Week 1: Structural Estimation

ResEcon 703: Topics in Advanced Econometrics

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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

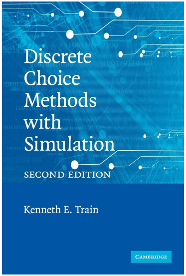
1. Gain an in-depth understanding of some of the most common structural estimation methods in modern empirical economics
    - Maximum likelihood estimation
    - Generalized method of moments
    - Maximum simulated likelihood
    - Method of simulated moments
2. Develop the technical ability to apply 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

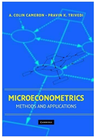


Discrete Choice Methods with Simulation (Second Edition)
Kenneth E. Train

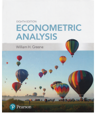
- Available for free at: `eml.berkeley.edu/books/choice2.html`
- Paperback copy is usually less than $50

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

Other References

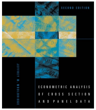


Microeconometrics: Methods and Applications
A. Colin Cameron and Pravin K. Trivedi



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 (ξ)
- Specifies a functional form ($g()$) and unknown parameters (Θ)

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

Statistical assumptions

- Give a joint distribution of x and ξ

$$f(x, \xi)$$

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 (ε_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 α and β 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 $\theta = (\theta_1, \theta_2, \ldots, \theta_p)$.
   - 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 θ using maximum likelihood subject to constraints

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

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 operations to create 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

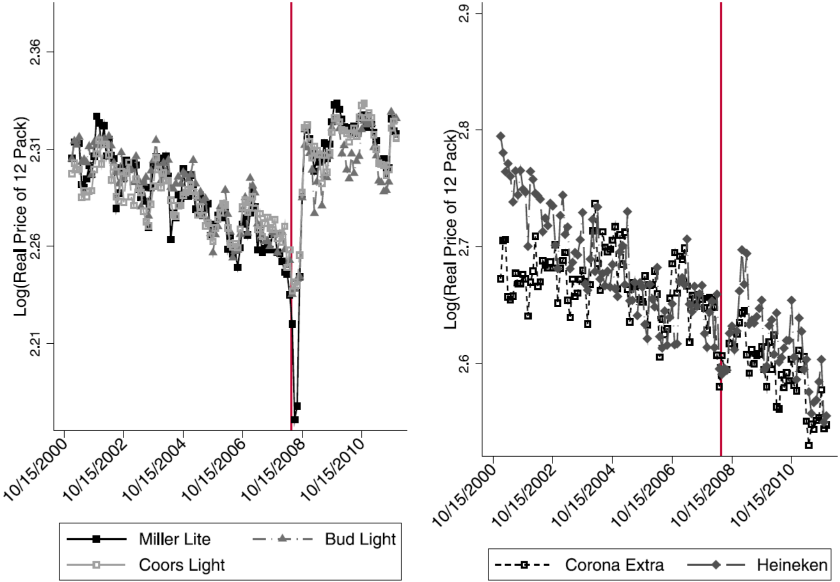
Locations of geographic regions and breweries

- 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



Regression Evidence of Time-Series Price Effects

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

	(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

Regression Evidence of Cross-Sectional Price Effects

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

	Pooled	MillerCoors	ABI	Imports
ΔHHI $\times$ $\mathbb{1}$\{Post-Merger\}	0.997	1.172	1.503	−0.005
	(0.454)	(0.542)	(0.531)	(0.534)
ΔMILES $\times$ $\mathbb{1}$\{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

