The Dynamics of Retail Oligopoly

Arie Beresteauñ1    Paul B. Ellickson2
Sanjog Misra3    James C. Reeder, III4

1University of Pittsburgh
2University of Rochester
3University of Chicago
4Purdue University

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Motivation: Retail Dynamics
Understanding the Nature of Disruptive Innovation in Retail

- Retail experiences constant disruption/innovation
  - A&P, Walmart, Home Depot, Costco, Dollar Stores, Amazon, ...
  - Usually about efficiency/convenience/quality → Scale & Standardization

- Economic tension: Innovators are more efficient & lower cost...
  - ...but may (eventually?) exploit market power (rising margins?)
  - ...and may reduce variety/diversity (Spence, Dixit/Stiglitz)
  - How does scale impact structure?

- Focus on particular disruption: Walmart’s ’90’s pivot into groceries
  - Big innovation: supercenters (mass-merch + grocery) → big cost advantage
  - Understand nature of advantage & assess impact on: welfare, market structure, variety...
  - ⇒ Build structural model & simulate
Overview

Propose a dynamic model of retail competition in which

1. firms are chains with multiple stores
2. market structure & chain size evolves over time
3. chains are one of two “formats”: supermarkets & supercenters
4. quality differs across chains, costs differ by format
5. chains compete in “store density”: a measure of spatial proximity

Use framework to

1. estimate dynamic structural model using 13 year panel ('94 -'06)
2. quantify sources of Walmart’s advantage
3. evaluate welfare impact of “new technology” and implications for market structure
The Supermarket Industry

- Supermarket format dates to 1950s, but many firms date to ’20s
  - Long term trend toward larger stores, increased variety/services

- Competitive structure
  - Locally concentrated: 3 to 5 dominant firms per market
  - High gross margins (30%), but low net margins (2%)
  - Elements of both vertical (assortment) and horizontal (location) differentiation
  - Quality/efficiency achieved through high fixed costs
  - Prices/assortment set at market level (at least...).

- Entry by Wal-Mart beginning in 1988
  - WM now accounts for 20-25% of overall sales
  - Believed to have huge cost advantage (Basker, 2007; Holmes, 2011).
  - Even more transformative internationally (Lagakos, 2016; Atkin et al., 2018).
Data

Locations, Ownership, Features & Revenues

- Store level census: Trade Dimension’s *Retail Tenant Database*.

Market Size & Prices

- Census of Retail Trade: sales of retail food and beverage stores
- Store level prices for (small) sample of markets (from ACCRA)

Chains and Markets

- Aggregate stores to MSA/chain level, linking prices to firms
  - Assume chains charge same prices in all stores in a given market
  - Assume all stores in chain are same format
  - Consistent with empirical findings (Hitsch et al., 2016; DellaVigna and Gentzkow, 2017)
- Exclude “fringe” firms (corner grocery stores)
## Data: Format Differences

<table>
<thead>
<tr>
<th></th>
<th>Supercenter</th>
<th>Supermarket</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Store Size</strong></td>
<td>65.2 (22.8)</td>
<td>36.3 (15.2)</td>
</tr>
<tr>
<td><strong>Checkouts</strong></td>
<td>29.4 (6.36)</td>
<td>10.1 (3.94)</td>
</tr>
<tr>
<td><strong>Stores per Market</strong></td>
<td>3.64 (5.48)</td>
<td>10.4 (22.6)</td>
</tr>
<tr>
<td><strong>Market Share</strong></td>
<td>16.6 (13.9)</td>
<td>15.1 (10.2)</td>
</tr>
<tr>
<td><strong>Basket Price</strong></td>
<td>82.08 (6.31)</td>
<td>95.66 (10.28)</td>
</tr>
<tr>
<td><strong>Firms per MSA</strong></td>
<td>.70 (.64)</td>
<td>4.38 (1.42)</td>
</tr>
</tbody>
</table>
## Data: Chain Dynamics

<table>
<thead>
<tr>
<th>Potential Entrants</th>
<th>Incumbents</th>
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Executive Summary

Ericson and Pakes (1995) style dynamic game of chain competition

Per Period Profits
- Logit demand system (for chains in MSAs)
- Prices/profits determined by static ‘Nash’ pricing game

