ECON-L1300 Empirical Industrial Organization: Static models – Lecture 8 – Market power

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This week

Lecture 7 – Mergers

- Mergers
- Diversion and unilateral effects
- Merger simulation (Nevo, 2000)

Lecture 8 – Market power

- Market power (Nevo 2001)
- Antitrust in practice

Market power

- Definition: Firms can raise prices above competitive level
  - Product price / quantity optimization of a firm or a group of firms with sufficiently high market share
  - Our focus
- Other common means to restrict competition
  - Predatory behavior
  - Tying and bundling
  - Exclusive dealing, foreclosing (vertical relations)
  - Lobbying

Does it matter how firms have gained market power?

- Market power may be achieved by collusion or merger
  - Collusion: explicit, tacit, or algorithmic
- Firms could achieve market power from innovations, higher investment (capital, labor), or coincidence
- Market power may be natural to the industry
  - Declining average costs (natural monopolies)
  - Network effects
- It may be granted by the government

Why IO important?

Learnings from modern IO

1. Market shares do not tell the full story of competitiveness
2. Industry specifics matter

> Economists accordingly have advocated a case-by-case or "rule of reason" approach to antitrust, away from rigid "per se" rules
> – Jean Tirole, Nobel prize lecture

Structural models of the industry

- Estimating price-cost margins from data requires a structural model
  - Data only gives us conditional densities of P & Q given demand and supply variants
  - Need to impose structure on demand and supply
- Still need to impose the particular form of competition
  - Competitive, oligopolistic, collusive, monopoly
  - Cournot, Bertrand, supply-functions, etc.

For more, Reiss & Wolak (2007) discusses this topic very well.

Recap of what's been covered

- Given a demand model, firms optimize their actions, e.g.

$$f_i(p) \equiv \left(\frac{\partial q_i(p)^\intercal}{\partial p_i}\right)^{-1} q_i(p) - (p_i - mc_i) = 0$$

- Identification relies on the economic model: distributional assumptions, assumptions on functional forms, etc.
- Further, we are restricted to few specific models of firm behavior in equilibrium, e.g. Bertrand-Nash
- Credible such assumptions may not be
- Alternative: test which models of competition can best explain observed prices and market shares
  - E.g. Miller & Weinberg, 2017 (MillerCoors) and Nevo, 2001

Nevo 2001: Measuring market power in the cereal industry

Plan:

1. Estimate brand-level demand:
   - Product characteristics
   - Heterogeneous consumer preference
   - Control for unobserved brand-specific demand intercepts

2. Use the estimates jointly with pricing rules implied by different models of firm conduct to recover markups

Nevo 2001: Cereal industry

Motivation:

- Industry characteristics
  - High concentration (share of top 3: 75%)
  - High price-cost margins (ca. 45%)
  - Large advertising to sales ratios (ca. 13%)
  - Numerous introductions of brands
- Industry where product characteristics are less discernible
  - Compared e.g. to the car market in BLP 1995
- Data to test the effects of different IVs

Nevo 2001: Research question

Generally interesting question and at the time new approach:

- Is the pricing in the industry collusive?
- Divide the markups to three parts
  - Product differentation
  - Multi-product firms
  - Potential price collusion

Set-up by now familiar:

- Estimate brand level demand
- Compute price cost markups predicted by different industry structures
  - Single-product firms
  - Current ownership (multi-product firms)
  - Fully collusive pricing (monopoly)

Utility as before

$$u_{ijt} = x_j \beta_i^* - \alpha_i^* p_{jt} + \xi_j + \Delta\xi_{jt} + \epsilon_{ijt},$$
$$i = 1, \ldots, I_t, \qquad j = 1, \ldots, J_t, \qquad t = 1, \ldots, T,$$

Allow for brand dummy variables, to capture the part of ξ_{jt} that does not vary by the market. And as before,

$$\begin{pmatrix} \alpha_i^* \\ \beta_i^* \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \qquad v_i \sim N(0, I_{K+1}),$$

where D_i contains demographies and Π gives how tastes vary by demographies and v_i are unobserved consumer attributes.