Regression Evidence of Cross-Sectional Price Effects

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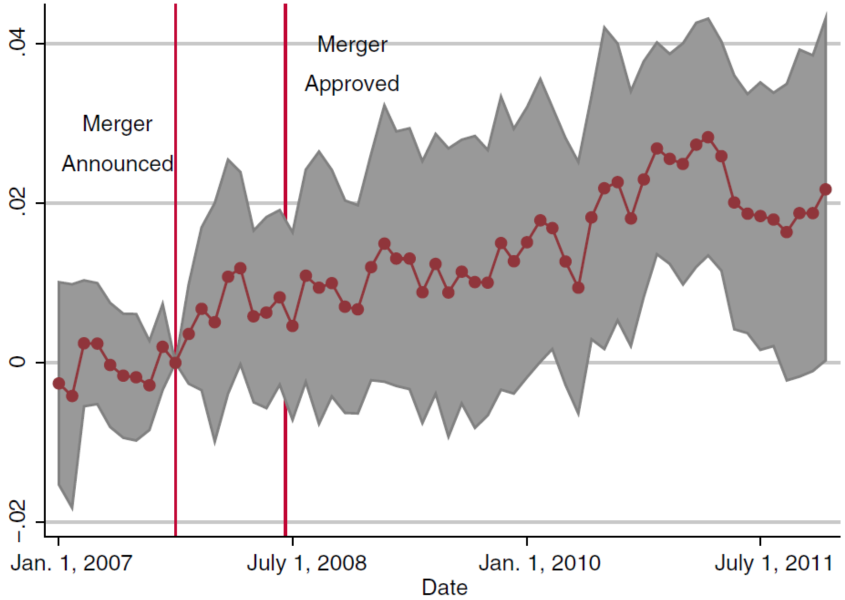
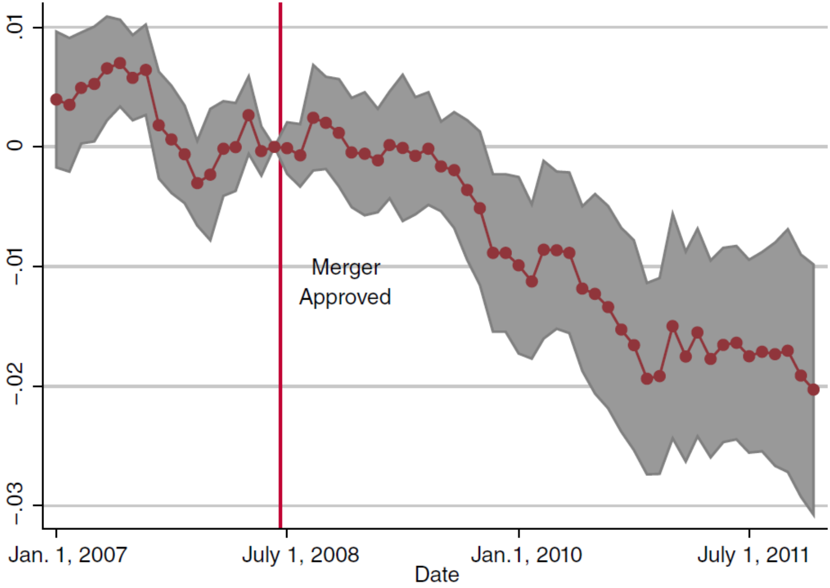
Event Study of Concentration Effects (AHW 2015)



Event Study of Distance Effects (AHW 2015)



Heterogeneity in Price Effects (AHW 2015)

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

Economic Model of 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, σ_j^D allows the mean valuation of unobserved product characteristics to vary freely by product, τ_t^D allows the mean valuation of the indirect utility from consuming the inside goods to vary freely over time, ξ_{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 σ_j^D and τ_t^D using product and time dummy variables, respectively. The term ξ_{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 α and β 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 ε_{ijrt} is the independent and identically distributed extreme value, ζ_{igrt} has the unique distribution such that $\overline{\varepsilon}_{ijrt}$ is extreme value, and ρ is a nesting parameter ($0 \leq \rho < 1$). Larger values of ρ 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.

Implied Market Shares

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

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

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

Demand 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)
Price	α	−0.1312	−0.0887	−0.1087	−0.0798	−0.0944
		(0.0884)	(0.0141)	(0.0163)	(0.0147)	(0.0146)
Nesting Parameter	ρ	0.6299	0.8299	0.7779	0.8079	0.8344
		(0.0941)	(0.0402)	(0.0479)	(0.0602)	(0.0519)
Demographic Interactions						
Income × Price	Π_1		0.0007	0.0009		
			(0.0002)	(0.0003)		
Income × Constant	Π_2		0.0143	0.0125	0.0228	0.0241
			(0.0051)	(0.0055)	(0.0042)	(0.0042)
Income × Calories	Π_3		0.0043	0.0045	0.0038	0.0031
			(0.0016)	(0.0017)	(0.0018)	(0.0015)
Income × Import	Π_4				0.0039	0.0031
					(0.0019)	(0.0016)
Income × Package Size	Π_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

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

Economic Model of Supply (or Pricing)

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

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

Statistical Assumptions of Supply Model

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, σ_j^S, μ_c^S, and τ_t^S, which we control for with fixed effects, as well as on η_{jrt}, which we leave as a structural error term.[13]

$$\eta_{rt}^*\left(\widetilde{\theta}^S; \widehat{\theta}^D\right) = p_{rt} - w_{jrt}\widetilde{\gamma} - \sigma_j^S - \tau_t^S - \mu_r^S - \left[\Omega_t(\widetilde{\kappa}) \circ \left(\frac{\partial s_t\left(p_{rt}; \widehat{\theta}^D\right)}{\partial p_{rt}}\right)^T\right]^{-1} s_t\left(p_{rt}; \widehat{\theta}^D\right).$$

