An Empirical Model of Quantity Discounts with Large Choice Sets

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- Lower unit-price for larger quantities.



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- Lower unit-price for larger quantities.
- Enable firms to screen between high- and low-demand consumers ...
- ... but may be **socially inefficient** (Varian, 1992, textbook).
- Prominent in packaged goods (food, drinks, toiletry, etc.) and services (energy, telecom, public transport, etc.).
- Despite widespread diffusion and a vast theoretical literature (Anderson and Renault, 2011; Armstrong, 2016), relatively **few empirical studies**.

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• Non-parametric estimation typically for small choice sets (Compiani, 2019).

- (Even) Parametric estimation can be hard with many bundles.
 - Berry et al. (2014); Iaria and Wang (2019).

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 - Multinomial logit and nested logit cannot capture this.
 - Mixed logit can but may be hard to estimate with large choice sets.
 - Product-Overlap Nested Logit (PONL): bundles belong to multiple nests.
 - More flexible than nested logit but simpler than mixed logit.
 - Concentrated 2SLS: extension of 2SLS by Berry (1994) to PONL.
 - Convenient with large choice sets.
 - Controls for price endogeity.

This Paper: Quantity Discounts in Carbonated Soft Drinks (CSDs)

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• As part of an anti-obesity strategy, **proposal in the UK to ban from supermarkets quantity discounts** on high-salt/sugar products.

• Use IRI data (USA, 2008-11) to estimate demand for bundles of CSDs.

- Simulate counterfactual linear pricing, a constant unit-price for each product.
 - Quantity \downarrow 20.7%, profit \downarrow 19.7%, and consumer surplus \downarrow 2.8%.
 - Added sugar intake \downarrow 22.1%.

Product-Overlap Nested Logit (PONL): Basic Idea



- Choice set defined over bundles, and bundle \mathbf{b} a collection of units of products.
- Any **b** that includes at least one unit of product j belongs to nest **N**_j, j = 1, ..., J.

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- Choice set defined over bundles, and bundle **b** a collection of units of products.
- Any **b** that includes at least one unit of product j belongs to nest **N**_j, j = 1, ..., J.
- Product-overlap among bundles determines the nests they share.
 - \uparrow similarity in product composition \Longrightarrow \uparrow correlation in unobserved preferences.

PONL Model: Average Indirect Utility and Demand Synergies

Average utility of **one unit of product** *j* in market *t* (Berry, 1994):

$$\delta_{tj} = \delta_j + x_{tj}\beta - \alpha p_{tj} + \xi_{tj} \tag{1}$$

while of **bundle b** in market *t* (Gentzkow, 2007):

$$\delta_{t\mathbf{b}} = \sum_{j \in \mathbf{b}} \delta_{tj} + \Gamma_{t\mathbf{b}}.$$
 (2)

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- Γ_{tb} is the **demand synergy**: extra-(dis)utility of joint purchase.
 - Complementarity (Gentzkow, 2007), shopping costs (Thomassen et al., 2017), preference for variety (Dubé, 2004), etc.
 - Quantity Discounts: $\Gamma_{tb} = -\alpha \left(p_{tb} \sum_{j \in b} p_{tj} \right) > 0.$

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• Γ_{tb} is the **demand synergy**: extra-(dis)utility of joint purchase.

• Remain agnostic about Γ_{tb} , a parameter to be identified and estimated.

The PONL inverse demand for **bundle b** in market t

$$\ln(\mathfrak{z}_{t\mathbf{b}}) - \ln(\mathfrak{z}_{t0}) = \sum_{j \in \mathbf{b}} (\delta_j + x_{tj}\beta - \alpha p_{tj} + \xi_{tj}) + \ln\left(\sum_{j \in \mathbf{b}} \omega_{\mathbf{b}j} \left(\mathfrak{z}_{t(\mathbf{b}|j)}\right)^{1-\lambda_j}\right) + \Gamma_{t\mathbf{b}} \quad (3)$$

with $\omega_{\mathbf{b}j} = \mathbb{1}_{\mathbf{b}\in\mathbf{N}_j} / \sum_{j'=1}^J \mathbb{1}_{\mathbf{b}\in\mathbf{N}_{j'}}$ a weight that proportionally allocates **b** to nests

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while for one unit of product $j \implies \mathbf{b} = j$, $\omega_{\mathbf{b}j} = 1$, and $\Gamma_{t\mathbf{b}} = 0$

$$\ln s_{tj} - \ln s_{t0} = \delta_j + x_{tj}\beta - \alpha p_{tj} + (1 - \lambda_j)\ln(s_{t(j|j)}) + \xi_{tj}, \tag{4}$$

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• If $\beta_{t(\mathbf{b}|j)}$ observed \implies Berry (1994): 2SLS from (4) + plug-in from (3).

