Demand Estimation

Mixtape Session

Jeff Gortmaker and Ariel Pakes

Who Am I?

- A fifth-year Economics PhD candidate at Harvard University.

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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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- 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.

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

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- Typically used for counterfactual analysis of something that hasn't happened.
  - $\rightarrow$ Need a structural model when we can't just estimate a treatment effect.
- Running example: What if we halved an important product's price?
  - $\rightarrow$ Practitioners: Increased sales vs. cannibalization?
  - $\rightarrow$ Regulators: Revenue loss from eliminating a tax?
  - $\rightarrow$ Academics: Welfare consequences?

Roadmap

The BLP Model

Pure Logit Estimation

Price Endogeneity

Coding Exercise 1

Model Overview

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- Each market has individuals with types denoted by $i \in \mathcal{I}_t$.
  - $\rightarrow$ Different demographics and preferences.
- Individuals are faced with choices denoted by $j \in \mathcal{J}_t$.
  - $\rightarrow$ Products, hospitals, candidates, etc.
  - $\rightarrow$ Outside option $j = 0$: no purchase, no treatment, no vote, etc.

Utility Maximization

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

- Individuals choose an alternative to maximize (indirect) utility u_{ijt}.
  - $\rightarrow$ We will specify a function for u_{ijt} and use revealed preference to estimate it.

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  3. Idiosyncratic preferences ε_{ijt}: Superimposed noise that accommodates estimation.

Aggregate Market Shares

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

- Assume a convenient distribution for ε_{ijt}: iid type I extreme value ("logit shocks").
  - $\rightarrow$ Want μ_{ijt} to be sufficiently flexible that this convenient assumption matters little.
  - $\rightarrow$ Possible to eliminate ε_{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:

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

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

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  $\rightarrow$ 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.
  $\rightarrow$ E.g. how many choices of which cereal to buy are made every day in a specific city?
  $\rightarrow$ Population $\times$ max cereals per day? Foot traffic estimate $\times$ max cereals per trip?

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  - $\rightarrow$ E.g. how many choices of which cereal to buy are made every day in a specific city?
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- You should try different assumptions and see how they change your results.
  - $\rightarrow$ In general, the bigger the market size, the more substitution to the outside good.
  - $\rightarrow$ 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.
  - $\rightarrow$ Holding μ_{ijt} fixed, a higher quantity $q_{jt} > q_{kt}$ implies a higher mean utility $\delta_{jt} > \delta_{kt}$.

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$$u_{ijt} > u_{ikt} \quad \overset{b>0}{\Longleftrightarrow} \quad a + b \cdot u_{ijt} > a + b \cdot u_{ikt}$$

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

Roadmap

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Pure Logit Estimation

Price Endogeneity

Coding Exercise 1

Pure Logit Model

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

- Start with the simplest case: no heterogenous utility. We'll add μ_{ijt} back on day 2.

Pure Logit Model

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- Start with the simplest case: no heterogenous utility. We'll add μ_{ijt} back on day 2.
- Market shares simplify. No aggregation over individual types.
  - $\rightarrow$ 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).
  - $\rightarrow$ If we specify a function for δ_{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?
  - $\rightarrow$ In your exercise, products j are breakfast cereals; markets t are city-quarters.
  - $\rightarrow$ If we estimate the model, we can change p_{jt} and estimate how consumers react.

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- Specify δ_{jt} as a function of price p_{jt} and other product characteristics x_{jt}.
  - $\rightarrow$ 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 ξ_{jt} as unobserved product quality not in our data.
  - → Unobserved characteristics, advertising, average taste variation, etc.

Interpreting Parameters

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- If x_{jt} is a "mushy" cereal dummy, β is "utils" from mushyness. Again, not helpful.
  - $\rightarrow$ Instead, report β/α, the dollar willingness to pay for mushyness.

Roadmap

Endogeneity Concerns

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- As usual, if a regressor is correlated with the error, then its coefficient is biased.
- Typically, we expect price to be strongly correlated with unobserved quality.
  - $\rightarrow$ Firms know more than us about demand when setting prices.
  - $\rightarrow$ Often, $\mathbb{C}(p_{jt}, \xi_{jt}) > 0$, so $\hat{\alpha} < 0$ is biased towards zero.

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  - $\rightarrow$ Often, $\mathbb{C}(p_{jt}, \xi_{jt}) > 0$, so $\hat{\alpha} < 0$ is biased towards zero.
- 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.
  - $\rightarrow$ E.g. if p_{jt} is correlated with product-specific ξ_j in $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$.
  - $\rightarrow$ But do need multiple observations per product and market to add ξ_j and ξ_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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  - $\rightarrow$ Dummies take too much memory, so we "absorb" them, i.e. iteratively de-mean.
  - $\rightarrow$ Stata: Reghdfe. R: Fixest. Python: PyFixest. Coding exercise: PyBLP via PyHDFE.
- Helpful but insufficient. Unobserved quality typically varies by product *and* market.
  - $\rightarrow$ And if prices don't, then we don't have any variation left to estimate α.

Instrumental Variables

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- With or without fixed effects, a carefully-chosen IV can be a good solution.
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- Always run a first-stage regression of p_{jt} on z_{jt} and x_{jt}.
  - $\rightarrow$ Does the sign of the coefficient on z_{jt} make sense?
  - $\rightarrow$ Is the instrument strong, or should you worry about weak instruments?

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- Always run a first-stage regression of p_{jt} on z_{jt} and x_{jt}.
  - $\rightarrow$ Does the sign of the coefficient on z_{jt} make sense?
  - $\rightarrow$ 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.
  - $\rightarrow$ Consumers should only care about them through their effect on prices.

Typical Instruments for Price

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

- Cost-shifters: Measures of input prices, tariffs, etc.
- Hausman: Price of the same product averaged across *other* locations.
  - $\rightarrow$ Need costs to be correlated across locations, but not unobserved quality.
  - $\rightarrow$ 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.
- Waldfogel: Average consumer characteristics in *nearby* locations.
  - $\rightarrow$ With uniform pricing, your neighbors' demographics will affect your prices.

Typical Instruments for Price

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

Typical Instruments for Price

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- Waldfogel: Average consumer characteristics in *nearby* locations.
- 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.
    - $\rightarrow$ Do the substitution patterns you estimate seem reasonable?

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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.
    → Modeling the supply side.
    → Checking your code by simulating data.

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