# Week 1: Structural Estimation

ResEcon 703: Topics in Advanced Econometrics

Matt Woerman
University of Massachusetts Amherst

# Agenda

This week's topics

- Course overview
- What is structural econometrics?
- Why add structure to an econometric model?
- How to construct a structural econometric model
- Miller and Weinberg (2017)

This week's reading

- Nevo and Whinston (2010)

## Course Overview

# Course Goals

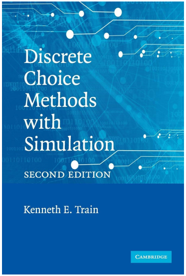
1. Gain an in-depth understanding of some of the most common structural estimation methods in modern empirical economics
    - Maximum likelihood estimation
    - Generalized method of moments
    - Maximum simulated likelihood
    - Method of simulated moments
2. Develop the technical ability to apply these structural estimation methods to your own research
3. Apply these methods to discrete choice models motivated by the random utility model
    - Logit model
    - Generalized extreme value models (nested logit model)
    - Mixed logit model (random coefficients logit model)

# Course Website

`github.com/woerman/ResEcon703`

I will use this GitHub repository to post lecture slides, R code, links to lecture videos, problem sets, datasets, etc.

# Textbook

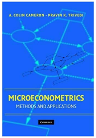



*Discrete Choice Methods with Simulation*
*(Second Edition)*
Kenneth E. Train

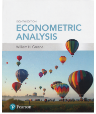
- Available for free at:
  `eml.berkeley.edu/books/choice2.html`
- Paperback copy is usually less than $50

- I will also post supplemental notes on some topics that we cover

# Other References

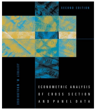



*Microeconometrics: Methods and Applications*
A. Colin Cameron and Pravin K. Trivedi




*Econometric Analysis*
William H. Greene

*Econometrics*
Fumio Hayashi



*Econometric Analysis of Cross Section and Panel Data*
Jeffrey M. Wooldridge

# Software

We will use the R statistical programming language in this course

But I already know Stata/Matlab/Python/SAS/Julia. Why R?

- R is free and open source
- R is powerful and flexible
    - Basic statistics, data cleaning, linear regression, matrix algebra, simulation methods, structural estimation, data visualization, etc.
- R is favored by employers

How can I learn R?

- R tutorial next week
- Many R resources available for free
- First problem set will be a (relatively) gentle introduction to R

# Installing R

Installing R is *usually* straightforward

Download (`cran.r-project.org`) and install R

Download (`www.rstudio.com/products/rstudio/download`) and install RStudio Desktop (Open Source License)

What is the difference between R and RStudio?

R is like a car's engine. It is the program that powers your data analysis.

RStudio is like a car's dashboard. It is the program you interact with to harness the power of your "engine."

# What Is Structural Econometrics?

# What is Structural Econometrics?

Many definitions!

Heckman and Vytlacil (2007)

- Summarize four definitions of "structure" in econometrics that have been used over the last 70+ years

Reiss and Wolak (2007)

- "Today economists refer to models that combine explicit economic theories with statistical models as *structural econometric models*."

Nevo and Whinston (2010)

- "Structural modeling attempts to use data to identify the parameters of an underlying economic model, based on models of individual choice or aggregate relations derived from them."

# Structural Econometric Model

Economic theory

- Tells us how a set of observed endogenous variables ($y$) are related to a set of observed exogenous variables ($x$)
- May also relate the endogenous variables to unobserved variables ($\xi$)
- Specifies a functional form ($g()$) and unknown parameters ($\Theta$)

$$y = g(x, \xi, \Theta)$$

Statistical assumptions

- Give a joint distribution of $x$ and $\xi$

$$f(x, \xi)$$

Estimating equation

- Log-likelihood function, conditional moments, etc.

$$\ell(y, x \mid \Theta) \quad \text{or} \quad E(y \mid x, \Theta)$$

# Nonstructural Econometric Model

Nonstructural econometric models are usually grounded in economic theory but do not incorporate it so directly

- Theory determines what variables to include in $y$ and $x$
- Typically the researcher estimates the joint density of $y$ and $x$ (or something related to this joint density)
- But this joint density may not have an "economic" interpretation

Nonstructural econometric models may or may not be based on formal statistical models

- Measurement studies that construct and summarize data
- Autoregressive conditional heteroskedasticity (ARCH) models
- Everything in-between

There is not an absolute dichotomy of structural vs. nonstructural

- Not uncommon to combine structural and nonstructural approaches

# Nonstructural Auction Example

We observe the winning bid and the number of bidders from many auctions, and we want to understand the relationship between the number of bidders and the winning bid

Nonstructural ("reduced-form") approach

- Regress winning bid on number of bidders
- No economic theory, microeconomic fundamentals, etc.

Suppose you estimate a marginal effect of $100 per bidder

- Is this a causal estimate? No!
- What use is this estimate? What can we do with it?

Maybe you find a clever research design to estimate a causal effect

- IV with an exogenous policy change or RD in auction rules
- Does a causal estimate of $100 per bidder tell us anything about the underlying valuations, preference, or behavior of bidders?

# Structural Auction Example

We observe the winning bid and the number of bidders from many auctions, and we want to understand the relationship between the number of bidders and the winning bid

Structural approach

- Incorporate economic and institutional details into relationship
- Combine auction theory with statistical assumptions to estimate underlying (and unobserved) distribution of valuations, risk preferences, etc.

