

Advertising and Market Share Dynamics

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Introduction

- Sutton (1991)'s Model of Endogenous Sunk Costs
 - As market size increases,
 - (1) Market structure in *exogenous* sunk cost industries gets fragmented
 - (2) Market structure in *endogenous* sunk cost (ESC) industries remains unfragmented.
 - Crucial elements for ESC
 - (1) Quality improvement falls on *fixed* costs
 - (2) A significant fraction of responsive consumers

Introduction

- US mutual fund industry
 - (1) Load funds: sold through brokers; consumers not very responsive to mass advertising
 - (2) No-load funds: sold directly to investors; consumers responsive to mass advertising
- Significant market growth from 1985 to 2004
- Research Question: different consumer responsiveness to ads in two segments
 - how evolution of advertising choices and market structure differ between the two?

Introduction

- Roadmap

- (1) Show data patterns

: evolution of ad spending and concentration ratio in load vs. no-load segments

- (2) Empirical model of advertising dynamics

: estimation using BBL (2007)

- (3) Results & Discussion

- (4) Conclusion

Market Structure

Year	Load Segment			No-Load Segment		
	AUM (\$b)	C ₃	C ₅	AUM (\$b)	C ₃	C ₅
1985	437.47	33.00	44.76	311.46	37.83	48.41
1986	655.53	33.18	45.94	426.63	40.75	51.05
1987	665.29	29.97	43.51	454.08	40.88	52.25
1992	1103.41	24.42	34.66	777.64	51.16	59.21
1993	1352.60	23.17	33.34	950.73	51.76	60.13
1994	1370.95	23.43	33.30	951.44	53.51	61.81
2000	3289.60	20.68	29.10	2734.43	54.97	63.66
2001	3298.93	19.31	27.25	2607.13	53.28	63.75
2002	2976.79	19.37	27.86	2408.24	52.63	61.88
2003	3292.62	21.32	28.94	2833.40	52.19	60.43
2004	3367.65	25.15	31.78	3120.83	52.81	60.39 ⁵

Year	Load Segment (No. of firms)	No-Load Segment (No. of firms)
	50% of market: Dominant firms	50% of market: Dominant firms
1985	6	6
1986	6	5
1987	7	5
1992	10	3
1993	10	3
1994	10	3
1995	11	3
1996	11	3
1997	10	3
2003	13	3
2004	12	3

- Ad-sales ratio
(sales = assets × expense ratio)

	Load	No-load
Top 5	0.521	1.504
Others	0.175	0.316

Two Tired Market	Load Segment (in \$000)		No-Load Segment (in \$000)	
	Av. Spending by Big 5	Av. Spending by (Big 5) ^c	Av. Spending by Big 5	Av. Spending by (Big 5) ^c
1985	366.11	63.86	1252.92	27.51
1986	787.55	72.91	3516.40	87.92
1987	878.62	126.04	4398.76	97.48
1988	1210.09	90.42	5941.99	61.53
1993	4322.38	107.64	7063.19	145.25
1997	4239.10	306.54	9674.95	183.57
1998	5327.54	215.49	13262.68	224.72
1999	2226.62	321.32	12859.21	148.95
2001	511.94	329.84	12703.01	87.93
2002	585.06	290.37	4058.71	88.35
2003	4543.84	152.21	10528.22	67.62
2004	4710.76	221.80	14619.30	92.86

Are Big Firms Also Big Ad Spenders?

	Load Segment	No-Load Segment
1985	3	4
1986	2	3
1987	1	3
1991	3	5
1992	3	5
1993	3	4
1994	2	4
2000	2	4
2001	0	3
2002	1	3
2003	1	4
2004	2	5

Model of Advertising Competition

- Firms $j = 1, 2, \dots, N$, each producing one good
- Discrete time with infinite horizon $t = 0, 1, \dots$
- Firms compete in advertising and price
- Focus on large players; Persuasive advertising
- Model Components
 - (1) State space and timing
 - (2) State transition and goodwill accumulation
 - (3) Demand and profits
 - (4) Markov Perfect Equilibrium

