

Repositioning Dynamics and Pricing Strategy

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- Repositioning is a key aspect of strategic decision-making
- Examples include...
 - Product line (Kodak, Hyundai, Netflix)
 - Pricing/Promotion (Wegmans, P&G)
 - Branding (UPS, Domino's)
- Like initial entry, repositioning involves anticipating consumer & rival reactions; adapting to market conditions
- Unlike initial entry, it depends upon past decisions
 - You're no longer painting on a blank canvas...
 - ...some choices may preclude others

Motivation: Repositioning Costs

- Repositioning costs are substantial
 - Repositioning costs can be large relative to entry costs
 - Costs of undoing the past
 - Repositioning costs involve complex investments
 - Costs of managerial risk aversion, consumer resistance, channel conflicts ...
- Repositioning costs are substantial
 - Lower repositioning costs may constrain market power
- This paper proposes and implements a framework to empirically examine the dynamics of repositioning.

- We examine repositioning in the context of supermarket pricing strategies
- US retailing: broadly split between EDLP & Promo (Hi-Lo)
 - Promo can facilitate intertemporal PD
 - Also allows greater response to demand shocks
 - EDLP reduces inventory costs/stock-outs by smoothing demand
 - But is hard to make credible
- In late 90s, perception was Wal-Mart would drive everyone to EDLP

ROCHESTER, N.Y. -- Wegmans Food Markets here converted more than 4,000 grocery items to an everyday low-pricing program last week -- a move apparently designed to blunt the impact of Wal-Mart Supercenters that are beginning to proliferate in its upstate New York marketing area, industry observers told SN.

- The EDLP “revolution” did not come to pass
- To understand why, we need to tackle several questions
 - Which strategy yields higher revenues (& where)?
 - Which strategy dominates on costs (& why)?
 - Are complementary investments required?
 - What role do repositioning costs play and how are they determined?
 - How large are repositioning costs?
- We model strategic choice of pricing format as dynamic game of incomplete information
- Using data on revenue, pricing format & repositioning decisions, we quantify the revenue and cost side implications of these dynamic decisions.

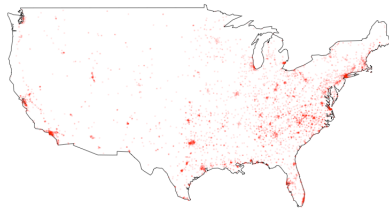
- The data on locations, store characteristics and revenue are drawn from the Trade Dimension TDLinx panel (yearly)
- The data on pricing strategies come from two additional frames collected by TD in 1994 and 1997.
- Store managers were asked which merchandising program best described their store
 - EDLP: Little reliance on promotional pricing strategies such as temporary price cuts. Prices are consistently low across the board, throughout all packaged food departments.
 - PROMO/Hi-Lo: Heavy use of specials - usually through manufacturer price breaks or special deals.
 - Hybrid: Combination of EDLP and Hi-Lo pricing (e.g. across categories).

Descriptive Statistics

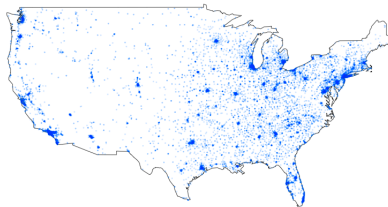
	Mean	Std Dev	Range
Market Demographics			
Population (in 1000s)	22	15.2	[0,112]
Per Capita Income (in \$1000s)	33.9	12.8	[0,135]
Median Rent (in \$s)	487.7	163.2	[0,1001]
Share Urban	.78	.33	[0,1]
Share Hispanic	.075	.143	[0,.979]
Share Black	.101	.179	[0,.995]
Market Structure (1994)			
All Stores	2.58	1.86	[1,16]
Chain Stores	2.08	1.78	[0,14]
Share EDLP	.282	.367	[0,1]
Wal-Mart in Local Market	.002	.024	[0,1]
Wal-Mart in MSA	.100	.300	[0,1]
Market Structure (1998)			
All Stores	2.57	1.82	[1,14]
Chain Stores	2.02	1.74	[0,13]
Share EDLP	.281	.371	[0,1]
Wal-Mart in Local Market	.009	.061	[0,1]
Wal-Mart in MSA	.466	.499	[0,1]

