Path Dependencies and the Long-term Effects of Routinized Marketing Decisions

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Path Dependencies and the Long-term Effects of Routinized Marketing Decisions

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Abstract

The purpose of this paper is to discuss a simulation of marketing budgeting rules that is based on a simplified version of the market share attraction model. The budgeting rules are roughly equivalent to those that may be used in practice. The simulation illustrates the concept of path dependence in dynamic marketing systems and shows how it might result from decision rules potentially applied by marketers and retailers. Path dependence results from positive feedback in dynamic systems that imparts momentum to market choices. Where the potential for path dependence exists, there are implications for defining and measuring long-term effects of marketing decisions in a way that is meaningful to managers and researchers. In the simulations presented we show that limited retail assortments may contribute to path dependence when firms use either percentage-of-revenue rules or "market learning" experiments to set budgets. While other budgeting procedures (e.g., matching competition) may stabilize market share, this stability in the share dimension comes at the cost of instability for budgets and profits.

1. Introduction

Researchers have questioned why managers continue to spend large sums on advertising in industries where disaggregate measures of advertising's effect on sales are minimal (Aaker & Carman, 1982; Abraham & Lodish, 1990). Some of the reasons proposed for the disparity between spending levels and apparent short-term effects are that the budgeting procedures, by which spending levels are determined, are too well ingrained: managers propose and approve budgets that are a fixed percentage of sales or to match competitive expenditures (Lodish, 1986). Certainly, a common thread running through the research into advertising budgeting practices is that the budgeting becomes routinized and institutionalized, a standard operating procedure or rule develops based on how the decision was made last time (Lodish, 1986; Anthony & Govindarajan, 1998). The first purpose of our paper is to explore the effect of budgeting rules on the path dependence. Path dependence in this paper refers to (some) market forces, once set in motion, may be difficult or impossible to reverse (Arthur, 1988). Some of the routinized budgeting rules have been explored in other domains, for example, Nelson and Winter's (1982) and Dickson (1996). Our study extends previous work in two ways: we include rules with a capacity for "market learning" through experiments and secondly we couple manufacturer budgeting rules with the effects of retailer stocking rules. For consumer packaged goods, one important routine is the decision rule used by retailers to discontinue slow-moving products. The decision-making behavior we study is that of restricting category assortment to brands that have a minimum share of market. Almost all retailers practice this "limited assortment" policy, to some degree.

The second purpose of our paper is to discuss what the long-term effects of marketing decisions mean from the perspective of complexity theory (Nicolis & Prigogine, 1989). Where there is path dependence, it may become very difficult to assess long-term effects of marketing investments. For example, when we speak of the long-term effects of a given marketing campaign, do these long-term effects include a particular sequence of retailer and competitor reactions? If no particular sequence is conjectured, are the results assumed to hold regardless of how competitors and retailers react? Given some uncertainty about these reactions, how should the analysis reflect the possibility that a given marketing action will trigger positive feedback? Eventually, the approach of using simulations may prove useful as learning tool for managers to improve their ability to conjecture about the future (Dickson, Farris & Verbeke, 1997; Reibstein & Chussil, 1997). Another possible application of this work is to give managers a better sense of the potential instability and marketing resource allocation risk in their markets. Historical patterns only show us what did happen, not that it had to happen that way (Araju, Easton, Georgieva & Wilkinson, 1996). Projecting what will happen, even if we know the causal processes very well, will always entail risk. Modeling processes without explicitly recognizing the element of risk is of questionable managerial or economic usefulness.

2. Marketing Budgeting and Path Dependence

In this section we will review some basic concepts underlying path dependence and show how they are related to resource allocation rules of marketers and retailers.

2.1. Positive Feedback and Perturbations

Markets are increasingly viewed as evolutionary, complex systems (Arthur, 1988; 1996). This sensitivity of evolutionary paths to a set of initial conditions prevailing at critical stages in the market evolution has been termed "path dependence [1]" (Arthur, 1988). Generally, path dependence results from positive feedback loops (Diehl & Sterman, 1995) that "account for the processes of growth and decline" (Forrester, 1961). Negative feedback loops are associated with stability. An implication of path dependence is that there are "windows of opportunity" where a little marketing effort may go a long way in determining market share winners and losers. Much of the research on path dependence has focused on the long-term response of a system of deterministic equations to a single "perturbation" (Arthur, 1988). We believe this focus is misplaced, because most marketing systems are constantly subjected to unpredictable influences of varying magnitudes (Winsor, 1995). Would a market that is sensitive to a single small perturbation also exhibit the same path dependencies with larger and more frequent random shocks? (Lusch & Laczniak, 1989).

[1] A related concept is "hysteresis" (DeKimpe & Hansen, 1995; Simon, 1997).

2.2 Positive Feedback and Marketing Budgeting

The potential for positive and negative feedback loops and perturbations from the imperfections in the processes exists in routinized marketing budget rules, consumer purchase behavior, and retail assortment decisions. Budgeting for marketing (which for our purposes includes advertising, promotion and R&D) is an ongoing process that is fraught with uncertainty for most companies (Lodish, 1986). Many "methods" are applied, and most firms seem to use more than one approach. Hung and West (1991) suggest that the major budgeting techniques fall into four categories: percentage of sales (unit or dollar, past or anticipated), competitive matching (absolute or relative to share), "affordable" (what is "left" of profits), and "objective and task." The last method is a loose form of short-term management calculus involving estimates of costs and benefits of spending. Taking competitive spending into consideration and insisting on a short-term payback of advertising expenditures might be considered a combination of the "affordable" and "objective and task" methods. This combination involves estimating a response function and solving for the profit-maximizing expenditure level for the next period. It is easy to see that some of the rules of thumb, such as “% of sales” or “match competition” could produce positive feedback. What is not so obvious is whether the same potential is present in other, more sophisticated budgeting procedures. While Hung and West (1991) provide evidence that firms are becoming more technically sophisticated in their tactical approaches to budgeting (short-term estimation of customer response functions), it is not clear which methods are indeed the most sophisticated from a strategic perspective. Strategy must surely involve anticipating competitive and retailer reactions and taking those into account.

One of the simplest (and most popular) methods of taking competition into account is the use of “attraction” model (Hanssens, Parson & Schultz, 1990). Typically, attraction models entail a calculation of the form “us/(us + them).” Although a number of market share models are constructed along similar "attraction" principles, we believe the competitive dynamics of such models are poorly understood, even when simplifying assumptions are made. When share of market is equated to share of marketing budgets, with a market assumed constant in size, the long-term marketing-sales response function depends almost totally on the reaction of competitors to each other. Depending on the competitive reaction to changes in brand *i*'s marketing, marginal returns to brand *i*'s spending can be positive, zero, or even negative. To clarify, suppose brand *i* sets its marketing budget according to the expectation that share of market will equal share of marketing, as represented in equation (1).

$$(1) \qquad P_{it} = \frac{M_{it}}{\sum_j M_{jt}}$$

Where P_{it} = share of consumer preference for brand *i* at time *t* and

M_{it} = market expenditures for brand *i* at time *t*.

