Demand Systems in Industrial Organization: Part I*

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January 3, 2017

1 Overview

Demand systems often form the bedrock upon which empirical work in industrial organization rests. The next few lectures aim to introduce you to the different ways empirical researchers have approached the issue of demand estimation in the applied contexts that we typical confront as IO economists. I will start by briefly overviewing the types of research questions and various instances in which demand estimation is useful, and the core problems we face when estimating demand.

We will begin with a basic overview of homogeneous product market competition (with which you should be familiar), and an overview of estimation in these markets. We will then move to models of differentiated product demand systems. I will review basic theory and standard data forms, after which I will go on to talk about the standard approaches to demand estimation and their advantages and disadvantages. All these approaches try to deal with the problem of estimating demand when we are in a market with many, differentiated goods. Specific papers will be used to illustrate the techniques once they have been discussed.

I will expect you to remember your basic econometrics, particularly the standard endogeneity problem of estimating demand (see Working 1927 or the treatment in standard econometrics texts, e.g. Hayashi 2000 in Ch 3).

There has been an explosion in the sophistication of technique used in demand estimation the last decade, due to a combination of advances in econometric technique, computation and data availability.

1.1 Why spend time on Demand Systems?

Many questions in IO require understanding how consumers choose among various goods and services as a function of market and individual characteristics. Though properly estimating a demand system in its own right may be an objective of interest, demand systems (and their underlying parameters) are more often than not used as an input into answering other, perhaps larger, questions. E.g., they are often used as providing the incentives for examining firm behavior (pricing, investment, product introduction, entry/exit, etc...), or computing consumer welfare from a policy change. For example...

- Infer firm conduct: sometimes it is difficult to observe/measure firm conduct directly, but we might be able to test certain theories by using consumer demand estimates to infer firm behavior.

*These notes draw from a variety of sources: in particular Ariel Pakes' lecture notes, and from (co-teaching with) Robin Lee and Allan Collard-Wexler.

COMPETITION AND COLLUSION 459

TABLE I

Year	(1) Auto Production[a]	(2) Real Auto Price-CPI[b]	(3) % Change Auto Price-Cagan[c]	(4) Auto Sales[d]	(5) Auto Quantity Index[e]
1953	6.13	1.01	NA	14.5	86.8
1954	5.51	0.99	NA	13.9	84.9
1955	7.94	0.95	−2.5	18.4	117.2
1956	5.80	0.97	6.3	15.7	97.9
1957	6.12	0.98	6.1	16.2	100.0

Notes: [a] Millions of units over the model year. [Source: *Automotive News.*]
[b] (CPI New automobile component)/CPI. [Source: *Handbook of Labor Statistics.*]
[c] Adjusted for quality change. [See Cagan (1971), especially pp. 232–3.]
[d] Auto output in constant dollars, *QIV* of previous year through *QIII* of named year, in billions of 1957 dollars. [Source: *National Income and Product Accounts.*]
[e] (4)/(2), normalized so 1957 = 100.

TABLE II

Year	(6) Per Capita Disposable Personal Income[f]	(7) Interest Rate[g]	(8) Durables Expenditures (Non-Auto)[h]	(9) Automakers Profits[i]
1953	1623	1.9	14.5	2.58
1954	1609	0.9	14.5	2.25
1955	1659	1.7	16.1	3.91
1956	1717	2.6	17.1	2.21
1957	1732	3.2	17.0	2.38

Notes: [f] Billions of 1957 dollars, *QIV* of previous year through *QIII* of named year. [Source: *National Income and Product Accounts.*]
[g] Three-month *T*-bill rate. [Source: *Statistical Abstract.*]
[h] Durables component of consumer expenditures minus component for automobiles and parts, billions of 1957 dollars. [Source: *National Income and Product Accounts.*]

  - **Example: Bresnahan 1987 Competition and Collusion in 1950s Auto Market**

    Bresnahan wanted to examine the hypothesis that the dramatic increase in quantity (45% greater than in two surrounding years) and decrease in the price of Autos in 1955 was due to the temporary breakdown of a collusive agreement. Unlikely to be demand shock: "any explanation of all of the 1955 events from the demand side will need to be fairly fancy."

    His idea was to assume that marginal costs were not varying and then ask whether the relationship between pricing and demand elasticities changed in a manner consistent with a shift from collusion to oligopolistic pricing.

    He exploits data on P and Q for different makes of automobiles. He has about 85 models over 3 years. The "magic" in these approaches is using demand data *combined with* an equilibrium assumption on firm conduct to back out marginal costs, *without using any cost data*. We'll come back to this later.

- Welfare impacts: to conduct welfare calculations subsequent to some market change brought about by, say, policy intervention, product introduction, or etc., one needs a well specified demand system. It allows us to quantify the "Value of Innovation": e.g., compute consumer surplus from the introduction of a new good (e.g., minivans, CAT scans) with similar "characteristics" of existing ones.

- Determinants of Innovation: with a demand system, a researcher can compute predicted markups for a given good; consequently, one will understand the types of products a firm will want to produce (e.g., minivans or SUV's, cancer drugs instead of malaria treatments). Demand systems, in other words, help us measure the incentives for investing in new goods.

- Usually demand is important to think about various forms of comparative statics: common ones for IO researchers include pre and post merger pricing, tax incidence, monopoly vs duopoly pricing, effect of predatory pricing policies, impact of new product introductions, etc.

- In IO and Marketing, there is considerable work on advertising which usually involves some demand estimation. This about policy questions of direct-to-consumer drug adverting, or advertising as a barrier to entry. Furthermore, carefully specified demand systems can assist with decomposing the mechanisms or channels through which various advertising (and other) effects work. E.g., persuasive vs. informative advertising.

- Understanding the cross-price elasticities of good is often crucial to "preliminary" issues in policy work, such as market definition in antitrust cases. Also, they inform determinants of market power: should we allow two firms to merge? Is there collusion going on in this industry (unusually large markups)? Cross-price elasticities are one input into this equation. (We will talk a bit (later) about the myriad antitrust applications of demand models. Note that this is the largest consumer of Ph.D's in Empirical I.O. by a long shot!)

- The tools used in demand estimation are starting to be applied in a variety of other contexts (e.g., political economy, development, education, health...) to confront empirical issues, of there is likely to be some intellectual arbitrage for your future research.