In equilibrium, first order conditions for firm j are

$$s_j(p) + \sum_{r \in \mathcal{F}_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0.$$

Defining the following matrix ($\mathcal{H}_t$ in Supply lecture notation)

$$\Omega_{jr}^{pre}(p) = \begin{cases} -\partial s_j(p)/\partial p_r, & \text{if } \exists f\text{: } \{r, j\} \subset \mathcal{F}_f; \\ 0, & \text{otherwise.} \end{cases}$$

gives the familiar markup and marginal cost equations

$$s(p) - \Omega(p - mc) = 0, \qquad p - mc = \Omega^{-1} s(p).$$

Nevo 2001: Data

What is required to estimate the model parameters:

- IRI Infoscan scanner data
  - Market shares (one serving per consumer per day)
  - Prices
  - 25 brands in 67 cities over 20 quarters
- Other observable data
  - Advertising data (brand level estimates)
  - Characteristics from cereal boxes
  - Demographics and cost instruments

Nevo 2001: Estimation

- Follows BLP. Identification based on the moment condition

$$E[\xi_{jt}|z_{jt}] = 0$$

  i.e. instrumentation of unobservable characteristics

- Instruments have a dual role
  - Generate moment conditions
  - Deal with the correlation of prices and error terms
  - Berry & Haile 2014: Need 2J of these

Industry and setting specific choices:

- Uses only demand side moments
  - Doesn't rely on specify functional form for the supply side
- Characteristics of competition vs. brand fixed effects
  - Essentially the same product selection across t, product characteristics of competitors don't offer enough variation
  - Brand dummies capture product specific characteristics that do not vary over the markets t
  - Are not allowed to vary by the individual $\rightarrow$ requires an estimate for the mean taste of all observable characteristics

Nevo 2001: Instruments

Variety of choices that affect through different channels:

- Alternative to fixed effects: use brand dummies as instruments
- Hausman-type
  - Use the panel nature of data: Average prices in other cities within the same region each quarter (Hausman type)
  - Problem if, e.g., common advertising within a region
- Cost-shifters
  - Not necessarily easy to come up with product or market level variation in cost data
  - Cost-shifter proxies on the plausible city level variation: rental costs (density), retails earnings, transportation costs

What to include in the presentation:

- Simple logit-demand model, gives two things:
  - Intuition on what drives the demand and how the instruments work
  - A reference point, cf. with OLS and IV
- Full model:
  - Report how precisely means and standard deviations are estimated
  - Additional insight from demographics
- Cross-product elasticities as a sanity check
- And to answer the research question: Margins

Nevo 2001: Logit demand

TABLE V

RESULTS FROM LOGIT DEMAND[a]

Variable	OLS (i)	OLS (ii)	OLS (iii)	IV (iv)	IV (v)	IV (vi)	IV (vii)	IV (viii)	IV (ix)	IV (x)
Price	−4.96	−7.26	−7.97	−8.17	−17.57	−17.12	−22.56	−23.77	−23.37	−23.07
	(0.10)	(0.16)	(0.15)	(0.11)	(0.50)	(0.49)	(0.51)	(0.53)	(0.47)	(1.17)
Advertising	0.158	0.026	0.026	0.157	0.020	0.020	0.018	0.017	0.018	0.013
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log of Median Income	—	—	0.89	—	—	—	1.06	1.13	1.12	—
			(0.02)				(0.02)	(0.02)	(0.02)	
Log of Median Age	—	—	−0.423	—	—	—	−0.063	0.003	−0.007	—
			(0.052)				(0.059)	(0.062)	(0.061)	
Median HH Size	—	—	−0.126	—	—	—	−0.053	−0.036	−0.038	—
			(0.027)				(0.029)	(0.031)	(0.031)	
Fit/Test of Over Identification[b]	0.54	0.72	0.74	436.9	168.5	181.2	83.96	82.95	85.87	15.06
				(26.30)	(30.14)	(16.92)	(30.14)	(16.92)	(42.56)	(42.56)
1st Stage R^2	—	—	—	0.889	0.908	0.908	0.910	0.909	0.913	0.952
1st Stage F-test	—	—	—	5119	124	288	129	291	144	180
Instruments[c]	—	—	—	brand dummies	prices	cost	prices	cost	prices, cost	prices, cost

[a] Dependant variable is $\ln(S_{jt}) - \ln(S_{0t})$. Based on 27,862 observations. All regressions include time dummy variables, and with the exception of columns (i) and (iv), all regressions also include brand dummy variables. The regressions in columns (i) and (iv) include product characteristics (calories from fat, sugar, fiber, mushy and segment dummy variables); see text for reported coefficients. The regression in column (x) includes city dummy variables. Asymptotically robust s.e. are reported in parentheses.

[b] Adjusted R^2 for the OLS regressions, and a test of over identification for the IV regressions (Hausman (1983)) with the 0.95 critical values in parentheses.

[c] Prices denote the average regional price of the brand; cost denotes cost proxies; both are described in the text.

