14.271: Industrial Organization I

Introduction to Empirical Models of Demand

Tobias Salz

*Lecture Notes are based on the most recent IO handbook chapters.

A brief introduction

Tobias Salz

- E52-460, OH by appointment
- PhD from NYU
- Research interests:
  - Decentralized market, in particular transportation markets.
  - Platforms and digital markets.
  - Consumer financial markets.

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The typical **IO approach**

- Phrase a question in terms of a counterfactual
- Build the "primitives" of the model
- Attention to institutional details
- Simulate a counterfactual world and analyze outcomes of interest
- More recently, we also see more model testing again

What is structural work? (II)

It seems that different fields have different appetite for reliance on model assumptions.

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Why does IO particularly emphasize the connection between theory and data? Why is there more reliance on model assumptions?

- In IO the counterfactual of interest is often not observed in the data
- Typically, we want to know more than what happens in response to specific price change.
  - What is consumer welfare under the monopoly price, even if the monopoly price is not observed in the data?
  - What are the equilibium consequences of some policy change? Hard to do GE experiments.

The next two lectures — roadmap

Goal: to teach you the essentials of static demand models, as they are used in modern empirical IO.

Why model demand?

1. Consumer welfare analysis
2. Back out supply parameters, such as marginal cost (often proprietary, accounting cost not a good substitute)
3. Quantify market power / markups
4. Counterfactual analysis (pricing, mergers, conduct, regulatory interventions)
5. Predict demand for new goods

The next two lectures — roadmap

Goal: to teach you the essentials of static demand models, as they are used in modern empirical IO.

(Conflicting) modeling objectives in this literature:

1. Ability to handle many products
2. Can be estimated with aggregate data
3. Realistic substitution patterns
4. Allow for unobserved product characteristics (“demand shocks”)
5. Be able to deal with price endogeneity
6. Maintain computational tractability

Applications of empirical demand models

Table 1 Example markets and topics

Topic	Example papers
Transportation demand	McFadden et al. 1977
Market power	Berry et al. 1995, Nevo 2001
Mergers	Nevo 2000, Capps et al. 2003, Fan 2013
Welfare from new goods	Petrin 2002, Eizenberg 2014
Network effects	Rysman 2004, Nair et al. 2004
Product promotions	Chintagunta & Honoré 1996, Allenby & Rossi 1999
Environmental policy	Goldberg 1998
Vertical contracting	Villas-Boas 2007, Ho 2009
Equilibrium product quality	Fan 2013
Media bias	Gentzkow & Shapiro 2010
Asymmetric information and insurance	Cardon & Hendel 2001, Lustig 2010, Bundorf et al. 2012
Trade policy	Goldberg 1995, Berry et al. 1999, Goldberg & Verboven 2001
Residential sorting	Bayer et al. 2007
Voting	Gordon & Hartmann 2013
School choice	Hastings et al. 2010, Neilson 2013

The endogeneity/simultaneity problem

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Working, QJE (1929): *"In the case of pig iron, however, Professor H. L. Moore finds a "law of demand" which is not in accord with Marshall's universal rule..."*

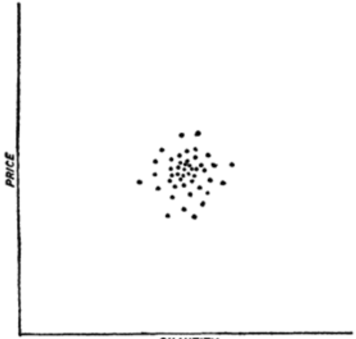

FIGURE III

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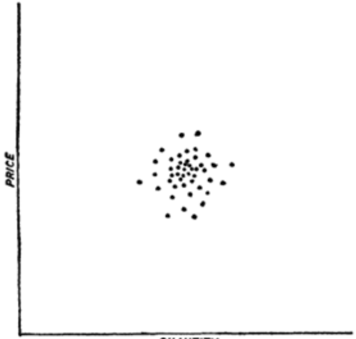

FIGURE III

Demand and Supply:

$$q_t^D(p) = \beta^D + \alpha \cdot p_t + \epsilon_t$$

$$q_t^S(p) = \beta^S + \gamma \cdot p_t + \eta_t$$

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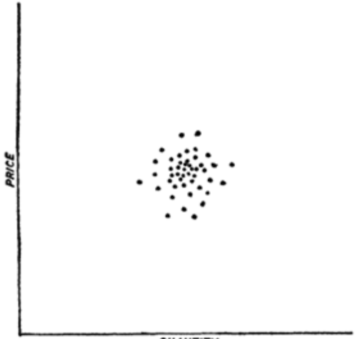