Pricing Landscape

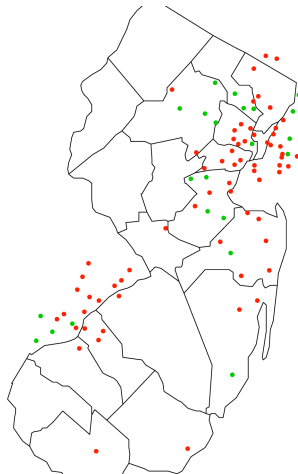
EDLP Stores



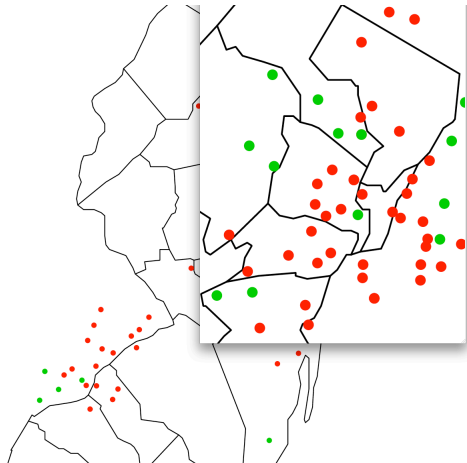
Promo Stores



Pathmark - New Jersey



Pathmark - New Jersey



LANDOVER, Md. -- Giant Food here is doing an about-face in its pricing and merchandising philosophies at its Northern division stores, which operate under the name Super G. The pricing change -- a switch to everyday low pricing -- will enable the chain to differentiate itself from its competition, while the merchandising change -- carrying products that meet local demand -- will make it easier to blend in.

...Until late May, the Giants and Super Gs had been virtually identical, except for the name. However, a Giant spokesman told SN last week that Giant has replaced its traditional highlow pricing format at the nine Super Gs with an everyday-low-pricing approach "due to competition."

Ellickson & Misra (2008) provide additional face validity and evidence of local variation.

Incumbent Choices

Counts	PROMO 98	EDLP 98	EXIT
PROMO 94	9314	494	1673
EDLP 94	836	3180	715

Probabilities	PROMO 98	EDLP 98	EXIT
PROMO 94	.575	.030	.103
EDLP 94	.051	.196	.044

Transitions	PROMO 98	EDLP 98	EXIT
PROMO 94	.811	.043	.146
EDLP 94	.177	.672	.151

Incumbent Choices (The Wal-Mart Effect)

No WalMart in Market			
	PROMO 98	EDLP 98	EXIT
PROMO 94	.819	.039	.142
EDLP 94	.185	.666	.149

WalMart in Market			
	PROMO 98	EDLP 98	EXIT
PROMO 94	.745	.080	.175
EDLP 94	.113	.719	.167

States and Actions

- Discrete time & discrete actions
- Two firm types: Supermarkets & Wal-Mart
- Players are stores in local markets (zip codes)
 - Incumbent SMs choose whether to exit, offer Promo, or offer EDLP
 - Potential SM entrants either stay out, enter Promo, or enter EDLP
 - WM only chooses enter/EDLP
- Assume independent decisions across markets (but allow FC to depend on network choices)

The Firm's Decision Problem

- Firms choose actions $d_t^i \in D_i$ to maximize expected discounted profits

$$E \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau-t} \tilde{\Pi}^i \left(x_{\tau}, d_{\tau}^i, d_{\tau}^{-i}, \epsilon_{\tau}^i \right) | x_t, \epsilon_t^i \right\}$$

where

- $\tilde{\Pi}_i(\cdot)$ is firm i 's per period profit function,
 - β is a common discount rate,
 - x_t is common state vector capturing market structure/demo &
 - ϵ_t^i is a privately observed "shock" to profits.
- Assume (x_t, ϵ_t^i) follows controlled Markov process with transition probability $f(x_{t+1}, \epsilon_{t+1}^i | x_t, d_t^i, \epsilon_t^i)$

Assumptions

Assumption 1: *Additive Separability:*

$$\tilde{\Pi}^i \left(x_t, d_t^i, d_t^{-i}, \epsilon_t^i \right) = \Pi^i \left(x_t, d_t^i, d_t^{-i} \right) + \epsilon_t^i$$

Assumption 2: *Conditional Independence:* $f(\cdot|\cdot)$ factors as

$$f(x_{t+1}, \epsilon_{t+1}^i | x_t, d_t^i, \epsilon_t^i) = f(x_{t+1} | x_t, d_t^i) g(\epsilon_{t+1}^i)$$