Nevo 2001: Full model

TABLE VI

RESULTS FROM THE FULL MODEL[a]

Variable	Means (β's)	Standard Deviations (σ's)	Interactions with Demographic Variables: Income	Income Sq	Age	Child
Price	−27.198 (5.248)	2.453 (2.978)	315.894 (110.385)	−18.200 (5.914)	—	7.634 (2.238)
Advertising	0.020 (0.005)	—	—	—	—	—
Constant	−3.592[b] (0.138)	0.330 (0.609)	5.482 (1.504)	—	0.204 (0.341)	—
Cal from Fat	1.146[b] (0.128)	1.624 (2.809)	—	—	—	—
Sugar	5.742[b] (0.581)	1.661 (5.866)	−24.931 (9.167)	—	5.105 (3.418)	—
Mushy	−0.565[b] (0.052)	0.244 (0.623)	1.265 (0.737)	—	0.809 (0.385)	—
Fiber	1.627[b] (0.263)	0.195 (3.541)	—	—	—	−0.110 (0.0513)
All-family	0.781[b] (0.075)	0.1330 (1.365)	—	—	—	
Kids	1.021[b] (0.168)	2.031 (0.448)	—	—	—	
Adults	1.972[b] (0.186)	0.247 (1.636)	—	—	—	
GMM Objective (degrees of freedom)			5.05 (8)			
MD χ^2			3472.3			
% of Price Coefficients > 0			0.7			

[a] Based on 27,862 observations. Except where noted, parameters are GMM estimates. All regressions include brand and time dummy variables. Asymptotically robust standard errors are given in parentheses.

[b] Estimates from a minimum-distance procedure.

TABLE VII

MEDIAN OWN AND CROSS-PRICE ELASTICITIES[a]

#	Brand	Corn Flakes	Frosted Flakes	Rice Krispies	Froot Loops	Cheerios	Total	Lucky Charms	P Raisin Bran	CapN Crunch	Shredded Wheat
1	K Corn Flakes	−3.379	0.212	0.197	0.014	0.202	0.097	0.012	0.013	0.038	0.028
2	K Raisin Bran	0.036	0.046	0.079	0.043	0.145	0.043	0.037	0.057	0.050	0.040
3	K Frosted Flakes	0.151	−3.137	0.105	0.069	0.129	0.079	0.061	0.013	0.138	0.023
4	K Rice Krispies	0.195	0.144	−3.231	0.031	0.241	0.087	0.026	0.031	0.055	0.046
5	K Frosted Mini Wheats	0.014	0.024	0.052	0.043	0.105	0.028	0.038	0.054	0.045	0.033
6	K Froot Loops	0.019	0.131	0.042	−2.340	0.072	0.025	0.107	0.027	0.149	0.020
7	K Special K	0.114	0.124	0.105	0.021	0.153	0.151	0.019	0.021	0.035	0.035
8	K Crispix	0.077	0.086	0.114	0.034	0.181	0.085	0.030	0.037	0.048	0.043
9	K Corn Pops	0.013	0.109	0.034	0.113	0.058	0.025	0.098	0.024	0.127	0.016
10	GM Cheerios	0.127	0.111	0.152	0.034	−3.663	0.085	0.030	0.037	0.056	0.050
11	GM Honey Nut Cheerios	0.033	0.192	0.058	0.123	0.094	0.034	0.107	0.026	0.162	0.024
12	GM Wheaties	0.242	0.169	0.175	0.025	0.240	0.113	0.021	0.026	0.050	0.043
13	GM Total	0.096	0.108	0.087	0.018	0.131	−2.889	0.017	0.017	0.029	0.029
14	GM Lucky Charms	0.019	0.131	0.041	0.124	0.073	0.026	−2.536	0.027	0.147	0.020
15	GM Trix	0.012	0.103	0.031	0.109	0.056	0.026	0.096	0.024	0.123	0.016
16	GM Raisin Nut	0.013	0.025	0.042	0.035	0.089	0.040	0.031	0.046	0.036	0.027
17	GM Cinnamon Toast Crunch	0.026	0.164	0.049	0.119	0.089	0.035	0.102	0.026	0.151	0.022
18	GM Kix	0.050	0.279	0.070	0.101	0.106	0.056	0.088	0.030	0.149	0.025
19	P Raisin Bran	0.027	0.037	0.068	0.044	0.127	0.035	0.038	−2.496	0.049	0.036
20	P Grape Nuts	0.037	0.049	0.088	0.042	0.165	0.050	0.037	0.051	0.052	0.047
21	P Honey Bunches of Oats	0.100	0.098	0.104	0.022	0.172	0.109	0.020	0.024	0.038	0.033
22	Q 100% Natural	0.013	0.021	0.046	0.042	0.103	0.029	0.036	0.052	0.046	0.029
23	Q Life	0.077	0.328	0.091	0.114	0.137	0.046	0.096	0.023	0.182	0.029
24	Q CapN Crunch	0.043	0.218	0.064	0.124	0.101	0.034	0.106	0.026	−2.277	0.024
25	N Shredded Wheat	0.076	0.082	0.124	0.037	0.210	0.076	0.034	0.044	0.054	−4.252
26	Outside good	0.141	0.078	0.084	0.022	0.104	0.041	0.018	0.021	0.033	0.021