2 Approaches to demand estimation

Approaches breakdown along the following lines:

- single vs multi-products
- within multi-product: whether you use a product space or characteristic space approach
- representative agent vs heterogenous agent
- Other breakdowns: continuous vs. discrete choice, horizontal vs. vertical, dynamic vs. static...

We will primarily focus on multi-product, demand systems with heterogeneous agents. We will cover both product and characteristics space approaches. We will focus on static settings, and later discuss methods for dealing with dynamics.

3 On Demand Estimation

3.1 Data... (briefly)

As always, the credibility and success of empirical work will hinge on the data that is leveraged. Depending on the industry and the application, data may be plentiful or sparse; it is always preferable to rely on richer data (when availabile and accessible at reasonable cost (both time and financial)) to inform our estimates than to implicitly assume them through structure or assumptions. That said, research is all about navigating these tradeoffs (and being explicit and honest about them).

To anchor discussion, the data that we should have in mind when discussing demand estimation tends to look as follows:

- The unit of observation will be quantity of product purchased (say 12 oz Bud Light beer) together with a price for a given time period (say a week) at a location (Store, ZIP, MSA, state, country...).
- You will generally need to take a stance on the relevant market and set of products within a consumer's choice set; in addition, there typically is an outside good (e.g., non purchase) that you will need to control for (either with data or via assumptions).
- There is now a large amount of consumer-level purchase data collected by marketing firms (for instance the ERIM panel used by Ackerberg RAND 1997 to look at the effects of TV ads on yogurt purchases). However, the vast majority of demand data is aggregated at some level. As we will discuss, less-aggregated data tends to allow us to estimate more detailed (ambitious) models.
- Note that you often have a lot of information: you can get many characteristics of the good (Alcohol by volume, calories, etc) from the manufacturer or industry publications or packaging since you know the brand. The location means we can merge the demand observation with census data to get information on consumer characteristics. The date means we can look at see what the spot prices of likely inputs were at the time (say gas, electricity etc).
- Typical data sources: industry organizations, marketing and survey firms (e.g. AC Nielson), proprietary data from manufacturer, marketing departments have some scanner data online (e.g. Chicago GSB).
- The survey of consumer expenditures also has some information on person-level consumption on product groups like cars or soft-drinks.
- More often than not, data will require some ingenuity, luck, and a lot of elbow grease to obtain. Theory can help fill in some holes, but at the end of the day, good data (and variation!) is necessary for a convincing paper.

3.2 Basics: Endogeneity of Prices and Other Definitions

Consider a market equilibrium in a competitive market with the following components:

Aggregate Demand. Say it takes a constant elasticity form, i.e.

$$ln(Q_n) = x_n\beta - \alpha ln(p_n) + \epsilon_n$$

where n indexes markets, x are *observed* and ϵ are *unobserved* (by the econometrician) factors that cause differences in demand at a given price. E.g.,: parameters of income distribution, price of substitutes or complements, environmental factors that cause differences in the demand for the good,...

Aggregate supply.

$$mc_n = w_n\gamma + \lambda Q_n + \omega_n$$

w are observed and ω are unobserved (by the analyst) factors that cause differences in marginal cost. The marginal cost curve is the marginal cost of the market maker; it need not be the true social marginal cost.

Equilibrium. We assume the market is in equilibrium, i.e. demand=supply, or that the auctioneer sets price at a level where the quantity it induces equates demand and supply

$$p_n = mc_n.$$

Note that under an auctioneer interpretation, this assumes that he knows (ϵ, ω) even More generally there often are variables that are either observed to all agents, or revealed while finding the equilibrium price, that we do not contain good measures of in our data sets.

Keep in mind that:

- if there are differences in ϵ or in ω that are not known by the "auctioneers" (i.e. not incorporated in price) then there can be excess demand or supply. You can introduce that into your model, but you need a way of dealing with it. In many markets you could introduce inventories (though then you might want to add dynamics) or a rationing system. One of the important facts about electricity generation is that it is very hard (though not impossible) to store energy, and this rules out inventories. What the market maker does in electricity generation is have a special reserve market where the ISO pays a "holding" fee to generators, and can bring them up or down from a central computer to make sure the market balances at all times.
- we have simplified by assuming that last period's price does not effect either marginal cost or demand (in keeping within the simple static framework). As noted in the first lecture there are many reasons why it might, but this would put us into a world where demand or supply today depends on past, and perceptions of future, prices. I.e. a world where to analyze the determinants of current price and quantity determinants we need dynamics.

3.3 Single Product Demand Estimation

Let's now move away from competitive markets, and abstract from the supply side for a moment.

- Begin with one homogenous product. Assume demand for product j in market t could be given by $q_{jt} = D(p_{jt}, X_{j,t}, \xi_{jt})$, where q_{jt} are quantities, p_{jt} are prices, X_{jt} are exogenous variables, and ξ_{jt} are random shocks.

- Let's assume now demand is iso-elastic:

$$\ln(q_{jt}) = \alpha_j \ln p_{jt} + X_{jt}\beta + \xi_{jt} \tag{1}$$

so that price elasticity $\eta_{jt} = \alpha_j$. X_{jt} could just be an intercept for now (constant term) or a vector of demand shifters. ξ_{jt} is a one-dimensional unobserved component of demand.

Problem 1: Endogeneity of Prices

Recall from the monopoly discussion that we might be interested in price elasticities: doing so would allow us to use theory to perhaps recover ("infer") marginal cost by simply observing the price charged in a market.

- Suppose we are in a situation where the error term ξ_{jt} is correlated with higher prices (p_{jt}), i.e. $E(\xi_{jt}p_{jt}) > 0$.

- Let's decompose this correlation into:

$$\xi_{jt} = \lambda p_{jt} + \epsilon_{jt}$$

where ϵ_{jt} is the remaining uncorrelated part, and λ will typically be positive. Then we can put this back in:

$$\begin{aligned} \ln(q_{jt}) &= \alpha_j p_{jt} + X_{jt}\beta + \xi_{jt} \\ &= \alpha_j p_{jt} + X_{jt}\beta + \lambda p_{jt} + \epsilon_{jt} \\ &= \underbrace{(\alpha_j + \lambda)}_{\hat{\alpha_j}} p_{jt} + X_{jt}\beta + \epsilon_{jt} \end{aligned}$$

So the coefficient that we estimate denoted $\hat{\alpha_j}$ will be biased upwards. This will lead to unrealistically low estimates of price elasticity. We call this the *simulataneity* problem. The simultaneity (or endogeneity) problem is a recurrent theme in Empirical I.O.

