Merger review using online experiments

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Background

- In recent years, between 1/2 and 2/3 of the EC's merger cases have used either upwards pricing pressures or diversion ratios

- Estimating demand functions is a more rigourus but oftentimes challenging exercise
  - Foundations of merger assessment

- 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

- Many of the quantitative measures used to observe price effects utilise estimated demand functions

Demand Estimation

- The use of structural empirical models such as random coefficient mixed logits (RCMLs) is a powerful tool to estimate demand functions
- Demand estimation 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/

What we do

> **Research Question**
>
> Can experiments be used to estimate demand parameters and contribute to merger assessment and other policy evaluations?

1. Run an online experiment using hypothetical choices to obtain demand parameters
2. Mix those parameters with real world, aggregate level data to back out marginal costs under a Nash-Bertrand equilibrium
3. Using estimated demand function and marginal costs, we estimate elasticities and mark-ups
4. Simulate a merger under various conditions by changing the ownership matrix

What we do

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 (SP)

- 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. Random variation 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
  4. May not apply to the full range of products (e.g. aeroplanes)

Experimental Design

0. Identify products of interest
   - beer

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

$J = 18$ (pseudo) 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 set of 54 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

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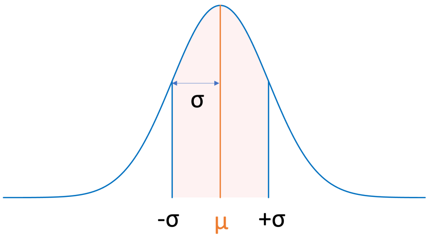
What is it that we estimate

Indirect utility with consumer heterogeneity: $u_{nj} = -\alpha_n p_j + {\beta_n}' x_{nj} + \varepsilon_{nj} \;\; \forall j$

- Each taste parameter varies over individuals in the population with density $f(\beta|\theta^*)$
- $\theta = [\mu, \sigma]$ of the taste parameters



- Assume non-price taste parameters are distributed normally
- Marginal utility of income α is distributed log normally
  - ensures all values are same sign

Baseline parameter estimates

Variable	Parameter	Unconditional	Conditional
Price (α)	Mean (μ_α)	-1.027*	-1.041
		(0.077)	
	Std. dev. (σ_α)	1.148*	0.876
		(0.185)	
ABV (β_1)	Mean (μ_{β_1})	1.444*	1.468
		(0.089)	
	Std. dev. (σ_{β_1})	1.430*	1.116
		(0.089)	
Container (β_2)	Mean (μ_{β_2})	-0.686*	-0.720
		(0.099)	
	Std. dev. (σ_{β_2})	1.675*	1.266
		(0.111)	
Volume (β_3)	Mean (μ_{β_3})	0.256*	0.260
		(0.016)	
	Std. dev. (σ_{β_3})	0.257*	0.190
		(0.019)	

Elasticity and Markups

- Once we have demand estimates we can estimate elasticity matrix

- 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

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

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

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TABLE 4. Unbranded real product set elasticity matrix