[a] Cell entries i, j, where i indexes row and j column, give the percent change in market share of brand i with a one percent change in price of j. Each entry represents the median of the elasticities from the 1124 markets. The full matrix and 95% confidence intervals for the above numbers are available from http://elsa.berkeley.edu/~nevo.

Nevo 2001: Margins

TABLE VIII

MEDIAN MARGINS[a]

	Logit (Table V column ix)	Full Model (Table VI)
Single Product Firms	33.6% (31.8%–35.6%)	35.8% (24.4%–46.4%)
Current Ownership of 25 Brands	35.8% (33.9%–38.0%)	42.2% (29.1%–55.8%)
Joint Ownership of 25 Brands	41.9% (39.7%–44.4%)	72.6% (62.2%–97.2%)
Current Ownership of All Brands	37.2% (35.2%–39.4%)	—
Monopoly/Perfect Price Collusion	54.0% (51.1%–57.3%)	—

[a] Margins are defined as $(p - mc)/p$. Presented are medians of the distribution of 27,862 (brand-city-quarter) observations. 95% confidence intervals for these medians are reported in parentheses based on the asymptotic distribution of the estimated demand coefficients. For the Logit model the computation is analytical, while for the full model the computation is based on 1,500 draws from this distribution.

Observed price cost margin is estimated at 46%.

Recap of the Nevo papers

- Showed how to extend the BLP model to a completely different industry (remember: industry specifics matter)
- New way to test the competitiveness of markets
- Easy to extend to merger simulations
- Bonus: PyBLP is like magic
  - Buys you time for thinking from coding
  - Levels the research competition

Antitrust in practice – Finland

- Finnish Competition and Consumer Authority
  - Enforcement
  - Merger control
  - Cartels
  - Research
- Case: merger of Mehiläinen and Pihlajalinna
- Emerging themes:
  - Research activities
  - Use of big data for screening (e.g., Ortner et al., 2022)

*) YLE news, 26 March 2023, https://yle.fi/a/74-20018862

Upcoming

- Identification by Ari
- To close, applications continue by Otto and Tanja

Appendix

Nevo 2001: Table V with fake data

	Dependent variable:						
	y			l.logitfm			
	OLS			*instrumental variable*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
prices	−31.519	−28.950	−27.491	−31.761	−30.098	−29.090	−29.863
	(0.423)	(0.985)	(0.913)	(0.443)	(1.001)	(0.928)	(0.923)
sugar	0.040			0.043			
	(0.005)			(0.005)			
mushy	−0.275			−0.265			
	(0.058)			(0.058)			
income			1.283			1.272	
			(0.082)			(0.082)	
age			0.540			0.537	
			(0.121)			(0.121)	
child			0.411			0.404	
			(0.226)			(0.226)	
Observations	2,256	2,256	2,256	2,256	2,256	2,256	2,256
R^2	0.892	0.950	0.957	0.892	0.950	0.957	0.960
Adjusted R^2	0.891	0.949	0.957	0.891	0.949	0.957	0.958