- In I.O. we almost never get experimental or quasi-experimental data.

- Unlike what you've been taught in econometrics, we need to think very hard about what goes into the "unobservables" in the model (try to avoid the use of the word error term, it masks what really goes into the ϵ's in I.O. models).

- Finally, it is a *very strong* assumption to think that the firm does not react to the unobservable because it does not see it – just because I don't have the data doesn't mean a firm doesn't!

- Remember that these guys spend their lives thinking about pricing.

- Moreover, won't firms react if they see higher than expected demand yesterday?

- <u>Note:</u> From here on, when you are reading the papers, think hard about "is there an endogeneity problem that could be generating erroneous conclusions, and how do the authors deal with this problem?"

3.3.1 Some History.

- Henry Moore (1914)'s O.L.S. analysis of quantity on price (an attempt to estimate demand curves). Finds
  - Demand curves for agricultural products sloped down
  - Demand curves for manufacturing products sloped up.
- Working's(1927) pictures. How do we connect equilibrium dots?

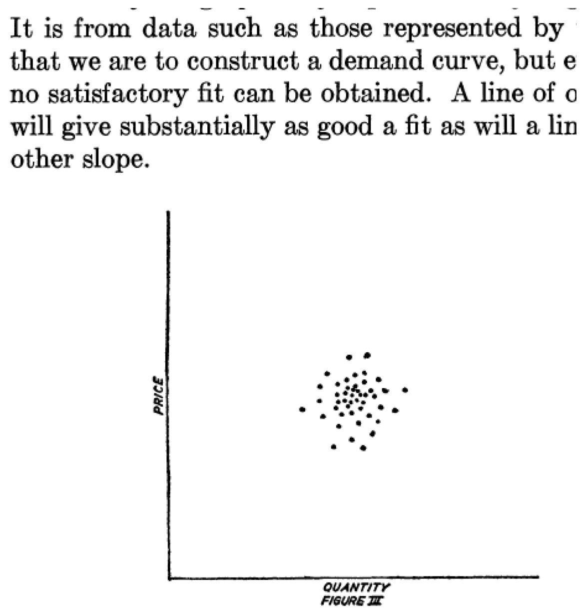
It is from data such as those represented by
that we are to construct a demand curve, but e
no satisfactory fit can be obtained. A line of o
will give substantially as good a fit as will a lin
other slope.

Figure 1: Working (1929 QJE)

- Needed assumption for O.L.S. on demand: $E[\epsilon|x,p] = 0$, or even $E[\epsilon(x,p)] = 0$ contradicts model and common sense (at least if the auctioneer or the firm that is pricing knows or discovers ϵ). I.e. for this to be true there is nothing that affects demand that the auctioneer knows that the empirical analyst does not know.
- Similarly needed equation for "supply" or price curve contradicts model
- Solve for price and quantity as a function of (x, w, ω, ϵ).
- Possible Solutions:
  - Estimation by 2SLS,
  - Estimation by covariance restrictions between the disturbances in the demand and supply equation.

  See any standard textbook, e.g. Goldberger(1991).

Lesson. Thought should be given to what is likely to generate the disturbances in our models, and given that knowledge we should try to think through their likely properties.

Review: What is an instrumental variable

The broadest definition of an instrument is as follows, a variable Z such that for all possible values of Z:

$$\Pr[Z|\xi] = \Pr[Z|\xi']$$

But for certain values of X we have

$$\Pr[X|Z] \neq \Pr[X|Z']$$

This second part makes it an instrumental variable.

So the intuition is the Z is not affected by ξ, but has some effect on X. The usual way to express these conditions is that an instrument is such that: $E[Z\xi] = 0$ and $E[XZ] \neq 0$.

Table 2

Ordinary Least Squares and Instrumental Variable Estimates of Demand Functions with Stormy Weather as an Instrument

	Ordinary least squares (dependent variable: log quantity)		*Instrumental variable*	
Variable	*(1)*	*(2)*	*(3)*	*(4)*
Log price	−0.54	−0.54	−1.08	−1.22
	(0.18)	(0.18)	(0.48)	(0.55)
Monday		0.03		−0.03
		(0.21)		(0.17)
Tuesday		−0.49		−0.53
		(0.20)		(0.18)
Wednesday		−0.54		0.58
		(0.21)		(0.20)
Thursday		0.09		0.12
		(0.20)		(0.18)
Weather on shore		−0.06		0.07
		(0.13)		(0.16)
Rain on shore		0.07		0.07
		(0.18)		(0.16)
R^2	0.08	0.23		
No. of Obs.	111	111	111	111

Source: The data used in these regressions are available by contacting the author.
Note: Standard errors are reported in parentheses.

Figure 2: Graddy (2006 JEP)

3.4 Multi-product Systems

Now let's think of a multiproduct demand system to capture the fact that most products have substitutes for each other. Generally this would be given by the relationship

$$\mathbf{q} = D(\mathbf{p}, \mathbf{X}, \xi)$$

where $\mathbf{q}, \mathbf{p}, \xi$ are $J \times 1$ vectors of quantities, prices, and random shocks, and $\mathbf{X}$ are exogenous variables. We can follow the same approach before and assume that demand takes the following isoelastic form:

$$\begin{aligned} \ln q_1 &= \sum_{j \in J} \gamma_{1j} \ln p_{1t} + \beta \mathbf{x}_{1t} + \xi_{1t} \\ &... \\ \ln q_J &= \sum_{j \in J} \gamma_{Jj} \ln p_{Jt} + \beta \mathbf{x}_{Jt} + \xi_{Jt} \end{aligned}$$

3.4.1 Product vs Characteristic Space

We can think of products as being:

- a single fully integrated entity (a lexus SUV); or
- a collection of various characteristics (a 1500 hp engine, four wheels and the colour blue).

  It follows that we can model consumers as having preferences over products, or over characteristics.

The first approach embodies the product space conception of goods, while the second embodies the characteristic space approach (see Lancaster (1966, 75, 79)).