Depending on how competitors react to brand *i*'s budget changes, the marginal returns to brand *i* will be qualitatively different. It is apparent that once competitor reactions are considered, even this simple formulation becomes potentially quite complex. For example, suppose competitors do not change their budgets, then equation (1) implies a positive, but diminishing, incremental returns function to marketing dollars (more marketing dollars buy an ever decreasing increase in share of marketing). If competitors simultaneously match percentage changes in brand *i*'s marketing, there are zero returns to brand *i* for increased marketing. If competitors increase marketing by an even larger percentage, returns to brand *i* for more marketing is negative. If competitors decrease their marketing budgets in response to brand *i*'s increase, then returns of brand *i* could be increasing, linear, or decreasing, depending on the range of brand *i*'s spending and rate at which competitors decrease their spending.

Competitors decreasing marketing might seem an unrealistic response to brand *i*'s increase, but if competitors budget a fixed percentage of last-period's sales for marketing this reaction (reducing marketing) could be an *indirect* result of brand *i*'s increase in budget. If brand *i*'s increase in marketing causes the market share (and, therefore, sales) of competitors to decline in time *t*, the fixed percentage of sales budgeting rule would lead to a decrease in absolute marketing for competitors in time t+1. Retailers may also influence these reaction functions and accentuate the positive feedback from market share changes.

2.3 Positive Feedback and Retail Assortment Decisions

There are two reasons for expecting retail assortment decisions to be associated with positive feedback for convenience goods. The first is that retailers often decide what to discontinue on the basis of sales rates. In other words, brands with low market shares are those that may be discontinued to make room for new items. Often retailers have expectations for minimum sales rates to justify retail shelf and warehouse space (Farris, Olver & DeKluyver, 1989). While there are certainly exceptions for categories in which private labels play a strong role, the presence of private labels can put even more shelf pressure on the marginal manufacturer's brands. The second reason is that the relative minimum sales rates are higher for small-assortment retailers, such as convenience stores, "mom & pop" stores, and limited assortment stores (wholesale clubs). For the brands that make the minimums the payoff can be very good. With fewer competitors on the shelf, it is easy to see why "the rich get richer" and positive feedback can result from retail assortments. Some marketers set minimum distribution targets before spending advertising and consumer promotion funds, confirming that marketers see retail penetration as an important key to advertising effectiveness.[2]

[2] Over the long-term, some aspects of negative feedback may also encountered, but these are more likely to apply to shopping goods. For example, "excess" retail availability causes some retailers to lose interest in promotion and stocking certain brands. Typically, this loss of interest is caused by lower retail margins and results in less push. At the extreme, "bait and switch" behavior can result.

Coupling the retailer's decision to the marketer's budgeting decision makes the feedback structure more complex and reinforces the budgeting decision, in the long-term. As Forrester (1961) wrote, "The company-market linkages form networks of feedback loops. In these loops an action by the company causes a response in the market which in turn produces the information on which the decisions are based to control future company actions. The dynamic behavior of these feedback loops is poorly understood and contains many surprises." Forrester (1961) also argued that " The only effective tool for understanding, non-linear, multiple-loop systems is the construction of a model that permits simulation of the behavior relationships which we perceive within the company and market." Our next section outlines the structure of the simulation designed to evaluate the some of these behaviors.

3. Simulation Structure

> "The modeling challenge is to devise a simple formal structure that enables the exploration of some of the more interesting of these connections and that is transparent enough so that the results of the model can be understood and reconsidered in the context of the more complicated reality." (Nelson & Winter, 1982)

In this section we describe the equations used for the simulations. Our descriptions are stylized and are not intended to capture all behaviors that might be represented by the system (just as the Prisoner's Dilemma and logistic equations are highly simplified versions of perceived negotiating positions and the dynamics of prey and predator population). Our purpose is not to represent particular kinds of management and consumer behavior completely and accurately, but merely to provide an approximate mathematical description of possible patterns in convenience goods markets. In this spirit, we ask the reader to consider how these rules might be modified to increase their realism without adding complexity. It will quickly become apparent that even our few relatively simple rules for behaviors of consumers, the trade, and marketers form a complete system that is very complex. The two major feedback effects that characterize our model are presented in Figure 1.

An exogenous perturbation or trigger increases the manufacturer's marketing effort. This increases the firm's mind share amongst customers who develop loyalties for particular brands and will search and shop to find the brand. An increase in loyal customer mind share increases share of sales. The relationship between current sales and next period marketing effort depends on the marketing budgeting rule that is applied and described below. In the case of the use of a percent of sales rule, as sales increase, marketing expenditure increases that continues the positive feedback-loop or virtuous circle. An increase in share of sales may also change the availability of the brand across the distribution system, depending on the brand stocking decision routines or rules that retailer's use and that are described below.

3.1 Model Overview

Our model uses five competing brands and simulates the interactions of their marketers, competitors, retailers, and consumers. Market share of the brands is based on consumer behavior in the form of preference, loyalty, and retail availability. Competitors use marketing (which, in our simulation, is a surrogate for *all* consumer advertising, promotion and R&D efforts) to affect consumer preferences for the brands. Retailers decide how many, and which, of the brands to stock based primarily on last-period sales of the brands. We assume a fixed market size and model the determinants of market share.

3.2 Consumer Behavior

The market share simulation is for a convenience good; retail availability is important, but loyal consumers may search for products. All consumers have a preferred brand and the fraction preferring brand *i* at time *t* is P_{it}. Depending on a brand's distribution, D_{it}, a fraction, $P_{it}D_{it}$, easily find their preferred brand on the shelf and do not have the depth of their loyalty tested by out-of-stock or low-distribution conditions. The rest, $P_{it}(1\text{-}D_{it})$, do not find their preferred brand stocked in the stores they visit. Of the latter group, a certain fraction, $\alpha_{it}P_{it}*(1\text{-}D_{it})$, have strong loyalties and search until they find their preferred brand. These "unswitchable" consumers always find their preferred brand. The rest preferring brand *i* buy a substitute brand from the selection that is stocked, and none forego purchase.

In the simulation, market share is the sum of three components:

- consumers who preferred the brand and found it with no special effort;
- "unswitchable" consumers who would not have been able to buy the brand without special effort;
- consumers who preferred brand *j*, but were not willing or able to find brand *j* and bought brand i instead.