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$$q_t^D(p) = \beta^D + \alpha \cdot p_t + \epsilon_t$$

$$q_t^S(p) = \beta^S + \gamma \cdot p_t + \eta_t$$

Equilibrium:

$$q_t^D(p^*) = q_t^S(p^*) \Leftrightarrow p_t^* = \frac{\beta^D - \beta^S + \epsilon_t - \eta_t}{\gamma - \alpha}$$

Econometric Problem:

$$\mathbb{E}[\epsilon \cdot p^*] = \mathbb{E}\left[\epsilon \cdot \left(\frac{\beta^D - \beta^S + \epsilon - \eta}{\gamma - \alpha}\right)\right] \neq 0$$

Demand systems — product space approach

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Build demand system up from products,

- Rotterdam model (Theil, 1965; Barten, 1966), Translog model (Christensen et al., 1975), AIDS (Deaton and Muellbauer, 1980).

Demand for each product is a function of the prices of all products in the market

$$q_{jt} = Q_j\left(\mathbf{p}_t, \mathbf{x}_t, \xi_t\right), \quad j = 1, \ldots J$$

These models suffer typically suffer from a dimensionality problem, consider:

$$\mathbf{q}_t = A \cdot \mathbf{p}_t + \epsilon\left(\xi_t\right), \text{with } \; dim(A) = J \times J$$

Issues:

- Number of parameters proportional to J^2; even with restrictions (two stage budgeting, Slutsky symmetry) curse of dimensionality may ensue
- Demanding in terms of instruments
- Can't predict demand for new goods

Characteristics space discrete choice models

Characteristics space discrete choice models

Products are described by **characteristics** (Gorman, 1956; Lancaster, 1966; Rosen, 1974)

Random Utility Model: Choice micro-founded in (indirect) utility for products. Consumer i with unit demand for products $j \in \{1, \ldots, J\}$:

$$U_{ij} = U(p_j, x_j, \xi_j, D_i, \varepsilon_i)$$

where

$$\begin{aligned} D_i, \varepsilon_i &: \quad \text{observed and unobserved consumer characteristics (taste shifters)} \\ x_j, \xi_j &: \quad \text{observed and unobserved product characteristics} \\ p_j &: \quad \text{price} \end{aligned}$$

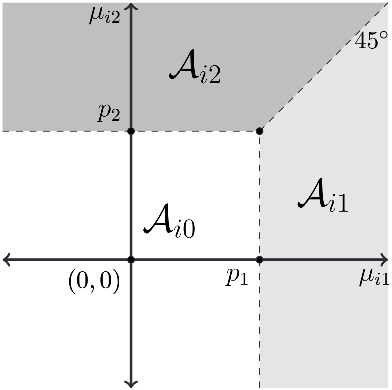
Consumers pick

$$\arg \max_{j \in \{1,\ldots,J\}} U_{ij}$$

Discrete choice models — choice probabilities

Suppose $U_{ij} = \mu_{ij} - p_j$. Those choosing j must have:

$$\mu_{ij} \in A_j(p) = \{\mu_{ij} - p_j \geqslant \mu_{ik} - p_k,\ \forall k \neq j\}$$



Discrete choice models — the logit error

Parametrize: $U_{ij} = V(D_i, x_j, p_j, \xi_j) + \varepsilon_{ij}$ where ε_{ij} is iid, Type 1 Extreme Value with CDF:

$$F(\varepsilon_{ij}) = exp(-exp(-\varepsilon_{ij}))$$

Probability that i chooses j:

$$P_{ij} = \mathbb{P}(\varepsilon_{ij} - \varepsilon_{ik} \geqslant V_{ik} - V_{ij}, \forall k)$$

$$P_{ij} = \frac{\exp(V_{ij})}{\exp(V_{i0}) + \sum_{k\geqslant 1} \exp(V_{ik})}$$

Normalizations:

- Location $V_{i0} = 0$ – adding a constant does not change choices
- Scale – invariance to multiplication by a constant – set variance of ε_{ij}
- Good 0 is often called the outside option (welfare is measured relative to that)

Discrete choice models — data scenario

Typical data scenario:

- Researcher observes aggregate market shares, prices, and product attributes.
- Distributions of consumer characteristics, such as income, location, family size, age.
- Instruments (more on this later)
- Can ignore sampling uncertainty in market shares (rules out zero market shares, small number of observations).
- Need to make a decision on the size of the market. Who are all the people that could have bought?