- State space $s_t \in S$
 - $(3 \times N + 2) \times 1$ vector
 - for each firm j , τ_j (type: load (1) or no-load (0)), GW_{jt-1} (goodwill stock), μ_{jt} (quality)
 - quality of fringe (μ_{Ft}) common to all firms
 - market size M_t common to all firms
- Each period consists of two stages
 - stage 1: after observing state vector s_t and an iid private shock v_{jt}^A , each firm chooses A_{jt}
 - stage 2: after observing updated GW and an iid private shock v_{jt}^P , each firm sets P_{jt}

- State transition
 - τ is fixed over time
 - μ_{jt} and M_t stochastically evolve over time indep. of actions; $F_\mu(\mu_{jt+1} | \mu_{jt})$, $F_M(M_{t+1} | M_t)$
 - μ_{Ft} determined by fringe firms' actions, but modeled ad hoc for now; $F_{\mu_F}(\mu_{Ft+1} | \mu_{Ft}, \mu_t, M_t)$
 - GW_{jt} deterministically evolves as a finite distributed lag of advertising

$$GW_{jt} = \sum_{k=0}^q \lambda^k A_{jt-k} : \text{carry-over effects of advertising}$$

- Demand: discrete choice

$$U_{ijt} = X_{jt}\beta - \alpha P_{jt} + \xi_{jt} + \varepsilon_{ijt}$$

$$- X_{jt}\beta = (\beta_1 + \beta_2 T_j) \times \ln(GW_{jt}) + Past\ Perf_{jt} + stuff_{jt}$$

$$- P_{jt} : P_{1jt} \text{ (load)}, P_{2jt} \text{ (expense ratio)}$$

$$- \varepsilon_{ijt} \sim \text{type 1 extreme value distribution}$$

- Per-period profits

$$\pi_{jt} = (P_{2jt} - MC_{jt})Q_{jt} - FC_{jt} - (1 + v^A_{jt})A_{jt} - c_2(T_j) 1(A_{jt} > 0)$$

$$- Q_{jt} = M_t \times \text{market share}_{jt}$$

$$- MC_{jt} = c_1(T_j) + v^P_{jt}, v^P \sim N(0, \sigma^2_{vP})$$

$$- v^A \sim N(\mu_{vA}, \sigma^2_{vA})$$

- Markov strategy for firm j
 $\sigma_j: S \times v_j \rightarrow (A_j, P_j), v_j = (v_j^A, v_j^P)$
- Strategy profile $\sigma = (\sigma_1, \dots, \sigma_N)$
 $\sigma: S \times v_1 \times \dots \times v_N \rightarrow (A, P)$
- $F(s' | \sigma, s)$: transition probability of s given σ
- The ex-ante value function of firm j in state s when firms follow strategy profile σ

$$V_j(s|\sigma) = E_{v_j} \left[\pi_j(\sigma(s, v), s, v_j) + \delta \int V_j(s' | \sigma) dF(s' | \sigma(s, v), s) \mid s \right]$$
- Strategy profile σ is an MPE if for all j, s , and σ_j'
 $V_j(s|\sigma) \geq V_j(s|\sigma_j', \sigma_{-j})$

Data

- CRSP
 - Info on asset size, management company, investment objective, return, etc. of each fund
 - Categorize firms into either load or no-load
- Ad \$ Summary
 - Covers major media (TV, magazines,...)
 - Reports annual ad spending for each fund company
- Fed Flow of Funds
 - Market Size = Financial Assets held by domestic financial sector

Estimation - BBL (2007)

- Computationally light two-step estimator
- If we use Nested Fixed Point Algorithm (Rust, 1987), need to solve the dynamic programming repeatedly for each trial value of the parameter vector. But solving the dynamic game even once is computationally burdensome!
- Two-step estimator (BBL, 2007; AM, 2007):
 - Step 1: Recover what agents *do*
 - Step 2: Find parameter values that *rationalize* the observed behavior using forward simulation

Estimation - BBL (2007)

