

# Demand Estimation

## *MIXTAPE SESSION*

Jeff Gortmaker and Ariel Pakes



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- A fifth-year Economics PhD candidate at Harvard University.
- Making BLP-style estimation more accessible to researchers.
  - Best practices papers ([Conlon and Gortmaker, 2020, 2023](#)).
  - Open-source Python package ([PyBLP](#)).
  - This course!

# This Course

- Three days, 6pm-9pm.
  1. Today: BLP model, pure logit, price endogeneity.
  2. Wednesday: Mixed logit, identification, numerical best practices.
  3. Friday: Micro BLP, consumer survey data, other extensions.

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  - Ask questions in the Discord chat or raise your hand on Zoom.

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- Please participate and ask questions!
  - Ask questions in the Discord chat or raise your hand on Zoom.
- Three coding exercises, one after each day.
  - Try these on your own or with your classmates' help. Use Discord rooms!
  - I'll do the first two exercises live at the start of days 2 and 3. We'll post solutions.

# Readings

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- Foundational papers:
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- None of these are required for the course, but I recommend taking a look afterwards.

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  - Need a structural model when we can't just estimate a treatment effect.
- Running example: **What if we halved an important product's price?**
  - Practitioners: Increased sales vs. cannibalization?
  - Regulators: Revenue loss from eliminating a tax?
  - Academics: Welfare consequences?

# Roadmap

The BLP Model

Pure Logit Estimation

Price Endogeneity

Coding Exercise 1

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  - Different demographics and preferences.
- Individuals are faced with [choices](#) denoted by  $j \in \mathcal{J}_t$ .
  - Products, hospitals, candidates, etc.
  - Outside option  $j = 0$ : no purchase, no treatment, no vote, etc.

# Utility Maximization

$$\max_{j \in \mathcal{J}_t \cup \{0\}} u_{ijt}$$

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  3. Idiosyncratic preferences  $\varepsilon_{ijt}$ : Superimposed noise that accommodates estimation.

# Aggregate Market Shares

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- Assume a convenient distribution for  $\varepsilon_{ijt}$ : iid type I extreme value (“logit shocks”).
  - Want  $\mu_{ijt}$  to be sufficiently flexible that this convenient assumption matters little.
  - Possible to eliminate  $\varepsilon_{ijt}$  but computation gets difficult (Berry and Pakes, 2007).



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- Aggregating over individuals with type sampling weights  $w_{it}$  gives market shares:

$$s_{jt} = \sum_{i \in \mathcal{I}_t} w_{it} \cdot s_{ijt} \quad \text{where} \quad s_{ijt} = \mathbb{P}_{\varepsilon_{it}} \left( u_{ijt} \geq u_{ikt} \text{ for all } k \in \mathcal{J}_t \cup \{0\} \right)$$

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- We'll match these to observed quantities  $q_{jt} = s_{jt} \cdot M_t$  in our data.

# Choosing a Market Size

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  - Market size for drugs to treat a condition is how many people have that condition.
- But typically, the choice of market size is **neither easy nor innocuous**.
  - E.g. how many choices of which cereal to buy are made every day in a specific city?
  - Population  $\times$  max cereals per day? Foot traffic estimate  $\times$  max cereals per trip?

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  - E.g. how many choices of which cereal to buy are made every day in a specific city?
  - Population  $\times$  max cereals per day? Foot traffic estimate  $\times$  max cereals per trip?
- You should try different assumptions and see how they change your results.
  - In general, the bigger the market size, the more substitution to the outside good.
  - We'll learn how to discipline these assumptions with data on day 3.

# Identification and Normalizations

$$\max_{j \in \mathcal{J}_t \cup \{0\}} u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}$$

- We will estimate our utility function with **revealed preference**.
  - Holding  $\mu_{ijt}$  fixed, a higher quantity  $q_{jt} > q_{kt}$  implies a higher mean utility  $\delta_{jt} > \delta_{kt}$ .



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- Now that our model can in theory be identified, how do we estimate it?

# Roadmap

The BLP Model

Pure Logit Estimation

Price Endogeneity

Coding Exercise 1

# Pure Logit Model

$$\max_{j \in \mathcal{J}_t \cup \{0\}} u_{ijt} = \delta_{jt} + \cancel{\mu_{ijt}}^0 + \varepsilon_{ijt}$$

- Start with the simplest case: no heterogeneous utility. We'll add  $\mu_{ijt}$  back on day 2.

# Pure Logit Model

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  - The 1 in the denominator is from our level normalization  $u_{i0t} = \varepsilon_{i0t}$ .
- We can recover mean utilities from observed market shares (Berry, 1994).
  - If we specify a function for  $\delta_{jt}$ , we'll have a linear regression!

# Pure Logit Estimating Equation

$$\log \frac{s_{jt}}{s_{0t}} = \delta_{jt}$$

- Running example: What if we halved an important product's price?
  - In your exercise, products  $j$  are breakfast cereals; markets  $t$  are city-quarters.
  - If we estimate the model, we can change  $p_{jt}$  and estimate how consumers react.