States and Actions
- Chain $f$ in market $m$ characterized by three own state variables $(\in M_{jft})$
  1. Number of stores per capita (may change over time)
  2. Format type (fixed over time)
  3. Perceived quality $\xi_{fm}$ (fixed over time, drawn upon entry)
- Controls are discrete and horizon is infinite
  - Firms choose entry, exit & investment actions, $a_{ft} \in A_f(M_{jft})$

Dynamic Estimation & Solution Approach
- Two-step (CCP) with value function approximation (VFA) and iteration
- VFA via random forest trained on per period profits
Dynamic Discrete Game

- Structure & notation follows closely Sweeting (2013).
- Grocery chains $f = 1, \ldots, F_m$ compete in MSAs $m = 1, \ldots, M$ in discrete periods $t = 1, \ldots, T$.
  - Markets differ by population levels ($pop_m$) and growth rates ($g_m$).
- Firms compete by offering a fixed basket of groceries consumers.
  - Chains differentiated by (basket) price and characteristics of chain.
  - Chain characteristics: format (SC or SM), store count, and quality ($\xi$).
- Assume chains set (market-level) prices to maximize flow profit $\pi(M_{jft})$
Product Market Competition

Demand, Costs and Variable Profit

- Utility given by

\[ u_{ift} = \gamma^{pm} + \gamma^{pm}_o \cdot SC_f + \gamma^{pm}_d \cdot \frac{stores_{ft}}{pop_t} - \gamma^{pm}_p \cdot p_{ft} + \zeta_f + \Delta \zeta_{ft} + \epsilon^{pm}_{ift} \] (1)

- Variable profits are constructed as

\[ \pi^\gamma_{ft} = (p_{ft} - mc_{ft}) \cdot s_{ft} \cdot pop_t \] (2)

where the dependence of \( p, mc \) and \( s \) on the current state is suppressed for brevity.

- Costs related to chain features via

\[ \ln(mc_{ft}) = \gamma^{mc} + \gamma^{mc}_o \cdot SC_f + \gamma^{mc}_d \cdot \frac{stores_{ft}}{pop_t} + \epsilon^{mc}_{ft} \] (3)

- Static parameters recovered using standard methods, treated as known in what follows.
Dynamics: Investment, Entry & Exit

- Assume $\zeta$ assigned randomly upon entry and format remains fixed
  - Note that incumbent actions do depend on $\zeta$ (and format) through the firm’s beliefs regarding future profits...

- Therefore, main dynamics are in
  - How many stores to open/close or whether to exit (incumbents)
  - Whether to enter and how many stores to build (entrants)
  - But there is dynamic selection in quality
Actions and Adjustment Costs

- Firms are assumed to make optimal decisions given their current state: store counts, firm types and quality levels.
- Denote state vector $M_{jft}$, where $j$ distinguishes a firm $f$’s state in period $t$.
- Per-period flow profits are denoted $\pi(M_{jft})$.
  - Includes variable profit from grocery sales and Fixed Cost of adjusting state $C(a)$.
    - Opening/closing stores, entering/exiting markets
    - Per-period fixed costs ‘normalized’ to zero.
- Incumbent firm actions $a_{ft} \in A_f(M_{jft})$ include opening and closing stores, or exiting.
- Potential entrants can enter (with 1 or 2 stores), or stay out.
  - Each action paired with a T1EV shock, $\varepsilon_{ft}(a_{ft})$. 

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Flow Profits

• The flow profit of firm $f$ in $t$ can now be written

$$\pi_{ft}(a_{ft}, M_{jft}, \theta, \gamma) + \theta^\varepsilon \varepsilon_{ft}(a_{ft})$$

$$= \pi^v(M_{jft}, \gamma) - C(a_{ft})\theta^C + \theta^\varepsilon \varepsilon_{ft}(a_{ft})$$  \hspace{1cm} (4)

• Variable profits depend on current state $M_{jft}$, but costs incurred at $t$ change state at $t + 1$ ("time to build" assumption)

• Key parameters of interest are $\gamma$’s (static) and $\theta$’s (dynamic)
  - Static parameters can be recovered from demand system and pricing FOCs
  - Dynamic parameters inferred from actions $\rightarrow$ need to account for future implications (continuation values)

• To infer dynamic parameters, need to match choices to valuations.
Value Functions

