Attention and Blur Effects of Advertising with Spill-overs: Nested Consideration Logit Approach

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Motivation

- The impact of advertising on sales remains debated
- Goeree [2008] studies U.S. PC industry with product-level data:
  - Random consideration set along with BLP
  - Highlights how ads are *effective* on both own and rivals' sales
- Shapiro et al. [2021] analyze TV ad spending across 288 CPG brands:
  - Quasilinear model with controls on various fixed effects and spill-overs
  - Find TV advertising to be *ineffective*
- The former restricts *spill-over*, the latter misses *limited attention*

Motivation

- Ignoring competitive structure can mislead conclusions
  - *Expensive* or *Cheap* equilibrium may occur at a time (*Spill-overs*)
  - Flat sales between the two (*limited attention*) $\Rightarrow$ ineffective ads?
  - Consequences of **deviation** from equilibrium
- Incorporating ad competition requires at least an industry-level study
  - Broader scope $\Rightarrow$ harder to obtain granular data
- Aggregate-level method may be needed

Categorization of Advertising Effects

- Existing literature: *image/prestige effect* and *information effect*
  - To distinguish the two, we need a rich dataset
    - Ackerberg [2001, 2003]: binary decision of newly entered brand
    - Honka et al. [2017] uses consumer-level survey on bank account choice

- We model with more coarse data $\Rightarrow$ needs a *new* framework
  - Johnson and Myatt [2006] suggest 'hype' and 'real info' of ads
    - 'Hype' shifts the willingness to pay (WTP) for a product
    - 'Real info' controls dispersion of the WTP distribution
  - 'Hype' **shifts** the demand, while 'Real info' **rotates** the demand rotation
  - No information congestion by ads: the more ads, the more info

AdsCategory

Main Idea

- As Johnson and Myatt [2006], we capture shift and rotation by ads
  - We use **Attention** (shift) and **Blur** (rotation) effects
- If a single product advertises, it will be attention grabbing
  - Limited attention of consumers $\Rightarrow$ scramble of products over it
  - Also a source of *spill-over* effects
  - Attention also embodies the product image
- Ads are source of information
  - Right amount may make product characteristics more salient
  - But ads can be congestive and *blur* the product quality

MainIdea

How does Blur work?

- Blur captures consumer **insensitivity** to the quality differences rotation

- Massive advertising campaign in an industry
  - Slogans ("Number 1"), visuals, spam mails $\Rightarrow$ **blur** kicks in

- Currently, what incurs blur is an ad hoc in our model
  - *Info Salience* and *Information Overload* being used
  - Distance between two previous market shares (consumer *learning*)?

BlurConcept

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Overview

- Nested logit integrating consideration probability formed by ads
  - Stage-wise choice naturally incorporate *spill-over* within industry
    - Nested Consideration models: Pancras [2011], Shapiro [2018]

- Attention effect enters into consideration probability of a product

- Blur effect will be modeled as another scale parameter in an industry
  - Higher the blur, Smaller the utility difference (the converse also holds)
  - Blur parameter will be a function of **aggregators** of ads in the nest
    - Salience: captured by a *bipolarization index* of ads in the nest
    - Information Overload: a *quadratic function* of total ads in the nest

Microfoundation of Nested Consideration Logit Model

Consumer i solves a discrete choice problem: $\max_{j \in \mathcal{J}} U_{ij}(\delta_j, \boldsymbol{A})$, where

$$U_{ij}(\delta_j, \boldsymbol{A}) = (\delta_j \cdot (y_i - p_j)^{\alpha})^{\frac{1}{\phi(\boldsymbol{A}^n)}} \varphi_{ij}(\boldsymbol{A})^{\eta_n} \varphi_{in}(\boldsymbol{A})^{(1-\eta_n)}$$