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- If $\beta_{t(\mathbf{b}|j)}$ observed \implies Berry (1994): 2SLS from (4) + plug-in from (3).
- Unfortunately, not in PONL: only observe $\delta_{tb} = \sum_{j=1}^{J} \delta_{t(b|j)} \delta_{tN_j}$. \rightarrow Details

Estimation: Concentrated Two-Stage Least Square (C2SLS)

• Consider each unobserved $\delta_{t(j|j)} = \pi_{tj}$ as an additional **auxiliary parameter**.

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- Augment 2SLS system with nonliner equations for $\pi_t = (\pi_{tj})_{j=1}^J$.
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• Intuitively: Concentrate out unknown π_t from 2SLS by Berry (1994).

- Properties of Concentrated 2SLS (C2SLS):
 - Good in theory: PONL identified; C2SLS consistent and asym. normal. Details
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• Use Gauss-Seidel iterative procedure to implement C2SLS (Hallett, 1982).

• Algorithm only involves iterating between linear regressions and plug-ins.

Three computational advantages:

- (i) Optimization-free.
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On the convergence of the algorithm:

- (Necessary Condition) Convergence of the algorithm \implies C2SLS.
- Numerical convergence (or lack of it) can be easily verified.

Quantity Discounts in Carbonated Soft Drinks

- **IRI Data**: 6,155 households purchasing 16,873 different bundles of CSDs in Pittsfield and Eau Claire (USA), 2008-2011.
- **Discretize Quantity**: Consider purchases up to 1L as one unit, between 1L and 2L as two units, etc.

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Facts in the data:

- 1. Prevalence of **purchases of multiple units** (93.24% shopping trips) of the same and of different products.
- 2. Multi-person households purchase larger bundles than single-person households.
- 3. Pervasiveness of quantity discounts.

Demand Specification: PONL Model by Household Size

Average utility of household of size *hs* ∈ {single, multi} for one unit of *j* and for bundle b, respectively:

$$\begin{split} \delta_{tj}^{hs} &= \delta_j^{hs} - \alpha^{hs} p_{tj} + \delta_{\text{store}(t)} + \delta_{\text{time}(t)} + \xi_{tj}^{hs} \\ \delta_{tb}^{hs} &= \sum_{j \in \mathbf{b}} \delta_{tj}^{hs} + \Gamma_{tb}^{hs}. \end{split}$$

• Because of quantity discounts, the \approx 176,700 demand synergies are:

$$\Gamma_{t\mathbf{b}}^{hs} = -\alpha^{hs} \left(\rho_{t\mathbf{b}} - \sum_{j \in \mathbf{b}} p_{tj} \right) + \gamma_{t\mathbf{b}}^{hs}.$$

- Practical implementation of C2SLS:
 - Hausman-type instruments, prices from other cities (Hausman, 1996; Nevo, 2001).
 - Iterative procedure converges in a couple of minutes (25 iterations).

- Nesting parameter λ similar across household sizes, around 0.88.
- Price coefficients: $\alpha^{\text{single}} = 0.75 <^{***} \alpha^{\text{multi}} = 1.03.$
- Multi-person households more price elastic.
 - When prices of multiple units increase, multi-person households substitute away from larger bundles more sharply than single-person households.

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- Multi-person households more price elastic.
 - When prices of multiple units increase, multi-person households substitute away from larger bundles more sharply than single-person households.
- Incentives for quantity discounts: demand synergies rather than cost savings.
 - Estimated marginal costs non-decreasing in quantities.

Counterfactual Linear Pricing

- 1. **Profitable for producers of CSDs** in line with Varian (1992).
 - From quantity discounts to linear pricing, industry profit down by 19.7%.
- 2. Large reduction in purchased quantities (-20.7%).
 - Price increase for larger quantities (+14.9%).
 - Price decrease for smaller quantities (-31.6%).
- 3. Consumer surplus remains small.
 - CV of +3.7\$ per household-year (2.8% of total expenditure of CSDs).
 - Contraction in purchased quantities, but also lower prices for single units.