This share can be expressed as:

$$(2) \qquad MS_{it} = P_{it}D_{it} + \alpha_{it}P_{it}(1-D_{it}) + \sum_{j\neq i}\frac{P_{it}D_{it}}{\sum_{k\neq j}P_{kt}D_{kt}}(1-\alpha_{jt})P_{jt}(1-D_{jt})$$

Where:

MS_{it} = market share of brand *i* at time *t*,

P_{it} = fraction of consumer preferring brand *i* at time *t*,

D_{it} = fraction of market sold through stores stocking brand *i* at time *t*,

α_{it} = fraction of consumers preferring brand *i* at time *t* who are "unswitchable".

$\alpha_{it}P_{it}(1\text{-}D_{it})$ = fraction who have their loyalty tested by out of stock conditions for their preferred brand.

$(1-\alpha_{jt})P_{jt}(1-D_{jt})$ = fraction of consumers preferring brand j at time t, who do not find j in stock and who buy brand i: i benefits from unavailability of j and competes for the demand "lost" by j with brand k.

Note that with either loyalty or D =1.0, the above reduces to Equation (1).

3.3 Brand Preference and Brand Loyalty

We assume that a fixed percentage of consumers who prefer a brand will be loyal to that brand, therefore, brand preference (P_{it}) is a state variable and brand loyalty (α_{it}) is a parameter of the dynamic system. In our simulation, if preferred brands are unavailable, non-loyal consumers switch, but loyal consumers never switch. Market measures of consumer loyalty suggest average values of α near .2. See Borin, Farris and Freeman, (1992) for a review of studies that investigate consumer loyalty to retail assortment. Consistent with many attraction models, preference is modeled with equation (1), as direct function of share of marketing expenditures).[3]

3.4 Budgeting Rules

Three budgeting rules are used for the simulations.

(i) Percent Rule (%R)

A firm-oriented rule, this means that the firm will spend a percentage of last period's sales that is calculated (or implemented) with error. This is equivalent to spending a fixed fraction of anticipated sales on marketing, if last period's sales are the best estimate of next period's sales. As trade sales are assumed to equal consumer sales (no change in inventory levels) and share of preference is a function of marketing share, the %R rule couples trade, consumer, and competitor decisions to each firm's marketing. An equation for this rule is:

$$(\%R) \quad M_{it} = K_{it} \quad MS_{i,t-1}$$

where M_{it} = marketing dollars of brand i at time t,

MS_{it-1} = share of market of brand i at time t-1, and

$K_i = S*k_i$, where S = market size in dollars and k_{it} = constant between 0 and 1, and

A firm uses the following formula to decide on the percentage k_{it} :

$$k_{it} = \left(\sum_{d=1}^{5} q_d k_{i,t-d} + q_0 k_{competitors} \right) \cdot (1 + \varepsilon_{it})$$

where $k_{competitors}$ is the average percentage of the competitors of the firm at t-1,

[3] We assume that carryover effects of past spending are zero in the simulation. We also assume that loyalty and preference are independent and constant over time. The effect of each assumption might be interesting to relax in future work.

q_d (d=1,..,5) reflect the influence of the firm's own previous percentages,

q_0 reflects how much the firm is influenced by the other firms' percentages.

ε_{it} is a stochastic determinant of k_{it} with mean of 0 and variance which determines the amount percentage "error."

We set q_d (d=1,..,5) equal to .1 and q_0 equal to .5. In this way, the formula reflects the way we believe firms arrive at a percentage. They base their decisions on experience from their own past and on what their competitors do. The error captures other possible considerations, but also mistakes in judgments a manager might make.

(ii) Match Competition Rule (MC)

This competitor-oriented rule equates brand *i*'s marketing dollars with the average of the other brands' marketing budgets in the previous period. Probably the most common implementation of "matching competition" is to use a share of market equals share of voice approximation. However, the latter interpretation of "matching" competition is virtually the same as the industry using a constant percentage of sales to set marketing budgets. We use a rule that matches the average dollar (not percentage) budget of the other brands in the last period:

$$(MC) \quad M_{it} = \frac{\sum_{i \neq j} M_{jt-1}}{N-1} \cdot (1 + \varepsilon_{it})$$

where M_{jt} = marketing budgets of competitors at time t and ε_{it} is a random error.

(iii) Market Learning (ML)

This rule estimates consumer response to marketing budgets and sets marketing spending based on those estimates. The learning model adjusts spending based on current competitive levels of marketing and own brand availability. For cases in which marketing is differentially effective among firms, adjustments for the differences in marketing effectiveness are also made. The response function used is equivalent to what a well-executed scanner experiment would provide. The response function is adjusted for current levels of availability in each period. Profit margins before allocation of marketing and other fixed costs are assumed equal to 50% of sales. The ML rule selects a budget at which incremental costs of marketing are balanced by the expected profitability of increased sales:

$$(ML) \quad \partial P_{it} \cdot S \cdot D_{it} \cdot \tfrac{1}{2} = \partial M_{it}$$

where

P_{it} = consumer preferences

S = market size

D_{it} = brand distribution

A random error is added to *M* to introduce management and measurement error into the process.

3.5 Retail Distribution

The simulation models retail availability (D_{it}) as a function of market share in the preceding period. As shown in Figure 2, a few large stores stock many brands and account for 35% of the market, somewhat smaller stores stock fewer brands and account for 30%, a third group accounts for 25%, and the smaller stores account for 8% and the very smallest account for only 2%. Three levels of availability were modeled: full availability for any brand, regardless of what value share, limited assortment and broad assortment. The structure of the limited and broad assortment conditions corresponds to the ranges observed by Reibstein and Farris (1996) in an empirical study of convenience goods.

3.6 Summary: Simulation Structure, Parameters, and Variables

The simulation model (Equation 2) calculates market shares and marketing budgets for the five firms. These calculations are based on market share, marketing budget, and product distribution from previous periods. All firms begin (t=0) the simulation with equal levels of market share (.2), initial advertising (6.6), consumer preference (.2) and retail distribution (1).

3.7 Simulation scenarios

Our objective in building these simulations was first to simply explore the market dynamics that might be implied by coupling routinized decisions of consumer, retailers, and competitors. Since the study of path independence has been associated with market share dominance, we were particularly interested in two dimensions of the coupled systems: 1) Numer of Surviving firms with market share greater than .001 at t = 50; 2) Marketing/Sales ratios: since marketing budgets are the only discretionary costs modeled, they are the sole determinant of industry profitability. Market size for all scenarios is fixed at 100, prices are assumed equal to \$1.00, and unit costs are \$.50.