What can we do with these estimated distributions/parameters?

- Plug these estimated distributions and parameters into the structural economic model to simulate expected auction outcomes under different numbers of bidders, different rules, etc.

# Why Add Structure to an Econometric Model?

# Why Add Structure to an Econometric Model?

Structural models can be used to:

- Estimate unobserved economic or behavioral parameters that cannot be estimated in a nonstructural (reduced-form) model
  - For example: marginal utility, marginal cost, risk preferences, discount rates, search costs, switching costs, etc.
- Conduct counterfactual simulations
  - What would happen if the economic environment changed?
  - Requires the underlying "structural" parameters that are invariant to the simulated change
- Compare competing economic theories
  - For example: Do firms set prices or quantities?
  - Model must account for the implications of the economic theories in order to test them

# Should You Always Add Structure?

Is a structural model always better than a nonstructural model?

- NO! The right approach depends on your research question, data, institutional details, etc.

Negatives of structural models

- Require existing economic theory appropriate for the empirical context
- Often require (many) assumptions by the researcher to align economic theory with available data and tractable estimation
  - If these assumptions are unrealistic, then the results are not credible
- Assumptions may not be transparent to readers

Advantages of nonstructural (reduced-form) models

- With a good research design, nonstructural models can provide
  - Causal estimates
  - Less reliance on researcher assumptions
  - Transparent assumptions, estimation, and results
- Without a good research design, advantages are less clear

# Structure and Credibility: Complements or Substitutes?

Is there always a tradeoff between structure and credibility?

- NO! In some cases, adding structure may be the only way to credibly answer your research question

Examples where structure adds credibility to research

- Generalization to other settings
- Out-of-sample counterfactual simulations
- Welfare calculations

Reduced-form treatment effects may not be applicable for out-of-sample extrapolation or for plugging into an economic model

- Structural parameters are more likely to be invariant to the setting and relevant for welfare calculations

Merger analysis is a classic example of credibility through structure

# Nonstructural Merger Analysis

We want to predict the welfare effects of a horizontal merger

Nonstructural approach

- Estimate the effect of “similar” mergers on prices
- Use estimated price effect in a “back-of-the-envelope” welfare calculation

Potential problems with this approach

- What counts as a “similar” merger? Similar industry, concentration, demand elasticity, cost structure?
- Are there a sufficient number of “similar” mergers?
- What is the control group? Or is it simply an event study of these mergers?
- Are these mergers (quasi-)exogenous?

# Structural Merger Analysis

We want to predict the welfare effects of a horizontal merger

Structural approach

- Construct an economic model of demand, supply, and competition in the industry
- Estimate the structural parameters that describe the industry
- Simulate the effects of the merger (including welfare effects) under a range of assumptions

Potential problems with this approach

- How do you credibly estimate the structural parameters? Are there valid instruments to identify every relevant parameter?

Both approaches have strengths and limitations

# Structure and Data: Complements or Substitutes?

If you have sufficient data to estimate credible reduced-form treatment effects, is structure still useful?

- YES! Credible treatment effects and credible structural parameters are both useful

Good data and identification often weaken the required assumptions

- When the data can do more of the work, the assumptions do less heavy lifting
- True for both structural and nonstructural approaches

Combining structural and nonstructural approaches

- Nonstructural methods can give a credible estimate of the overall treatment effect
- Structural methods can help to corroborate treatment effects and identify the underlying mechanisms

# How to Construct a Structural Econometric Model

# How to Construct a Structural Econometric Model

Step 1: Start with economic theory

- Description of the economic setting
  - Markets, institutions, agents, information
- List of primitives
  - Technologies, preferences, endowments
- Exogenous variables
  - Constraints, regulations, shifters
- Objective function and decision variables
  - Utility maximization and quantities demanded, profit maximization and input quantities
- Equilibrium concept
  - Walrasian equilibrium with price-taking, Nash equilibrium with quantity selection

# How to Construct a Structural Econometric Model

Step 2: Transform economic model into econometric model

- Unobservables that account for the data not perfectly fitting the economic model
  - Researcher uncertainty about the economic setting
  - Agent uncertainty about the economic setting
  - Optimization error by agents
  - Measurement error in observed variables

Step 3: Estimate the econometric model

- Functional forms
- Distribution assumptions
- Estimation method
- Specification tests

# A Simple Example of a Structural Model

We want to estimate the output elasticities of capital and labor for a firm

- We observe output ($Y_t$), capital ($K_t$), and labor ($L_t$)

1. Start with a Cobb-Douglas production function

$$Y_t = AK_t^{\alpha} L_t^{\beta}$$

   Rewrite this production function as

$$\ln(Y_t) = \gamma + \alpha \ln(K_t) + \beta \ln(L_t)$$

2. Add an error term ($\varepsilon_t$) to capture measurement error and make statistical assumptions about it. (Are these assumptions reasonable?)

$$\varepsilon_t \sim N(0, \sigma^2) \quad \text{and} \quad E(\varepsilon_t \mid K_t, L_t) = 0$$

3. Estimate the output elasticities $\alpha$ and $\beta$ using OLS

$$\ln(Y_t) = \gamma + \alpha \ln(K_t) + \beta \ln(L_t) + \varepsilon_t$$

# A More Complex Example of a Structural Model

We observe the winning bid ($w_t$) from $T$ procurement auctions with $N_t$ risk-neutral bidders, and we want to estimate the underlying common distribution of costs, $f(c)$, which is known to all bidders