- $j \in \mathcal{J} = \{0, 1, \ldots, J\}$: product space
- $n \in \mathcal{N}$: nest space, a partition of $\mathcal{J}$, and $\{0\}$ forms own nest
- $\boldsymbol{A} = (A_0, A_1, \ldots, A_J)$: advertising vector, $\boldsymbol{A}^n$: nest specific ads vector
- y_i: income of consumer i, p_j: price of product j
- $\alpha > 0$: price sensitivity

Microfoundation of NCL

$$U_{ij}(\delta_j, \boldsymbol{A}) = (\delta_j \cdot (y_i - p_j)^{\alpha})^{\frac{1}{\phi(\boldsymbol{A}^n)}} \varphi_{ij}(\boldsymbol{A})^{\eta_n} \varphi_{in}(\boldsymbol{A})^{(1-\eta_n)}$$

- δ_j: systematic utility from observed/unobserved characteristics of j
- $\phi(\boldsymbol{A}^n)$: blur parameter of nest n, which could be larger than 1
  - η_n: nest (dissimilarity) parameter between $[0, 1)$ (McFadden [1978])
- $\varphi_{ij}(\boldsymbol{A}) = \frac{\gamma_j(\boldsymbol{A})}{e_{ij}\nu_{in}}$: attention factor of j, $\varphi_{in}(\boldsymbol{A}) = \frac{\gamma_n(\boldsymbol{A})}{\nu_{in}}$ of n for i
- $\gamma_j(\boldsymbol{A})$: consideration probability of j, $\gamma_n(\boldsymbol{A}) = \sum_{j \in n} \gamma_j(\boldsymbol{A})$ of nest n
- e_{ij}: perception heterogeneity of j, ν_{in} of n for i

Specifications of Utility Function

- By taking a log on U_{ij}, and assuming BLP utility we get

$$\ln U_{ij} = \frac{\boldsymbol{x}_j \beta + \xi_j - \frac{\alpha}{y_i} p_j}{\phi(\boldsymbol{A}^n)} + \underbrace{\eta_n \ln \gamma_j(\boldsymbol{A}) + (1-\eta_n) \ln \gamma_n(\boldsymbol{A}) - ln \nu_{in} - \eta_n \ln e_{ij}}_{\text{ln(Attention factors)}}$$

- $\ln \delta_j \equiv \boldsymbol{x}_j \beta + \xi_j$
  - $\boldsymbol{x}_j$: observable characteristics of product j with linear coefficients β
  - ξ_j: unobservable utility component of j

- Flexibility on what should be blurred (x_1) and what should not (x_2)
  - We can set unknown ratio, κ^n, of ξ_j that will be blurred:

$$\frac{\boldsymbol{x}_{1j} \beta_1 + \kappa^n \xi_j - \frac{\alpha}{y_i} p_j}{\phi(\boldsymbol{A}^n)} + \boldsymbol{x}_{2j} \beta_2 + (1-\kappa^n)\xi_j, \text{ for } \kappa^n \in [0,1]$$

Hedging between product image and industry image

- By taking a log on U_{ij}, and assuming BLP utility we get

$$\ln U_{ij} = \frac{\boldsymbol{x}_j\beta + \xi_j - \frac{\alpha}{y_i}p_j}{\phi(\boldsymbol{A}^n)} + \underbrace{\eta_n \ln \gamma_j(\boldsymbol{A}) + (1-\eta_n)\ln \gamma_n(\boldsymbol{A}) - ln\nu_{in} - \eta_n \ln e_{ij}}_{\text{ln(Attention factors)}}$$

- Consumer hedges between product & industry image with weight η_n
  - Real life plausibility?
    - ★ Premium image of a particular brand vs. Obsolete image of the industry

      e.g. Nokia phones, Montblanc fountain pens, etc.
    - ★ Exciting image of drinking beer vs. Not interested in brands
  - More weight on product image when products are dissimilar ($\eta_n \uparrow$)