Refer to TABLE 1

4. Simulation results

Table 2 contains the results of the simulations. This table has three sections, (A, B, and C), each corresponding to a different level of error (epsilon). Section A has zero error, B an average of 8.5%, and C an average of 17%. Within each section simulations for the three marketing budgeting rules and the three retail distribution conditions are reported. The summary statistics are based on 50 simulation runs. Each run simulated 50 periods.

4.1 Baseline Simulations: Number of Firms Surviving and Marketing/Sales ratios

Refer TABLE 2

The simulations in Table 2A are to establish the baseline. These simulations are completely deterministic with no random error. Even these simulations had some surprises, however. As expected, with zero error no firms drop out and the Number of Firms Surviving remains at the starting value of 5.0, with a standard deviation of zero. For Marketing/Sales the results are more interesting. The ML rules result in Marketing/Sales ratios that decline as the assortment conditions move from Full to Limited. The ML rule "chooses" a Marketing/Sales based on assortment condition, while the MC and %R rules result in spending that simply reflects starting values.[4] The reason for this decline is that each competitor underestimates the percentage market that the firm can achieve and undervalues advertising to that extent. Although the standard deviation of the Marketing/Sales is zero, indicating that each simulation run looks exactly like the other as far as Marketing/Sales ratios are concerned, the Minimum and Maximum Marketing/Sales ratios within individual runs show consistent and extreme variations. Forrester's (1961) observation that the dynamic behavior of feedback loops contains many surprises was borne out in these "baseline" simulations. Based on earlier simulations of the same models with three competing firms, we expected the ML rules to generate stable Marketing/Sales ratios that depend only on the assortment restrictions. However, increasing the firms from three to five completely changed the within-run stability of the Marketing/Sales ratio. Therefore, in an attempt to understand why this variation in Marketing/Sales occurred, we constructed a "pure" market share attraction model, as per Equation (1). Using the same contribution margins and industry size, we examined the Marketing/Sales behavior for the basic attraction model with 2, 3, 4, and 5 firms when each firm used the ML rule. Figure 3 A-D show the total Marketing/Sales ratios for the simulations with the 2, 3, 4, and 5 firms. Notice that the number of firms in combinations with the ML rule causes a large shift in the Marketing/Sales ratios. Because there is no stochastic term, the run-to-run variations are zero. Within runs, however, increasing the number of firms from 3 to 4 and 4 to 5 causes budgets to cycle between low and high values. As far as we know, the fact that the spending levels and dynamic stability of the basic attraction model depends on the number of firms has not been previously explored.

4.2. Effects of error on number of surviving firms

Tables 2B and 2C report the effects of introducing a random error the budgeting rules. This error causes the ML and %R rules to become more concentrated. When all of the players use a percentage of sales (%R) decision heuristic, dominance by one brand is inevitable (we believe), but this dominance may happen at a faster or slower rate depending on the amount of randomness and the structure of the distribution channel. With %R, once on a path upward or downward, this path (or dominance of shares) can only be reversed by a lucky sequence of events. The simulations exhibit stochastic equivalents to the concepts of "bifurcation" and "multiple equilibria." "Near a bifurcation point the system is extremely sensitive to small fluctuations both in its parameters <distribution channel in this case> and to external disturbances. The fluctuations influence the evolutionary path that the system will follow" (Crosby, 1987). The parameters that cause this bifurcation are the distribution channels, and the disturbances are the introduction of random noise in the system. The other long-term effect of temporary perturbations is the notion of multiple equilibria, which means that a variety of outcome are possible from the same set of parameters within the same system (Arthur, 1988). In other words, given virtually identical starting points, the market might have evolved along a different path. Figures 4-7 show wide variations in the market share paths that result from the same starting conditions. The "A" graphs show the market share "path" for each of the five firms for a single run. The "B" graphs show the market share path of firm 1 for six different runs. These patterns emphasize that there is a high degree of variability in the outcomes for some of the parameter values.

For both %R and ML rules, the limited assortment policies by retailers and higher error rates result in the emergence of leaders sooner rather than later. Whether the Market Learning (ML) rules lead to market dominance depends on the amount of randomness and the distribution structure. With full assortment, the ML rule does not become more concentrated, even with higher levels of random influences. Limited assortment policies combined with budgeting error cause the ML rules to push brands to exit the market earlier. Matching Competitors (MC) spending levels leads to no brands exiting the market and a tendency toward equal shares among the remaining brands. As discussed below, however, the stability in shares comes at a cost. Once again, changes in the parameters of the system serve as an explanation for these different scenarios. These conditions create the stochastic equivalent of what would be called a "bifurcation" point in purely deterministic systems. When the budget rule ML or %R are used, assortment limitations create path dependencies. Market share changes acquire momentum and some firms are forced out. In addition, the outcome is more predictable as to how *many* firms will survive than *which* firms will survive.

4.3 Marketing Budgets

The Match Competition (MC) rule trades off stability in market shares for instability in Marketing/Sales ratios. This can be seen from Tables 2B and 2C: switching from MC to either ML or %R, causes the standard deviation of Marketing/Sales to decrease. Although not shown, the MC and %R are very sensitive to starting budgets; if the

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[4] The ML spending levels would also be affect by contribution, but we have fixed that parameter at 50%.

starting budget is high (or low) the industry spending for that run will tend to be high (or low). Adding error to the process amplifies the budgeting instability. The Market Learning (ML) rules have the lowest Marketing/Sales for the industry. As the firms are forced from the market, the industry marketing rates are reduced and Marketing/Sales ratios for the surviving firms improve. An interesting aspect of the ML rules is that they result in spending levels that are virtually fixed as a percentage of sales once exit has occurred and the number of firms has stabilized. Until the exit occurs and leaves 2-3 firms, spending may exhibit large swings. As described in section 4.1, the number of firms in an industry has a large impact on the dynamic pattern of Marketing/Sales of the firms using the ML rules. The ML spending level depends on the distribution environment (assortment level) as well. Lower industry spending is apparent for more limited assortments, even when exit does not occur (see Table 2). The "spikes" that result from the ML-rule with 4 or 5 firms appear to come just before and accelerate exit.

4.4 Regression Summaries of Data in Table 2

Table 3 shows the results of multiple regression analysis of the simulations in Table 2.[5] The regressions in Table 3 are an attempt to capture some of the main simulation results in a more compact form. Taking the averages over the periods 41 to 50 for the marketing to sales ratios suppresses some of the random variation due to budgeting error. This averaging over the ending periods emphasizes differences that develop over the course of the simulation runs.