1. Economic theory tells us each firm will maximize expected profit

$$E[\pi_i(b_1, \ldots, b_N)] = (b_i - c_i)\Pr(b_i < b_j \; \forall j \neq i \mid c_i)$$

Differentiate to get the first-order condition for the bid function

$$b_i = \beta(c_i) = c_i + \frac{\int_{c_i}^{\infty} [1 - F(\tau)]^{N-1} d\tau}{[1 - F(c_i)]^{N-1}}$$

Then the distribution of the winning bid is

$$h(w) = \frac{N[1 - F(\beta^{-1}(w))]^{N-1} f(\beta^{-1}(w))}{\beta'(\beta^{-1}(w))}$$

# A More Complex Example of a Structural Model

2. Assume that the distribution of costs, $f(c)$, comes from a family of distributions parameterized by $\theta = (\theta_1, \theta_2, \dots, \theta_p)$.
   - The lower bound of the distribution of winning bids is

$$\mathcal{J}(\theta, N) = \int_0^{\infty} [1 - F(\tau; \theta)]^{N-1} d\tau$$

3. Estimate $\theta$ using maximum likelihood subject to constraints

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \sum_{t=1}^{T} \ln h(w_t; \theta, N_t) \text{ subject to } \mathcal{J}(\theta, N_t) \leq w_t \ \forall t$$

# Structural Estimation

Some structural models can be estimated using OLS or related regression

- Easy and fast to implement
- Estimation procedure and underlying assumptions are transparent
- Results are easily interpreted

Some structural models require more advanced estimation methods

- Structural model cannot be simplified to a linear regression model
- Methods are broadly defined as "structural estimation"

This course will focus on "structural estimation" that follows from this second class of structural models

# This Course

1. Economic model: Discrete choice to maximize utility
2. Econometric model: Random utility model
    - Logit model
    - Generalized extreme value models (nested logit model)
    - Mixed logit model (random coefficients logit model)
3. Estimation methods: Structural estimation
    - Maximum likelihood estimation
    - Generalized method of moments
    - Maximum simulated likelihood
    - Method of simulated moments

# Miller and Weinberg (2017)

# Research Setting and Research Question

US beer industry

- Dominated by three larger firms: Miller, Coors, and ABI

MillerCoors merger

- Miller and Coors combined their operations in the US through a new joint venture
- Merger was reviewed by US DOJ and approved in June 2008
  - Some concern that increased concentration would harm consumers
  - But cost efficiencies could reduce consumer prices
  - DOJ determined that consumers would benefit on net
- But what if the merger changed the nature of competition?

Research question: Did the MillerCoors merger lead to new coordinated pricing between MillerCoors and ABI?

# Data

Retail scanner data on supermarket beer sales

- Weekly revenue and unit sales by UPC code, week, and store
- 2001–2011, 39 geographic regions, 13 flagship brands
- Aggregated to region-month or region-quarter levels

American Community Survey Public Use Microdata Sample

- Household demographics (income) for a subsample of US households

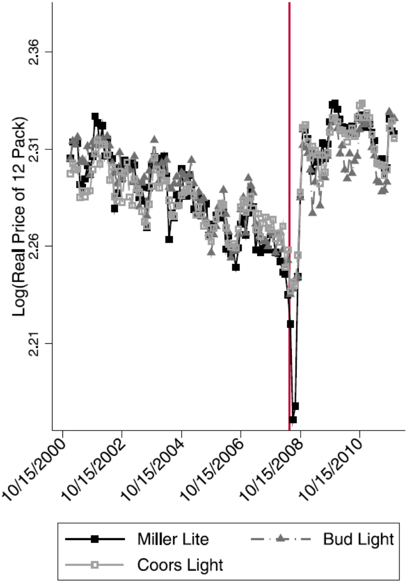
Locations of geographic regions and breweries

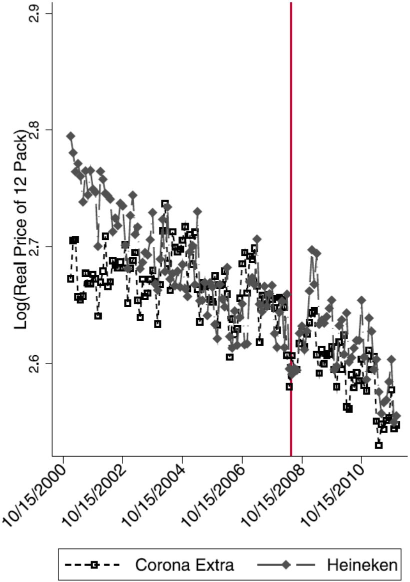
- Driving distance from nearest brewery to market

Diesel fuel prices from US EIA and US DOE

- Transportation cost to deliver goods to market

# Descriptive Evidence of Price Effects



# Descriptive Evidence of Price Effects

After the merger, prices of Miller Lite, Coors Light, and Bud Light increase by 8% and the downward trend ceases

- No change in price levels or trends for Corona Extra and Heineken

This descriptive evidence is consistent with coordinated pricing by MillerCoors and ABI

- So the research question appears plausible

But the evidence is also consistent with

- Unilateral pricing effects
- Institutional practices by retailers
- Macroeconomic conditions of the Great Recession