Nested Consideration Logit choice probability

Assume that $\{-(\eta_n \ln e_{ij} + \ln \nu_{in})\}$ $\sim$nested logit distribution: $\mathcal{NL}(\{\eta_n\}_n)$

$$P_j(\boldsymbol{v}, \boldsymbol{A}) := \underbrace{\frac{\gamma_{j|n}(\boldsymbol{A}) e^{\frac{v_j}{\eta_n \phi_n}}}{\sum_{j' \in n} \left(\gamma_{j'|n}(\boldsymbol{A}) e^{\frac{v_{j'}}{\eta_n \phi_n}} \right)}}_{=:P_{j|n}(v,\boldsymbol{A})} \cdot \underbrace{\frac{\gamma_n(\boldsymbol{A}) \left(\sum_{j' \in n} \gamma_{j'|n}(\boldsymbol{A}) e^{\frac{v_{j'}}{\eta_n \phi_n}} \right)^{\eta_n}}{\sum_{n' \in \mathcal{N}} \left[\gamma_{n'}(\boldsymbol{A}) \left(\sum_{j' \in n'} \gamma_{j'|n'}(\boldsymbol{A}) e^{\frac{v_{j'}}{\eta_{n'} \phi_{n'}}} \right)^{\eta_{n'}} \right]}}_{=:P_n(v,\boldsymbol{A})},$$

where $\phi_n \equiv \phi(\boldsymbol{A}^n)$ and $v_j \equiv \ln \delta_j - \frac{\alpha}{\bar{y}} p_j$ NCLprobability

- Consideration probability within nest $\left(\gamma_{j|n} := \frac{\gamma_j}{\sum_{j' \in n} \gamma_{j'}} \right)$ adjusts $e^{\frac{v_j}{\eta_n \phi_n}}$
- Consideration probability across nest $\left(\gamma_n = \frac{\sum_{j' \in n} \gamma_{j'}}{\sum_{k \in \mathcal{J}} \gamma_k} \right)$ to inclusive value

CS:Attention

Blur inducing attention dependence

$$P_j(\boldsymbol{v}, \boldsymbol{A}) := \underbrace{\frac{\gamma_{j|n}(\boldsymbol{A}) e^{\frac{v_j}{\eta_n \phi_n}}}{\sum_{j' \in n} \left(\gamma_{j'|n}(\boldsymbol{A}) e^{\frac{v_{j'}}{\eta_n \phi_n}} \right)}}_{=:P_{j|n}(v,\boldsymbol{A})} \cdot \underbrace{\frac{\gamma_n(\boldsymbol{A}) \left(\sum_{j' \in n} \gamma_{j'|n}(\boldsymbol{A}) e^{\frac{v_{j'}}{\eta_n \phi_n}} \right)^{\eta_n}}{\sum_{n' \in \mathcal{N}} \left[\gamma_{n'}(\boldsymbol{A}) \left(\sum_{j' \in n'} \gamma_{j'|n'}(\boldsymbol{A}) e^{\frac{v_{j'}}{\eta_{n'} \phi_{n'}}} \right)^{\eta_{n'}} \right]}}_{=:P_n(v,\boldsymbol{A})},$$

- The systematic utility is going to be closer to 0 as $\phi_n \uparrow$

Fact 1 (Convergence to image formed by ads)

For each $n \in \mathcal{N}$ and $j \in n$, $\lim_{\phi_n \to \infty} P_{j|n} \to \gamma_{j|n}(\boldsymbol{A})$, $\lim_{\phi_n \to \infty} P_n \to \gamma_n(\boldsymbol{A})$, and $\lim_{\phi_n \to \infty} P_j \to \gamma_j(\boldsymbol{A})$ holds.