Assumption 3: *Independent Private Values:* Private information is independently distributed across players

$$g(\epsilon_t) = \prod_{i=1}^N g(\epsilon_t^i)$$

Assumption 4: *T1EV:* $g(\cdot)$ is the pdf of the T1EV distribution

Choice Probabilities & Per-period Payoffs

- Focus on anonymous Markovian strategies.
- Given player j 's conditional choice probability (CCP) $p^j(d_t^j|x_t)$, we can express player i 's beliefs (and ours) regarding its rival actions as

$$P(d_t^{-i}|x_t) = \prod_{j \neq i}^I p^j(d_t^j|x_t) \quad (1)$$

- Player i 's expected current payoff is then

$$\pi^i(x_t, d_t^i) = \sum_{d_t^{-i} \in D} P(d_t^{-i}|x_t) \Pi^i(x_t, d_t^i, d_t^{-i}) \quad (2)$$

Bellman Equation & CSVF

- Player i 's value function is given by

$$V_t^i(x_t, \epsilon_t) = \max_{d_t^i} \left[\pi^i(x_t, d_t^i) + \epsilon_t + \beta \int V_{t+1}(x_{t+1}, \epsilon_{t+1}) f^i(x_{t+1} | x_t, d_t^i) g(\epsilon_{t+1}) dx_{t+1} d\epsilon_{t+1} \right]$$

- To connect values to choices we employ the choice specific value function (CSVF)

$$v_t^i(x_t, d_t^i) \equiv \pi^i(x_t, d_t^i) + \beta \int \bar{V}_{t+1}^i(x_{t+1}) f(x_{t+1} | x_t, d_t^i) dx_{t+1}$$

- Since we have a terminal choice (exit, denoted d_t^{*i}) whose payoff we normalize to zero, the CSVF simplifies to

$$v^i(x_t, d_t^i) = \pi^i(x_t, d_t^i) - \beta \int \ln[p^i(d_{t+1}^{*i} | x_{t+1})] f^i(x_{t+1} | x_t, d_t^i) dx_{t+1} + \beta \gamma$$

(see Altug & Miller (1998) and Arcidiacono & Miller (2011))

Choices and Choice Probabilities

- As in a static choice problem, firm i 's optimal decision rule satisfies

$$\delta_t^i(x_t, \epsilon_t) = \arg \max_{d_t} \left[v_t^i(x_t, d_t) + \epsilon_t \right] \quad (3)$$

- Integrating over ϵ_t yields the associated CCPs

$$p^i(d_t^i | x_t) = \frac{\exp(v^i(x_t, d_t^i))}{\sum_{d_t^i \in \mathbb{D}_i} \exp(v^i(x_t, d_t^i))} \quad (4)$$

- MPE requires that these best response probability functions accord with rivals beliefs (1).

Focal Player Type

- Focus of analysis is incumbent supermarkets (potential switchers)
- Their decisions depend on actions of all 4 player types
- We exploit incomplete information structure to bypass solving for equilibrium
 - condition on CCPs of all four types, only recover structural parameters for focal type
- Benefits
 - reduces computational burden
 - accommodates Wal-Mart's sparse action space

Decomposing Payoffs

- While we don't observe prices, quantities or costs, we do observe revenues.
- Incorporating revenues
 - facilitates dollar metric (but still need level normalization)
 - ... and a richer decomposition of choice problem
 - but does raise selection issues (only see them for chosen action)
- To incorporate the additional outcome data, we decompose per period profits as follows

$$\Pi^i(x_t, d_t^i, d_t^{-i}; \Theta) = R^i(x_t, d_t^i, d_t^{-i}; \theta_R) - C^i(x_t, d_t^i, d_{t-1}^i; \theta_C)$$

- To deal with selectivity, we partition observed revenues as

$$R^i(x_t, d_t^i, d_t^{-i}; \theta_R) = R(x_t, d_t^i, d_t^{-i}; \theta_R) + \eta_t^i(d_t^i) + \epsilon_t^i(d_t^i) \quad (5)$$

where η_t^i *unanticipated* but ϵ_t^i structural (same as before)

- $E(\epsilon_t^i(d_t^i) | d_t^i) \neq 0$: Use CCPs to construct appropriate control function
- Use selectivity corrected $R(\cdot)$ function to predict revenues
- Construct expected revenues as with $\pi^i(\cdot)$, i.e.

$$r^i(x_t, d_t^i) = \sum_{d_t^{-i} \in D} P(d_t^{-i} | x_t) R^i(x_t, d_t^i, d_t^{-i})$$