# Regression Evidence of Time-Series Price Effects

To more rigorously quantify the time-series price effects of the merger and to analyze more brands, the authors use a difference-in-differences regression design

$$
\begin{aligned}
\log p_{jrt} = {} & \beta_1 \mathbb{1}\{\text{MillerCoors}\}_{jt} \times \mathbb{1}\{\text{Post-Merger}\}_t \\
& + \beta_2 \mathbb{1}\{\text{ABI}\}_{jt} \times \mathbb{1}\{\text{Post-Merger}\}_t \\
& + \beta_3 \mathbb{1}\{\text{Post-Merger}\}_t + \phi_{jr} + \tau_t + \varepsilon_{jrt},
\end{aligned}
$$

- Allow for heterogeneous effects of the merger by firm
- Control for cross-sectional variation and time trends

# Regression Evidence of Time-Series Price Effects

| | (i) | (ii) | (iii) | (iv) |
|---|---|---|---|---|
| $\mathbb{1}\{\text{MillerCoors}\} \times \mathbb{1}\{\text{Post-Merger}\}$ | 0.098 | 0.050 | 0.047 | 0.069 |
| | (0.007) | (0.004) | (0.005) | (0.007) |
| $\mathbb{1}\{\text{ABI}\} \times \mathbb{1}\{\text{Post-Merger}\}$ | 0.087 | 0.040 | 0.038 | 0.062 |
| | (0.007) | (0.005) | (0.005) | (0.007) |
| $\mathbb{1}\{\text{Post-Merger}\}$ | −0.031 | −0.007 | −0.002 | 0.010 |
| | (0.005) | (0.004) | (0.004) | (0.009) |
| log(Employment) | – | – | −0.051 | 0.131 |
| | – | – | (0.080) | (0.081) |
| log(Earnings) | – | – | 0.156 | 0.152 |
| | – | – | (0.029) | (0.035) |
| Pre-Merger Average Price | 11.75 | 11.14 | 11.14 | 11.14 |
| Product Trends | No | No | Yes | Yes |
| Covariates | No | No | Yes | Yes |
| # Observations | 25,740 | 167,695 | 167,695 | 151,525 |

Conclusions are similar as before

- MillerCoors prices increase 5–10% relative to import brands
- ABI prices increase by roughly the same amount (4–9%)

# Regression Evidence of Cross-Sectional Price Effects

Under unilateral pricing, these price effects may be explained by

- Changes in industry concentration: larger price increases in markets with greater predicted increases in concentration
- Changes in transportation costs: smaller price increases in markets with greater transportation cost savings

The authors use another reduced-form regression to determine how well these market-level factors explain the observed price patterns

$$\begin{aligned}\log p_{jrt} = {} & \alpha_1 \Delta \mathrm{HHI}_r \times \mathbb{1}\{\text{Post-Merger}\}_t \\ & + \alpha_2 \Delta \mathrm{MILES}_r \times \mathbb{1}\{\text{Post-Merger}\}_t \\ & + \alpha_3 \mathbb{1}\{\text{Post-Merger}\}_t + \phi_{jr} + \tau_t + \varepsilon_{jrt},\end{aligned}$$

# Regression Evidence of Cross-Sectional Price Effects

| | Pooled | MillerCoors | ABI | Imports |
|---|---|---|---|---|
| $\Delta$HHI $\times$ $\mathbb{1}$\{Post-Merger\} | 0.997 | 1.172 | 1.503 | −0.005 |
| | (0.454) | (0.542) | (0.531) | (0.534) |
| $\Delta$MILES $\times$ $\mathbb{1}$\{Post-Merger\} | −0.042 | −0.040 | −0.053 | −0.028 |
| | (0.013) | (0.016) | (0.013) | (0.014) |
| $\mathbb{1}$\{Post-Merger\} | 0.037 | 0.049 | 0.040 | 0.019 |
| | (0.012) | (0.014) | (0.013) | (0.014) |
| # Observations | 167,695 | 75,315 | 50,810 | 41,570 |

The signs of these coefficients are as expected

- MillerCoors and ABI—but not import brands—price increases are larger in markets with greater predicted increases in concentration
- Prices increases are smaller in markets with greater transportation cost savings

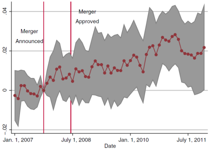
The net effect is roughly zero on average

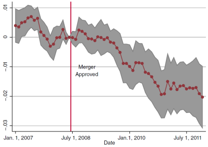
- Most of the price increases are not explained by these factors
- Unilateral effects may not explain the observed price increases

# Additional Reduced-Form Analyses (AHW 2015)

Ashenfelter, Hosken, and Weinberg (2015) conduct additional reduced-from analyses of this merger to further characterize how these factors could explain unilateral price effects

