Automobile Industry by D′Haultfoeuille, Durrmeyer, Fournel, Iaria

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Great paper, pleasure to read!

Summary

- Estimate demand for cars with
  - unobserved price discrimination (D'Haultfœuille, Durrmeyer, and Février, 2019)
  - transportation costs
- Consumers i in groups d live in municipalities m. Utility for product j is

$$U_{ijdm} = \underbrace{X_j'\beta_d + \alpha_d p_{jd} + \xi_{jd}}_{\delta_{jd}} + \underbrace{\mu_{jdm}(\nu_i)}_{\text{heterogeneity within } d} + \gamma_d dist_{jm} + \varepsilon_{ijdm}$$

- d: e.g., young and poor vs old and rich
- Prices p_{jd} and unobserved quality ξ_{jd} vary with group d (but not geographically)
- Data: car purchases at the group-municipality (dm) level

Recovering prices

- Goal: for any parameters θ, find transaction prices $p(\theta)$ that rationalize both demand and supply. Then we are back to standard BLP.
- There is an observed list price $\bar{p}_j$
- True prices p_{jd} are not observed
  - firms choose a different price for product j in each group d
  - assumed to be chosen nationally to maximize profit (on average across municipalities)
- Marginal cost c_j is assumed constant across d

Recovering prices

- Assume firms use optimal pricing:

$$p_{jd} = c_j - [M_d(p_d, \theta)]_j$$

  where $_j$ indicates the j-th row of the vector. c_j are marginal costs
- matrix M_d is the "markup" for group d (contains s_d, ownership matrix, etc)
  - depends on price and parameters θ
- Assume list price is the maximum price paid:

$$\bar{p}_j = \max_d p_{jd}$$

- Then

$$\bar{p}_j = c_j - \min_d \left\{ [M_1]_j, \ldots, [M_D]_j \right\}$$

$$p_{jd} = \bar{p}_j + \min_d \left\{ [M_1]_j, \ldots, [M_D]_j \right\} - [M_d]_j$$

- D'Haultfœuille, Durrmeyer, and Février (2019):
  - given θ, this fixed-point equation is a contraction in p_d (under some conditions)
  - also works if, e.g., average price is observed

How the algorithm works

1. Search over parameters θ
    1.1 price-loop: find optimal prices for each group p^d, given θ and current values of mean utilities δ^d, using the procedure above.
        1.1.1 delta-loop: update mean utilities δ^d to rationalize market shares in data

Iterate the price-loop and the delta-loop until convergence

Great Paper!

- Novel dataset of dealer locations
- Very careful data construction (driving distances, list prices net of rebates, etc)
- Very interesting and detailed counterfactuals

Main counterfactual: online sales

- Individuals can buy:
  - in-person (as in the data)
  - online: lower travel costs, no price discrimination
- Short-term effects
  - assume no entry or exit of car dealers
  - no change in vertical relations between car manufacturers and car dealers
- Consider transportation cost reductions of 75%, 50%, 25%, 0%
- A share $1 - \psi_d$ of group d does not use online (is "captive" to in-person dealers).
  - ψ_d constructed from a survey: proportion of consumers in d who bought (anything) online in the previous year
- For computational reasons, demand is a nested logit: each j is a nest with two options, in-person and online
- online prices set optimally and can be different from in-person prices
- Robustness:
  - lowest-profit dealerships close
  - marginal cost of selling online are lower

Main Results

1. Travel costs are very important, much more important than price discrimination
2. Price discrimination
   2.1 lowers overall CS slightly (young/poor win, old/rich lose)
   2.2 increases overall profit slightly (not obvious, in oligopoly)
3. Reducing transport costs
   3.1 prices don't change much
   3.2 eliminating transportation costs increases CS and profit by about 10%
4. Introducing online distribution
   4.1 market expansion: 2-9%, mostly driven by old/rich
   4.2 firms reduce the amount of price discrimination in the in-person channel
   4.3 profits increase
   4.4 CS increases on average but most of the benefit accrues to the old/rich, while the others either gain little or lose out

Main suggestions

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- The availability of online might also make products easier to compare and thereby increase competition between brands? Maybe distance affects demand via consideration sets (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022). Ie, I'm more likely to consider nearby brands, but not faraway brands. Online, all products are considered equally.

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- The "estimation" of ψ_d from a survey is quite "rough", especially since this seems very important for the results. It's not clear what the responses in that survey correspond to in terms of structural parameters for this model, in the car market. Moreover, these ψ_d might change if there are great deals to be found online.

Other suggestions

- MC constant across demographics: maybe clients require more maintenance than others?
- Maybe add to appendix results with heterogeneity in price coeffs
- "In some sense, consumers save on transportation costs and "reinvest" part of these savings by spending more on better car" - there are no income effects
- Einav, Jenkins, and Levin (2012) estimate car demand when individuals get discounts. Prices are fully "latent" and depend on list prices (in a way that is estimated)
- Why don't profits increase for small reductions in transport cost?
- Figure 1: the coeffs seem pretty similar to each other. This suggests limited scope for price discrimination?
- Can there be at stock-out of a particular model at a dealership?
- "Our estimated willingness to pay to reduce travel distance by one kilometer is EUR18.1 - 27.7" This seems high to me, even if it does reflect ALL future interactions with dealership
- "Group 6 (old/rich) is the demographic group estimated to always pay the observed list price for all car models." - is this true in the surveys?

References

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