- People totally rely on consideration probability formed by ads

Blur may shape competition

- Firms who command fair amount of attention would want to blur
  - May increase advertising to cause info congestion
- Decrease in blur may increase the nest choice probability
  - Dominant firm may decrease ads to purify “spam” imaged industry
- Qualities subject to the blur will be regarded homogenous as $\phi_n \uparrow$
- Firms will compete with the characteristics that are not blurred
  - For example, price may not be blurred
  - Increase in ad spending may incur **price competition**

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Comparative Statics: Attention effect

- $\gamma_j(\boldsymbol{A}) = \frac{\exp(\gamma^n A_j)}{\sum_{n' \in \mathcal{N}} \sum_{k \in n'} \exp(\gamma^{n'} A_k)}$ with γ^n: **attention effect** of nest n

- For exposition, assume we can change attention *separately* from blur

- What happens when other nest-mate increases advertising?

$$\frac{\partial P_j}{\partial A_{j'}} = \gamma^n P_j \Big[\underbrace{\Big\{ (1-\eta_n)\,\gamma_{j'|n} + \eta_n P_{j'|n} \Big\}}_{\text{nest-stealing power}} (1 - P_n) - P_{j'|n} \Big]$$

  - $\Big[\Big\{(1-\eta_n)\gamma_{j'|n}+\eta_n P_{j'|n}\Big\}(1-P_n)-P_{j'|n}\Big] > (<) 0$: **Positive (Negative)** spill-over
  - $\eta_n \to 1$, negative spill-over will occur
  - $\eta_n \to 0$, depends on how much $\gamma_{j'|n}$ is larger than $P_{j'|n}$

NCLprobability CS:Attention

Comparison with Shapiro [2018]

$$\text{Shapiro [2018]} : U_{in} = \gamma_2 \sum_{j \in n} A_j + \boldsymbol{x}_n \beta_2 + \xi_n + \varepsilon_{in}, \ \{\varepsilon_{in}\}_n \overset{iid}{\sim} T1EV(1)$$

$$U_{ij} = \gamma_1 A_j + \boldsymbol{x}_j \beta_1 + \xi_j + \varepsilon_{ij}, \ \{\varepsilon_{ij}\}_j \overset{iid}{\sim} T1EV(1)$$

$$\text{Nested Logit} : U_{ij} = \gamma^n A_j + \boldsymbol{x}_j \beta + \xi_j + \varepsilon_{ij}, \ \{\varepsilon_{ij}\}_j \sim \mathcal{NL}(\{\eta_n\}_n)$$

$$\text{NCL} : U_{ij} = \frac{\boldsymbol{x}_j \beta + \xi_j - \alpha \boldsymbol{p}_j}{\phi(\boldsymbol{A}^n)} + \eta_n \ln \gamma_j(\boldsymbol{A}) + (1 - \eta_n) \ln \gamma_n(\boldsymbol{A}) + \varepsilon_{ij},$$

$$\{\varepsilon_{ij}\}_j \sim \mathcal{NL}(\{\eta_n\}_n)$$

$<$ Comparison of the comparative statics $>$

$$\text{Shapiro [2018]} : \frac{\partial P_j}{\partial A_{j'}} = P_j \left[\gamma_2 (1 - P_n) - \gamma_1 P_{j'|n}\right]$$

$$\text{Nested Logit} : \frac{\partial P_j}{\partial A_{j'}} = P_j \left[\gamma^n P_{j'|n} (1 - P_n) - \frac{\gamma^n}{\eta_n} P_{j'|n}\right]$$

$$\text{NCL} : \frac{\partial P_j}{\partial A_{j'}} = P_j \left[\gamma^n \left\{(1 - \eta_n) \gamma_{j'|n} + \eta_n P_{j'|n}\right\} (1 - P_n) - \gamma^n P_{j'|n}\right].$$

Comparison with Shapiro [2018]

$$\text{Shapiro [2018]}: \frac{\partial P_j}{\partial A_{j'}} = P_j \left[\gamma_2(1 - P_n) - \gamma_1 P_{j'|n}\right]$$

$$\text{Nested Logit}: \frac{\partial P_j}{\partial A_{j'}} = P_j \left[\gamma^n P_{j'|n} (1 - P_n) - \frac{\gamma^n}{\eta_n} P_{j'|n}\right]$$

$$\text{NCL}: \frac{\partial P_j}{\partial A_{j'}} = P_j \left[\gamma^n \left\{(1 - \eta_n)\,\gamma_{j'|n} + \eta_n P_{j'|n}\right\} (1 - P_n) - \gamma^n P_{j'|n}\right].$$