The canonical random coefficient demand model — Berry, Levinsohn, and Pakes (1995)

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Indirect linear utility model of consumer i in market t for product j:

$$u_{ijt} = x_{jt}\beta_{it} + \alpha_{it}p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \quad \text{for } j > 0$$

Where:

- $u_{i0t} = \varepsilon_{i0t}$
- ε_{ijt} are assumed to be iid type-1 extreme value distributed.
- $x_{jt} \in \mathbb{R}^K$ is a (row) vector of observed product characteristics
- $\xi_{jt} \in \mathbb{R}$ is a demand shock that consumers and firms observe, but we do not.

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Coefficients:

$$\beta_{it}^{(k)} = \beta_0^{(k)} + \sum_{l=1}^{L} \beta_d^{(l,k)} D_{ilt} + \beta_\nu^{(k)} \nu_{it}^{(k)}$$

$$\alpha_{it} = \alpha_0 + \sum_{l=1}^{L} \alpha_l D_{ilt} + \alpha_\nu \nu_{it}^{(0)}$$

The canonical random coefficient demand model

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$$u_{ijt} = x_{jt}\beta_{it} + \alpha_{it} p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \quad \text{for } j > 0$$

Define:

$$\delta_{jt} = x_{jt}\beta_0 + \alpha_0 p_{jt} + \xi_{jt} \;\; \text{and} \quad \mu_{ijt} = (x_{jt}, p_{jt}) \cdot (\Gamma \cdot D_{it} + \Sigma \cdot \nu_{it})$$

Consumer choice probabilities:

$$\mathbb{P}[i \text{ chooses } j] = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J} \exp(\delta_{kt} + \mu_{ikt})}$$

Market Shares:

$$s_{jt} = \sigma_j(\boldsymbol{\delta}_t, \mathbf{x}_t, \mathbf{p}_t; \Gamma, \Sigma) = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J} \exp(\delta_{kt} + \mu_{ikt})} dF(D_{it}, \nu_{it})$$

Why do we need the "error term" ξ_{jt}?

$$u_{ijt} = x_{jt}\beta_{it} + \alpha_{it} p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \quad \text{for } j > 0$$

Since ε_{ijt} is *iid* $\rightarrow$ without ξ_{jt} there is no j-specific unobserved variation.

- Products with the same x_{jt} and p_{jt} would need to have the same market share.
- All else equal, lower price products need to have larger market share.
- iPhone has $\geqslant$ 50% market share in the U.S. despite being much more expensive than average Android phone

What is the argument for the random coefficient? (I)

Without random coefficients:

$$u_{ijt} = x_{jt}\beta_0 + \alpha_0 p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \quad \text{for } j > 0$$

Get the **standard logit model:**

$$s_{jt} = \frac{\exp(\delta_{jt})}{1 + \sum_{k=1}^{J} \exp(\delta_{kt})}$$

Taking $log(\cdot)$ of market shares and subtract log-share of outside option (see Berry (1994))

$$log(s_{jt}) - log(s_{0t}) = \delta_{jt} = x_{jt}\beta_0 + \alpha_0 p_{jt} + \xi_{jt}$$

$\rightarrow$ can estimate this with OLS/2SLS!

What is the argument for the random coefficient? (II)

Price sensitivity:

$$\frac{\partial s_{jt}}{\partial p_{kt}} = \alpha_0 s_{kt} s_{jt}$$

Diversion ratios in the logit model:

$$\frac{\partial s_{jt}}{\partial p_{kt}} / \frac{\partial s_{kt}}{\partial p_{kt}} = s_{jt} / \left(1 - s_{kt}\right)$$

Price elasticities in the logit model:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} \alpha_0 \cdot p_{jt} \cdot \left(1 - s_{jt}\right) & \text{if } j = k \\ -\alpha_0 \cdot p_{kt} \cdot s_{kt} & \text{otherwise} \end{cases}$$

What is the argument for the random coefficient? (III)