Refer to TABLE 3

The regressions show that the greatest market concentration (low number of surviving firms) results when the assortment is limited, budgeting error is large, and the %R budgeting rules are applied. Moving from a limited to a broad assortment reduces market concentration more than moving from % revenue to market learning rules. Distribution patterns that increase concentration also decrease Marketing/Sales for the ML rule because of fewer competitors. For the %R rule, limited distribution affects concentration, but not Marketing/Sales. Given a distribution pattern (full, broad, or limited), the budgeting rules have no affect on average industry profitability. As noted above, MC does affect the standard deviation of industry spending, but probably not the expected mean for Marketing/Sales.

5. Discussion: Path Dependencies and Long-term Effects of Marketing

A key question for marketers to consider is whether path dependence in a system can be exploited by the application of additional marketing effort a certain times. At critical points (bifurcation points), such as those described by Arthur (1988) in his description of the VHS-Beta struggle for share, a well-timed marketing effort might mean the difference between market dominance and being forced out altogether. This "amplification" of the

[5] We owe thanks to Don Lehmann for suggesting this method of presenting results from many simulations.

effects of small initial differences is quite different from the usual assumptions of initial advantages being competed away over time.

5.1 Using the Simulations to Assess Marketing "Shocks"

We tested the effects of one-time spending shocks equivalent to increasing brand 1's spending by a factor equal to 40% of industry marketing in period 2. We were interested in whether this temporary increase in spending would act as a trigger that through the positive feedback effects would lead to a sustainable advantage (hysteresis?) for the brand. These analyses compared the long-term average market shares and survival rates with and without the marketing shock for each of the three rules. The shock results in an advantage for two of the three budgeting rules. The shock changes expected survival rates for %R from .2 to .9 and for ML from .4 to .92. Only when other brands immediately match (as with the MC rule) does the shock not influence long-term average market share and survival rates. (Of course, with the MC, the cost of the matching is to increase Marketing/Sales by almost 40%.) If the other brands are using %R or ML rules the shock is much more likely to change the long-term average share and survival rates to the advantage of the initiating brand, but the increase in industry marketing is far less (12% for %R and 2% for ML).

Although some might attribute the difference in outcomes to the budgeting shock, we believe it is the feedback mechanisms that ought to retain center stage. In other words, it makes no sense, in our view, to attribute a thunderstorm in New York to the flapping of a butterfly's wings in China. The weather system may indeed be vulnerable to any number of random influences, but if it is, there is virtually no chance of attributing a given outcome to a particular system perturbation. Only if it can be shown that a given perturbation is relatively rare and exceeds the threshold of local stability would it make sense to speak about the long-term effects of a given random shock. At the present, we believe it might be better to try to identify system bifurcation potential by thinking through the feedback system. At the very least, this kind of process can make explicit what we mean by long-term effects. Hypotheses about the behavior of the feedback system can be subjected to the kind of "thought experiments" represented by simulations. We emphasize the potential for these outcomes, because as our simulations show, even if we know the processes very well, there is an almost incredible variety of outcomes possible

5.2 Implications for risk

> "..the simulation's output will be different in each run, and managers run the model repeatedly – perhaps many thousand of times – to see not only the most likely outcomes but also the variations in outcomes." (Reibstein & Chussil, 1997)

For many, the concept of an "effect" often means to hold all else equal. The perspective of complex systems challenges this view and forces us to consider the repercussive "effects of effects" over time. On the other hand, we cannot "guarantee" that a particular pattern of effects will occur. An appreciation of this risk is necessary to understand how managers see the decisions that researchers are attempting to model. This understanding might avoid naïve prescriptions that stem from partial analyses of market dynamics. At some points the system (bifurcation points) is precariously balanced between different paths to the future. Which path is taken may be more easily influenced by the actions taken at such bifurcation points. We have constructed a simulation that begins with such a bifurcation point for some of our budgeting rules and distribution patterns. Whether we can ever identify these points in practice is quite another question. It is one thing to say that, in principle, such leverage points exist. It is quite another to say that we can find them in the real world. Even if we believe that bifurcation points can be identified with historical data, it is not clear how to make use of this knowledge. It is possible that by the time they can be identified with econometric approaches, it will be too late to exploit the potential leverage of path dependency. When in doubt, managers may find that their time is more productively applied in attempts to understand and foster the kind of feedback loops they desire than using historical data to identify missed opportunities.

6. Conclusions

It is not clear which of our three rules is "best." Making this judgment would imply that we had a good set of criteria for judging budgeting appoaches. We do not. However, we can offer a few conclusions about the different behaviors of the budgeting rules in an environment characterized by the market share attraction model. For ML rules, the competitive dynamics and stability of the attraction model appears to depend in interesting ways on the number of competitors. Two or three competitors generate smooth patterns. Four show spending patterns that oscillate between two points. Five is even more erratic and may be chaotic. The other two rules, MC and %R, were uninteresting until error and limited retail assortments were introduced. The %R stabilized marketing spending, but increased the odds that all of the profits will go to a few survivors. The MC rule shares the profit pie equally, but induces greater uncertainty about how large that pie will be by fostering advertising "wars." Although not shown, both %R and MC rules require "starting points" and are only stable around those starting points. The ML rules find their own level for the industry, but also incur significant risk of failure when retail assortments are limited and may create chaotic budgeting patterns. For many of the %R and ML runs, there was a great deal of variation in the market share paths from run to run with the same simulation parameters. The run-to-run variations is directly related to our interest was using these simulations to explore the notion of path dependence and long-term effects of marketing actions.

In these simulations it became apparent that the combination of limited retail assortments and certain budgeting procedures can impart path dependence to marketing decisions when random influences are present. Where path dependence exists, there may also be the opportunity to apply marketing resources at critical bifurcation points and influence which path is taken. This possibility raises interesting and disturbing implications for the definitions and measures of long-term marketing effects. There may be other deeper insights and understanding that this kind of modeling can provide managers. First, as argued above from theoretical premises, the conjecture of management about what is likely to occur in the future in a particular market requires thinking about the dominant feedback effects that currently are driving the evolution of the market (Dickson et al. 1997). We believe this kind of thinking can be reinforced and improved by actually building the system of such effects and simulating the system. Second, simulations of such feedback effect systems serve as a heuristic to shift manager's mental models to focus on changes (Diehl & Sterman, 1995). These are changes both in the system's current state to give a sense of momentum missing from static analyses and changes in the relationships that underlie the feedback loops. Third, we argue that these approaches may give managers and researchers a better concept of the notion of risk that underlies market evolution. The fact that a market evolved in a certain way does not mean that the same starting circumstances would have always lead to the same end result. Historical data presents a reality that feedback system models should be able to explain. However, if explanations of historical reality are not made in a way that reflects the risk and uncertainty inherent in the dynamic processes then an historical determinism bias may be introduced into managers' thinking. The apparent certainty of past outcomes leads to a projection of past trends into the future where a more valid approach to understand the risks being taken is to simulate the future behavior of the underlying feedback system. Araju et al., (1996) make the following remark:

> " Observed patterns of competition "represent the results of historical circumstances and accidents. Even if we fully understand the mechanisms at work, we may need simulations to teach us about possible market behaviors. As Langton, observes, "We trust implicitly that there are lawful regularities at work in the determination of this set, but it is unlikely that we will discover many of these regularities by restricting ourselves only to the set of biological entities that nature actually provided us with."