- In Shapiro [2018], nest stealing is **irrelevant** to **who** does the stealing
- In NL, positive spill-over **cannot arise** at all for $\eta_n \in [0, 1)$
- In NCL, it differs by who does the stealing
  - Conglomerate entrant ($\gamma_{j'|n} \gg P_{j'|n}$): likely **positive** spill-over
  - Existing giant ($\gamma_{j'|n} \approx P_{j'|n}$): likely **negative** spill-over

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The effect of a product's ad on the blur parameter

For example, we can specify the blur parameter as follows

$$\phi(\boldsymbol{A}^n) = \psi e^{\zeta(A_n - A^*)^2},$$

where $A_n = \sum_{j \in n} A_j$: total ads of nest n, and A^*: *Information Load* cap

- The blur parameter behave differently depending on the environment
  - $(A_n - A^*)^2$ may move in both directions by the increase of A_j
- It may be heterogeneous across products with other specifications:
  - If the blur is a function of polarization index of ads

Comparative Statics: Blur effect

- $\frac{\partial P_j}{\partial \phi_n} = \left(\frac{\partial P_{j|n}}{\partial \phi_n}\right) P_n + P_{j|n}\left(\frac{\partial P_n}{\partial \phi_n}\right)$
  - $\frac{\partial P_{j|n}}{\partial \phi_n} = P_{j|n}\frac{1}{\eta_n \phi_n^2}\left[\underbrace{\sum_{j' \in n} \frac{\gamma_{j'|n} e^{\frac{v_{j'}}{\eta_n \phi_n}}}{\sum_{j' \in n} \gamma_{j'|n} e^{\frac{v_{j'}}{\eta_n \phi_n}}} v_{j'}}_{=:\overline{v}_n} - v_j\right] = P_{j|n}\frac{1}{\eta_n \phi_n^2}[\overline{v}_n - v_j]$

    : a bad news for j s.t. $v_j > \overline{v}_n$
  - $\frac{\partial P_n}{\partial \phi_n} = -\frac{1}{\phi_n^2}\overline{v}_n P_n(1-P_n)$: a bad news for nest n with $\overline{v}_n > 0$

- In the end, $\frac{\partial P_j}{\partial \phi_n} = \frac{1}{\eta_n \phi_n^2} P_j\left[(1-\eta_n(1-P_n))\overline{v}_n - v_j\right]$ determines
  - The effect of blur will be **heterogeneous** across firms rotation

$$v_j \begin{Bmatrix} > \\ < \end{Bmatrix} (1-\eta_n(1-P_n))\overline{v}_n \Leftrightarrow \frac{\partial P_j}{\partial \phi_n} \begin{Bmatrix} < \\ > \end{Bmatrix} 0$$

CS:Blur

Blur effect on price elasticity

Let the elasticity of j with respect to k's price is

$$\varepsilon_{jk} = -\frac{\alpha}{\eta_{n'}\phi_{n'}} p_k \left[\mathbf{1}\{j=k\} - (1-\eta_{n'})P_{k|n'}\mathbf{1}\{n=n'\} - \eta_n P_k\right] \qquad \text{for } k \in n'$$

$$\frac{\partial \varepsilon_{ik}}{\partial \phi_{n'}} = -\frac{\varepsilon_{jk}}{\phi_{n'}} + \frac{\alpha}{\eta_{n'}^2 \phi_{n'}^3} p_k \big[(1-\eta_{n'})P_{k|n'}(\overline{v}_{n'} - v_k)\mathbf{1}\{n=n'\} + \eta_{n'} P_k((1-\eta_{n'}(1-P_{n'}))\overline{v}_{n'} - v_k)\big]$$