Back to the **random coefficient** specification:

$$u_{ijt} = x_{jt}\beta_{it} + \alpha_{it} p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \quad \text{for } j > 0$$

Price elasticities:

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More realistic **substitution patterns:**

- Different consumers value quality and price differently
- Different consumers substitute “locally” in different segments of the market

$\rightarrow$ In IO we often discard analytic tractability and elegance in favor of (realism + solid identification)

Consumer welfare

Note that **expected welfare** is a complicated object

- Integral over all possible ε draws and consumer choosing optimally conditional on draw

Logit model gives a closed form solution for **expected welfare**

$$\omega_{iAt} = \ln\left(\sum_{j\in A} \exp\{\delta_{jt} + \mu_{ijt}\}\right)$$

$\rightarrow$ measured in utils, can be converted to $-value by dividing through the price coefficient.

Some awkwardness arises because of the dual role of ε as an econometric <u>and</u> structural error term:

- ε-draws interpreted as real utility and not an optimization friction
- Problematic in markets with many products or where observed attributes poorly describe choices.
- Berry and Pakes (2007) argue that the random coefficient ameliorates this problem

Instruments (I)

Firms will price ξ_{jt}, which leads prices to be endogenous. What makes **good instruments** and **how many** do we need?

For simple multinomial logit models with:

$$log(s_{jt}) - log(s_{0t}) = x_{jt}\beta_0 + \alpha_0 p_{jt} + \xi_{jt}$$

we need only one excluded instrument.

The same is not true for mixed logit models a la BLP. **Intuition:**

- With non-linear parameters prices depend on the whole vector $\boldsymbol{\xi}_t$.
- Need variation that shifts how consumers substitute across different types of products to identify non-linear parameters.

Instruments (II)

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- Concern: firm prices reflect both demand and supply factors. Need costs to be correlated and demand shocks to be uncorrelated across markets.

Instruments (III)

BLP instruments:

- Attributes of other products, $\sum_{j' \neq j} \mathbf{x}_{j't}$, always part of the data
- Idea: product attributes are exogenous and firm j's price is responding to the strength of other firms' attributes.

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- Concern: product attributes may be endogenous and (like prices) set after firms observe ξ_{jt}.
- There are many ways to construct these instruments
- Gandhi and Houde (2020) argue that it is better do define distances between own and other product attributes

Waldfogel instruments:

- Average demographic measures of nearby markets
- Idea: If firms price in zones that span markets (DellaVigna and Gentzkow (2019)), demographics in one market may affect demographics in another
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- Concern: Those demographics may be correlated with the demand shock.

Estimation

Objective function

$$\min_{\theta} \; g(\xi(\theta))' \cdot \Omega \cdot g(\xi(\theta))$$

where

$$g(\xi(\theta)) = \frac{1}{N} \sum_{\forall j,t} z'_{jt} \cdot \xi_{jt}(\theta)$$

$$\xi_{jt}(\theta) = \delta_{jt}(\theta_2) - x_{jt}\beta_0 + \alpha_0 p_{jt}$$

$$\tilde{s}_{jt} = \sigma_{jt}(\delta_t, x_t, \theta_2)$$

$$\sigma_{jt}(\delta_t, x_t, \theta_2) = \int \frac{\exp\left[\delta_{jt}(\theta_2) + \mu_{ijt}(D_i, x_j; \theta_2)\right]}{1 + \sum_k \exp\left[\delta_{jt}(\theta_2) + \mu_{ikt}(D_i, x_j; \theta_2)\right]} dF(D_{it}, v_{it}|\theta_2)$$

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Pseudocode

Outer loop

1. minimize objective function over non-linear parameters θ_2

Inner loop

1. Fix a guess of θ_2
2. For every market t solve for $\boldsymbol{\delta}_t(\theta_2)$ so that $\tilde{s}_{jt} = \sigma_{jt}$

$$\boldsymbol{\delta}_t^{(k)} = \boldsymbol{\delta}_t^{(k-1)} + \left[\log(\mathbf{s}_j) - \log\left(\boldsymbol{\sigma}_j\left(\boldsymbol{\delta}_t^{(k-1)}\right)\right)\right]$$

3. Recover $\boldsymbol{\xi}_t$, α_0, β_0 through regression.
4. Build sample moments

Challenges and open questions with the current demand approach

Many challenges for digital markets:

- Social networks hard to summarize as a collection of characteristics (Aridor (2022))
- Consumers often don't face prices
- Magnolfi et al. (2022): ask people about how close they think different products are to each other.
- Role for surveys and experiments.