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Policy question: Could a ban on quantity discounts serve as a policy to limiting added sugar intake from CSDs?

Counterfactual Linear Pricing: Changes in Added Sugar Intake

	Ban on quantity discounts		Sugar tax
	on all CSDs	only on sugary CSDs	1 c/oz of added sugar
Predicted added sugar change	-22.93%	-22.08%	-22.90%
Quantity change	-20.66%	-8.93%	-10.35%
Sugary CSDs	-23.95%	-21.89%	-21.98%
Non-Sugary CSDs	-17.83%	+1.71%	+2.14%
Profit change	-19.74%	-9.46%	-7.01%
CV (\$ per household-year)	+3.70\$	+1.77\$	+2.35\$
CV/Expenditure	+2.82%	+1.29%	+1.61%

Conclusions

- Propose empirical model of demand for bundles:
 - 1. Accommodates intuitive form of correlation in the preferences of bundles.
 - 2. Convenient in applications with large choice sets.
- Inform policy debate on a ban on quantity discounts in CSDs.

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- Propose empirical model of demand for bundles:
 - 1. Accommodates intuitive form of correlation in the preferences of bundles.
 - 2. Convenient in applications with large choice sets.
- Inform policy debate on a ban on quantity discounts in CSDs.
- Proposed model can also facilitate the study of:
 - Demand across multiple product categories (grocery, online shopping, etc.).
 - Mergers in markets with both substitutes and complements.
 - Spillovers of taxes from a product category to others.
 - Portfolio choice models of asset pricing.
 - ...

Backup Slides

Lack of Observability of Within-Nest Purchase Probabilities (** Back)

- Because some **b** \in **multiple nests**, cannot determine $\delta_{t(\mathbf{b}|i)}$'s from $\delta_{t\mathbf{b}}$'s.
- $N_1 = \{1, (1, 1), (1, 2), (1, 3)\}$, $N_2 = \{2, (2, 2), (1, 2)\}$, and $N_3 = \{3, (1, 3)\}$.
- Then 8 observed purchase probabilities and 9 unknowns:

$$\begin{aligned}
\delta_{tk} &= \delta_{t(k|k)} \delta_{tN_{k}} \quad k = 1, 2, 3 \\
\delta_{t(j,j)} &= \delta_{t(j,j|j)} \delta_{tN_{j}} \quad j = 1, 2 \\
\delta_{t(1,2)} &= \delta_{t(1,2|1)} \delta_{tN_{1}} + \left(1 - \delta_{t(2|2)} - \delta_{t(2,2|2)}\right) \delta_{tN_{2}} \\
\delta_{t(1,3)} &= \left(1 - \delta_{t(1|1)} - \delta_{t(1,1|1)} - \delta_{t(1,2|1)}\right) \delta_{tN_{1}} + \left(1 - \delta_{t(3|3)}\right) \delta_{tN_{3}} \\
\delta_{t0} &= 1 - \sum_{j=1}^{3} \delta_{tN_{j}}.
\end{aligned}$$
(5)

Details: Estimation (** Back)

(i) **Uniqueness** of Γ_t and π_t given λ for each market t.

- π_t uniquely determined as $\pi_t = \pi(\lambda; s_t)$.
- Γ_{tb} uniquely determined as $\Gamma_{tb} = \Gamma_{b}(\lambda; \pi_{t}, s_{t}) = \Gamma_{b}(\lambda; \pi(\lambda; s_{t}), s_{t}).$
- This means that we can **concentrate out** Γ_t and π_t in each t.
- (ii) Given (i), C2SLS reduces to a nonlinear system in $(\delta, \beta, \alpha, \lambda)$.
 - Assume rank condition at the true parameters of the nonlinear system. Two roles:
 - First, in finite samples existence of $(\hat{\delta}, \hat{\beta}, \hat{\alpha}, \hat{\lambda})$ in neighbourhood of true values with probability one as $T \to \infty$.
 - Second, asymptotically $(\hat{\delta}, \hat{\beta}, \hat{\alpha}, \hat{\lambda})$ consistent and normal.

