

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

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- ▶ Great paper!
- ▶ Novel extension of cutting edge estimation techniques
- ▶ Novel dataset of dealer locations
- ▶ Very careful data construction (driving distances, list prices net of rebates, etc)
- ▶ Very interesting, detailed and important counterfactuals

# Summary

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

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

- ▶ Groups  $d$ : e.g., young&poor, young&rich, old&rich, ...

## Recovering transaction prices

- ▶ Problem: transaction prices  $p_{jd}$  vary with group  $d$  and are not observed
- ▶ Goal: for any parameters  $\theta$ , find transaction prices  $p(\theta)$  that rationalize both demand and supply.
  - ▶ Then we are back to standard BLP.
- ▶ There is an observed list price  $\bar{p}_j$
- ▶ Firms choose  $p_{jd}$  nationally to maximize profit
  - ▶ prices vary across  $d$  (price discrimination) but not within  $d$
- ▶ Marginal cost  $c_j$  constant across  $d$

## Recovering transaction prices

- ▶ Optimal pricing for group  $d$ :

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

where  $j$  indicates the  $j$ -th row of the vector.

- ▶ Matrix  $M_d$  is the “markup” for group  $d$  (contains  $s_d$ , ownership matrix, derivatives of demand)
  - ▶ depends on all prices  $p_d$  and parameters  $\theta$
- ▶ Assume list price is the maximum price paid:

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

- ▶ Then

$$\bar{p}_j = c_j - \min_k \{ [M_k]_j \}$$
$$p_{jd} = \underbrace{\bar{p}_j + \min_k \{ [M_k]_j \}}_{c_j} - [M_d]_j$$

## Recovering transaction prices

- ▶ D'Haultfœuille, Durrmeyer, and Février (2019):
  - ▶ given  $\theta, \delta$ : this fixed-point equation is a contraction in  $p_d$  (under some conditions)
  - ▶ given  $\theta, p$ : find  $\delta$  via BLP contraction
  - ▶ also works if, e.g., average price is observed
- ▶ In practice: iterate between  $\delta$  and  $p$  until convergence

## Main counterfactual: online sales

- ▶ New online distribution channel:
  - ▶ lower travel costs by up to 75%
  - ▶ no price discrimination
- ▶ Short-term effects: no entry/exit, no change in vertical relations
- ▶ Only a share  $\psi_d$  of group  $d$  can use online channel
  - ▶  $\psi_d$  estimated from a survey: proportion of those in  $d$  who bought (anything) online in the previous year
- ▶ For computational reasons, demand is a nested logit: each product is a nest with two options, in-person and online
- ▶ Online prices
  - ▶ are set optimally
  - ▶ can be different from in-person prices

# Main Results

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



## Main suggestions

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  - ▶ Maybe  $\xi$ 's for products sold online are more similar?
  - ▶ Maybe distance affects demand via consideration sets (Abaluck and Adams-Prassl, [2021](#); Agarwal and Somaini, [2022](#)): I'm more likely to consider nearby brands, but not faraway brands, but online all products are considered equally?

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- ▶ What if everyone receives less than the list price? How would this bias the results? In surveys, do we see anyone paying the list price?
- ▶ The estimation of  $\psi_d$  from a survey is quite "rough", and these parameters seem central to counterfactuals. It's not clear what the responses in that survey correspond to in terms of structural parameters in this model and market. Also,  $\psi_d$  might increase if there are great deals to be found online (especially longer-term).
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## Other suggestions (for the authors)

- ▶ Why don't profits increase for small reductions in transport cost?
- ▶ Can there be a stock-out of a particular model at a dealership? (I've never bought a car)
- ▶ MC constant across demographics: maybe clients require more maintenance than others?
- ▶ Add to appendix results with heterogeneity in price coeffs
- ▶ "consumers save on transportation costs and "reinvest" part of these savings by spending more on better car" - there are no income effects, so this intuition can't be quite right
- ▶ Worth citing Einav, Jenkins, and Levin (2012)? They estimate car demand when individuals get discounts. Prices are fully "latent" and depend on list prices (in a way that is estimated)
- ▶ Figure 1: the coeffs seem pretty similar to each other. This suggests limited scope for price discrimination?
- ▶ "Our estimated willingness to pay to reduce travel distance by one kilometer is EUR18.1 - EUR27.7" Seems high, even if it does reflect all future interactions with dealership
- ▶ "(old/rich) is the demographic group estimated to always pay the observed list price for all car models." - is this true in the surveys?
- ▶ Why do firms reduce price discrimination offline when the online channel arises? Intuition is not clear to me...
- ▶ Show that estimates imply total industry profit in line with outside sources (e.g., expert assessments)

Great paper!  
Thank you

# References

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