Standard demand approach assumes posted and known prices

- In many important markets prices are negotiated and consumer-specific
- Consumers often lack knowledge of prices

BLP — empirical results

Data:

- All car makes from 1971-1990, market defined as the whole US
- List prices
- 2217 year-model observations

Characteristics from Automotive News Market Data Book:

- # of cylinders
- # of doors
- horsepower
- length, width, weight, wheelbase
- EPA rating for miles per gallon
- dummies for air conditioning, automatic

BLP — empirical results

TABLE 1

DESCRIPTIVE STATISTICS

Year	No. of Models	Quantity	Price	Domestic	Japan	European	HP/Wt	Size	Air	MPG	MP$
1971	92	86.892	7.868	0.866	0.057	0.077	0.490	1.496	0.000	1.662	1.850
1972	89	91.763	7.979	0.892	0.042	0.066	0.391	1.510	0.014	1.619	1.875
1973	86	92.785	7.535	0.932	0.040	0.028	0.364	1.529	0.022	1.589	1.819
1974	72	105.119	7.506	0.887	0.050	0.064	0.347	1.510	0.026	1.568	1.453
1975	93	84.775	7.821	0.853	0.083	0.064	0.337	1.479	0.054	1.584	1.503
1976	99	93.382	7.787	0.876	0.081	0.043	0.338	1.508	0.059	1.759	1.696
1977	95	97.727	7.651	0.837	0.112	0.051	0.340	1.467	0.032	1.947	1.835
1978	95	99.444	7.645	0.855	0.107	0.039	0.346	1.405	0.034	1.982	1.929
1979	102	82.742	7.599	0.803	0.158	0.038	0.348	1.343	0.047	2.061	1.657
1980	103	71.567	7.718	0.773	0.191	0.036	0.350	1.296	0.078	2.215	1.466
1981	116	62.030	8.349	0.741	0.213	0.046	0.349	1.286	0.094	2.363	1.559
1982	110	61.893	8.831	0.714	0.235	0.051	0.347	1.277	0.134	2.440	1.817
1983	115	67.878	8.821	0.734	0.215	0.051	0.351	1.276	0.126	2.601	2.087
1984	113	85.933	8.870	0.783	0.179	0.038	0.361	1.293	0.129	2.469	2.117
1985	136	78.143	8.938	0.761	0.191	0.048	0.372	1.265	0.140	2.261	2.024
1986	130	83.756	9.382	0.733	0.216	0.050	0.379	1.249	0.176	2.416	2.856
1987	143	67.667	9.965	0.702	0.245	0.052	0.395	1.246	0.229	2.327	2.789
1988	150	67.078	10.069	0.717	0.237	0.045	0.396	1.251	0.237	2.334	2.919
1989	147	62.914	10.321	0.690	0.261	0.049	0.406	1.259	0.289	2.310	2.806
1990	131	66.377	10.337	0.682	0.276	0.043	0.419	1.270	0.308	2.270	2.852
All	2217	78.804	8.604	0.790	0.161	0.049	0.372	1.357	0.116	2.099	2.086

BLP — empirical results

TABLE II

THE RANGE OF CONTINUOUS DEMAND CHARACTERISTICS (AND ASSOCIATED MODELS)

Variable	Percentile 0	25	50	75	100
Price	90 Yugo 3.393	79 Mercury Capri 6.711	87 Buick Skylark 8.728	71 Ford T-Bird 13.074	89 Porsche 911 Cabriolet 68.597
Sales	73 Toyota 1600CR .049	72 Porsche Rdstr 15.479	77 Plym. Arrow 47.345	82 Buick LeSabre 109.002	71 Chevy Impala 577.313
HP/Wt.	85 Plym. Gran Fury 0.170	85 Suburu DH 0.337	86 Plym. Caravelle 0.375	89 Toyota Camry 0.428	89 Porsche 911 Turbo 0.948
Size	73 Honda Civic 0.756	77 Renault GTL 1.131	89 Hyundai Sonata 1.270	81 Pontiac F-Bird 1.453	73 Imperial 1.888
MP$	74 Cad. Eldorado 8.46	78 Buick Skyhawk 15.57	82 Mazda 626 20.10	84 Pontiac 2000 24.86	89 Geo Metro 64.37
MPG	74 Cad. Eldorado 9	79 BMW 528i 17	81 Dodge Challenger 20	75 Suburu DL 25	89 Geo Metro 53