Note: *p<0.1; **p<0.05; ***p<0.01

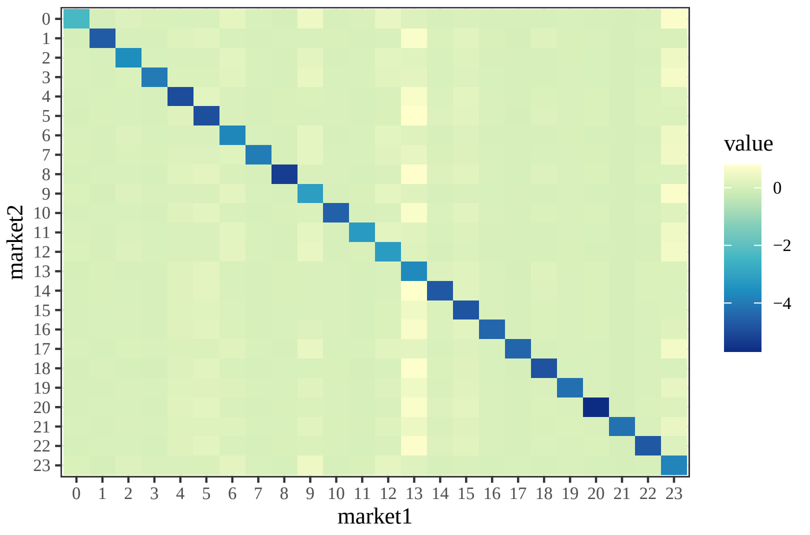
PyBPL example: Elasticities

product_ids	F1B04	F1B06	F1B07	F1B09	F1B11	F1B13	F1B17	F1B30	F1B45	F2B05	F2B08	F2B15	F2B16	F2B19	F2B26	F2B28	F2B40	F2B48	F3B06	F3B14	F4B02	F4B10	F4B12	F6B18
F1B04	-2.281	0.044	0.139	0.055	0.119	0.026	0.107	0.030	0.015	0.128	0.039	0.017	0.130	0.027	0.031	0.065	0.015	0.027	0.018	0.107	0.034	0.024	0.029	0.113
F1B06	0.008	-4.056	0.044	0.018	0.180	0.091	0.033	0.014	0.046	0.031	0.095	0.006	0.034	0.103	0.080	0.128	0.025	0.011	0.113	0.096	0.085	0.019	0.084	0.022
F1B07	0.038	0.059	-2.582	0.045	0.144	0.032	0.094	0.029	0.019	0.105	0.051	0.014	0.118	0.033	0.035	0.091	0.017	0.026	0.024	0.115	0.044	0.024	0.032	0.098
F1B09	0.037	0.061	0.105	-2.821	0.196	0.052	0.080	0.036	0.030	0.152	0.074	0.012	0.104	0.054	0.053	0.068	0.027	0.034	0.025	0.161	0.061	0.036	0.058	0.116
F1B11	0.013	0.113	0.067	0.035	-4.425	0.091	0.042	0.027	0.056	0.073	0.112	0.007	0.052	0.088	0.098	0.121	0.034	0.021	0.052	0.168	0.109	0.031	0.093	0.058
F1B13	0.009	0.179	0.046	0.027	0.264	-4.240	0.026	0.021	0.068	0.049	0.131	0.005	0.032	0.121	0.109	0.102	0.036	0.017	0.091	0.136	0.122	0.028	0.111	0.035
F1B17	0.038	0.052	0.129	0.047	0.137	0.026	-2.828	0.029	0.017	0.109	0.044	0.016	0.131	0.030	0.032	0.080	0.016	0.026	0.020	0.113	0.038	0.023	0.027	0.103
F1B30	0.029	0.062	0.100	0.055	0.213	0.051	0.076	-3.401	0.032	0.138	0.082	0.012	0.096	0.057	0.059	0.076	0.027	0.032	0.026	0.162	0.067	0.035	0.059	0.107
F1B45	0.008	0.169	0.046	0.027	0.287	0.121	0.029	0.020	-4.444	0.049	0.127	0.006	0.033	0.114	0.105	0.113	0.036	0.016	0.096	0.140	0.125	0.029	0.112	0.037
F2B05	0.042	0.044	0.118	0.063	0.170	0.038	0.090	0.038	0.024	-3.124	0.059	0.013	0.118	0.042	0.044	0.059	0.023	0.035	0.017	0.154	0.051	0.034	0.046	0.128
F2B08	0.012	0.146	0.056	0.032	0.275	0.110	0.038	0.025	0.060	0.068	-3.565	0.007	0.045	0.103	0.102	0.104	0.034	0.020	0.077	0.150	0.111	0.030	0.103	0.052