Supply Estimation Results

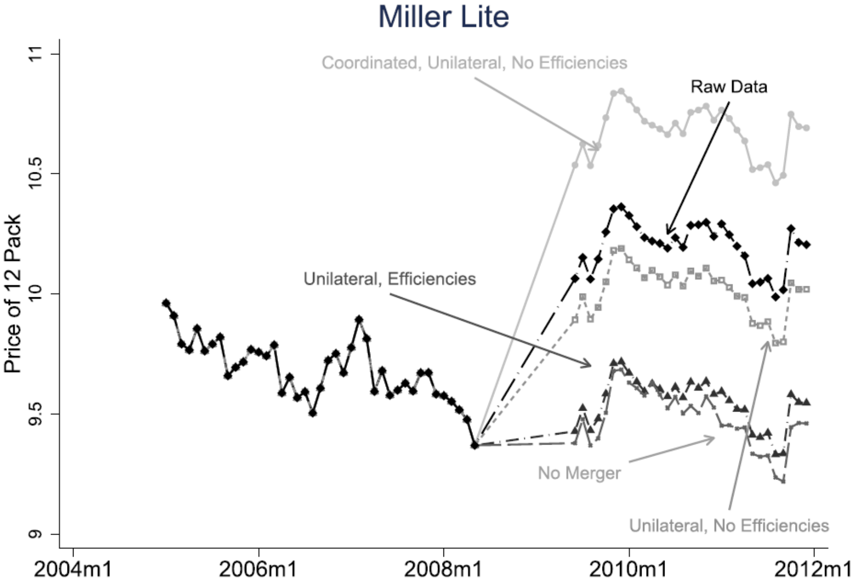
Demand Model:		NL-1	RCNL-1	RCNL-2	RCNL-3	RCNL-4
Data Frequency:		Monthly	Monthly	Quarterly	Monthly	Quarterly
Variable	Parameter	(i)	(ii)	(iii)	(iv)	(v)
Post-Merger Internalization	κ	0.374	0.264	0.249	0.286	0.342
of Coalition Pricing Externalities		(0.034)	(0.073)	(0.087)	(0.042)	(0.054)
Marginal Cost Parameters						
MillerCoors × PostMerger	γ_1	−0.608	−0.654	−0.649	−0.722	−0.526
		(0.039)	(0.050)	(0.060)	(0.042)	(0.040)
Distance	γ_2	0.142	0.168	0.163	0.169	0.148
		(0.046)	(0.059)	(0.059)	(0.060)	(0.049)

Estimated Markups and Implied Cost Shocks

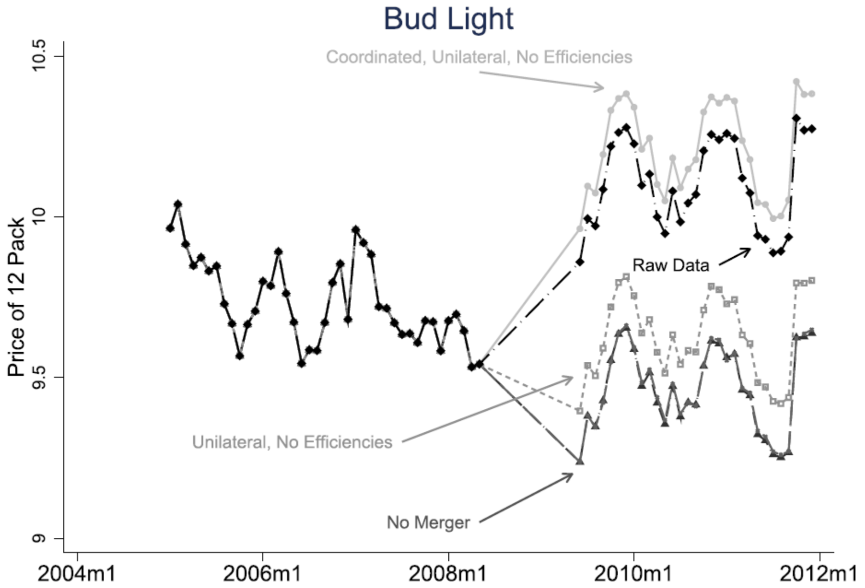
	6 Packs		12 Packs		24 Packs	
Brand	Pre	Post	Pre	Post	Pre	Post
Bud Light	3.63	4.34	3.52	4.24	3.43	4.13
Budweiser	3.79	4.49	3.66	4.38	3.55	4.25
Coors	2.70	4.39	2.56	4.31	2.44	4.18
Coors Light	2.47	4.21	2.36	4.14	2.28	4.04
Corona Extra	3.30	3.18	3.04	2.91	3.04	3.03
Corona Light	3.02	2.91	2.75	2.65	2.87	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

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

Counterfactual Price Simulations



Counterfactual Price Simulations



Welfare Calculations

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%	–