- Event studies of concentration (left) and distance (right) effects




- Heterogeneous effects by initial market characteristics

| | Dependent Variable=log(price) | |
|---|---|---|
| | Interaction Variables | |
| | Initial HHI | Anheuser-Busch Initial Share |
| Sim $\Delta HHI$*PostApproval | 1.045 | 0.895 |
| | (0.262) | (0.326) |
| Sim $\Delta HHI$*PostApproval*(variable) | −2.929 | −1.479 |
| | (1.124) | (0.821) |
| $\Delta$ Distance*PostApproval | −0.0298 | −0.0502 |
| | (0.0113) | (0.0198) |
| $\Delta$ Distance*PostApproval*(variable) | 0.0124 | 0.0530 |
| | (0.0500) | (0.0454) |
| Average pre-merger price | 9.73 | 9.73 |
| Average -$\Delta$ Distance (thousands of miles) | 0.364 | 0.364 |
| Average Sim $\Delta HHI$ | 0.036 | 0.036 |
| Average (variable) | 0.24 | 0.40 |
| Number of observations | 345,379 | 345,379 |
| Number of regions | 48 | 48 |

# Reduced-Form vs. Structural Analysis

Advantages of these reduced-form results

- Simple and transparent method to show substantial price effects
- Some evidence that prices exceed unilateral effects

Shortcomings of these reduced-form results

- Analysis does not fully capture consumer substitution patterns, which are critical for firm pricing decisions

Advantages of a structural econometric model

- Model both demand and supply sides of market
- Directly estimate firm conduct parameters
- Simulate the market under counterfactual assumptions

# Economic Model of Demand

The authors start with an economic model of consumer demand

Suppose we observe $r = 1, \ldots, R$ regions over $t = 1, \ldots, T$ time periods. There are $i = 1, \ldots, N_{rt}$ consumers in each region–period combination. Each consumer purchases one of the observed products ($j = 1, \ldots, J_{rt}$) or selects the outside option ($j = 0$). We refer to observed products as inside goods. The conditional indirect utility that consumer $i$ receives from inside good $j$ in region $r$ and period $t$ is

$$u_{ijrt} = x_j \beta_i^* + \alpha_i^* p_{jrt} + \sigma_j^D + \tau_t^D + \xi_{jrt} + \overline{\varepsilon}_{ijrt}, \tag{3}$$

where $x_j$ is a vector of observable product characteristics, $p_{jrt}$ is the retail price, $\sigma_j^D$ allows the mean valuation of unobserved product characteristics to vary freely by product, $\tau_t^D$ allows the mean valuation of the indirect utility from consuming the inside goods to vary freely over time, $\xi_{jrt}$ is an unobserved quality valuation specific to the region–period, and $\overline{\varepsilon}_{ijrt}$ is a stochastic term.

The observable product characteristics include a constant (i.e., an indicator that equals 1 for an inside good), calories, package size, and an indicator for whether the product is imported. Calories is highly correlated with alcohol content and serves to distinguish the "light" beers. We control for $\sigma_j^D$ and $\tau_t^D$ using product and time dummy variables, respectively. The term $\xi_{jrt}$ is left as a structural error term. We specify the consumer-specific coefficients as $[\alpha_i^*, \beta_i^*]' = [\alpha, \beta]' + \Pi D_i$, where $D_i$ is (demeaned) consumer income. The $\alpha$ and $\beta$ parameters are the average effect of observables on indirect utility. Because the

# Statistical Assumptions of Demand Model

We decompose the stochastic term using the distributional assumptions of the nested logit model, following Berry (1994) and Cardell (1997). Define two groups, $g = 0, 1$, such that group 1 includes the inside goods and group 0 the outside good. Then

$$\overline{\varepsilon}_{ijrt} = \zeta_{igrt} + (1 - \rho)\varepsilon_{ijrt}, \tag{4}$$

where $\varepsilon_{ijrt}$ is the independent and identically distributed extreme value, $\zeta_{igrt}$ has the unique distribution such that $\overline{\varepsilon}_{ijrt}$ is extreme value, and $\rho$ is a nesting parameter ($0 \leq \rho < 1$). Larger values of $\rho$ correspond to greater correlation in preferences for products of the same group and thus less consumer substitution between the inside and outside goods. To close the model, we normalize the indirect utility of the outside good such that $u_{i0rt} = \varepsilon_{i0rt}$, and assume that the market sizes are 50% greater than the maximum observed unit sales within each region. The outside good includes brands outside the sample (e.g., craft beers), beer sold outside supermarkets, and non-beer beverages such as wine. Placing these products in the outside good group prompts their prices to become non-strategic in the model. Time fixed effects help control for the trend toward craft beer during the sample period.

This economic model of consumer demand probably does not make sense

- Do not worry, it will by the end of the semester!

# Implied Market Shares

This demand model implies that the market share for product $j$ in market $r$ in year $t$ is

$$s_{jrt} = \frac{1}{N_{rt}} \sum_{i=1}^{N_{rt}} \frac{\exp\big((\delta_{jrt} + \mu_{ijrt})/(1-\rho)\big)}{\exp\big(I_{igrt}/(1-\rho)\big)} \frac{\exp I_{igrt}}{\exp I_{irt}},$$

where indirect utility has been rewritten as

$$u_{ijrt} = \delta_{jrt}\big(x_j, p_{jrt}, \sigma_j^D, \tau_t^D, \xi_{jrt}; \alpha, \beta\big) + \mu_{ijrt}(x_j, p_{jrt}, D_i; \Pi) + \zeta_{igrt} + (1-\rho)\varepsilon_{ijrt},$$

$$\delta_{jrt} = x_j\beta + \alpha p_{jrt} + \sigma_j^D + \tau_t^D + \xi_{jrt},$$

$$\mu_{ijrt} = [p_{jrt}, x_j]' * \Pi D_i,$$

# Estimation of Demand Model

If $\Pi = 0$, which means consumer preference do not vary with income, then the expression for market shares simplifies to

$$\log(s_{jrt}) - \log(s_{0rt}) = x_j\beta + \alpha p_{jrt} + \sigma_j^D + \tau_t^D + \rho \log(\bar{s}_{jrt|g}) + \xi_{jrt},$$

which can be estimated with an OLS regression

To estimate the more general demand model without making this assumption, the authors

- Derive moment conditions from this economic model
- Estimate its parameters using generalized method of moments (GMM)

"Moment conditions" and "GMM" probably do not make sense

- Do not worry, they will by the end of the semester!