F2B15	0.036	0.059	0.117	0.046	0.143	0.031	0.097	0.029	0.020	0.106	0.053	-2.588	0.119	0.032	0.036	0.091	0.018	0.026	0.026	0.115	0.043	0.024	0.033	0.095
F2B16	0.036	0.052	0.133	0.046	0.133	0.025	0.104	0.028	0.016	0.103	0.043	0.016	-3.125	0.029	0.030	0.086	0.015	0.026	0.020	0.112	0.040	0.022	0.027	0.099
F2B19	0.009	0.166	0.046	0.028	0.271	0.117	0.031	0.022	0.066	0.053	0.126	0.006	0.036	-3.945	0.105	0.103	0.035	0.018	0.093	0.140	0.120	0.027	0.112	0.038
F2B26	0.010	0.149	0.054	0.030	0.279	0.109	0.036	0.024	0.061	0.060	0.122	0.007	0.039	0.111	-4.320	0.110	0.035	0.018	0.073	0.145	0.119	0.030	0.107	0.043
F2B28	0.014	0.134	0.073	0.023	0.194	0.056	0.053	0.019	0.036	0.045	0.074	0.009	0.059	0.062	0.072	-4.407	0.022	0.015	0.065	0.113	0.080	0.022	0.058	0.039
F2B40	0.013	0.118	0.063	0.036	0.275	0.091	0.046	0.028	0.055	0.085	0.111	0.008	0.053	0.093	0.100	0.102	-3.795	0.022	0.065	0.163	0.108	0.032	0.092	0.061
F2B48	0.032	0.058	0.104	0.057	0.203	0.048	0.081	0.037	0.029	0.147	0.072	0.012	0.105	0.053	0.054	0.071	0.027	-3.384	0.022	0.164	0.061	0.036	0.055	0.114
F3B06	0.007	0.225	0.037	0.015	0.173	0.102	0.025	0.012	0.051	0.024	0.099	0.005	0.024	0.106	0.080	0.124	0.026	0.009	-4.741	0.084	0.087	0.018	0.093	0.018
F3B14	0.019	0.081	0.088	0.045	0.250	0.065	0.061	0.032	0.043	0.114	0.096	0.009	0.077	0.066	0.076	0.100	0.030	0.026	0.036	-3.805	0.083	0.034	0.075	0.085
F4B02	0.010	0.150	0.053	0.030	0.279	0.110	0.031	0.024	0.062	0.055	0.120	0.007	0.039	0.102	0.104	0.111	0.035	0.018	0.077	0.152	-4.647	0.029	0.106	0.041
F4B10	0.023	0.097	0.087	0.048	0.237	0.069	0.064	0.033	0.041	0.121	0.096	0.010	0.077	0.075	0.075	0.086	0.031	0.026	0.039	0.163	0.084	-2.987	0.082	0.087
F4B12	0.010	0.169	0.045	0.028	0.260	0.117	0.029	0.022	0.067	0.058	0.124	0.006	0.035	0.113	0.105	0.094	0.035	0.018	0.092	0.137	0.120	0.028	-3.597	0.039
F6B18	0.041	0.039	0.121	0.065	0.161	0.035	0.095	0.038	0.022	0.164	0.056	0.013	0.122	0.038	0.041	0.058	0.023	0.036	0.014	0.152	0.046	0.034	0.042	-3.623