Product Space: disadvantages for estimation

[Note that disadvantages of one approach tend to correspond to the advantages of the other]

- Dimensionality: if there are J products then we have in the order of J^2 parameters to estimate to get the cross-price effects alone (the γ_{jk} terms above).
  - Can get around this to some extent by imposing more structure. For example, one can use functional form assumptions on utility: this leads to "grouping" or "nesting" approaches whereby we group products together and consider substitution across and within groups as separate things - means that ex ante assumptions need to be made that do not always make sense. More on this later.
  - Can also impose symmetry: e.g., CES demand of J products with utility given by:

$$U(q_1, \ldots, q_J) = (\sum_{i=1}^{J} q_i^{\rho})^{1/\rho} \tag{2}$$

  yields demand for good k:

$$q_k = \frac{p_k^{-1/(1-\rho)}}{\sum_{i=1}^{J} p_i^{-\rho/(1-\rho)}} I \tag{3}$$

  where I is the income for the consumer. Note now only have to estimate ρ as opposed to number of parameters proportional to J^2. However, note this model implies:

$$\frac{\partial q_i}{\partial p_j} \frac{p_j}{q_i} = \frac{\partial q_k}{\partial p_j} \frac{p_j}{q_k} \qquad \forall i, k, j \tag{4}$$

which means all goods i and k have the same cross-price elasticities with respect to good j. This is an extremely strong assumption, and imposes strong restrictions on the demand system. Though popular for analytic tractability, it is not generally used in empirical IO.

- Product space methods are not well suited to handle the introduction of new goods prior to their introduction (consider how this may hinder the counterfactual exercise of working out welfare if a product had been introduced earlier - see Hausman on Cell Phones in Brookings Papers 1997 - or working out the profits to entry in successive stages of an entry game...)

Characteristic Space: disadvantages for estimation

- getting data on the relevant characteristics may be very hard and dealing with situations where many characteristics are relevant
- this leads to the need for unobserved characteristics and various computational issues in dealing with them.
- dealing with new goods when new goods have new dimensions is hard (consider the introduction of the laptop into the personal computing market)
- dealing with multiple choices and complements is a area of ongoing research, currently a limitation although work advances slowly each year.

We will explore product space approaches and then spend a fair amount of time on the characteristic space approach to demand. Most recent work in methodology has tended to use a characteristics approach and this also tends to be the more involved of the two approaches.

4 Product Space Approaches: AIDS Models

I will spend more than an average amount of time on AIDS (Almost Ideal Demand System (Deaton and Mueller 1980 AER), which wins the prize for worst acronym in all of economics models), which remain the state of the art for product space approaches. Moreover, AIDS models are still the dominant choice for applied work in things like merger analysis and can be coded up and estimated in a manner of days (rather than weeks for characteristics based approaches). Moreover, the AIDS model shows you just how far you can get with a "reduced-form" model, and these less structural models can fit the data much better than more structural models in some applications.

The main disadvantage with AIDS approaches, is that when anything changes in the model (more consumers, adding new products, imperfect availability in some markets), it is difficult to modify the AIDS approach to account for this type of problem.

- Starting point for dealing with multiple goods in product space:

$$\ln q_j = \alpha p_j + \beta \mathbf{p}_K + \gamma \mathbf{x}_j + \epsilon_j$$

- What is in the unobservable (ϵ_j)?
  - anything that shifts quantity demanded about that is not in the set of regressors

- Think about the pricing problem of the firm ... depending on the pricing assumption and possibly the shape of the cost function (e.g. if constant cost and perfect comp, versus differentiated bertrand etc) then prices will almost certainly be endogenous. In particular, all prices will be endogenous.
- This calls for a very demanding IV strategy, at the very least

- Also, as the number of products increases the number of parameters to be estimated will get very large, very fast: in particular, there will be J^2 price terms to estimate and J constant terms, so if there are 9 products in a market we need at least 90 periods of data!

The last point is the one to be dealt with first, then, given the specification we can think about the usual endogeniety problems. The way to reduce the dimensionality of the estimation problem is to put more structure on the choice problem being faced by consumers. This is done by thinking about specific forms of the underlying utility functions that generate empricially convenient properties. (Note that we will also use helpful functional forms in the characteristics approach, although for somewhat different reasons)

The usual empirical approach is to use a model of multi-level budgeting[1]:

- The idea is to impose something akin to a "utility tree"
  - steps:
    1. group your products together is some sensible fashion (make sure you are happy to be grilled on the pros and cons of whatever approach you use). In Hausmann et al, the segments are Premium, Light and Standard.

	Elasticity	Standard Error
Budweiser	−4.196	0.127
Molson	−5.390	0.154
Labatts	−4.592	0.247
Miller	−4.446	0.149
Coors	−4.897	0.205
Old Milwaukee	−5.277	0.118
Genesee	−4.236	0.129
Milwaukee's Best	−6.205	0.170
Busch	−6.051	0.332
Piels	−4.117	0.469
Genesee Light	−3.763	0.072
Coors Light	−4.598	0.115
Old Milwaukee Light	−6.097	0.140
Lite	−5.039	0.141
Molson Light	−5.841	0.148

    2. allocate expenditures to these groups [part of the estimation procedure].
    3. allocate expenditures within the groups [again, part of the estimation procedure]: Molson, Coors, Budweiser and etc...

Dealing with each step in reverse order:

[1]Note also that this is useful in other contexts - see for instance Fanyin Zhengs use of this, in her 2015 Job Market Paper, in a dynamic entry game to ease computational burdens and capture some of the reality of the data generating process.

3. When allocating expenditures within groups it is assumed that the division of expenditure within one group is independent of that within any other group. That is, the effect of a price change for a good in another group is only felt via the change in expenditures at the group level. If the expenditure on a group does not change (even if the division of expenditures within it does) then there will be no effect on goods outside that group.

2. To be allocate expenditures across groups you have to be able to come up with a price index which can be calculated without knowing what is chosen within the group.

These two requirements lead to restrictive utility specifications, the most commonly used being the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980 AER).