- **The first term** will impose inelastic change (pushing closer to 0)
- **The second term** will depend on the relative utility position
  - ε_{jj}:
    - ★ the beneficiary of blur ⇒ inelastic change (pushing closer to 0)
    - ★ the loser of blur ⇒ elastic (or less inelastic) change
  - ε_{jk}:
    - ★ k being the beneficiary of blur ⇒ elastic change
    - ★ k being the loser of blur ⇒ inelastic change

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Data Requirement

- The key data requirement: panel data structure
  - Panel data will be needed to control for the unobserved quality
- The existence of IVs for ad intensities and prices
  - Better to think after choosing area to apply the model
- Fair amount of products within a nest
  - The first stage regression uses within nest variation of covariates

Identification Strategy: 1st stage

Let $\Delta y_{jj'} := y_j - y_{j'}$ for any variable y, where j':be the baseline for each n

- First, identify the mixed model parameters

$$\begin{aligned}\ln \frac{P_{j|n}}{P_{j'|n}} &= \frac{v_j - v_{j'}}{\eta_n \phi_n} + \ln \frac{\gamma_{j|n}(\boldsymbol{A})}{\gamma_{j'|n}(\boldsymbol{A})} \\ &= \frac{\Delta x_{jj'}\beta - \alpha \Delta p_{jj'} + \Delta \xi_{jj'}}{\eta_n \phi_n} + \gamma^n \Delta A_{jj'}\end{aligned}$$

- Given IVs, $\boldsymbol{Z}$, for each $n \in \mathcal{N}$, $\frac{\beta}{\eta_n \phi_n}$, $\frac{\alpha}{\eta_n \phi_n}$, $\frac{\Delta \xi_{jj'}}{\eta_n \phi_n}$, and γ^n identified
  - $\mathbb{E}\left[\boldsymbol{Z} \cdot \left(\frac{\Delta \xi_{jj'} - \beta_0}{\eta_n \phi_n}\right)\right] = 0$
  - Note that $\eta_n \phi_n$ are fixed for the 1st stage regression

Identification Strategy: Challenge in the 2nd stage

$$\ln \frac{P_n}{P_0} = (1-\eta_n) \ln \left[\sum_{j \in n} e^{\gamma^n A_j} \right] + \eta_n \ln \left[\sum_{j \in n} e^{\gamma^n A_j + \frac{v_j}{\eta_n \phi_n}} \right]$$

$$\underbrace{\ln \frac{P_n}{P_0} - \ln \left[\sum_{j \in n} e^{\gamma^n A_j} \right]}_{\text{Known or identified above}} = \underbrace{\frac{\xi_{j'}}{\phi_n}}_{\text{Unknown}} + \underbrace{\eta_n}_{\text{Unknown}} \underbrace{\ln \left[\sum_{j \in n} e^{x_j \frac{\beta}{\eta_n \phi_n} - \frac{\alpha}{\eta_n \phi_n} p_j + \frac{\Delta \xi_{jj'}}{\eta_n \phi_n}} \right]}_{\text{Identified above}}$$

- Two unknowns, η_n and $\frac{\xi_{j'}}{\phi_n}$, and one equation for each $n \in \mathcal{N}$
- η_n is not time dependent: time-variation within a nest needed
- We introduce panel data to overcome the problem

Identification Strategy: 2nd stage

Let $t \in \mathcal{T}$ be the time index.

Assumption 1 (DGP of Unobserved Utilities)

$\xi_{jt} = \xi_j + \varepsilon_{jt}$, where $\{\varepsilon_\tau\}_\tau$ are independently distributed with $\mathbb{E}[\varepsilon_{j\tau}] = 0$ for all $\tau \in \mathcal{T}$.

$$\underbrace{\ln \frac{P_{nt}}{P_{0t}} - \ln \left[\sum_{j \in n} e^{\gamma^n A_{jt}} \right]}_{=: y_{nt}} = \frac{\xi_{j'}}{\phi_{nt}} + \eta_n \underbrace{\ln \left[\sum_{j \in n} e^{x_{jt} \frac{\beta}{\eta_n \phi_{nt}} - \frac{\alpha}{\eta_n \phi_{nt}} p_{jt} + \frac{\Delta \xi_{jj't}}{\eta_n \phi_{nt}}} \right]}_{=: S_{nt}} + \frac{\varepsilon_{j't}}{\phi_{nt}},$$