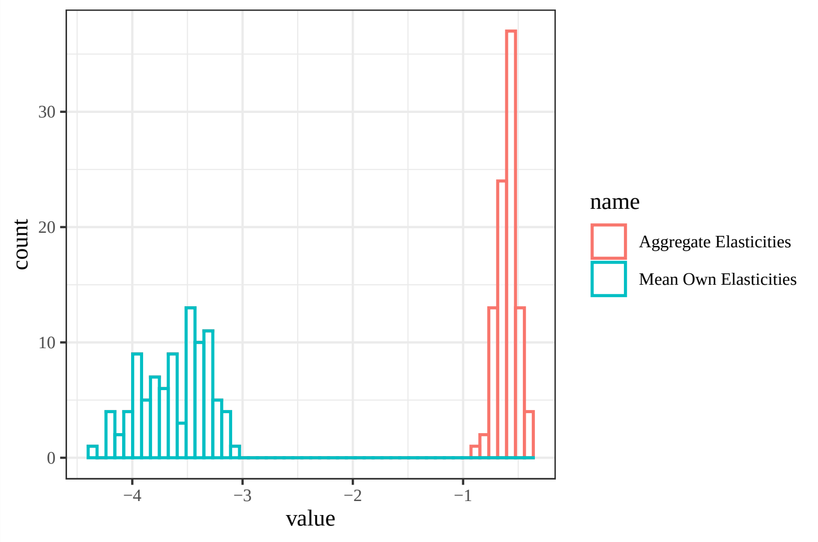
PyBPL example: Diversions

product_ids	F1B04	F1B06	F1B07	F1B09	F1B11	F1B13	F1B17	F1B30	F1B45	F2B05	F2B08	F2B15	F2B16	F2B19	F2B26	F2B28	F2B40	F2B48	F3B06	F3B14	F4B02	F4B10	F4B12	F6B18
F1B04	0.401	0.014	0.049	0.020	0.026	0.008	0.036	0.009	0.004	0.041	0.013	0.006	0.038	0.008	0.008	0.014	0.004	0.008	0.006	0.026	0.008	0.009	0.011	0.028
F1B06	0.003	0.524	0.012	0.005	0.031	0.022	0.008	0.004	0.011	0.008	0.026	0.002	0.007	0.024	0.019	0.021	0.006	0.002	0.028	0.019	0.017	0.006	0.025	0.005
F1B07	0.018	0.021	0.387	0.018	0.037	0.011	0.033	0.009	0.006	0.040	0.017	0.006	0.036	0.011	0.012	0.020	0.006	0.008	0.009	0.033	0.011	0.010	0.014	0.028
F1B09	0.015	0.019	0.037	0.319	0.039	0.017	0.023	0.011	0.008	0.050	0.023	0.005	0.024	0.016	0.015	0.013	0.007	0.009	0.008	0.036	0.015	0.012	0.020	0.029
F1B11	0.006	0.037	0.025	0.013	0.314	0.028	0.014	0.008	0.016	0.025	0.037	0.003	0.015	0.029	0.028	0.024	0.011	0.007	0.018	0.042	0.027	0.011	0.032	0.015
F1B13	0.003	0.045	0.013	0.008	0.044	0.381	0.006	0.005	0.015	0.013	0.035	0.002	0.007	0.028	0.025	0.017	0.009	0.004	0.023	0.027	0.024	0.008	0.034	0.007
F1B17	0.017	0.019	0.054	0.020	0.034	0.010	0.368	0.010	0.005	0.041	0.016	0.007	0.039	0.010	0.010	0.019	0.005	0.008	0.007	0.031	0.010	0.010	0.013	0.030
F1B30	0.012	0.020	0.036	0.020	0.045	0.017	0.024	0.292	0.009	0.049	0.025	0.005	0.025	0.018	0.016	0.014	0.008	0.009	0.009	0.039	0.016	0.013	0.021	0.027
F1B45	0.003	0.045	0.013	0.008	0.051	0.029	0.008	0.005	0.352	0.013	0.032	0.002	0.008	0.028	0.023	0.017	0.009	0.004	0.023	0.031	0.025	0.008	0.033	0.008
F2B05	0.017	0.015	0.045	0.024	0.040	0.012	0.028	0.012	0.007	0.339	0.022	0.005	0.031	0.014	0.013	0.011	0.007	0.010	0.005	0.039	0.013	0.013	0.017	0.033
F2B08	0.004	0.042	0.018	0.011	0.051	0.029	0.010	0.007	0.014	0.019	0.353	0.002	0.011	0.026	0.024	0.018	0.009	0.005	0.020	0.033	0.023	0.009	0.032	0.011
F2B15	0.017	0.020	0.046	0.017	0.032	0.010	0.032	0.009	0.006	0.039	0.016	0.372	0.034	0.011	0.011	0.017	0.005	0.007	0.008	0.030	0.010	0.009	0.014	0.026
F2B16	0.017	0.019	0.057	0.019	0.035	0.010	0.039	0.010	0.006	0.040	0.017	0.007	0.359	0.011	0.011	0.021	0.005	0.008	0.007	0.032	0.011	0.010	0.012	0.030
F2B19	0.003	0.044	0.013	0.009	0.044	0.029	0.007	0.006	0.016	0.014	0.035	0.002	0.008	0.374	0.023	0.015	0.009	0.004	0.023	0.028	0.023	0.008	0.034	0.008
F2B26	0.004	0.044	0.017	0.010	0.054	0.029	0.010	0.007	0.015	0.018	0.035	0.002	0.010	0.027	0.328	0.019	0.009	0.005	0.021	0.032	0.026	0.010	0.033	0.010
F2B28	0.006	0.051	0.028	0.009	0.050	0.020	0.017	0.006	0.011	0.017	0.027	0.004	0.017	0.024	0.021	0.387	0.008	0.004	0.021	0.031	0.019	0.008	0.022	0.010
F2B40	0.006	0.038	0.022	0.012	0.055	0.026	0.011	0.008	0.013	0.025	0.033	0.003	0.013	0.025	0.024	0.018	0.320	0.006	0.018	0.037	0.023	0.010	0.030	0.013
F2B48	0.014	0.018	0.041	0.022	0.042	0.016	0.026	0.012	0.008	0.050	0.024	0.005	0.026	0.017	0.015	0.014	0.007	0.299	0.007	0.038	0.015	0.013	0.021	0.029
F3B06	0.002	0.050	0.010	0.004	0.026	0.022	0.005	0.002	0.011	0.005	0.023	0.001	0.005	0.024	0.017	0.018	0.006	0.002	0.527	0.016	0.016	0.005	0.025	0.003
F3B14	0.009	0.028	0.036	0.018	0.060	0.021	0.020	0.010	0.013	0.038	0.032	0.004	0.021	0.022	0.021	0.020	0.010	0.009	0.013	0.301	0.021	0.012	0.027	0.022
F4B02	0.004	0.044	0.016	0.010	0.054	0.030	0.009	0.007	0.015	0.016	0.036	0.002	0.010	0.029	0.026	0.019	0.010	0.005	0.023	0.036	0.338	0.009	0.033	0.010
F4B10	0.009	0.028	0.030	0.017	0.047	0.020	0.019	0.009	0.011	0.034	0.027	0.004	0.018	0.021	0.018	0.016	0.009	0.008	0.013	0.038	0.019	0.319	0.026	0.020
F4B12	0.003	0.044	0.012	0.008	0.043	0.029	0.007	0.005	0.014	0.014	0.031	0.002	0.008	0.028	0.024	0.014	0.008	0.004	0.023	0.027	0.022	0.008	0.404	0.008
F6B18	0.018	0.014	0.048	0.025	0.037	0.011	0.030	0.012	0.006	0.060	0.020	0.006	0.032	0.013	0.012	0.012	0.006	0.011	0.005	0.035	0.013	0.013	0.016	0.310