BLP — empirical results

TABLE III

RESULTS WITH LOGIT DEMAND AND MARGINAL COST PRICING (2217 OBSERVATIONS)

Variable	OLS Logit Demand	IV Logit Demand	OLS ln (*price*) on *w*
Constant	−10.068	−9.273	1.882
	(0.253)	(0.493)	(0.119)
*HP/Weight**	−0.121	1.965	0.520
	(0.277)	(0.909)	(0.035)
Air	−0.035	1.289	0.680
	(0.073)	(0.248)	(0.019)
MP$	0.263	0.052	—
	(0.043)	(0.086)	
*MPG**	—	—	−0.471
			(0.049)
*Size**	2.341	2.355	0.125
	(0.125)	(0.247)	(0.063)
Trend	—	—	0.013
			(0.002)
Price	−0.089	−0.216	—
	(0.004)	(0.123)	
No. Inelastic Demands	1494	22	*n.a.*
(+/− 2 *s.e.'s*)	(1429–1617)	(7–101)	
R^2	0.387	*n.a.*	.656

TABLE IV

ESTIMATED PARAMETERS OF THE DEMAND AND PRICING EQUATIONS: BLP SPECIFICATION, 2217 OBSERVATIONS

Demand Side Parameters	Variable	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Means ($\bar{\beta}$'s)	*Constant*	−7.061	0.941	−7.304	0.746
	HP/Weight	2.883	2.019	2.185	0.896
	Air	1.521	0.891	0.579	0.632
	MP\$	−0.122	0.320	−0.049	0.164
	Size	3.460	0.610	2.604	0.285
Std. Deviations (σ_β's)	*Constant*	3.612	1.485	2.009	1.017
	HP/Weight	4.628	1.885	1.586	1.186
	Air	1.818	1.695	1.215	1.149
	MP\$	1.050	0.272	0.670	0.168
	Size	2.056	0.585	1.510	0.297
Term on Price (α)	$\ln(y-p)$	43.501	6.427	23.710	4.079
Cost Side Parameters					
	Constant	0.952	0.194	0.726	0.285
	$\ln(HP/Weight)$	0.477	0.056	0.313	0.071
	Air	0.619	0.038	0.290	0.052
	$\ln(MPG)$	−0.415	0.055	0.293	0.091
	$\ln(Size)$	−0.046	0.081	1.499	0.139
	Trend	0.019	0.002	0.026	0.004
	$\ln(q)$			−0.387	0.029

TABLE VI

A SAMPLE FROM 1990 OF ESTIMATED OWN- AND CROSS-PRICE SEMI-ELASTICITIES: BASED ON TABLE IV (CRTS) ESTIMATES

	Mazda 323	Nissan Sentra	Ford Escort	Chevy Cavalier	Honda Accord	Ford Taurus	Buick Century	Nissan Maxima	Acura Legend	Lincoln Town Car	Cadillac Seville	Lexus LS400	BMW 735i
323	−125.933	1.518	8.954	9.680	2.185	0.852	0.485	0.056	0.009	0.012	0.002	0.002	0.000
Sentra	0.705	−115.319	8.024	8.435	2.473	0.909	0.516	0.093	0.015	0.019	0.003	0.003	0.000
Escort	0.713	1.375	−106.497	7.570	2.298	0.708	0.445	0.082	0.015	0.015	0.003	0.003	0.000
Cavalier	0.754	1.414	7.406	−110.972	2.291	1.083	0.646	0.087	0.015	0.023	0.004	0.003	0.000
Accord	0.120	0.293	1.590	1.621	−51.637	1.532	0.463	0.310	0.095	0.169	0.034	0.030	0.005
Taurus	0.063	0.144	0.653	1.020	2.041	−43.634	0.335	0.245	0.091	0.291	0.045	0.024	0.006
Century	0.099	0.228	1.146	1.700	1.722	0.937	−66.635	0.773	0.152	0.278	0.039	0.029	0.005
Maxima	0.013	0.046	0.236	0.256	1.293	0.768	0.866	−35.378	0.271	0.579	0.116	0.115	0.020
Legend	0.004	0.014	0.083	0.084	0.736	0.532	0.318	0.506	−21.820	0.775	0.183	0.210	0.043
TownCar	0.002	0.006	0.029	0.046	0.475	0.614	0.210	0.389	0.280	−20.175	0.226	0.168	0.048
Seville	0.001	0.005	0.026	0.035	0.425	0.420	0.131	0.351	0.296	1.011	−16.313	0.263	0.068
LS400	0.001	0.003	0.018	0.019	0.302	0.185	0.079	0.280	0.274	0.606	0.212	−11.199	0.086
735*i*	0.000	0.002	0.009	0.012	0.203	0.176	0.050	0.190	0.223	0.685	0.215	0.336	−9.376

