Merger review using online experiments

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Background

- Regulators face time constraints when evaluating a merger
  - In the UK, CMA has 40 working days to complete Phase 1
  - In the US, either the FTC or DoJ have 30 days to complete the Initial Review

- Look at both price and non-price considerations

- Quantitative measures include upward pricing pressure, diversion ratios

Merger Simulation

- Merger simulation is an exercise that typically uses a structural empirical model to estimate changes in price post merger and short term changes in consumer welfare

- Merger simulation is difficult to do
  - Make assumptions about what the world will look like under certain conditions
  - Data not always available
  - Right models can be difficult to estimate

- Along with time constraints, these factors limit the ability of competition authorities to apply empirical models

> *"In my three years as Chief Economist at the EC, I have not encountered a random-coefficient BLP model a single time"*
>
> — Tomasso Valletti, Chief Competition Economist, DG for Competition, 2016-2019

Source: Valetti, Tomasso. "Doubt is Their Product: The Difference Between Research and Academic Lobbying ". ProMarket. Stigler Center at The University of Chicago Booth School of Business, 20 Sept. 2020, https://promarket.org/2020/09/28/difference-between-research-academic-lobbying-hidden-funding/

Research Question

- How effectively can we obtain baseline demand parameters to use in a merger assessment through an experiment?

- This paper is going to show

  1. How close we came
     - Our parameters end up matching previous empirical estimates fairly closely
     - Although we do not do a fully-fledged merger simulation, we go all the way up to estimating marginal costs and markups

  2. Some of the pitfalls of the methodology
     - Do's and don't for the next iteration

What we do

Combine a **mixed logit model** with data obtained from an **experiment/survey** to estimate baseline demand parameters for the purposes of merger assessment

Our requirements

Mixed Logit
Experimental Data

Market Level Data

Demand Parameters	⊕	Ownership Shares Prices	⊜	(Own- and cross-price) Elasticities Markups

Scanner Data
Econometric Training
Computing Power
Time

Empirical model requirements

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Stated Preference

- Data collected in experimental or survey situations
  - Hypothetical choice situations and hypothetical responses
- Common in other branches of economics (e.g. transport) and other disciplines (e.g. marketing)
- SP experiments have several advantages over their revealed preference cousins
  1. Data can be collected quickly
  2. Can be designed to contain as much variation in each attribute as is appropriate
  3. Use of hypothetical products can eliminate endogeneity of prices
  4. Ability to target specific demographics
- They also have their limitations
  1. Incentivisation is very difficult
  2. What people say they will do versus what they actually do
  3. Can be influenced by perceptions of what the researcher wants

Experimental Design

0. Identify products of interest
   - beer, movie rentals, broadband

1. Define a set of attributes for each product type
2. Define number and values of attribute levels
3. Define number of choice sets and options in each choice set

4. Statistical design
   - What combinations of products do subjects see?

Experimental Design

		Levels		
Attributes	Number of levels	1	2	3
Price/6-pack	3	\$6.49	\$7.99	\$10.99
ABV	3	3.6%	4.6%	5.5%
Container	2	0 = can	1 = bottle	
Volume/unit	3	8.4-oz	12-oz	16-oz

$J = 18$ products, each shown at 3 price levels

Possible options subjects could be faced with = 54

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Experimental design

- Participants shown **8 choice sets** each per product type with **4 alternatives** and asked to **select their preferred option**
- 4 random alternatives were drawn from J without replacement to construct each choice set

- Experiment administered on online subject recruitment platform Prolific
- Relatively homogeneous sample: US beer drinkers aged 21-30
  - allows estimation of parameters with tighter standard errors
- Subjects were paid a flat fee of £2 to participate
- We collected observations on 486 subjects in 3 days
  - 3888 choice observations per product type
  - very easily scalable

Example Screen

Choice set 1

If STELLA ARTOIS launched a new beer, which would you prefer?

Product name	A	B	C	D
Price/6 pack	$6.49	$6.49	$10.99	$7.99
ABV	3.6%	5.5%	3.6%	4.6%
Container	Bottle	Bottle	Can	Can
Volume per container	12-oz	16-oz	8.4-oz	16-oz
Your choice:	○	○	○	○

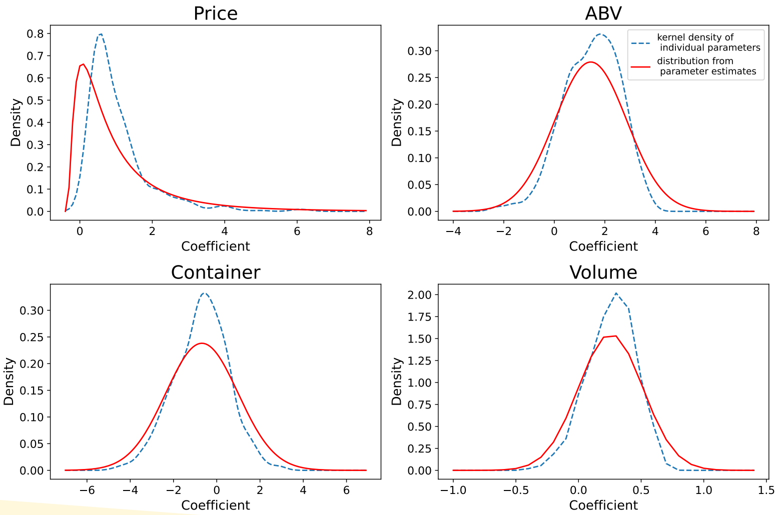
Next

Laboratory for Economic and Decision Research, University of East Anglia

Baseline parameter estimates (Beer)

