Extensions and Variants

Chris Conlon

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Grad IO

BLP Extensions: Demographics

- It is helpful to allow for interactions with consumer demographics (such as income).
- A few ways to do this:
  - You could just use cross sectional variation in s_{jt} and $\overline{y}_t$ (mean or median income).
  - Better: Divide up your data into additional "markets" by demographics: do you observe $\mathfrak{s}_{jt}$ at this level? [May not be possible!]
  - Better: Draw y_{it} from a geographic specific income distribution. Draw ν_i from a general distribution of unobserved heterogeneity.
- Ex: Nevo (2000) Cereal demand sampled individual level D_i from geographic specific CPS data
- Joint distribution of income, income-squared, age, child at home.

$$\beta_i = \overline{\beta} + \Pi D_i + \sigma \nu_i$$

BLP Extensions: Panel Data

- with enough observations on the same product it is possible to include fixed effects

$$\delta_{jt}(\widetilde{\theta}_2) = x_{jt}\beta - \alpha p_{jt} + \underbrace{\xi_{jt}}_{\xi_j + \xi_t + \Delta\xi_{jt}}$$

- What does ξ_j mean in this context?
- What would ξ_t mean in this context?
- $\Delta\xi_{jt}$ is now the structural error term, this changes our identification strategy a little.
- We need instruments that change within product and across market.
  - ie: $z_{jt} - \overline{z}_{\cdot t} - \overline{z}_{j\cdot} = \Delta z_{jt}$ has to have some variation left!

Extensions: Micro Data (Petrin 2002), (microBLP 2004)

Suppose we had additional data on behavior of individuals (in addition to aggregate market shares).

- Examples:
  - For some customers have answer to "Which car would you have purchased if the car you bought was not available?"
  - Demographic data on purchasers of a single brand.
  - Full individual demographic and choice data.

Extensions: Micro Data: Nielsen Panelists

Nielsen data surveys panelists on everything they buy with a UPC code including what store they purchased from.

- Also tracks household characteristics (Race, Income, Education, HH Size, etc.)
- Can calculate covariance of characteristics (such as price) with demographics (income, education, etc.) conditional on purchase
- Can calculate purchase probability conditional on demographics: Did you buy any yogurt this trip, week, month, year?

Should we use these as individual data? Or Aggregate data from scanner data with additional moments?

Extensions: Micro Data (Petrin 2002), (microBLP 2004)

- Previously we had moment conditions from orthogonality of structural error (ξ) and (X, Z) in order to form our GMM objective.

$$E[\xi_{jt}|z_{jt}] = 0 \rightarrow E[\xi'_{jt} Z_{jt}] = 0$$

- We can incorporate additional information using "micro-moments" or additional moment conditions to match the micro data.
  - $Pr($ i buys j $|y_i \in [0, \$20K]) = c_1$ or $Cov(d_i, s_{ijt}) = c_2$
  - Construct an additional error term ζ_1, ζ_2 and interact that with instruments to form additional moment conditions.
  - Econometrics get tricky when we have a different number of observations for $E[\zeta' Z_m] = 0$ and $E[\xi' Z_d] = 0$.
    - May not be able to get covariance of moments taken over different sets of observations!
    - People often assume optimal weight matrices are block diagonal.

Alternative: Vertical Model (Bresnahan 1987)

- Imagine everyone agreed on the quality of the products offered for sale.
- The only thing people disagree on is willingness to pay for quality

$$U_{ij} = \overline{u} + \delta_j - \alpha_i p_j$$

- How do we estimate?
    - Sort goods from $p_1 < p_2 < p_3 \ldots < p_J$.
      It must be that $\delta_1 < \delta_2 < \ldots < \delta_J$. Why?
    - Normalize o.g. to 0 so that $0 > \delta_1 - \alpha_i p_1$ or $\alpha_i > \delta_1 / p_1$.
    - $s_0 = F(\infty) - F(\frac{\delta_1}{p_1}) = 1 - F(\frac{\delta_1}{p_1})$ where $F(\cdot)$ is CDF of α_i.
    - In general choose j IFF:

$$\frac{\delta_{j+1} - \delta_j}{p_{j+1} - p_j} < \alpha_i < \frac{\delta_j - \delta_{j-1}}{p_j - p_{j-1}}$$
$$s_j = F\left(\frac{\delta_{j+1} - \delta_j}{p_{j+1} - p_j}\right) - F\left(\frac{\delta_j - \delta_{j-1}}{p_j - p_{j-1}}\right)$$

Alternative: Vertical Model (Bresnahan 1987)

Estimation

- Choose parameters θ of $F(\cdot)$ in order to best match s_j.
    - Can do MLE $\arg\max_\theta \sum_j -\mathfrak{s}_j \log s_j(\theta)$.
    - Can do least squares $\sum_j (\mathfrak{s}_j - s_j(\theta))^2$.
    - Can do IV/GMM if I have an instrument for price. $\delta_j = x_j \beta + \xi_j$.
    - Extremely easy when $F \sim \exp(\lambda)$.
- What about elasticities?
    - When I change the price of j it can only affect (s_{j-1}, s_j, s_{j+1}).
    - We have set all of the other cross-price elasticities to be zero.
    - If a luxury car and a truck have similar prices, this can create strange substitution patterns.

Pure Characteristics Model: Berry Pakes (2001/2007)

$$u_{ij} = \delta_j + \beta_i x_{jt} + \xi_{jt} + \underbrace{\sigma_e}_{\to 0} \cdot \varepsilon_{ijt}$$

- Can think of this like random coefficients model where we take the variance of ϵ to zero.
- Can think of this a vertical model, with vertical tastes over several characteristics.
  - PCs: everyone prefers more Mhz, more RAM, and more storage but differ in WTP.
  - Possible that there is no PC specific ε.
- Advantages
  - Logit error means there is always some substitution to all other goods.
  - Reality may be you only compete with a small number of competitors.
  - Allows for crowding in the product space.
- Disadvantage: no closed form for s_j, so estimation is extremely difficult.
- Minjae Song (Homotopy) and Che-Lin Su (MPCC) have made progress using two different approaches.