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$$\log \frac{s_{jt}}{s_{0t}} = \delta_{jt} = \alpha p_{jt} + x'_{jt} \beta + \xi_{jt}$$

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- Specify  $\delta_{jt}$  as a function of price  $p_{jt}$  and other product characteristics  $x_{jt}$ .
  - In your exercise,  $p_{jt}$  is per serving;  $x_{jt}$  includes a constant, a “mushy” dummy, etc.

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  - In your exercise,  $p_{jt}$  is per serving;  $x_{jt}$  includes a constant, a “mushy” dummy, etc.
- Interpret the regression error  $\xi_{jt}$  as unobserved product quality not in our data.
  - Unobserved characteristics, advertising, average taste variation, etc.

# Interpreting Parameters

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- Let's say we estimate this equation. How to interpret our parameter estimates?

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→ Instead, report own-price elasticities, or a quantity-weighted average/median.

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  - Instead, report  $\beta/\alpha$ , the dollar willingness to pay for mushyness.

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# Endogeneity Concerns

$$\delta_{jt} = \alpha p_{jt} + x'_{jt}\beta + \xi_{jt}$$

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  - Often,  $\mathbb{C}(p_{jt}, \xi_{jt}) > 0$ , so  $\hat{\alpha} < 0$  is biased towards zero.

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- Today we'll focus on handling just price endogeneity for simplicity.

# Fixed Effects

$$\delta_{jt} = \alpha p_{jt} + x'_{jt}\beta + \xi_{jt}$$

- Adding product and market fixed effects to  $x_{jt}$  can help a lot.
  - E.g. if  $p_{jt}$  is correlated with product-specific  $\xi_j$  in  $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$ .
  - But do need multiple observations per product and market to add  $\xi_j$  and  $\xi_t$ .

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- Modern grocery scanner datasets have many thousands of products/markets.
  - Dummies take too much memory, so we “absorb” them, i.e. iteratively de-mean.
  - Stata: [Reghdfe](#). R: [Fixest](#). Python: [PyFixest](#). Coding exercise: [PyBLP](#) via [PyHDFE](#).

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- Helpful but insufficient. Unobserved quality typically varies by product *and* market.
  - And if prices don't, then we don't have any variation left to estimate  $\alpha$ .

# Instrumental Variables

$$\delta_{jt} = \alpha p_{jt} + x'_{jt}\beta + \xi_{jt}$$

- With or without fixed effects, a carefully-chosen IV can be a good solution.  
→ Relevance:  $\mathbb{C}(p_{jt}, z_{jt}) \neq 0$ . Exclusion:  $\mathbb{C}(\xi_{jt}, z_{jt}) = 0$ .

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  - Is the instrument strong, or should you worry about weak instruments?
- Many places to look. I'll discuss the most common ones.

# Typical Instruments for Price

$$\delta_{jt} = \alpha p_{jt} + x'_{jt}\beta + \xi_{jt}$$

- **Cost-shifters**: Measures of input prices, tariffs, etc.
  - Consumers should only care about them through their effect on prices.

# Typical Instruments for Price

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- **Cost-shifters**: Measures of input prices, tariffs, etc.
- **Hausman**: Price of the same product averaged across *other* locations.
  - Need costs to be correlated across locations, but not unobserved quality.
  - Helpful that retailers tend to do “uniform pricing” (**DellaVigna and Gentzkow, 2019**).

# Typical Instruments for Price

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- **Cost-shifters**: Measures of input prices, tariffs, etc.
- **Hausman**: Price of the same product averaged across *other* locations.
- **Waldfoegel**: Average consumer characteristics in *nearby* locations.
  - With uniform pricing, your neighbors' demographics will affect your prices.



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- **Hausman**: Price of the same product averaged across *other* locations.
- **Waldfoegel**: Average consumer characteristics in *nearby* locations.
- **BLP**: Average characteristics  $x_{kt}$  of *competing* products  $k \neq j$ .
  - Price is marginal cost plus a markup. Substitutes affect markups.
  - We'll come back to these later, since they can also serve a different purpose.

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- **BLP**: Average characteristics  $x_{kt}$  of *competing* products  $k \neq j$ .
- I recommend starting with just one. A straightforward cost-shifter if you have it.

# Roadmap

The BLP Model

Pure Logit Estimation

Price Endogeneity

Coding Exercise 1

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- Try to do the first exercise before day 2's class, when I'll do it live.
  1. Getting set up with Python and PyBLP.
  2. Pure logit estimation.
  3. Running the price cut counterfactual.

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- When doing the exercise, think critically about the pure logit model's limitations.
  - Do the substitution patterns you estimate seem reasonable?
- If you have time, try the supplemental exercises.
  - Statistical inference.
  - Modeling the supply side.
  - Checking your code by simulating data.

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