	Brand	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Bud Light	**-3.941**	0.144	0.057	0.136	0.069	0.089	0.019	0.053	0.034	0.451	0.062	0.062	0.144
2	Budweiser	0.050	**-4.882**	0.014	0.352	0.100	0.148	0.028	0.054	0.037	0.551	0.135	0.136	0.374
3	Michelob Ultra	0.111	0.080	**-4.047**	0.073	0.041	0.051	0.051	0.033	0.093	0.262	0.155	0.153	0.080
4	Natural Light	0.019	0.138	0.005	**-8.757**	0.057	0.193	0.008	0.041	0.038	3.701	0.135	0.030	0.138
5	Busch Light	0.063	0.260	0.019	0.381	**-4.884**	0.163	0.026	0.068	0.047	0.618	0.124	0.090	0.260
6	Busch	0.047	0.227	0.014	0.749	0.096	**-5.751**	0.019	0.069	0.054	1.144	0.151	0.066	0.227
7	Stella Artois	0.042	0.173	0.056	0.130	0.061	0.078	**-4.594**	0.039	0.106	0.205	0.268	0.300	0.173
8	Coors Light	0.070	0.203	0.022	0.395	0.099	0.170	0.024	**-4.771**	0.054	0.657	0.116	0.068	0.203
9	Miller Lite	0.044	0.137	0.062	0.366	0.068	0.133	0.064	0.054	**-5.276**	0.63	0.457	0.192	0.137
10	Keystone Light	0.032	0.114	0.01	1.941	0.049	0.154	0.007	0.036	0.035	**-6.635**	0.113	0.028	0.114
11	Miller High Life	0.032	0.198	0.041	0.504	0.070	0.145	0.064	0.045	0.179	0.801	**-5.663**	0.264	0.198
12	Blue Moon	0.038	0.235	0.047	0.134	0.060	0.074	0.084	0.031	0.089	0.232	0.311	**-4.591**	0.235
13	Coors Banquet	0.050	0.374	0.014	0.352	0.100	0.148	0.028	0.054	0.037	0.551	0.135	0.136	**-4.882**
14	Corono Extra	0.054	0.138	0.077	0.136	0.060	0.081	0.076	0.043	0.122	0.251	0.258	0.235	0.138
15	Modelo Especial	0.054	0.138	0.077	0.136	0.060	0.081	0.076	0.043	0.122	0.251	0.258	0.235	0.138
16	Heineken	0.044	0.193	0.058	0.116	0.058	0.070	0.083	0.034	0.091	0.206	0.265	0.347	0.193
17	Dos Equis	0.057	0.117	0.084	0.178	0.062	0.095	0.07	0.051	0.154	0.328	0.285	0.186	0.117
18	Pabst Blue Ribbon	0.040	0.315	0.011	0.754	0.098	0.198	0.021	0.058	0.045	1.104	0.169	0.093	0.315
19	Outside	0.037	0.181	0.016	1.510	0.066	0.161	0.020	0.044	0.050	2.737	0.160	0.080	0.181
	Median X-PeD	0.046	0.177	0.032	0.352	0.064	0.139	0.028	0.045	0.054	0.551	0.158	0.136	0.177
	Mean X-PeD	0.049	0.187	0.038	0.464	0.071	0.124	0.043	0.047	0.077	0.816	0.198	0.150	0.187

Own-Price Elasticity Comparisons

	Our estimates[1]	Miller-Weinberg[2]
Bud Light	-3.941	-4.389
Budweiser	-4.882	-4.272
Michelob Ultra	-4.047	-4.970
Coors Light	-4.771	-4.628
Miller Lite	-5.276	-4.517
Miller High Life	-5.663	-3.495
Coors Banquet	-4.882	-4.371
Corona Extra	-4.529	-5.178
Heineken	-4.579	-5.147

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

Elasticity, marginal costs 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

	Our estimates	Miller-Weinberg
Median own price elasticity	-4.83	-4.73 – -4.33
Median marginal cost	$9.17	
Median price cost margin	21.9%	34%

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

Simulated merger between ABInBev and Miller-Coors at constant MC

	Pre-merger values			Post-merger values				
	Price	MC	PCM	New Firm	Price	PCM	% pt. Chg Mkt Share	% Chg Price
Bud Lgt	15.99	11.51	28.0	AM	16.57	30.6	-0.033	3.64
Budweiser	11.99	9.23	23.0	AM	12.56	26.5	-0.029	4.75
Michelob	18.99	13.87	27.0	AM	19.63	29.4	-0.014	3.39
Natural Lgt	7.99	6.99	12.5	AM	8.51	17.8	-3.299	6.45
Busch Lgt	11.99	9.12	24.0	AM	12.55	27.3	-0.099	4.66
Busch	9.99	7.92	20.7	AM	10.53	24.8	-0.296	5.37
Stella Art	15.99	12.11	24.2	AM	16.68	27.4	-0.031	4.30
Coors Lgt	11.99	8.94	25.4	AM	12.49	28.4	-0.045	4.14
Miller Lte	11.99	9.03	24.7	AM	12.43	27.4	-0.031	3.70
Keyst. Lgt	7.99	6.69	16.3	AM	8.38	20.1	-2.048	4.83
Miller HL	10.99	8.46	23.0	AM	11.42	25.9	-0.106	3.90
Blue Moon	14.99	11.09	26.1	AM	15.47	28.3	-0.034	3.17
Coors Bnqt	11.99	9.10	24.1	AM	12.49	27.2	-0.190	4.19
Corona	15.99	12.41	22.4	-	16.13	23.0	0.031	0.84
Modelo Esp	15.99	12.41	22.4	-	16.13	23.0	0.031	0.84
Heineken	15.99	12.47	22.0	-	16.13	22.7	0.077	0.85
Dos Equis	14.99	11.65	22.3	-	15.13	23.0	0.032	0.91
Pabst BR	9.99	8.27	17.2	-	10.13	18.4	0.847	1.40