Parameterizations

- Heterogeneity is manifest: markets/consumers differ in format tastes
- We parameterize predicted revenue as a rich function of demographics and market/firm characteristics
 - Pop, income, HH size, %urban/black/Hispanic
 - Count of rival firms, rival share EDLP, WM in MSA, focus
 - Store and chain size
- Costs, which are latent, are further decomposed as follows

$$C^i(x_t, d_t^i, d_{t-1}^i; \theta_C) = FC^i(\tilde{x}_t, d_t^i; \theta_{FC}) + \mathbb{I}(d_t^i \neq d_{t-1}^i) RC^i(x_t, d_t^i; \theta_{RC})$$

where $FC^i(\cdot)$ represents fixed operating costs and $RC^i(\cdot)$ repositioning costs

- Both cost terms are treated as flexible functions of states & demographics

- Estimation takes place in three steps
 - ① Estimate (non-structural) CCPs and exogenous state transition functions (e.g. demographics)
 - ② Estimate selectivity corrected revenue functions (using 1) and construct expected revenues
 - ③ Match 'predicted' CSVF to empirical counterpart (inverted CCPs) via Minimum Distance
- Standard errors obtained by bootstrapping over markets

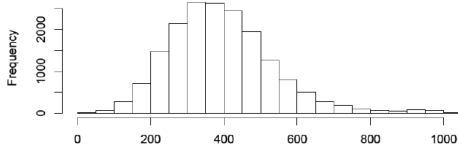
Identification

Mapping Data to Estimates

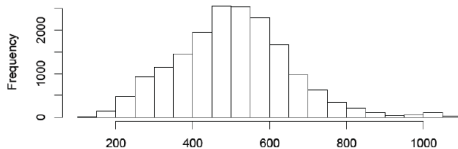
- Counterfactual Revenue
 - Identification comes from observed revenue data for both strategies (conditional on selectivity correction)
 - Selection Exclusion - Vertical Integration
- WalMart Effects
 - Distance to Bentonville
 - Distance to McLane distribution centers
- Strategic Interactions
 - Chain and Store Characteristics
- Costs
 - Identified from revenue data and action choice
 - Switching Costs identified from switching patterns (and exit)

Revenues by Pricing Strategy

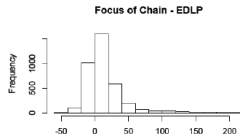
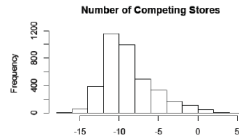
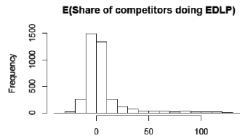
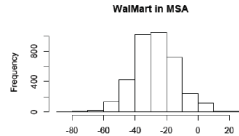
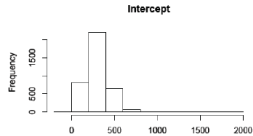
Counterfactual Revenues - EDLP



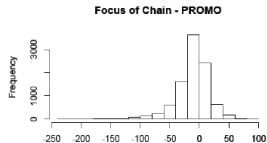
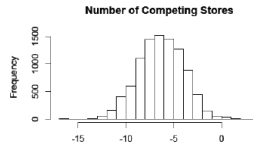
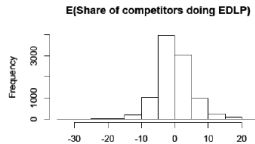
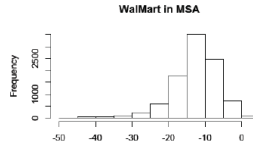
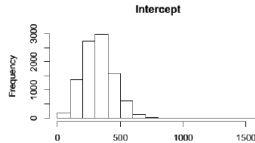
Counterfactual Revenues - PROMO



Revenue Components: EDLP



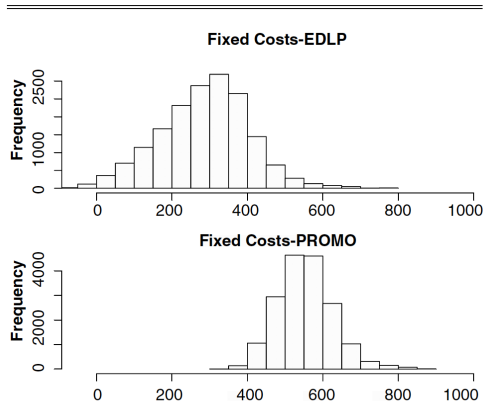
Revenue Components: PROMO



- PROMO has higher revenues...
 - \$6.4M on average for the median store/market
- Wal-Mart has a significantly higher negative impact on EDLP Revenues (than PROMO)
 - 133% higher!
- Scope economies for EDLP, not so for Promo
- Competition is also important
- Substantial heterogeneity across markets