- Model 30 largest firms' choices
- The rest is aggregated into “fringe”; fringe not an active player
- First stage
 - (1) Demand
 - logit; do Berry inversion; use BLP-type IV
 - following A&R (2005), use $\ln(N)$ as a regressor
 - back out μ_{jt} and μ_{Ft}

	OLS Logit	IV Logit (IV for P)
β_1	0.251 (22.974)	0.247 (18.530)
β_2	-0.161 (-11.332)	-0.153 (-8.483)
λ	0.570 (7.040)	0.602 (5.696)
P_1	-0.008 (-0.587)	0.113 (0.874)
P_2	-50.716 (-29.692)	-150.486 (-8.490)
$\ln(N)$	-0.221 (-1.415)	0.247 (1.152)
Age	0.081 (5.920)	0.050 (2.932)
$1(\text{Age} < 2)$	-0.625 (-7.553)	-0.613 (-6.217)
Perf_{t-1}	2.351 (13.445)	0.969 (2.953)
Perf_{t-1}^2	-1.231 (-6.576)	0.050 (0.121)
Perf_{t-2}	1.985 (10.361)	0.056 (0.167)
Perf_{t-2}^2	-0.983 (-4.923)	0.571 (1.497)
No. obs	8153	8153
Adjusted R^2	0.674	0.537

Implied
own price
elasticity

OLS Logit	
P_1	-0.025
P_2	-0.735

IV Logit	
P_1	0.354
P_2	-2.183

: Consumers more responsive to ads by no-load firms than to ads by load firms; Other coefficients plausible

(2) State transition

- Estimate $F_{\mu}(\mu_{t+1} | \mu_t)$ as AR(1) process
- Estimate $F_{\mu_F}(\mu_{Ft+1} | \mu_{Ft}, \mu_t, M_t)$
- Estimate first-differenced market size as AR(1) for stationarity
- GW depreciation parameter λ from demand estimation

$$\mu_{jt+1} = -0.336 + 0.895\mu_{jt} + N(0, 0.47)$$

(0.090) (0.015) $R^2 = 0.90$

$$\mu_{Ft+1} = -0.987 + 0.223\mu_{Ft} + 0.010\sum\mu_t$$

+ 0.036($M_t/1000$) + $N(0, 0.098)$ $R^2 = 0.96$

$$\Delta M_{t+1} = 128.10 + 0.808\Delta M_t + N(0, 281.3)$$

(70.156) (0.097) $R^2 = 0.64$

(3) Product market competition

- static Bertrand-Nash
- back out MC and σ^2_{VP}

$$MC_j = 0.0003 + 0.0055T_j + N(0, 0.003)$$

- load firms hire wholesalers for sales pitch and give incentive pay, hence higher MC

(4) Policy function

- π_j has Inc. Diff. in $(A_j, -v^{A_j})$

$$\sigma^A(s, v^{A_j}) = F^{-1}(1 - \Phi(v^{A_j}/\sigma_{vA}) \mid s)$$

where $F(A_j \mid s) = Pr(\sigma^A(s, v^{A_j}) \leq A_j \mid s)$ is estimated as truncated normal (tobit)