Theories of competitive dynamics enable a manager to understand what is driving competition and change in the product-market and to develop greater market insight and foresight. The tactical behavior of rivals is viewed as partially understandable and its feedback effects on the market can be appreciated, even if not precisely assessed. But, when the feedback systems show the potential for bifurcation the risks assume totally different proportions. Distribution path dependencies often result in such bifurcation potential. However, it is not yet clear how to integrate such path dependencies into assessment of marketing actions, such as the "Intel Inside" marketing campaign (Grove, 1996). It is unlikely, in our opinion, that the long-term, strategic effects of the "Intel Inside" campaign would be apparent in a short-term change in consumer purchase probabilities. Further, even if a general window of opportunity existed, it does not make sense to try to identify the *precise point* at which the decision to increase Intel's marketing set off an avalanche of marketing actions and reactions throughout the channel. We have to acknowledge the power of the Intel brand in the context of these actions and reactions, but we also have to better understand and learn to analyze the risk faced by managers who set out to *create* such market turning initiatives.

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Figure 1: Marketing Decision Routine Feedback Effects

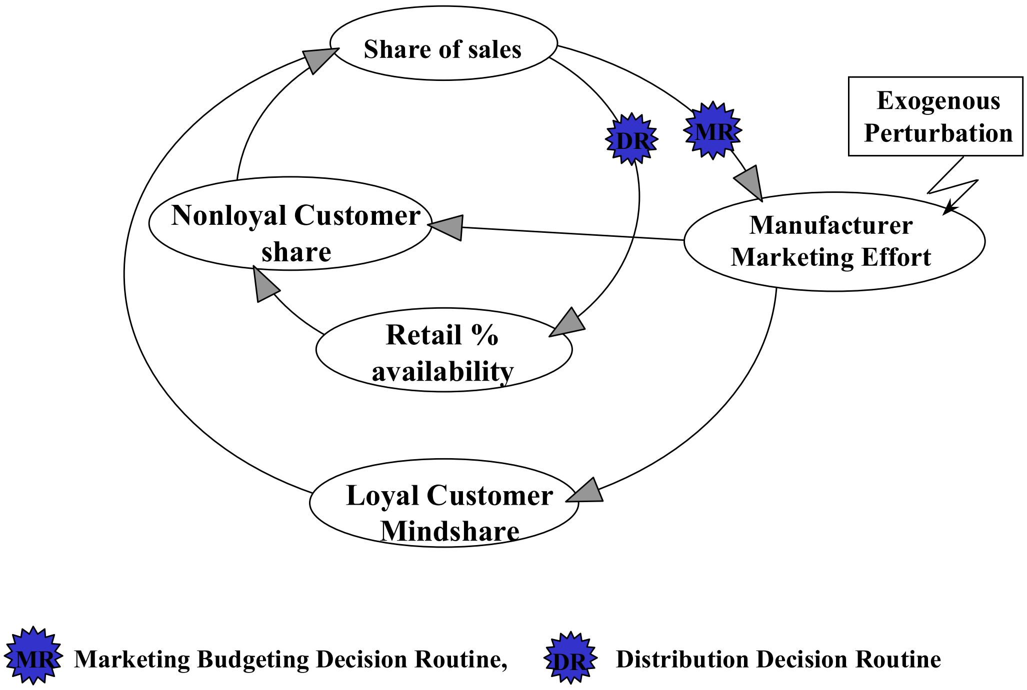


Figure 2: Share and Availability Relationships for Three Assortment Conditions

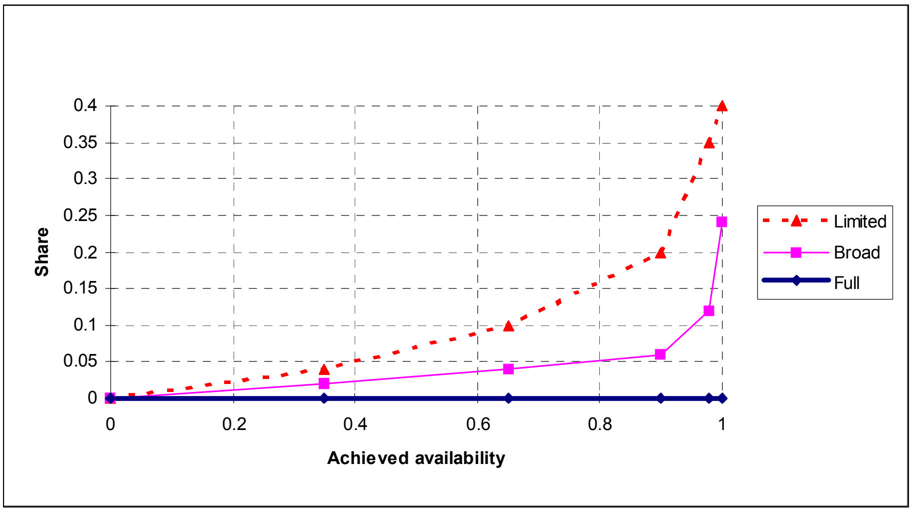
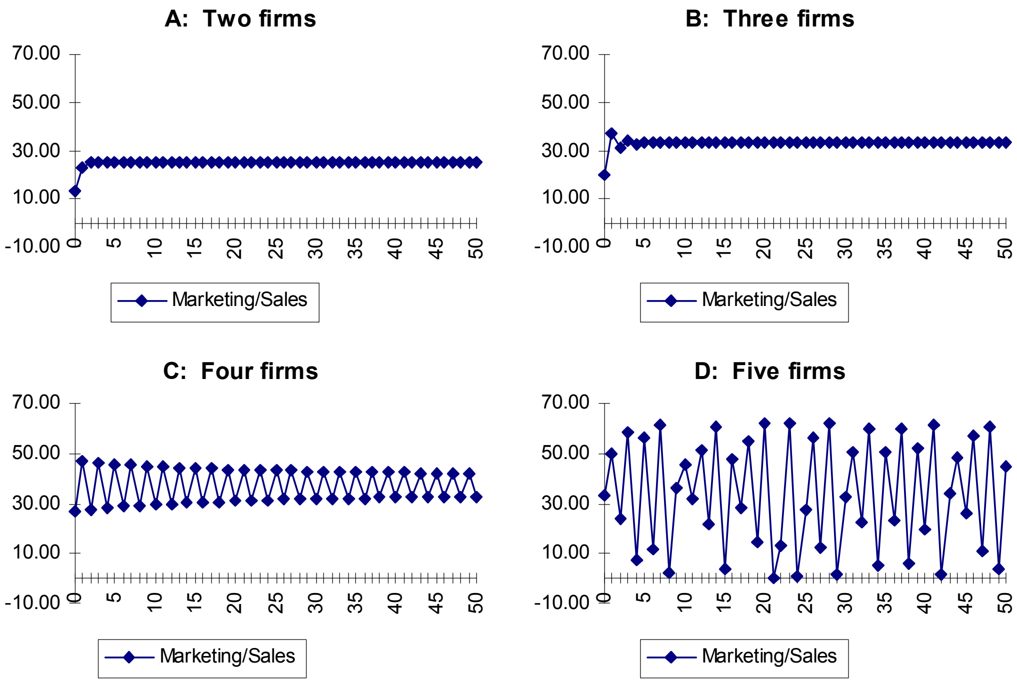