(iii) Finally, $\hat{\Gamma}_t$ and $\hat{\pi}_t$ also consistent and asymptotically normal as functions of $(\hat{\delta}, \hat{\beta}, \hat{\alpha}, \hat{\lambda})$.

Choice of Instruments (PBack)

- Despite the lack of observability of π_{tj} , instruments for $\frac{\delta_{tj}/\delta_{t0}}{\pi_{tj}}$ can be chosen on the basis of their correlation with $\delta_{t(j|j)}$.
- Denote by $\pi_j(\lambda; s_t)$ the unique π_{tj} that rationalizes the model for given $(\lambda; s_t)$.
- 1st-order Taylor approx. of $\ln(\pi_j(\lambda; s_t))$ around true value $\ln(\pi_j(\lambda^0; s_t))$:

$$\ln \delta_{tj} - \ln \delta_{t0} = \delta_j + x_{tj}\beta - \alpha p_{tj} + (1 - \lambda_j) \left[\ln \left(\frac{\delta_{tj}/\delta_{t0}}{\pi_{tj}^0} \right) - \frac{1}{\beta_t^j} \frac{\partial \pi_j(\lambda^0; \delta_t)}{\partial \lambda} (\lambda - \lambda^0) \right] + \xi_{tj}$$
$$= \delta_j + x_{tj}\beta - \alpha p_{tj} + (1 - \lambda_j) \left[\ln \delta_{t(j|j)} - \frac{1}{\beta_t^j} \frac{\partial \pi_j(\lambda^0; \delta_t)}{\partial \lambda} (\lambda - \lambda^0) \right] + \xi_{tj}$$

• $\ln \delta_{t(j|j)}$ leading term: valid IVs "shift" $\ln \delta_{t(j|j)}$ independently of ξ_{tj} .

Choice of Instruments (Press)

Re-express $\delta_{t(j|j)}$ as:

$$s_{t(j|j)} = \frac{\exp(\delta_{tj})^{1/\lambda_j}}{\sum_{\mathbf{b}' \in \mathbf{N}_j} (\omega_{\mathbf{b}'j} \exp(\delta_{t\mathbf{b}'}))^{1/\lambda_j}} = \frac{1}{1 + \sum_{\mathbf{b}' \in \mathbf{N}_j, \mathbf{b}' \neq j} (\omega_{\mathbf{b}'j} \exp(\delta_{t\mathbf{b}'} - \delta_{tj}))^{1/\lambda_j}}.$$

- Valid IVs shift $\delta_{tb'} \delta_{tj}$ independently of ξ_{tj} for $\mathbf{b}' \in \mathbf{N}_j$.
- Differentiation IVs (Gandhi and Houde, 2019)
 - $x_{tb'} x_{tj}$.
 - $x_{tk} x_{tj}$ for $k \neq j$ as long as nests j and k are overlapping, $\mathbf{N}_k \cap \mathbf{N}_j \neq \emptyset$.
- Excluded prices as p_k for $k \neq j$ and $\mathbf{N}_k \cap \mathbf{N}_j \neq \emptyset$
 - Cost shifters (or their proxies) for p_k .

References

Anderson, S. P. and Renault, R. (2011). Price discrimination. Edward Elgar Publishing.
Armstrong, M. (2016). Nonlinear pricing. Annual Review of Economics, 8:583–614.
Berry, S., Khwaja, A., Kumar, V., Musalem, A., Wilbur, K. C., Allenby, G., Anand, B., Chintagunta, P., Hanemann, W. M., Jeziorski, P., et al. (2014). Structural models of complementary choices. Marketing Letters, 25(3):245–256.

- Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.
- Compiani, G. (2019). Market counterfactuals and the specification of multi-product demand: A nonparametric approach. *Working Paper*.
- Dubé, J.-P. (2004). Multiple discreteness and product differentiation: Demand for carbonated soft drinks. *Marketing Science*, 23(1):66–81.
- Gandhi, A. and Houde, J.-F. (2019). Measuring substitution patterns in differentiated products industries. Technical report, National Bureau of Economic Research.
 Gentzkow, M. (2007). Valuing new goods in a model with complementarity: Online newspapers. *The American Economic Review*, 97(3):713–744.
 Hallett, A. H. (1982). Alternative techniques for solving systems of nonlinear