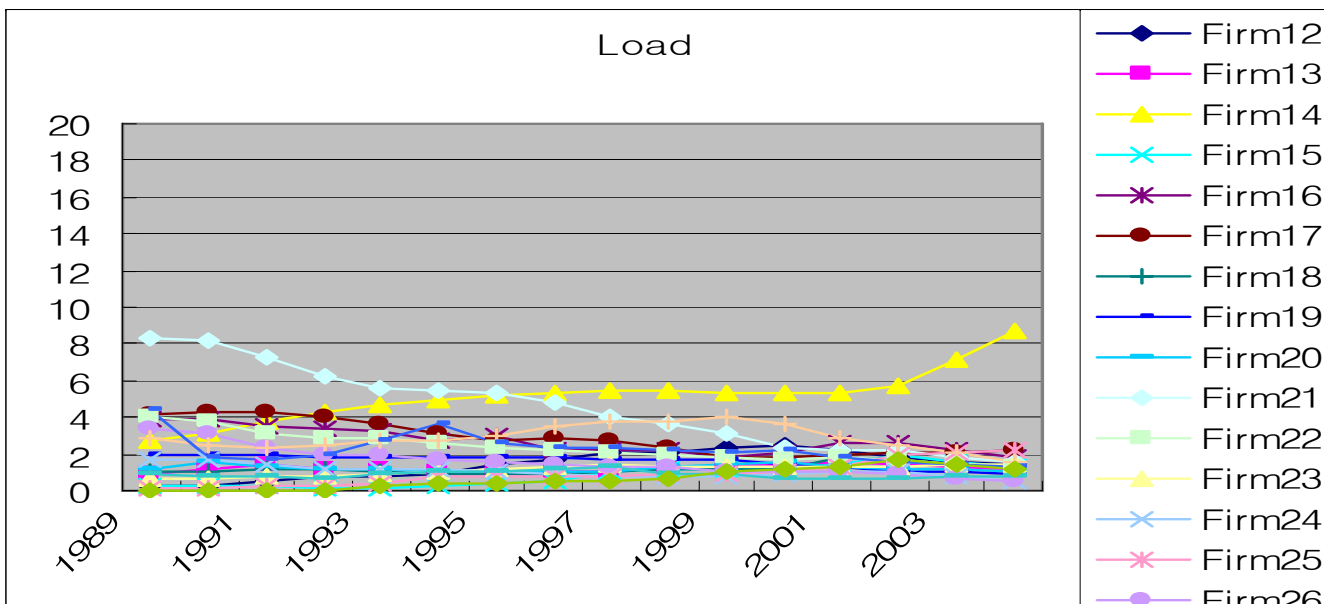
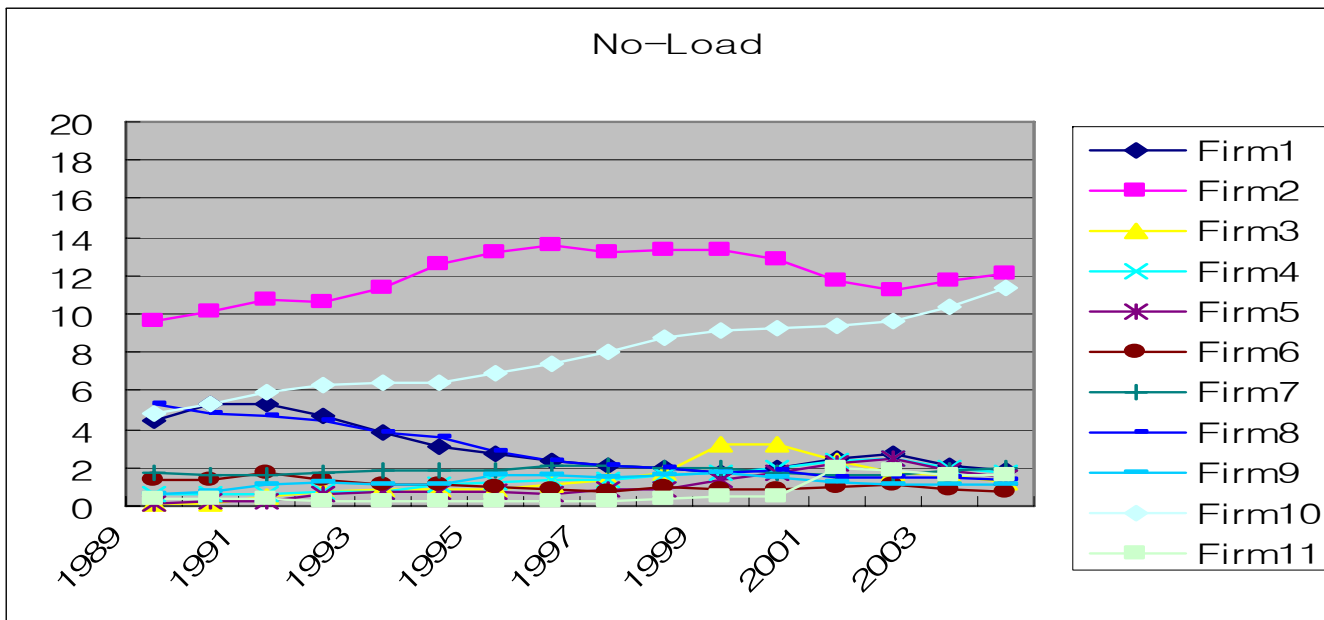
$$\begin{aligned} A_{jt} &= A_{jt}^* \text{ if } A_{jt}^* > 0 \\ &= 0 \text{ if } A_{jt}^* \leq 0 \end{aligned}$$