TABLE VII

SUBSTITUTION TO THE OUTSIDE GOOD

Model	Given a price increase, the percentage who substitute to the outside good (as a percentage of all who substitute away.) Logit	BLP
Mazda 323	90.870	27.123
Nissan Sentra	90.843	26.133
Ford Escort	90.592	27.996
Chevy Cavalier	90.585	26.389
Honda Accord	90.458	21.839
Ford Taurus	90.566	25.214
Buick Century	90.777	25.402
Nissan Maxima	90.790	21.738
Acura Legend	90.838	20.786
Lincoln Town Car	90.739	20.309
Cadillac Seville	90.860	16.734
Lexus LS400	90.851	10.090
BMW 735*i*	90.883	10.101

TABLE VIII

A SAMPLE FROM 1990 OF ESTIMATED PRICE-MARGINAL COST MARKUPS AND VARIABLE PROFITS: BASED ON TABLE 6 (CRTS) ESTIMATES

	Price	Markup Over MC $(p - MC)$	Variable Profits (in \$'000's) $q*(p - MC)$
Mazda 323	\$5,049	\$ 801	\$18,407
Nissan Sentra	\$5,661	\$ 880	\$43,554
Ford Escort	\$5,663	\$1,077	\$311,068
Chevy Cavalier	\$5,797	\$1,302	\$384,263
Honda Accord	\$9,292	\$1,992	\$830,842
Ford Taurus	\$9,671	\$2,577	\$807,212
Buick Century	\$10,138	\$2,420	\$271,446
Nissan Maxima	\$13,695	\$2,881	\$288,291
Acura Legend	\$18,944	\$4,671	\$250,695
Lincoln Town Car	\$21,412	\$5,596	\$832,082
Cadillac Seville	\$24,353	\$7,500	\$249,195
Lexus LS400	\$27,544	\$9,030	\$371,123
BMW 735*i*	\$37,490	\$10,975	\$114,802

Supply

Firm's profit function:

$$\pi_f = \sum_{j \in \mathcal{J}_f} \left[(p_j - mc_j)\, q_j(\mathbf{p}) - FC_j \right]$$

Define **ownership**-matrix:

$$H_{jk} = \begin{cases} 1, & \text{if } \exists f : \{j, k\} \subset \mathcal{J}_f; \\ 0, & \text{otherwise} \end{cases} \qquad j, k = 1, \ldots, J$$

Let Ω be a matrix with elements $\Omega_{jk} = -\partial q_k / \partial p_j \cdot H_{jk}$ and assume Nash-Bertrand pricing, we get **FOC**s:

$$\mathbf{q}(\mathbf{p}) - \Omega(\mathbf{p} - \mathbf{mc}) = 0 \Leftrightarrow \mathbf{p} = \mathbf{mc} + \Omega^{-1}\mathbf{q}(\mathbf{p})$$

Using supply side restrictions for estimation

Assume that **marginal cost** are given by:

$$mc_{jt} = \mathrm{w}_{jt}\gamma + \omega_{jt}$$

This leads to:

$$\mathbf{p}_t = \mathrm{w}_{\mathbf{t}}\gamma + \Omega^{-1}\mathbf{q}\left(\mathbf{p}_{\mathbf{t}}\right) + \omega_t$$

We can now construct **additional moments**, which are informative about both supply and demand.

$$E\left(\omega_{jt} \mid \mathbf{Z}_t\right) = 0$$

Comment:

- These moments can be very useful in identifying parameters of random coefficients.
- They require conduct assumption (FOCs from static price competition), which we may not want to make.