- Assume firms play stationary MPE, with strategies $\Gamma_f : (M_{jft}, \varepsilon_{ft}) \rightarrow a_{ft}$.
- Firm $f$’s value in state $(M_{jft}, \varepsilon_{ft})$ when it employs an optimal strategy (and all rivals follow $\Gamma$) is given by:

$$V_{\Gamma}^f (M_{jft}, \varepsilon_{ft}) = \max_{a \in A_f (M_{jft})} \left[ \pi (a, M_{jft}) + \theta^\varepsilon \varepsilon_{ft} (a) \right.$$  

$$+ \beta \int \tilde{V}_{\Gamma}^f (M_{jft+1}) g (M_{jft+1} | a, \Gamma_{-f}, M_{jft}) dM_{jft+1} \big]$$

where $g(\cdot)$ is transition kernel (given $a$ and $\Gamma_{-f}$) and $\tilde{V}_{\Gamma}^f (M_{jft+1})$ is the integrated value function (IVF)

$$\tilde{V}_{\Gamma}^f (M_{jft}) = \int V_{\Gamma}^f (M_{jft}, \varepsilon_{ft}) f (\varepsilon_{ft}) d\varepsilon_{ft}$$
CCPs, CSVFs and IVFs

- T1EV ε’s provide analytic solutions for CCPs (strategies)

\[ P^{\Gamma_f}(a, M_{jft}, \Gamma_{-f}) = \frac{\exp \left( \frac{v_f^\Gamma(a, M_{jft}, \Gamma_{-f})}{\theta} \right)}{\sum_{a' \in A_f(M_{jft})} \exp \left( \frac{v_{f'}^\Gamma(a', M_{jft}, \Gamma_{-f})}{\theta} \right)} \]  

(7)

where \( v_f^\Gamma(a, M_{jft}, \Gamma_{-f}) \) is the choice specific VF (CSVF)

\[ v_f^\Gamma(a, M_{jft}, \Gamma_{-f}) = \pi(a, M_{jft}) + \beta \int \tilde{V}_f^\Gamma(M_{jft+1}) g(M_{jft+1}|a, \Gamma_{-f}, M_{jft}) dM_{jft+1} \]  

(8)

- IVF also simplifies to

\[ \tilde{V}_f^\Gamma(M_{jft}) = \ln \left[ \sum_{a_t' \in A} \exp(v_f^\Gamma(a_t, M_{jft}, \Gamma_{-f})) \right] + \lambda^{Euler} \]  

(9)
Estimation Approach

- Estimation matches observed choices to those in data

\[ P_{\Gamma}^{f}(a, M_{jft}, \Gamma_{-f}) = \frac{\exp \left( \frac{v_{f}^{(a,M_{jft},\Gamma_{-f})}}{\theta^e} \right) \right)}{\sum_{a' \in A_{f}(M_{jft})} \exp \left( \frac{v_{f}^{(a',M_{jft},\Gamma_{-f})}}{\theta^e} \right)} \]  

(10)

- Generic challenges of estimating DDC models
  - Computing \( v_{f}^{\Gamma} \); integrating over next period’s states.

- Specific challenge here
  - Continuous/very large state space.

- Solution
  - Value Function Approximation + CCP estimation
  - Alternative: Sieves (Arcidiacono et al., 2013; Barwick and Pathak, 2015)
Value Function Approximation

- Following Sweeting (2013), we use value function approximation paired with a two-step CCP approach.
  - Value function iteration for focal firm (Keane and Wolpin, 1994; Crawford and Shum, 2005)
  - CCPs for rivals (“two-step” approaches)
- Key difference: Approximate IVF using a random forest

\[
\bar{V}_f^\Gamma (M_{jft}) \approx \frac{1}{B} \sum_{b=1}^{B} \hat{\phi}_V^b (M_{jft})
\]

where

\[
\hat{\phi}_V^b (X) = \sum_{n=1}^{N} \hat{\mu}_n 1(X \in R_n)
\]

where \(1(X \in R_n)\) indicates being in region \(R_n\) (one of \(N\) partitions of the regressor space), and \(\hat{\mu}_n\) is the predicted value for region \(R_n\).
Random Forest and Approximating States