4.1 Overview

This comes out of the work on aggregation of preferences in the 1970s and before. (Recall Chapter 5 of Mas-Colell, Whinston and Green)

Starting at the within-group level: assume expenditure functions for utility u and price vector p look like

$$\log(e(u,p) = (1-u)\log(a(p)) + u\log(b(p))$$

where it is assumed:

$$\begin{aligned} \log(a(p)) &= \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2}\sum_k\sum_j \gamma^*_{kj}\log p_k \log p_j && (5) \\ \log(b(p)) &= \log(a(p)) + \beta_0 \Pi_k p_k^{\beta_k} && (6) \end{aligned}$$

Using Shepards Lemma we can get shares of expenditure within groups as:

$$w_i = \frac{\partial log(e(u,p))}{\partial \log p_i} = \alpha_i + \sum_j \gamma_{ij}\log(p_j) + \beta_i \log\left(\frac{x}{P}\right)$$

where x is total expenditure on the group, $\gamma_{ij} = \frac{1}{2}(\gamma^*_{ij} + \gamma^*_{ji})$, P is a price index for the group and everything else should be self explanatory.

Dealing with the price index can be a pain. It can be thought of as a price index that "deflates" income. There are two ways that are used. One is the "proper" specification

$$\log(P) = \alpha_0 + \sum_k \alpha_k \log(p_k) + \frac{1}{2}\sum_j\sum_k \gamma_{kj}\log(p_k)\log(p_j)$$

which is used in the Goldberg paper, or a linear approximation (as in Stone 1954) used by most of the empirical litterature:

$$\log(P) = \sum_k w_k \log(p_k)$$

Deaton and Muellbauer go through all the micro-foundations in their AER paper.

For the allocation of expenditures across groups you just treat the groups as individual goods, with prices being the price indexes for each group. Again, note how much depends on the initial choice about how grouping works.

Steps

1. Calculate expenditure share w_i of each good i using prices p_i, quantities q_i, and total expenditure $x = \sum_k p_k q_k$.

2. Compute Stone price index: $\log P = \sum_k w_k \log(p_k)$

3. Run regression (e.g., IV):

$$w_i = \alpha_i + \sum_k \gamma_{ik} \log(p_k) + \beta_i \log(\frac{x}{P}) + \xi_i \tag{7}$$

   where ξ_i is the error term.

4. Recover $J+2$ parameters $(\alpha_i, \gamma_{i1}, \ldots, \gamma_{iJ}, \beta_i)$

4.2 Hausman, Leonard & Zona (1994) on Beer

This is Hausman, Leonard & Zona (1994) Competitive Analysis with Differentiated Products, Annales d'Econ. et Stat.

It is included here as it is one of the classic applications in the context of merger analysis. I likely will skip this in class.

Here the authors want to estimate a demand system so as to be able to do merger analysis and also to discuss how you might test what model of competition best applies. The industry that they consider is the American domestic beer industry.

Note, that this is a well known paper due to the types of instruments used to control for endogeniety at the individual product level. This is where the phrase 'Hausman instrument' comes from in the context of demand estimation.

They use a three-stage budgeting approach: the top level captures the demand for the product, the next level the demand for the various groups and the last level the demand for individual products with the groups.

The bottom level uses the AIDS specification where spending on brand i in city n at time t is given by:

$$w_{i,n,t} = \alpha_{in} + \sum_j \gamma_{ij} \log(p_{jnt}) + \beta_i \log\left(\frac{y_{Gnt}}{P_{nt}}\right) + \varepsilon_{int}$$

where y_{Gnt} is expenditure on segment G. [note the paper makes the point that the exact form of the price index is not usually that important for the results]

The next level uses a log-log demand system

$$\log q_{mnt} = \beta_m \log y_{Bnt} + \sum_k \delta_k \log(\pi_{knt}) + \alpha_{mn} + \varepsilon_{mnt}$$

where q_{mnt} is the segment quantity purchased, y_{Bnt} is total expenditure on beer, π are segment price indices and α is a constant. [Does it make sense to switch from revenue shares at the bottom level, to quantities at the middle level?] The top level just estimates at similar equation as the middle level, but looking at the choice to buy beer overall. Again it is a log-log formulation.

$$\log u_t = \beta_0 + \beta_1 \log y_t + \beta_2 \log \Pi_t + Z_t \delta + \varepsilon_t$$

where u_t is overall spending on beer, y_t is disposable income and Π_t is a Price Index for Beer overall, and Z_t are variables controlling for demographics, monthly factors, and minimum age requirements.

Identification of price coefficients:

- recall that, as usual, price is likely to be correlated with the unobservable (nothing in the complexity that has been introduced gets us away from this problem)
- what instruments are available, especially at the individual brand level?
  - The authors propose using the prices in one city to instrument for prices in another. This works under the assumption that the pricing rule looks like:

    $$\log(p_{jnt}) = \delta_j \log(c_{jt}) + \alpha_{jn} + \omega_{jnt}$$

    where p_{jnt} is the price of good j in city n at time t, c_{jt} represents nation-wide product-costs at time t, α_{jn} are city specific shifters which reflect transportation costs or local wage differentials, and ω_{jnt} is a mean zero stochastic disturbance (e.g., local sales promotions.

    Here they are claiming that city demand shocks ω_{jnt} are uncorrelated. This allows us to use prices in other markets for the same product in the same time period as instruments (if you have a market fixed effect). Often these are referred to as *Hausman instruments*. This has been criticized for ignoring the phenomena of nation-wide ad campaigns. Still, it is a pretty cool idea and has been used in different ways in several different studies.
- Often people use factor price instruments, such as wages, the price of malt or sugar as variables that shift marginal costs (and hence prices), but don't affect the ξ's.
- You can also use instruments if there is a large price change in one period for some external reason (like a strategic shift in all the companies's pricing decisions). Then the instrument is just an indicator for the pricing shift having occurred or not.

Substitution Patterns

The AIDS model makes some assumptions about the substitution patterns between products. You can't get rid of estimating J^2 coefficients without some assumptions!

- Top level: Coors and another product (chips). If the price of Coors goes up, then the price index of beer P_B increases.
- Medium level: Coors and Old Style, two beers in separate segements. Increase in the price of Coors raises π_P, which raises the quantity of light beer sold (and hence increases the sales of Old Style in particular).
- Bottom level: Coors and Budweiser, two beers in the same segment. Increase in the price of Coors affects Budweiser through $\gamma_{c,b}$.

So the AIDS model restricts subsitution patterns to be the same between two products any two products in different segments. Is this a reasonable assumption?

TABLE 1

Beer Segment Conditional Demand Equations.