# Demand Estimation Results

These parameters define consumer preferences for product characteristics

| Demand Model: | | NL-1 | RCNL-1 | RCNL-2 | RCNL-3 | RCNL-4 |
|---|---|---|---|---|---|---|
| Data Frequency: | | Monthly | Monthly | Quarterly | Monthly | Quarterly |
| Variable | Parameter | (i) | (ii) | (iii) | (iv) | (v) |
| Price | $\alpha$ | −0.1312 | −0.0887 | −0.1087 | −0.0798 | −0.0944 |
| | | (0.0884) | (0.0141) | (0.0163) | (0.0147) | (0.0146) |
| Nesting Parameter | $\rho$ | 0.6299 | 0.8299 | 0.7779 | 0.8079 | 0.8344 |
| | | (0.0941) | (0.0402) | (0.0479) | (0.0602) | (0.0519) |
| *Demographic Interactions* | | | | | | |
| Income × Price | $\Pi_1$ | | 0.0007 | 0.0009 | | |
| | | | (0.0002) | (0.0003) | | |
| Income × Constant | $\Pi_2$ | | 0.0143 | 0.0125 | 0.0228 | 0.0241 |
| | | | (0.0051) | (0.0055) | (0.0042) | (0.0042) |
| Income × Calories | $\Pi_3$ | | 0.0043 | 0.0045 | 0.0038 | 0.0031 |
| | | | (0.0016) | (0.0017) | (0.0018) | (0.0015) |
| Income × Import | $\Pi_4$ | | | | 0.0039 | 0.0031 |
| | | | | | (0.0019) | (0.0016) |
| Income × Package Size | $\Pi_5$ | | | | −0.0013 | −0.0017 |
| | | | | | (0.0007) | (0.006) |
| *Other Statistics* | | | | | | |
| Median Own Price Elasticity | | −3.81 | −4.74 | −4.33 | −4.45 | −6.10 |
| Median Market Price Elasticity | | −1.10 | −0.60 | −0.72 | −0.60 | −0.69 |
| Median Outside Diversion | | 29.80% | 12.96% | 16.98% | 13.91% | 11.82% |
| *J*-Statistic | | | 13.94 | 13.75 | 13.91 | 14.15 |

# Estimated Demand Elasticities

The authors combine these parameter estimates with their demand model to calculate own-price and cross-price elasticities

| Brand/Category | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | *Product-Specific Own and Cross-Elasticities* | | | | | | | |
| (1) | Bud Light | −4.389 | 0.160 | 0.019 | 0.182 | 0.235 | 0.101 | 0.146 | 0.047 | 0.040 | 0.130 | 0.046 | 0.072 | 0.196 |
| (2) | Budweiser | 0.323 | −4.272 | 0.019 | 0.166 | 0.258 | 0.103 | 0.166 | 0.047 | 0.039 | 0.121 | 0.043 | 0.068 | 0.183 |
| (3) | Coors | 0.316 | 0.154 | −4.371 | 0.163 | 0.259 | 0.102 | 0.167 | 0.046 | 0.038 | 0.119 | 0.042 | 0.066 | 0.180 |
| (4) | Coors Light | 0.351 | 0.160 | 0.019 | −4.628 | 0.230 | 0.100 | 0.142 | 0.047 | 0.041 | 0.132 | 0.047 | 0.073 | 0.199 |
| (5) | Corona Extra | 0.279 | 0.147 | 0.018 | 0.137 | −5.178 | 0.108 | 0.203 | 0.047 | 0.035 | 0.104 | 0.035 | 0.061 | 0.158 |
| (6) | Corona Light | 0.302 | 0.151 | 0.018 | 0.153 | 0.279 | −5.795 | 0.183 | 0.048 | 0.037 | 0.113 | 0.039 | 0.065 | 0.171 |
| (7) | Heineken | 0.269 | 0.145 | 0.018 | 0.131 | 0.311 | 0.108 | −5.147 | 0.047 | 0.035 | 0.101 | 0.034 | 0.059 | 0.153 |
| (8) | Heineken Light | 0.240 | 0.112 | 0.014 | 0.124 | 0.210 | 0.086 | 0.138 | −5.900 | 0.026 | 0.089 | 0.028 | 0.051 | 0.135 |
| (9) | Michelob | 0.301 | 0.140 | 0.015 | 0.146 | 0.208 | 0.089 | 0.135 | 0.042 | −4.970 | 0.116 | 0.036 | 0.061 | 0.175 |
| (10) | Michelob Light | 0.345 | 0.159 | 0.019 | 0.181 | 0.235 | 0.101 | 0.146 | 0.047 | 0.041 | −5.071 | 0.046 | 0.072 | 0.196 |
| (11) | Miller Gen. Draft | 0.346 | 0.159 | 0.019 | 0.182 | 0.235 | 0.101 | 0.146 | 0.047 | 0.040 | 0.130 | −4.696 | 0.072 | 0.196 |
| (12) | Miller High Life | 0.338 | 0.159 | 0.019 | 0.177 | 0.242 | 0.102 | 0.153 | 0.047 | 0.040 | 0.127 | 0.045 | −3.495 | 0.191 |
| (13) | Miller Lite | 0.344 | 0.159 | 0.019 | 0.180 | 0.237 | 0.101 | 0.148 | 0.047 | 0.040 | 0.129 | 0.046 | 0.071 | −4.517 |
| (14) | Outside Good | 0.016 | 0.007 | 0.001 | 0.009 | 0.011 | 0.005 | 0.006 | 0.002 | 0.002 | 0.006 | 0.002 | 0.003 | 0.009 |
| | | | | | | | *Cross-Elasticities by Category* | | | | | | | |
| | 6 Packs | 0.307 | 0.152 | 0.018 | 0.155 | 0.275 | 0.104 | 0.180 | 0.047 | 0.038 | 0.115 | 0.039 | 0.065 | 0.174 |
| | 12 Packs | 0.320 | 0.154 | 0.019 | 0.163 | 0.250 | 0.102 | 0.161 | 0.047 | 0.039 | 0.121 | 0.042 | 0.068 | 0.183 |
| | 24 Packs | 0.356 | 0.160 | 0.019 | 0.189 | 0.222 | 0.099 | 0.136 | 0.047 | 0.041 | 0.134 | 0.048 | 0.073 | 0.201 |
| | Domestic | 0.349 | 0.160 | 0.019 | 0.184 | 0.229 | 0.100 | 0.142 | 0.047 | 0.040 | 0.131 | 0.047 | 0.072 | 0.197 |
| | Imported | 0.279 | 0.147 | 0.018 | 0.138 | 0.301 | 0.108 | 0.200 | 0.047 | 0.035 | 0.104 | 0.035 | 0.061 | 0.158 |