- Approximate VF on subset/aggregation of full state vector $f(M_{jft})$.
  - e.g. own state but summary stats for rivals, plus market shares & profits
- Call these variables the “approximating state variables”.
- Choose partitions and weights of forest by fitting PDV of (observed!) flow profits to approximating state variables.
  - Exploits ‘shape’ of profit function in selecting ‘shape’ of VF (Barwick and Pathak, 2015)
  - Discrete/interactive structure better captures VF discontinuities due to rival entry/exit
  - Split-sample variable selection
- Only done once at start of procedure.
- Freeze partitions during dynamic estimation, update only leaf values ($\hat{\mu}_n$’s) during VF iteration.
List of Approximating States

Variables used in the value function approximation:

- Own Q: Own Quality Level
- Avg Opp Q: Average Quality Level of the Opposing Chains currently in the Market
- Own Dens: Own Density
- Avg Opp Dens: Average Density of the Opposing Chains currently in the Market
- SC Dnum: Dummy Variable for being a SuperCenter
- Num Stores: Current number of stores owned by the chain
- Num SC: Total Number of Supercenter Chains in the Market
- Num SM: Total Number of Supermarket Chains in the Market
- Grow: Growth rate
- Pop: Population (in 10,000s)
- Own Q - Max Q: Own Quality Level less the Maximum Level of Quality of others in the Market
- Own Q - Min Q: Own Quality Level less the Minimum Level of Quality of others in the Market
- Own Q - W Avg Q: Own Quality Level less the weighted (by number of stores) Average Level of Quality of others in the Market
- Own Store - Max Store: Total Number of Stores you own less the Maximum Number of Stores of others in the Market
- Own Store - Min Store: Total Number of Stores you own less the Minimum Number of Stores of others in the Market
- Proportion of Stores in Market: Number of Stores you Own Divided by Total number of stores in the market (including your stores)
- Market Share: Current Market Share
- Own Profit: Current Period Profit
Estimation Procedure: Preliminary Stage

1. Estimate demand and mc parameters (2SLS/OLS)
2. Estimate reduced form CCPs (on natural states) using observed choices (flexible MNL)
3. Choose set of approximating states variables
4. Build value function approximation grid (observed + perturbations, \( N = 11000 \) points)
5. Train random forest on grid with PDV of variable profits as initial IVF ‘outcome’. Save partitions.
6. Enumerate the set of one-period-ahead states and the frequency with which they occur (for integrating over \( g(\cdot) \)).
Policy Function Estimation

Purpose: Estimate policy functions that govern state transitions
  - Construct CCPs and simulate $g(\cdot)$ functions
Implementation: flexible MNLs
Parameter estimates in appendix

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Results from Demand Estimation

- Utility parameter estimates

\[ \hat{u}_{ift} = 1.64 + 0.063 \cdot SC_f + 5.60 \cdot \frac{stores_{ft}}{pop_t} - 0.049 \cdot p_{ft}, \quad R^2 = 0.49 \]

where \( SC_f \) is SC dummy & regression includes 18,889 observations over 1,762 firms.

- The corresponding marginal cost estimates are

\[ \ln(mc_{ft}) = 4.32 - 0.237 \cdot SC_f - 0.301 \cdot \frac{stores_{ft}}{pop_t}, \quad R^2 = 0.27 \]

and include 651 observations.

- Predicted gross margins (\( \approx 28\% \)) match literature (\( \approx 27-31\% \)) very closely.
- SCs have big \( mc \) advantage, but density offsets (slightly).
- ‘Back of Envelope’ Static Welfare Calculation: Adding Wal-Mart \( \uparrow \) CS by about 12%.
Limitations of Static Analysis

- Static welfare analysis ignores supermarkets' equilibrium response to Wal-Mart's entry
  - Changing characteristics; exit & consolidation
- Static supply side analysis ignores extensive margin
  - Some firms closed stores & traded down
  - Others opened stores & expanded offerings
- Solution:
  - Estimate full dynamic oligopoly framework
  - Solve for equilibrium prices, quantities & characteristics
Estimation Procedure: Dynamic Parameters

1. Choose initial guess of adjustment cost parameters $\theta_i^C$.

2. Calculate flow profit for each point on the VFA grid (add adjustment cost to precomputed $\pi^v(M_{jft})$ value).

3. Solve for the (approximate) value function by iterating on the Bellman equation ((9) and (8)) until tolerance is reached (1e-4), updating RF projection at each step.