	Premium	Popular	Light
Constant	0.501	−4.021	−1.183
	(0.283)	(0.560)	(0.377)
log (Beer Exp)	0.978	0.943	1.067
	(0.011)	(0.022)	(0.015)
log ($P_{PREMIUM}$)	−2.671	2.704	0.424
	(0.123)	(0.244)	(0.166)
log ($P_{POPULAR}$)	0.510	−2.707	0.747
	(0.097)	(0.193)	(0.127)
log (P_{LIGHT})	0.701	0.518	−2.424
	(0.070)	(0.140)	(0.092)
Time	−0.001	−0.000	0.002
	(0.000)	(0.001)	(0.000)
log (# of Stores)	−0.035	0.253	−0.176
	(0.016)	(0.034)	(0.023)

Number of Observations = 101.

Figure 3: Demand Equations: Middle Level- Segment Choice

Brand Share Equations: Premium.

	1 Budweiser	2 Molson	3 Labatts	4 Miller	5 Coors
Constant	0.393	0.377	0.230	−0.104	−
	(0.062)	(0.078)	(0.056)	(0.031)	−
Time	0.001	−0.000	0.001	0.000	−
	(0.000)	(0.000)	(0.000)	(0.000)	−
log (Y/P)	−0.004	−0.011	−0.006	0.017	−
	(0.006)	(0.007)	(0.005)	(0.003)	−
log ($P_{Budweiser}$)	−0.936	0.372	0.243	0.150	−
	(0.041)	(0.231)	(0.034)	(0.018)	−
log (P_{Molson})	0.372	−0.804	0.183	0.130	−
	(0.231)	(0.031)	(0.022)	(0.012)	−
log ($P_{Labatts}$)	0.243	0.183	−0.588	0.028	−
	(0.034)	(0.022)	(0.044)	(0.019)	−
log (P_{Miller})	0.150	0.130	0.028	−0.377	−
	(0.018)	(0.012)	(0.019)	(0.017)	−
log (# of Stores)	−0.010	0.005	−0.036	0.022	−
	(0.009)	(0.012)	(0.008)	(0.005)	−
Conditional Own	−3.527	−5.049	−4.277	−4.201	−4.641
Price Elasticity	(0.113)	(0.152)	(0.245)	(0.147)	(0.203)

$$\Sigma = \begin{Bmatrix} 0.000359 & -1.436\text{E}-05 & -0.000158 & -2.402\text{E}-05 \\ - & 0.000109 & -6.246\text{E}-05 & -1.847\text{E}-05 \\ - & - & 0.005487 & -0.000392 \\ - & - & - & 0.000492 \end{Bmatrix}$$

Note: Symmetry imposed during estimation.

Figure 4: Demand Equations: Bottom-Level Brand Choice

Overall Elasticities.

	Elasticity	Standard Error
Budweiser	−4.196	0.127
Molson	−5.390	0.154
Labatts	−4.592	0.247
Miller	−4.446	0.149
Coors	−4.897	0.205
Old Milwaukee	−5.277	0.118
Genesee	−4.236	0.129
Milwaukee's Best	−6.205	0.170
Busch	−6.051	0.332
Piels	−4.117	0.469
Genesee Light	−3.763	0.072
Coors Light	−4.598	0.115
Old Milwaukee Light	−6.097	0.140
Lite	−5.039	0.141
Molson Light	−5.841	0.148

Light Segment Own and Cross Elasticities.

	Genesee Light	Coors Light	Old Milwaukee Light	Lite	Molson Light
Genesee Light	−3.763	0.464	0.397	0.254	0.201
	(0.072)	(0.060)	(0.039)	(0.043)	(0.037)
Coors Light	0.569	−4.598	0.407	0.452	0.482
	(0.085)	(0.115)	(0.058)	(0.075)	(0.061)
Old Milwaukee Light	1.233	0.956	−6.097	0.841	0.565
	(0.121)	(0.132)	(0.140)	(0.112)	(0.087)
Lite	0.509	0.737	0.587	−5.039	0.577
	(0.095)	(0.122)	(0.079)	(0.141)	(0.083)
Molson Light	0.683	1.213	0.611	0.893	−5.841
	(0.124)	(0.149)	(0.093)	(0.125)	(0.148)

Figure 5: Segment & Overall Elasticities

Merger Analysis (Preview)

Recall a single firm sets price according to

$$\frac{p_1 - mc_1}{p_1} = -\frac{1}{\eta_{11}}$$

Imagine firm owns goods $j = 1 \ldots m$. Then the first order condition for the firm will be for each j:

$$\left[\frac{p_j}{\sum_{k=1}^{m} p_k q_k}\right] \frac{\partial \pi}{\partial p_j} = s_j + \sum_{k=1}^{m} \left[\frac{p_k - mc_k}{p_k} s_k\right] \eta_{kj} = 0$$

HLZ consider an hypothetical merger between two premium beers, Labatt and Coors. They find post-merger prices do not rise by too much – Coors price is constrained by Budweiser, and Labatt by Molson (another Canadian import). Without the premium beers constraining their prices, the estimates predict post-merger prices would rise by $> 20\%$.

We will come back to these types of analysis later.

Estimated Price Increases for Hypothetical Merging Brands Assumed Efficiency Gains.

	0%	5%	10%
Coors	4.4%	−0.8%	−6.1%
	(1.2)	(1.2)	(1.1)
Labatts	3.3	−1.9	−7.0
	(1.0)	(1.0)	(0.9)

Figure 6: Merger Effects

4.3 Chaudhuri, Goldberg and Jia (2006) on Quinolones

Question: The WTO has imposed rules on patent protection (both duration and enforcement) on member countries. There is a large debate on should we allow foreign multinationals to extent their drugs patents in poor countries such as India, which would raise prices considerably.

- Increase in IP rights raises the profits of patented drug firms, giving them greater incentives to innovate and create new drugs (or formulations such as long shelf life which could be quite useful in a country like India).
- Lower consumer surplus dues to generic drugs being taken off the market.

To understand the tradeoff inherent in patent protection, we need to estimate the magnitude of these two effects. This is what CGJ do.