where $A_{jt}^* = f(\text{GW}_{t-1}, M_t, \mu_t, \mu_{Ft}) + N(0, \sigma^2)$

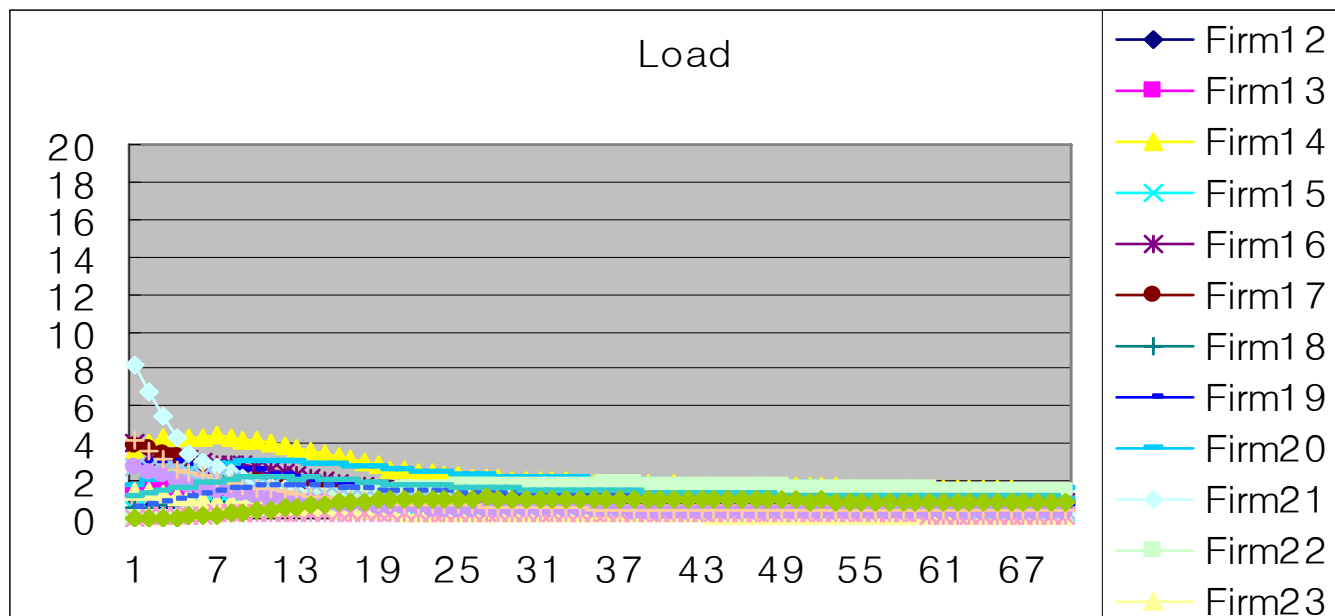
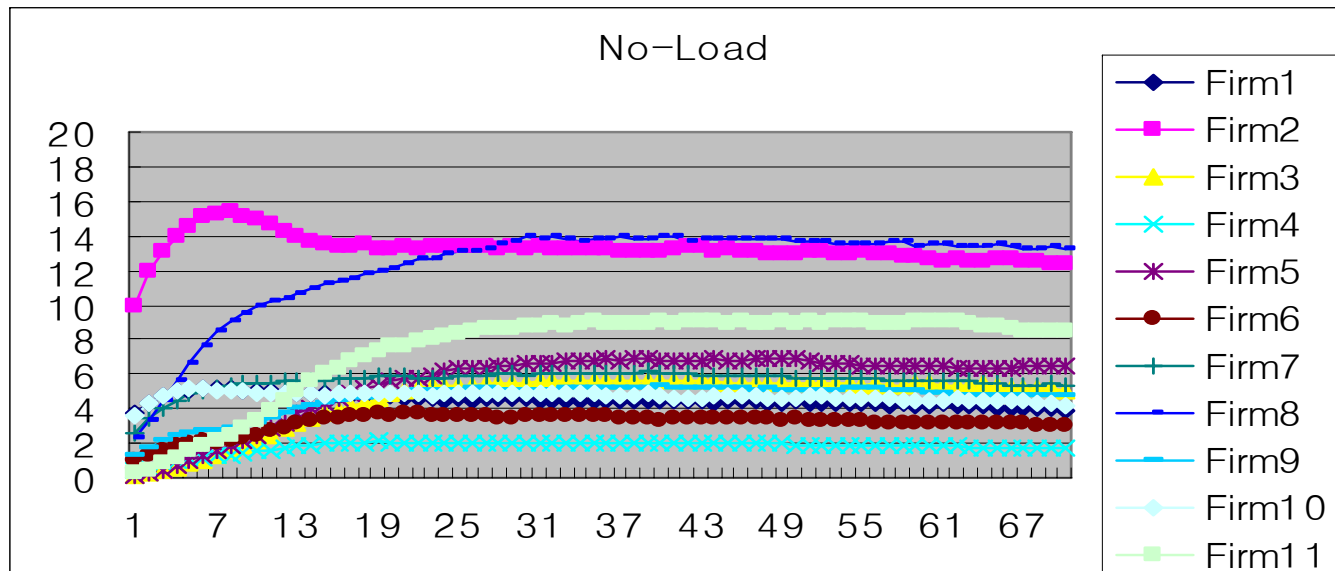
- Separately estimate for L and NL firms