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Brand Effects

- Common feedback was that without brand effects, results may not be realistic

- Adding brands
  - Captures large proportion of unobserved (to the researcher) effects
  - Allows for more realistic predicted market shares

- Presents new challenges
  - Increases number of parameters to estimate
  - Characteristics fixed within a brand are difficult to identify

Example Screen

Choice set 2

Product name	A	B	C	D
Brand	 Modelo Especial	 Bud Light	 Dos Equis	 Miller Lite
ABV	4.5%	4.2%	4.2%	4.2%
Container	Bottle	Can	Bottle	Bottle
Volume/unit	12-oz	16-oz	12-oz	12-oz
Price/6-pack	$6.49	$6.49	$10.99	$7.99
Your choice:	○	○	○	○

Next

Baseline parameter estimates

			Branded experiment	
Variable	Parameter	Unbranded experiment	w/o brand dummies	w/ brand dummies
Price (α)	Mean (μ_α)	-1.027*	-0.275*	-0.220*
		(0.077)	(0.047)	(0.030)
	Std. dev. (σ_α)	1.148*	0.836*	0.652*
		(0.185)	(0.354)	(0.224)
ABV (β_1)	Mean (μ_{β_1})	1.444*	1.605*	0.202*
		(0.089)	(0.104)	(0.027)
	Std. dev. (σ_{β_1})	1.430*	1.741*	
		(0.089)	(0.109)	
Container (β_2)	Mean (μ_{β_2})	-0.686*	1.215*	0.589*
		(0.099)	(0.081)	(0.037)
	Std. dev. (σ_{β_2})	1.675*	1.411*	
		(0.111)	(0.081)	
Volume (β_3)	Mean (μ_{β_3})	0.256*	-0.001*	-0.147*
		(0.016)	(0.026)	(0.009)
	Std. dev. (σ_{β_3})	0.257*	0.369*	
		(0.019)	(0.032)	

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Elasticity comparisons

	Unbranded experiment	Branded experiment: w/o brand dummies	Branded experiment: w/ brand dummies
Median own price elasticity	-4.83	-1.72	-1.40
Median cross price elasticity	0.059	0.056	0.025
Median marginal cost	\$9.17	\$4.20	\$1.36
Median price cost margin	21.9%	70.6%	91.5%

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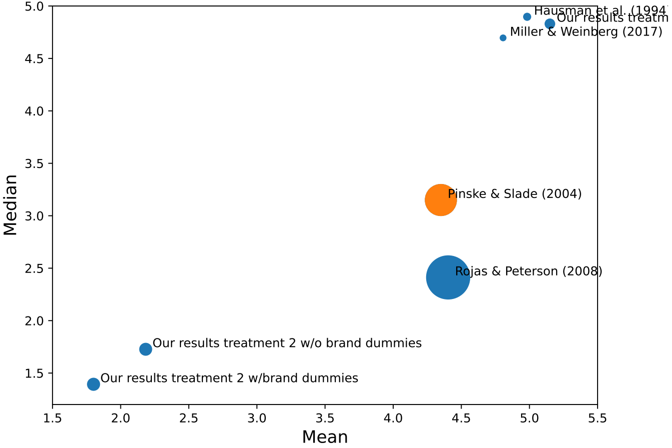
Further Elasticity Comparisons



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Summary

- We combine experiment and real world data with a structural model with the aim of simplifying demand estimation and merger simulation as a compliment to other methods

- Our initial experiment and analysis achieved believable substitution patterns

- Our second experiment add brands in an attempt to improve model predicted markets shares and add a degree of realism

- However, adding brands moved our results away from previous studies; more testing is required in this area