Market: Indian Market for antibiotics

- Foreign and Domestic, Licensed and Non-Licensed producers.
- Different types of Antibiotics, in particular CGJ look at a particular class: Quinolones.
- Different brands, packages, dosages etc...
- Question: What would prices and quantities look like if there were no unlicensed firms selling this product in the market? [2]

Data

- The Data come from a market research firm. This is often the case for demand data since the firms in this market are willing to pay large amounts of money to track how well they are doing with respect to their competitors. However, prying data from these guys when they sell it for 10 000 a month to firms in the industry involves a lot of work and emailing.
- Monthly sales data for 4 regions, by product (down to the SKU level) and prices.
- The data come from audits of pharmacies, i.e. people go to a sample of pharmacies and collect the data.
- Some products have different dosages than others. How does one construct quantity for this market?
- Some products enter and exit the sample. How can the AIDS model deal with this?

[2] One of the reasons I.O. economists use structural models is that there is often no experiment in the data, i.e. a case where some markets have this regulation and others don't.

Estimation and Results

- CGJ estimate the AIDS specification with the aggregation of different brands to product level.

  Product groups are defined to be indexed by molecule M and domestic/foreign status DF.

  Revenue share of each product group i in each region r at time t:

$$\omega_{irt} = \alpha_i + \alpha_{ir} + \sum_j \gamma_{ij} \ln p_{jrt} + \beta_i \ln(\frac{X_{Qrt}}{P_{Qrt}}) + \epsilon_{irt} \tag{8}$$

  where $\omega_{irt} = x_{irt}/X_{Qrt}$, prices for each group are aggregated/weighted over individual SKUs, and X_{Qrt} is expenditures on quinolones; and price index:

$$\ln P_Q = \alpha_0 + \sum_i \alpha_i \ln p_i + \frac{1}{2} \sum_i \sum_j \tilde{\gamma}_{ij} \ln p_i \ln p_j \tag{9}$$

  and upper level demand:

$$\omega_{Grt} = \alpha_G + \alpha_{Gr} + \sum_H \gamma_{GH} \ln P_{Hrt} + \beta_G \ln(\frac{X_{rt}}{P_{rt}}) + \epsilon_{Grt} \tag{10}$$

  across different segments H of antibiotics.

- Do not model the choice of individual SKU products:
  - Large # of SKUs within each group (dimensionality), lack of price variation at SKU level, and varying choice sets over time (entry/exit of SKUs).
  - Discrete choice approach difficult due to difficulty mapping revenue shares to physical shares – dosage of drugs not welll defined.

- Problem for the AIDS model: Over 300 different products, i.e. 90,000 cross product interaction terms to estimate! CGJ need to do some serious aggregating of products to get rid of this problem: they will aggregate products by therapeutic class into 4 of these, interacted with the nationality of the producer. I.e., each product will have an own price coefficient $\gamma_{i,i}$, and a price coefficient for products of different molecules and/or nationalities, denoted $\gamma_{i,10}, \gamma_{i,01}, \gamma_{i,00}$. (Note that these coefficients are not whether or not the molecule is licensed). Thus, a product i will exhibit the same cross-price elasticity for two different drugs if those two drugs differ in the same way both in molecule and foreign/domestic status. This yields 7 product groups (one group is only produced by foreign firms), and 7×4 price terms.

- Simultaneity bias: SKU revenue share weights (used in computation of price index for each product group) depend on expenditure, and will be correlated with demand shock. Instruments: # SKUs within group (violated if # of SKUs affect perceived quality of drug or is correlated with advertising), prices at SKU level (due to price controls)

- Supply Side: You can get upper and lower bounds on marginal costs by assuming either that firms are perfect competitors within the segment (i.e. $p = mc$) or by assuming that firms are operating a cartel which can price at the monopoly level (i.e. $p = \frac{mc}{1+1/\eta_{jj}}$). This is very smart: you just get a worse case scenario and show that even in the case with the highest possible producer profits, these profits are small compared to the loss in consumer surplus. Often it is better to bound the bias from some estimates rather than attempt to solve the problem.

- Use estimated demand system to compute the prices of domestic producers of unlicensed products that make expenditures on these products 0 (this is what "virtual prices" mean).
- Figure out what producer profits would be in the world without unlicensed firms (just $(p-c)q$ in this setup).
- Compute the change in consumer surplus (think of integrating under the demand curve).
  - Product Variety Effect
  - Expenditure Switching effect (substitution to other types of antibiotics, not quinolones); holds fixed prices of other products
  - Reduced-competition effect: firms adjust prices upwards due to removal of domestic products

Table 3—Summary Statistics for the Quinolones Subsegment: 1999–2000

	North	East	West	South
Annual quinolones expenditure per household (Rs.)	31.25	19.75	27.64	23.59
	(3.66)	(3.67)	(4.07)	(2.86)
Annual antibiotics expenditure per household (Rs.)	119.88	84.24	110.52	96.24
	(12.24)	(12.24)	(9.60)	(9.96)
No. of SKUs				
Foreign ciprofloxacin	12.38	11.29	13.08	12.46
	(1.50)	(1.90)	(1.02)	(1.06)
Foreign norfloxacin	1.83	1.71	2.00	1.58
	(0.70)	(0.75)	(0.88)	(0.83)
Foreign ofloxacin	3.04	2.96	2.96	3.00
	(0.86)	(0.86)	(0.91)	(0.88)
Domestic ciprofloxacin	106.21	97.63	103.42	105.50
	(5.99)	(4.34)	(7.22)	(4.51)
Domestic norfloxacin	38.96	34.96	36.17	39.42
	(2.71)	(2.68)	(2.51)	(3.79)
Domestic ofloxacin	18.46	16.00	17.25	17.25
	(6.80)	(6.34)	(5.86)	(6.35)
Domestic sparfloxacin	29.83	28.29	31.21	29.29
	(5.57)	(6.38)	(6.88)	(6.57)
Price per-unit API* (Rs.)				
Foreign ciprofloxacin	9.58	10.90	10.85	10.07
	(1.28)	(0.66)	(0.71)	(0.58)
Foreign norfloxacin	5.63	5.09	6.05	4.35
	(0.77)	(1.33)	(1.39)	(1.47)
Foreign ofloxacin	109.46	109.43	108.86	106.12
	(6.20)	(6.64)	(7.00)	(11.40)
Domestic ciprofloxacin	11.43	10.67	11.31	11.52
	(0.16)	(0.15)	(0.17)	(0.13)
Domestic norfloxacin	9.51	9.07	8.88	8.73
	(0.24)	(0.35)	(0.37)	(0.20)
Domestic ofloxacin	91.63	89.64	85.65	93.41
	(16.15)	(15.65)	(14.22)	(14.07)
Domestic sparfloxacin	79.72	78.49	76.88	80.28
	(9.76)	(10.14)	(11.85)	(10.37)
Annual sales (Rs. mill)				
Foreign ciprofloxacin	41.79	24.31	45.20	29.47
	(15.34)	(8.16)	(12.73)	(6.48)
Foreign norfloxacin	1.28	1.00	0.58	0.73
	(1.01)	(0.82)	(0.44)	(0.57)
Foreign ofloxacin	54.46	31.84	35.22	31.11
	(13.99)	(9.33)	(9.06)	(7.03)
Domestic ciprofloxacin	962.29	585.91	678.74	703.81
	(106.26)	(130.26)	(122.26)	(87.40)
Domestic norfloxacin	222.55	119.71	149.18	158.29
	(38.84)	(19.45)	(26.91)	(16.26)
Domestic ofloxacin	125.02	96.21	149.36	112.05
	(44.34)	(30.11)	(52.82)	(42.59)
Domestic sparfloxacin	156.17	121.75	161.30	98.11
	(31.41)	(25.76)	(46.74)	(34.20)