Want to subtract by $y_{nt'} = \dfrac{\xi_{j'}}{\phi_{nt'}} + \eta_n S_{nt'} + \dfrac{\varepsilon_{j't'}}{\phi_{nt'}}$

- Non-zero $\frac{\xi_{j'}}{\phi_{nt}}$ cannot be eliminated through subtraction

Identification Strategy: 2nd stage

$B_n := B(\boldsymbol{A}^n)$ for $B : \mathbb{R}_+^{|n|} \to \mathbb{R}_+^K$: a vector of aggregators for $n \in \mathcal{N}$

Assumption 2 (Existence of Composition-only change)

$\forall n \in \mathcal{N}, \exists t, t' \in \mathcal{T}$ *s.t.* $B = B(\boldsymbol{A}_t^n) = B(\boldsymbol{A}_{t'}^n)$.

- The difference between the two nest choice ratios is as follows:

$$\Delta y_{ntt'} = \eta_n \Delta S_{ntt'} + \frac{\Delta \varepsilon_{j'tt'}}{\phi_{nt}}$$

- Prices are still contained in $\Delta S_{ntt'}$, being the source of endogeneity
- Make use of the exogenous regressors in the first stage regression: $\mathbb{E}\left[\Delta \boldsymbol{x}_{tt'}^n \cdot \frac{\Delta \varepsilon_{j'tt'}}{\phi_{nt}}\right] = 0 \Rightarrow \eta_n$ is identified

Identification Strategy: 2nd stage

- Identified objects for each $t \in \mathcal{T}$: $\frac{\beta}{\eta_n \phi_{nt}}$, $\frac{\alpha}{\eta_n \phi_{nt}}$, $\frac{\Delta \xi_{jj'}}{\eta_n \phi_{nt}}$, γ^n, and η_n
  - $\beta^1 = 1$ (normalization) $\Rightarrow \phi_{nt}$ is identified **non-parametrically**

Proposition 1

Given **Assumption 1,2**, *the model parameters are identified under normalization of an element in* α, β.

- Higher level nest (or time trend) will need stronger version of **Assumption 2**: $\exists t, t'$ s.t. $\phi_{nt} = \phi_{n't} = \phi_{nt'} = \phi_{n't'}$ $\forall n, n'$.

- If other variables, W_t^n, enter ϕ, $W_t^n = W_{t'}^n$ should also hold.

Identification of κ^n

$$\frac{v_j(\boldsymbol{x}_j, \xi_j, p_j)}{\phi_n} = \frac{\boldsymbol{x}_j\beta + \kappa^n\xi_j - \frac{\alpha}{y_i}p_j}{\phi_n} + (1-\kappa^n)\xi_j$$

- Using **Assumption 1,2**, obtain $\Delta y_{ntt'} = \frac{\kappa^n \Delta\varepsilon_{j'tt'}}{\phi_{nt}} + (1-\kappa^n)\Delta\varepsilon_{j'tt'} + \eta_n \Delta S_{ntt'}$
  - κ^n only affects the scale not the position, i.e., η_n: identified
  - ϕ_{nt} can be identified as above without knowledge of κ^n
  - $y_{nt} - \eta_n S_{nt} = \kappa^n \frac{\xi_{j'} + \varepsilon_{j't}}{\phi_{nt}} + (1-\kappa^n)(\xi_{j'} + \varepsilon_{j't})$: identified

- κ^n is identified at infinity: $\mathbb{E}_t\left[\lim_{\phi_{nt}\to\infty} y_{nt} - \eta_n S_{nt}\right] = (1-\kappa^n)\xi_{j'}$
  - $\frac{\mathbb{E}_t[y_{nt} - \eta_n S_{nt}] - (1-\kappa^n)\xi_{j'}}{\mathbb{E}_t[\phi_{nt}^{-1}](1-\kappa^n)\xi_{j'}} = \frac{\kappa^n}{1-\kappa^n}$: κ^n is identified