- These elasticities would be difficult to generate from reduced-form regressions

# Economic Model of Supply (or Pricing)

The authors next model the supply side of the market

The resulting first-order condition gives equilibrium prices as a function of

- Marginal cost
- Market shares and elasticities
- Ownership structure

$$p_t = mc_t - \left[\Omega_t(\kappa) \circ \left(\frac{\partial s_t(p_t;\theta^D)}{\partial p_t}\right)^T\right]^{-1} s_t(p_t;\theta^D),$$

where the ownership structure changes due to the merger

$$\Omega_{t_1^*} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \qquad \Omega_{t_2^*} = \begin{bmatrix} 1 & \kappa & \kappa & 0 \\ \kappa & 1 & 1 & 0 \\ \kappa & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

# Statistical Assumptions of Supply Model

The authors do not observe marginal costs, so they model them as a function of transportation costs and unobservables

> To complete the supply-side model, we parameterize the marginal cost of product $j$ in region $r$ and period $t$ as follows:
>
> $$mc_{jrt} = w_{jrt}\gamma + \sigma_j^S + \tau_t^S + \mu_r^S + \eta_{jrt}, \tag{11}$$
>
> where $w_{jrt}$ is a vector that includes the distance (miles $\times$ diesel index) between the region and brewery and an indicator for MillerCoors products in post-merger periods. This allows the Miller/Coors merger to affect marginal costs through the rationalization of distribution and through residual cost synergies unrelated to distance. Unobserved costs depend on the product, region, and period-specific effects, $\sigma_j^S$, $\mu_c^S$, and $\tau_t^S$, which we control for with fixed effects, as well as on $\eta_{jrt}$, which we leave as a structural error term.[13]

They then construct supply-side moment conditions and estimate parameters using method of moments

Reminder: it is ok if this does not make sense right now!

- Just an example to show what structural estimation can achieve

# Supply Estimation Results

| Demand Model: | | NL-1 | RCNL-1 | RCNL-2 | RCNL-3 | RCNL-4 |
|---|---|---|---|---|---|---|
| Data Frequency: | | Monthly | Monthly | Quarterly | Monthly | Quarterly |
| Variable | Parameter | (i) | (ii) | (iii) | (iv) | (v) |
| Post-Merger Internalization | $\kappa$ | 0.374 | 0.264 | 0.249 | 0.286 | 0.342 |
| of Coalition Pricing Externalities | | (0.034) | (0.073) | (0.087) | (0.042) | (0.054) |
| *Marginal Cost Parameters* | | | | | | |
| MillerCoors × PostMerger | $\gamma_1$ | −0.608 | −0.654 | −0.649 | −0.722 | −0.526 |
| | | (0.039) | (0.050) | (0.060) | (0.042) | (0.040) |
| Distance | $\gamma_2$ | 0.142 | 0.168 | 0.163 | 0.169 | 0.148 |
| | | (0.046) | (0.059) | (0.059) | (0.060) | (0.049) |

The parameter $\kappa$ captures the extent that one firm internalizes its price effects on the other firm's profits

- 25–34% of these price effects are internalized

The $\gamma$ parameters describe marginal costs

- Marginal cost of Coors Light fell by 14% post-merger
- Transportation costs account for 2–3% of retail prices