Note: Standard deviations in parentheses.
* API: Active pharmaceutical ingredient.

Figure 7: Summary Statistics

Table 6A—Demand Patterns within the Quinolones Subsegment: Unconditional Price and Expenditure Elasticities in the Northern Region

	Elasticity with respect to:							
	Prices of foreign product groups			Prices of domestic product groups				Overall quinolones expenditure
Product group	Cipro	Norflo	Oflo	Cipro	Norflo	Oflo	Sparflo	
Foreign ciprofloxacin	−5.57*	−0.13†	−0.15*	4.01*	0.11†	0.11†	0.16*	1.37*
	(1.79)	(0.07)	(0.07)	(1.84)	(0.06)	(0.06)	(0.06)	(0.29)
Foreign norfloxacin	−4.27†	−0.45	−4.27†	3.50†	−6.02	4.51*	4.65*	2.20*
	(2.42)	(1.12)	(2.42)	(2.10)	(6.23)	(1.84)	(1.83)	(1.05)
Foreign ofloxacin	−0.11*	−0.10†	−1.38*	−0.09	0.09†	0.23	0.11*	1.16*
	(0.05)	(0.05)	(0.31)	(0.27)	(0.05)	(0.28)	(0.04)	(0.17)
Domestic ciprofloxacin	0.18*	0.01*	−0.01	−1.68*	0.08*	0.08*	0.10*	1.17*
	(0.08)	(0.00)	(0.01)	(0.23)	(0.02)	(0.02)	(0.02)	(0.03)
Domestic norfloxacin	0.04*	−0.03	0.04*	0.58*	−2.23*	0.42*	0.40*	0.73*
	(0.01)	(0.03)	(0.01)	(0.17)	(0.11)	(0.04)	(0.03)	(0.09)
Domestic ofloxacin	0.05*	0.05*	0.11	0.77*	0.74*	−3.42*	0.74*	0.89*
	(0.02)	(0.02)	(0.13)	(0.28)	(0.08)	(0.25)	(0.08)	(0.21)
Domestic sparfloxacin	0.07*	0.04*	0.07*	1.15*	0.63*	0.63*	−2.88*	0.28*
	(0.02)	(0.01)	(0.02)	(0.15)	(0.06)	(0.06)	(0.17)	(0.12)

Notes: Standard errors in parentheses. Elasticities evaluated at average revenue shares. Asterisk (*) denotes significance at the 5-percent significance level, and dagger (†) denotes significance at the 10-percent level.

Figure 8: Elasticity Estimates

Table 7—Upper and Lower Bounds for Marginal Cost, Markup, and Annual Profit by Product Groups within the Quinolone Subsegment

Product group	Lower bound for MC (Rs.)	Upper bound for markup	Upper bound for profit (Rs. mill)	Upper bound for MC (Rs.)	Lower bound for markup	Lower bound for profit (Rs.)
Foreign ciprofloxacin	8.3*	19%	26.9	10.3	0%	0.0
	(1.23)	(0.12)	(16.55)			
Foreign norfloxacin	NA	NA	NA	5.3	0%	0.0
Foreign ofloxacin	32.3	70%*	106.1*	108.5	0%	0.0
	(23.16)	(0.21)	(31.85)			
Domestic ciprofloxacin	4.7*	59%*	1,701.9*	11.2	0%	0.0
	(1.14)	(0.10)	(298.58)			
Domestic norfloxacin	5.2*	43%*	280.7*	9.0	0%	0.0
	(0.20)	(0.02)	(15.32)			
Domestic ofloxacin	58.7*	34%*	161.2*	90.1	0%	0.0
	(2.18)	(0.02)	(12.80)			
Domestic sparfloxacin	49.5*	37%*	198.5*	78.8	0%	0.0
	(1.57)	(0.02)	(11.00)			

Notes: Standard errors in parentheses. Asterisk (*) denotes significance at the 5-percent level. Estimated lower bound for foreign norfloxacin's marginal cost is negative, since the estimated price elasticity is less than one in absolute value.

Figure 9: Marginal Costs

Table 8—Counterfactual Estimates of Consumer Welfare Losses from Product Withdrawal due to the Introduction of Pharmaceutical Patents (Rs. Bill Per Year)

Counterfactual scenarios: withdrawal of one or more domestic product groups	Pure loss of variety	Loss of variety and: Cross-segment expenditure switching	Loss of variety and: Within-segment price-adjustment and cross-segment expenditure switching
Only ciprofloxacin	4.98*	4.92*	7.32*
	(0.87)	(0.89)	(1.46)
Only ofloxacin	0.08	0.08	0.23*
	(0.08)	(0.08)	(0.10)
Ciprofloxacin, ofloxacin, and norfloxacin	7.52*	7.40*	12.53*
	(1.77)	(1.80)	(4.15)
Ciprofloxacin, ofloxacin, and sparfloxacin	6.14*	6.03*	10.58*
	(1.42)	(1.45)	(3.31)
All four domestic quinolones products	11.76†	11.35†	17.81
	(6.43)	(6.34)	(12.70)

Notes: Standard errors in parentheses. Asterisk (*) denotes significance at the 5-percent significance level, and dagger (†) denotes significance at the 10-percent level.

Figure 10: Counterfactuals