CompeteGrok Analysis Report

Query: """ explain step by step BLP demand estimation. how is it being used in competition analysis? """

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Step-by-Step Explanation of BLP Demand Estimation

The **Berry-Levinsohn-Pakes (BLP)** model (Berry, Levinsohn, Pakes 1995, *Econometrica*) is a workhorse for estimating demand in markets with **differentiated products** (e.g., automobiles, cereals, airlines). It overcomes the multinomial logit (MNL)'s rigid **Independence of Irrelevant Alternatives (IIA)** assumption by incorporating **random coefficients** on product characteristics and price, capturing consumer heterogeneity and realistic substitution patterns.

BLP uses **market-level data** (shares, prices, characteristics) and a **generalized method of moments (GMM)** estimator. Here's the step-by-step process:

1. Model Specification: Random Coefficients Utility

- Utility for consumer i, product j in market t:

$$u_{ijt} = \underbrace{x_{jt}'\beta + \alpha p_{jt} + \xi_{jt}}_{\delta_{jt}} + \underbrace{\sigma\nu_i \odot x_{jt} + \sigma_p \nu_{ip} p_{jt}}_{\mu_{ijt}(\theta_2)} + \epsilon_{ijt}$$

  - δ_{jt}: **Mean utility** (linear in observed chars x_{jt}, price p_{jt}, unobserved demand shock ξ_{jt}).
  - μ_{ijt}: **Heterogeneous component** (random taste shocks $\nu_i \sim N(0, I)$, interacted with chars; $\theta_2 = \{\sigma, \sigma_p\}$).
  - ϵ_{ijt}: i.i.d. Type I extreme value (logit shocks).
- **Outside option**: $u_{i0t} = \epsilon_{i0t}$, share $s_{0t} = 1 - \sum_j s_{jt}$.
- Parameters: $\theta = \{\theta_1 = \{\beta, \alpha\}, \theta_2\}$.

2. Market Share Equation

- Choice prob:

$$s_{jt}(\delta_t, \theta_2) = \int \frac{\exp(\delta_{jt} + \mu_{ijt}(\theta_2))}{1 + \sum_m \exp(\delta_{mt} + \mu_{imt}(\theta_2))} dF(\nu_i)$$

- **Simulate** integral with $R = 500 - 1000$ draws (quasi-Monte Carlo, e.g., Halton sequences).
- Observed share s_{jt} identifies model implicitly.

3. **Contraction Mapping: Recover δ_{jt} (Inner Loop)**

- Shares **monotonically increasing** in δ_{jt}, so **invert**:

$$\delta_{jt} = \mathcal{D}_t(s_{jt}, s_{0t}; \theta_2)$$

- Solve fixed-point: Start with logit $\delta^{(0)}$, iterate:

$$\delta^{(r+1)} = \ln(s_j) - \ln(s_0) + \ln\left(1 + \sum_m s_m[\exp(\mu_m(\delta^{(r)}, \theta_2)) - 1]\right)$$

- Converges rapidly (~10 iterations); Broyden's method accelerates.

4. **Decompose Mean Utility (Endogeneity Setup)**

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

- **Price endogeneity**: $\text{Cov}(p_{jt}, \xi_{jt}) > 0$ (firms mark up quality).

5. **GMM Estimation (Outer Loop)**

- Instruments Z_{jt}: Cost shifters (input prices), Hausman (mean char of other firms), BLP-optimal ($E[x_k|x_j]$).
- Moments: $E[Z_{jt}\xi_{jt}(\theta)] = 0$.
- Minimize:

$$\hat{\theta} = \arg\min_{\theta} \left(\frac{1}{T}\sum_t \xi_t(\theta)' Z_t\right) W \left(\frac{1}{T}\sum_t Z'_t \xi_t(\theta)\right)$$

- **Two-step**: $W = I$ first, then $W = \hat{V}^{-1}$ (optimal).
- **Iteration**: Update $\theta_2 \to \delta \to \xi \to$ GMM until convergence.
- Std. errors via **cluster-robust** GMM variance.

6. **Post-Estimation Outputs**

- **Elasticities**:

$$e_{jm} = \frac{\partial s_j}{\partial p_m}\frac{p_m}{s_j} = s_j\left(\frac{w_{jm}}{s_m} - \delta_{jm}\right)$$

  (analytical form; $w_{jm} =$ avg. share-weighted choice prob).
- **Marginal costs** (w/ supply): $mc_{jt} = \frac{p_{jt}}{1+\omega_{jt}s_{jt}}$, where ω_{jt} from markup eq.
- Diversion ratios: $d_{jm} = \frac{\partial s_j/\partial p_m}{\partial s_m/\partial p_m}$.

Implementation Summary

Step	Computation	Tools
Simulate Shares	$R = 500$ Halton draws	pyblp (Python), BLPestimatoR (R)
Inversion	Contraction (10 iter.)	~1s/market
GMM	BFGS/NLM	Full est: minutes-hours
Data	Shares = revenue/(P·Q_market), chars, prices	Nielsen/IRI, Census

Challenges: Weak IVs → over-rejection; multiple equilibria (rare); large s_0.

Use in Competition Analysis

BLP dominates **antitrust economics** (DOJ/FTC Horizontal Merger Guidelines 2010/2023) for **structural simulation**:

1. **Merger Review**:
   - **Pre/post-simulation**: Fix demand params, re-optimize prices under new ownership (Nash-Bertrand).
   - **UPP/GUPPI**: $p \cdot d_{jm}$ · margin$_m$ predicts price pressure.
   - Example: Staples-Office Depot (blocked 1997; BLP showed 10% price rise).

2. **Market Power Measurement**:
   - Lerner: $L_j = s_j / |e_{jj}|$.
   - Test collusion: Compare simulated vs. observed markups.

3. **Counterfactuals**: | Policy | BLP Role | |——–|———-| | Horizontal merger | ΔP = 5-20% typical | | Entry/exit | Equilibrium price effects | | Cartel damages | Overcharge = Σ markup excess | | Vertical | Bargaining power |

4. **Real Cases**: | Industry | Key Papers/Cases | |———-|—————–| | Automobiles | BLP (1995), Petrin (2002 minivan entry) | | Airlines | Berry et al. (1995 routes) | | Pharma | FDA generic entry (Dubois/Garoupa) | | Tech | Google Shopping (EU), Apple e-books (DOJ) |

Advantages over reduced-form: Endogenous prices, heterogeneity → credible causal elasticities/diversions. Guides HHI screens + simulations.

Code: `pyblp` tutorial (pip install pyblp) simulates cereals in ~2min. See Nevo (2000 QJE) for yogurt application.

Questions on IVs, supply-side, or extensions (dynamic BLP)?

Privacy: Ephemeral RAG; zero retention. **Disclaimer:** Not legal advice. Models have caveats (e.g. IIA assumption). Verify 2025 data. **LaTeX:** Inline x, display

$$E = mc^2$$

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