		1	2
		Unconditional	Conditional
Variable	Parameter	α, β	$\bar{\alpha}_n, \bar{\beta}_n$
Price	Mean	-1.027	-1.041
	Std. dev.	1.148	0.876
ABV	Mean	1.444	1.468
	Std. dev.	1.430	1.116
Container	Mean	-0.686	-0.720
	Std. dev.	1.675	1.266
Volume	Mean	0.256	0.260
	Std. dev.	0.257	0.190
Observations		3888	3888

Population versus individual parameters



Elasticity and Markups

- Once we have demand estimates we can estimate elasticity matrix

$$\eta_{jk} = \begin{cases} -\frac{p_j}{s_j} \int \alpha_n \hat{L}_{nj}(1 - \hat{L}_{nj}) f(\alpha) d\alpha & \text{if } j = k, \\ \frac{p_j}{s_k} \int \alpha_n \hat{L}_{nj} \hat{L}_{nk} f(\alpha) d\alpha & \text{otherwise} \end{cases}$$

- p is price
- s is predicted market shares
- $\hat{L}$ is individual predicted probabilities

- To our demand parameter estimates we add a real data set comprised of the **18 top beers by market share** in the US (2019) plus an outside good

	Brand	1	2	3	4	5	8	9	10	12	13	14	16	18
1	Bud Light	-7.069	0.037	0.103	0.133	0.155	0.243	0.058	0.108	0.78	0.229	0.067	0.2	0.133
2	Coors Light	0.018	-6.504	0.045	0.267	0.026	0.456	0.111	0.203	0.753	0.148	0.031	0.383	0.267
3	Miller Lite	0.02	0.018	-3.527	0.094	0.265	0.088	0.032	0.047	0.268	0.304	0.109	0.109	0.094
4	Budweiser	0.016	0.064	0.057	-6.555	0.016	0.49	0.117	0.196	0.793	0.214	0.043	0.462	0.352
5	Michelob Ultra	0.021	0.007	0.179	0.018	-4.048	0.015	0.01	0.011	0.057	0.315	0.127	0.019	0.018
6	Corono Extra	0.02	0.013	0.169	0.061	0.306	0.045	0.022	0.028	0.091	0.312	0.121	0.065	0.061
7	Modelo Especial	0.02	0.013	0.169	0.061	0.306	0.045	0.022	0.028	0.091	0.312	0.121	0.065	0.061
8	Natural Light	0.012	0.045	0.022	0.202	0.006	-6.12	0.074	0.204	2.043	0.084	0.012	0.52	0.202
9	Busch Light	0.018	0.069	0.05	0.301	0.023	0.461	-6.536	0.2	0.76	0.176	0.036	0.412	0.301
10	Busch	0.017	0.063	0.037	0.253	0.013	0.639	0.101	-6.442	1.197	0.132	0.024	0.429	0.253
11	Heineken	0.019	0.018	0.16	0.099	0.278	0.071	0.033	0.043	0.117	0.311	0.115	0.106	0.099
12	Keystone Light	0.017	0.032	0.029	0.141	0.009	0.879	0.053	0.165	-4.886	0.107	0.008	0.411	0.141
13	Miller High Life	0.02	0.026	0.135	0.156	0.207	0.15	0.05	0.075	0.44	-3.751	0.094	0.183	0.156
14	Stella Artois	0.019	0.018	0.16	0.104	0.276	0.072	0.034	0.045	0.107	0.312	-4.367	0.11	0.104
15	Pabst Blue Ribbon	0.015	0.056	0.04	0.282	0.01	0.77	0.098	0.203	1.414	0.153	0.028	-6.768	0.282
16	Blue Moon	0.019	0.023	0.149	0.143	0.244	0.102	0.045	0.061	0.167	0.309	0.108	0.153	0.143
17	Dos Equis	0.02	0.012	0.169	0.055	0.309	0.043	0.021	0.027	0.102	0.312	0.121	0.059	0.055
18	Coors Banquet	0.016	0.064	0.057	0.352	0.016	0.49	0.117	0.196	0.793	0.214	0.043	0.462	-6.555
19	Outside	0.011	0.028	0.04	0.123	0.044	0.466	0.046	0.11	1.092	0.108	0.025	0.255	0.123

Own-Price Elasticity Comparisons

	Real Products[1]	Miller-Weinberg[2]
Bud Light	-7.069	-4.389
Coors Light	-6.504	-4.628
Miller Lite	-3.527	-4.517
Budweiser	-6.555	-4.272
Michelob Ultra	-4.048	-4.970
Corona Extra	-3.995	-5.178
Heineken	-4.278	-5.147
Miller High Life	-3.751	-3.495
Coors Banquet	-6.555	-4.371

1. Own-price elasticities from table on previous slide
2. Own-price elasticities from Miller & Weinberg (2017)

Elasticity and markups

To our demand parameter estimates we add a real data set comprised of the **18 top beers by market share** in the US (2019) plus an outside good

	Pseudo-products	Real Products	Miller-Weinberg
Median own price elasticity	-4.71	-4.63	-4.73 – -4.33
Market price elasticity	-0.12	-0.13	-0.72 – -0.60
Median price cost margin		21.9%	34%

Price cost margin = $\frac{p-c}{p}$

Lessons and opportunities

- Correct specification of product characteristics
- Use of brand fixed-effects (or labelled vs. unlabelled alternatives)
  - No brand effects, only product characteristics
  - Mixture of brand effects and product characteristics
  - Only brands and price
- Specification of mixing distribution
- Restrict estimates to sub-group of population by bootstrapping conditional estimates
- Understanding online platforms