- Second Stage
 - Remaining parameters ($\mu_{v_A}, \sigma^2_{v_A}, c_2(\tau_j)$) are estimated using forward simulation
 - Estimates:
$$\mu_{v_A} = 0.733; \quad \sigma^2_{v_A} = 2.396; \quad c_2(\tau_j) = 2.164 + 2.361 \tau_j$$
- Crucial to get policy functions right (extrapolation to states unobserved in data)
 - Compare actual market share dynamics to simulated paths to check the performance of estimated policy function

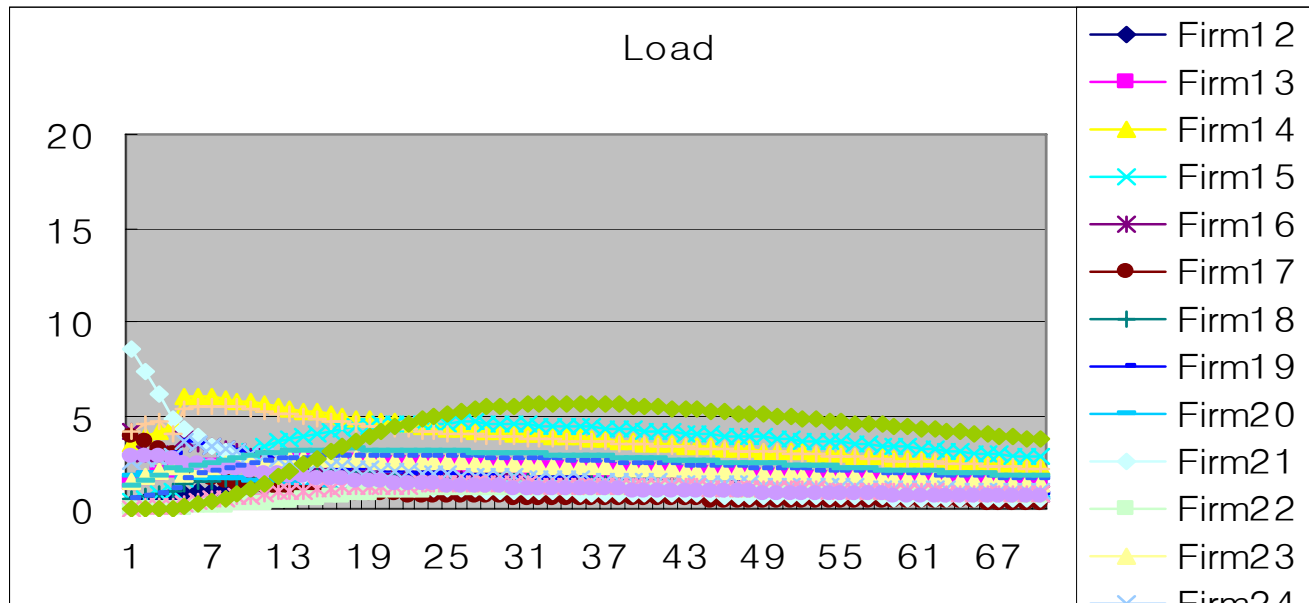
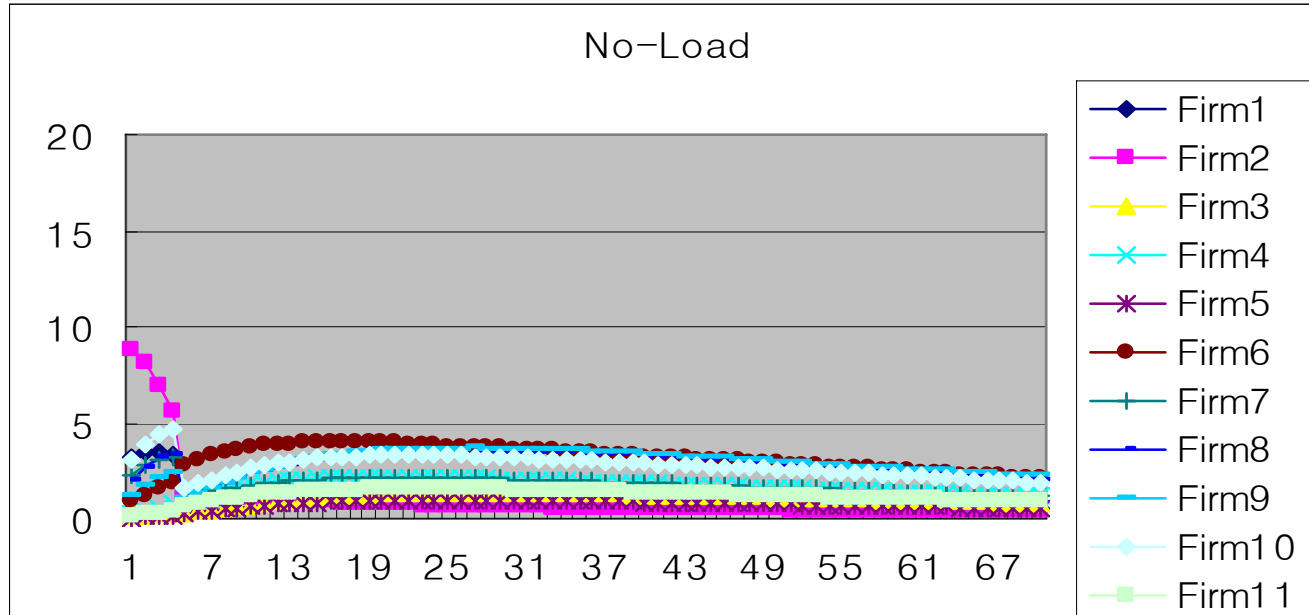
- Market Share Dynamics - Data



- Market Share Dynamics – Prediction



- Counterfactual: If no firm advertises



- Model does a reasonable job in explaining difference between L and NL segments
- But underestimates differences among firms within segment → need richer firm heterogeneity
- Advertising is an important strategic tool for keeping a concentrated market structure in a growing market

Conclusion

- Empirically show the role of advertising in keeping market structure concentrated
- Fill in the gap in empirical work on dynamic advertising
- Future Work
 - Deal with endogeneity of advertising in demand estimation
 - Add random coefficients in demand estimation
 - Add demand dynamics (due to switching costs)