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Future Project Directions

- Find industry/market that we can apply the model
  - Exogenous nest structure should hold plausibly
  - Industry that has various competitive dynamics may be ideal
  - Stayed rather in Economics literature $\Rightarrow$ **Marketing** literature
- Supply side analysis
  - Given a game setting, how would firm behave in terms of advertising
  - Bertrand competition with ads or also with quality in the long-run
  - Compare the analysis with Johnson and Myatt [2006]
    - Firms will prefer extremes (U-shaped profit in dispersion (rotation))

Future Project Directions

- Weak foundation of the blur effect
  - How can it be related to information of individual advertising?
  - How will it connect with tacit collusion
    - Obfuscation: (Gabaix and Laibson [2006], Ellison and Ellison [2009])
- Instead of coming up with IV for ads expenditure: make use of theory
  - Bertrand competition with price and ad spending
  - Gives a relationship between the optimal quantity of the two
  - IVs for price may resolve lack of IV for ad spending

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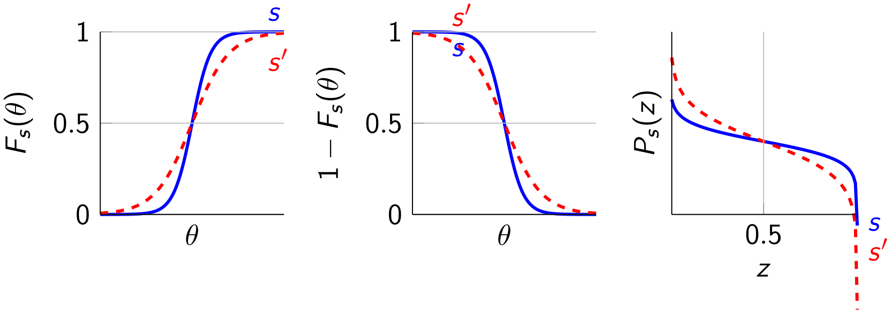
Appendix: Rotation in Johnson and Myatt [2006]

Let $F_s(\cdot)$: a willingness to pay CDF of a product with parameter s

Definition (Rotation)

*If $\exists\theta_s^\dagger$ s.t. $\forall\theta \in (\underline{\theta}_s, \overline{\theta}_s)$, $\theta \left\{ \substack{\geq \\ <} \right\} \theta_s^\dagger \Leftrightarrow \frac{\partial F_s}{\partial s}(\theta) \left\{ \substack{\leq \\ >} \right\} \frac{\partial F_s}{\partial s}(\theta_s^\dagger) = 0$, then change in s leads to **rotation** of $F_s(\theta)$.*

rotation AdsCategory MainIdea BlurConcept



Appendix: Rotation in Johnson and Myatt [2006]

- In demand function ($D_s(p) = 1 - F_s(p)$), $\exists p_s^\dagger$ s.t.

$$p \begin{Bmatrix} > \\ < \end{Bmatrix} p_s^\dagger \Leftrightarrow \frac{\partial D_s(p)}{\partial s} \begin{Bmatrix} > \\ < \end{Bmatrix} 0$$

- In our model, $\exists v_{\phi_n}^\dagger = (1 - \eta_n(1 - P_n))\overline{v}_n$ ($\overline{v}_n$: nest average) s.t.

$$v_j \begin{Bmatrix} > \\ < \end{Bmatrix} v_{\phi_n}^\dagger \Leftrightarrow \frac{\partial P_j(\boldsymbol{v})}{\partial \phi_n} \begin{Bmatrix} < \\ > \end{Bmatrix} 0$$

- Caveat: s increases dispersion of WTP, ϕ_n is **not**
  - The dispersion is determined by scale parameters of errors
  - ϕ_n intensifies the role of the dispersion

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