# Estimated Markups

The authors combine the estimated parameters with the economic model to calculate markups before and after the merger

| | 6 Packs | | 12 Packs | | 24 Packs | |
|---|---|---|---|---|---|---|
| Brand | Pre | Post | Pre | Post | Pre | Post |
| Bud Light | 3.63 | 4.34 | 3.52 | 4.24 | 3.43 | 4.13 |
| Budweiser | 3.79 | 4.49 | 3.66 | 4.38 | 3.55 | 4.25 |
| Coors | 2.70 | 4.39 | 2.56 | 4.31 | 2.44 | 4.18 |
| Coors Light | 2.47 | 4.21 | 2.36 | 4.14 | 2.28 | 4.04 |
| Corona Extra | 3.30 | 3.18 | 3.04 | 2.91 | 3.04 | 3.03 |
| Corona Light | 3.02 | 2.91 | 2.75 | 2.65 | 2.87 | 2.80 |
| Heineken | 3.20 | 3.14 | 2.98 | 2.92 | 3.22 | 3.33 |
| Heineken Light | 2.87 | 2.81 | 2.61 | 2.50 | 2.75 | 2.69 |
| Michelob | 3.69 | 4.47 | 3.62 | 4.38 | 3.34 | 4.28 |
| Michelob Light | 3.61 | 4.34 | 3.53 | 4.23 | 3.46 | 4.06 |
| Miller Gen. Draft | 2.89 | 4.26 | 2.77 | 4.16 | 2.68 | 4.09 |
| Miller High Life | 2.91 | 4.28 | 2.80 | 4.20 | 2.74 | 4.13 |
| Miller Lite | 2.89 | 4.25 | 2.78 | 4.18 | 2.69 | 4.07 |

- Markups increase substantially for MillerCoors and ABI beers, but not for import brands

# Implied Cost Shocks

An alternate explanation for the observed prices is that ABI experiences a post-merger cost shock

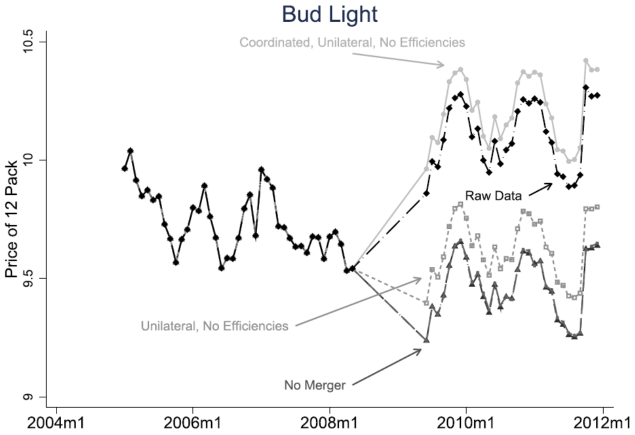
- The authors estimate what cost shocks would have been required to explain the observed prices under each competitive regime

| | Budweiser | Bud Light | Michelob Light | Michelob Ultra |
|---|---|---|---|---|
| $\mathbb{1}\{$Post-Merger and Bertrand$\}$ | 0.122 | 0.120 | 0.089 | 0.102 |
| | (0.006) | (0.006) | (0.004) | (0.007) |
| $\mathbb{1}\{$Post-Merger$\}$ | 0.016 | −0.002 | 0.124 | 0.050 |
| | (0.014) | (0.011) | (0.016) | (0.013) |

If firms priced unilaterally, ABI marginal cost increases of 12–21% would be required to explain prices

# Counterfactual Price Simulations

The authors use their parameters and model to simulate price trajectories under a variety of counterfactual market assumptions




- ABI price increases are almost entirely due to coordinated pricing

# Welfare Calculations

The authors also calculate welfare effects for each counterfactual

| | | | | | |
|---|---|---|---|---|---|
| Coordinated Effects: | yes | yes | no | no | no |
| Unilateral Effects: | yes | yes | yes | yes | no |
| Efficiencies: | yes | no | yes | no | no |
| | (i) | (ii) | (iii) | (iv) | (v) |
| | | | *Retail Prices* | | |
| ABI | 10.03 | 10.14 | 9.38 | 9.55 | 9.43 |
| Miller | 8.94 | 9.37 | 8.28 | 8.72 | 8.19 |
| Coors | 10.18 | 10.85 | 9.56 | 10.22 | 9.26 |
| | | | *Brewer Markups* | | |
| ABI | 4.45 | 4.56 | 3.81 | 3.97 | 3.84 |
| Miller | 4.52 | 4.32 | 3.83 | 3.63 | 3.05 |
| Coors | 4.25 | 4.06 | 3.61 | 3.41 | 2.68 |
| | | | *Welfare Statistics* | | |
| Producer Surplus | 22.1% | 19.1% | 10.3% | 8.2% | – |
| ABI | 10.3% | 19.8% | −0.08% | 9.3% | – |
| Miller | 37.8% | 20.2% | 24.6% | 9.1% | – |
| Coors | 47.8% | 12.9% | 34.7% | 3.5% | – |
| Consumer Surplus | −3.7% | −5.3% | −0.2% | −2.1% | – |
| Total Surplus | 1.3% | −0.6% | 1.8% | −0.1% | – |

- Welfare effects depend on whether cost efficiencies are realized and whether pricing is coordinated
- Merger could improve total surplus under reasonable assumptions