Figure 3: Industry Marketing/Sales for ML* Rules with a "Pure Attraction Model" for 50 periods, no stochastic term (zero error).



*** ML optimal based on 50% contribution margins and zero carryover effect and competitive spending assumed constant at level observed at t-1.**

Figure 4A – **Single run market shares of all 5 brands with** **%R,**
full distribution,
epsilon=.5

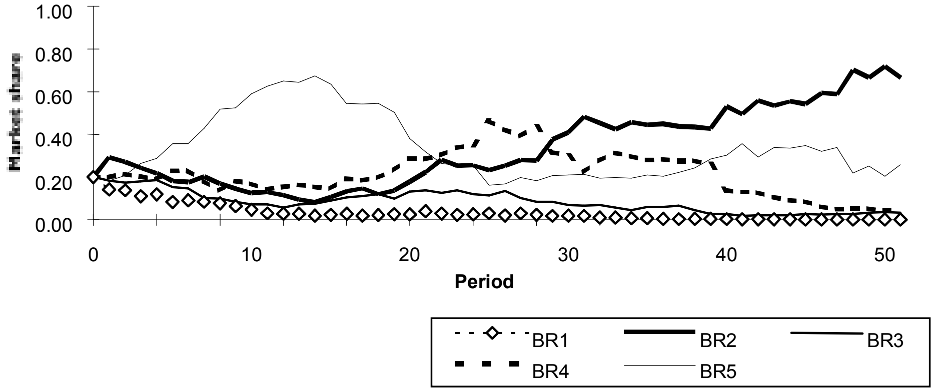
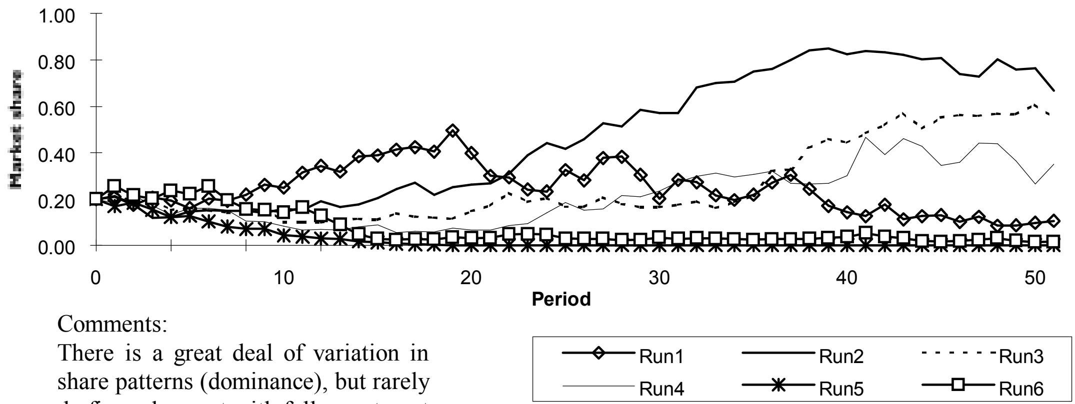


Figure 4B – 6 different runs for brand 1 with %R,
full distribution,
epsilon=.5



Comments:
There is a great deal of variation in share patterns (dominance), but rarely do firms drop out with full assortment

Figure 5A – Single run market shares with %R,
limited distribution,
epsilon=.5

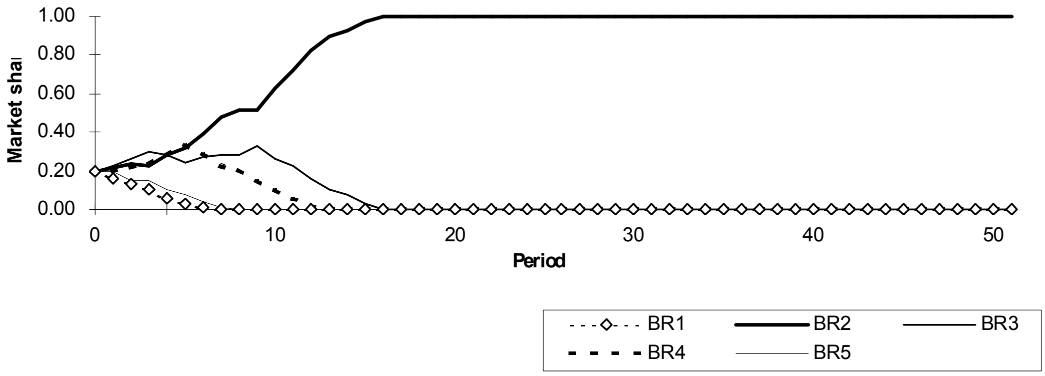
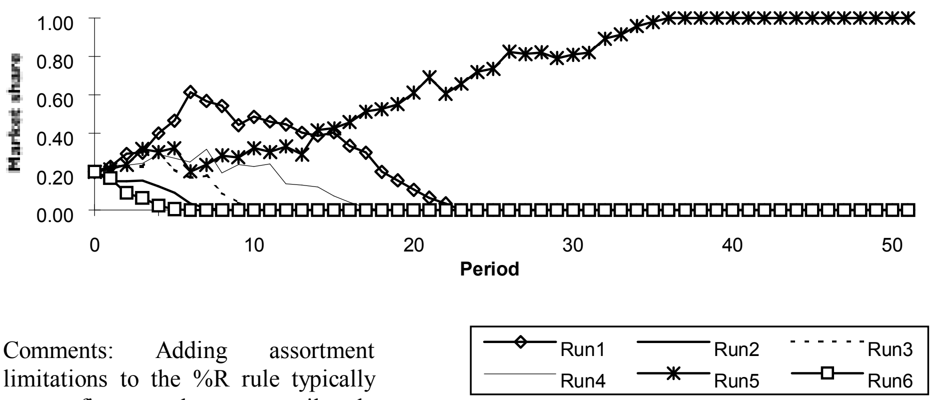


Figure 5B – 6 different runs with %R,
limited distribution,
epsilon=.5



Comments: Adding assortment limitations to the %R rule typically causes firms to drop out until only one is left.