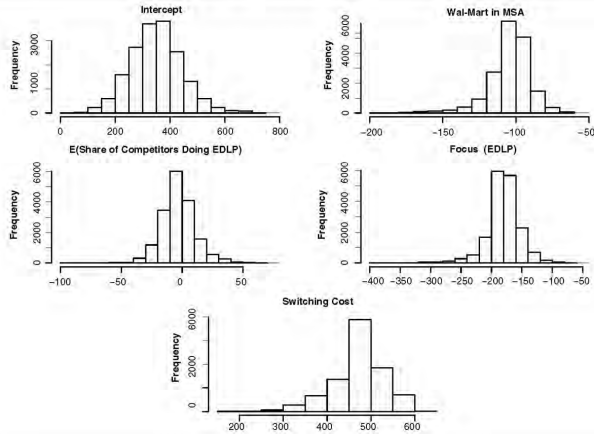
Fixed Costs by Pricing Strategy

Figure 5
ESTIMATED FIXED COSTS



Cost Components: EDLP

Figure 6
COST COMPONENTS OF EDLP



Cost Components: PROMO

Figure 7
COST COMPONENTS OF PROMO

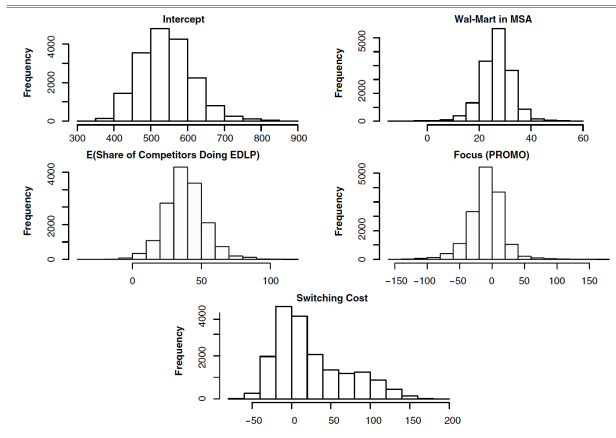


Table 9
DISTRIBUTION OF ESTIMATED COSTS

	5%	50%	95%
<i>EDLP</i>			
Intercept	201.20	349.04	510.47
Wal-Mart	-128.93	-102.75	-84.44
E(Share of competitors EDLP)	-24.33	-3.65	21.05
Focus of chain (EDLP)	-226.71	-179.66	-138.66
Total fixed costs (for Nonswitchers)	81.12	293.75	465.87
<i>PROMO</i>			
Intercept	433.89	538.61	665.55
Wal-Mart	17.17	27.05	35.60
E(Share of competitors' EDLP)	15.65	37.69	61.78
Focus of chain (PROMO)	-54.01	-7.48	26.90
Total fixed costs (for Nonswitchers)	440.83	550.17	677.98
Switching cost (EDLP to PROMO)	-30.36	11.13	112.13
Switching cost (PROMO to EDLP)	357.59	477.34	563.36

Discussion

Costs

- EDLP reduces fixed operating costs
- Wal-Mart lowers fixed costs for EDLP (increases for PROMO)
- Scale economies exist on cost side as well
- Repositioning Costs are large, asymmetric & heterogeneous
- Four times more costly to go from Promo to EDLP than the reverse
- Repositioning costs moderated by Wal-Mart, own scale
 - Wal-Mart lowers costs of switching to EDLP but raises costs of switching to PROMO
 - Switching into the focal strategy of the chain lowers repositioning costs

Epilogue

Beyond the 1990s

- Again, the domination of EDLP never came to pass.
- Our findings suggest that WalMart did have a significant impact on pricing strategy...
- ...but repositioning as EDLP was not for everyone
 - If you were not really an 'EDLP type', costs were large.
 - Sometimes cheaper to just give up!
- WalMart itself shifted away from pure EDLP with its “rollbacks”
 - Now moving back to “Mr. Sam's winning formula”

Conclusion

Repositioning Decisions

- There is limited research on how firms make repositioning decisions.
- In the context of supermarket pricing we have shown that these decisions are strategic and have dynamic considerations.
- More generally, the paper provides a framework for modeling and investigating repositioning.