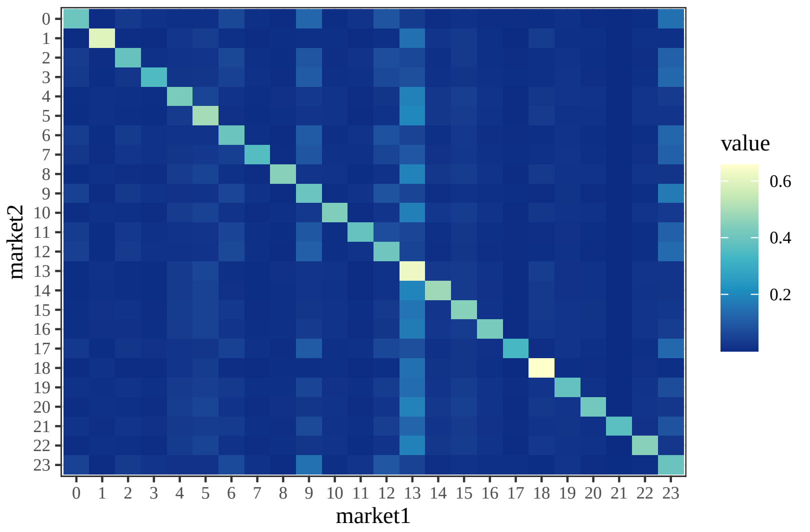
Nevo 2001: Elasticities



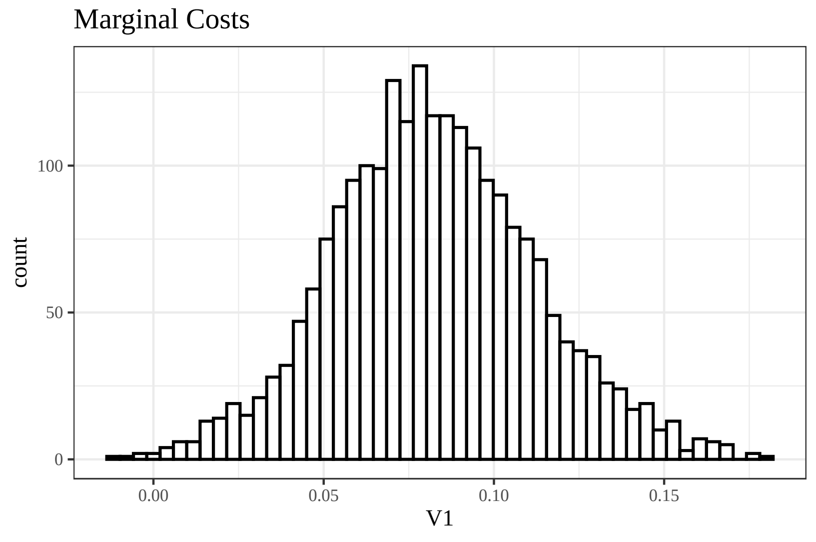
Nevo 2001: Elasticities compared



Nevo 2001: Diversion ratios



Nevo 2001: Marginal costs



Nevo 2001: Markups