4. Update final random forest projection using converged IVF values for all points on the VFA grid.

5. Using fitted values from random forest, compute model implied CCPs from (7).

6. Update $\theta_i^C$ using PML estimator matching model implied CCPs to choices observed in the data (Aguirregabiria and Mira, 2007).

7. Stop if convergence in $\theta_i^C$ reached, otherwise return to step 1.
### Dynamic Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>SM Cost Per Store</td>
<td>-20.317296</td>
</tr>
<tr>
<td>SM Scrap Value Per Store</td>
<td>3.3597981</td>
</tr>
<tr>
<td>SC Cost Per Store</td>
<td>-15.569178</td>
</tr>
<tr>
<td>SM Entry Cost (per 10,000 people)</td>
<td>-0.5461629</td>
</tr>
<tr>
<td>SC Entry Cost (per 10,000 people)</td>
<td>-2.6227452</td>
</tr>
<tr>
<td>Scale (x log population)</td>
<td>0.5445898</td>
</tr>
<tr>
<td>Scale (x SC dummy)</td>
<td>0.3653624</td>
</tr>
</tbody>
</table>

Standard Errors TBD.

- Average store entry cost for SMs: $200M
  - Average SV for SMs: $33M
- Average store entry cost for SCs: $150M
Do These Costs Make Sense?

- Conditional ECs and SVs:
  - Average store entry cost for SMs: $162M
  - Average SV for SMs: $73M
  - Average store entry cost for SCs: $138M

- Interpretation
  - Aguirregabiria and Suzuki (2014): Under $FC = 0$ normalization, estimated EC and SV parameters are true EC and SV plus PDV of Fixed Costs for life of investment.
    - Average Var Prof for entering SM is $4.1M ($83M NPV)
    - Exiting SM: $2.7M ($57M NPV)
    - Average Var Prof for entering SC is $37M ($220M NPV)
Counterfactuals

- Simulate three scenarios
  1. No Walmart at all
  2. Walmart can enter, but supermarkets must stay
  3. Walmart can enter, and supermarkets react

- Comparing 2 to 1 is like static analysis
- Comparing 3 to 1 includes dynamic reaction (MPE)
Counterfactuals

- Walmart enters, Supermarkets stay

<table>
<thead>
<tr>
<th>Counterfactual Type</th>
<th>Consumer Surplus</th>
<th>Avg Store Density</th>
<th>Avg Chain Quality</th>
<th>Average Price</th>
<th>Avg SM Price</th>
<th>Avg SC Price</th>
<th>Avg SM Share</th>
<th>Avg SC Share</th>
<th>% Markets with SCs</th>
<th>Avg Number SM Firms</th>
<th>Avg Number SC Firms</th>
<th>Profit (Millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No SC</td>
<td>15.698</td>
<td>0.937</td>
<td>0.079</td>
<td>94.538</td>
<td>94.538</td>
<td>0.098</td>
<td>5.675</td>
<td>119.034</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SC, but SMs stay</td>
<td>18.606</td>
<td>1.079</td>
<td>0.073</td>
<td>92.457</td>
<td>94.182</td>
<td>80.268</td>
<td>0.092</td>
<td>0.151</td>
<td>0.721</td>
<td>5.312</td>
<td>1.079</td>
<td>130.250</td>
</tr>
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- Walmart enters, Supermarkets react

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<tr>
<td>SC, but SMs react/reposition</td>
<td>18.717</td>
<td>1.033</td>
<td>0.045</td>
<td>92.107</td>
<td>94.796</td>
<td>80.405</td>
<td>0.130</td>
<td>0.154</td>
<td>0.780</td>
<td>3.868</td>
<td>1.145</td>
<td>143.848</td>
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Conclusions/Summary

- Propose & estimate dynamic model of retail oligopoly.
- Combine ML + CCP + ADP techniques to address scale of problem.
- Isolate & quantify sources of Walmart’s competitive advantage (MC vs. FC).
- Distinguish short vs. long run implications of Walmart entry.
- Highlight potential downside (reduced variety) of scale-based retail innovation (natural oligopoly?).
References