Figure 6A – <u>Single run</u> market shares with ML,
full distribution,
epsilon=.5

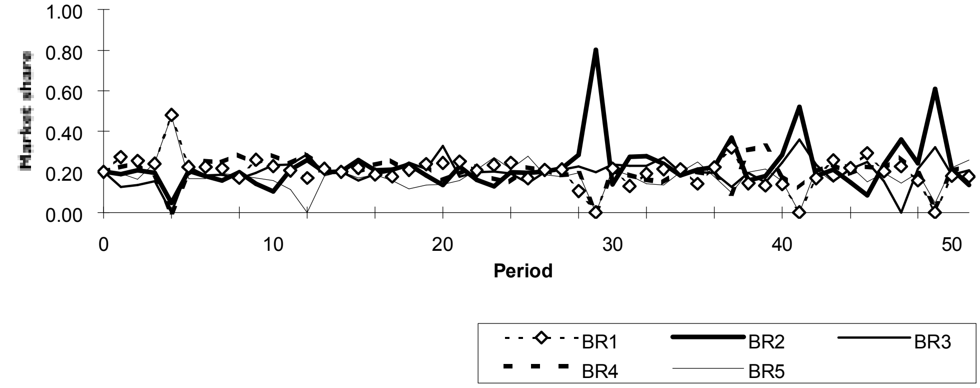
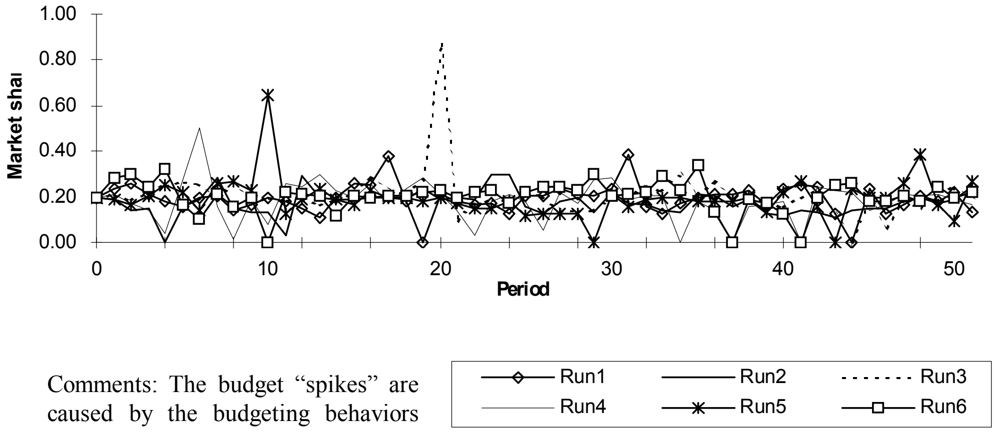


Figure 6B – <u>6 different runs</u> for brand 1 with ML,
full distribution,
epsilon=.5



Comments: The budget "spikes" are caused by the budgeting behaviors illustrated in Figures 3A-3D.

Figure 7A – Single run market shares with ML,
limited distribution,
epsilon=.5

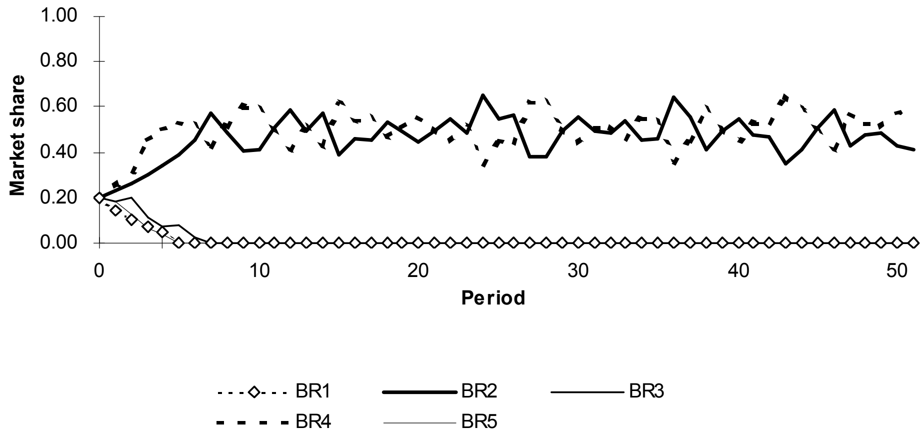
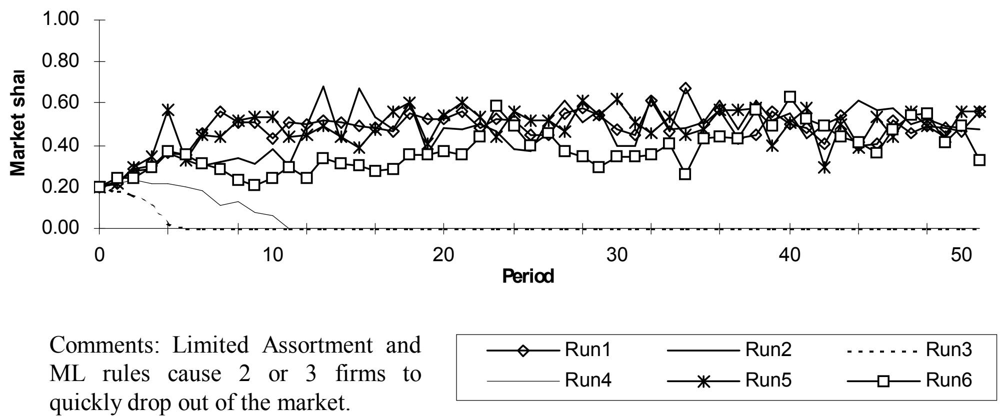


Figure 7B – 6 different runs for brand 1 with ML,
limited distribution,
epsilon=.5



Comments: Limited Assortment and ML rules cause 2 or 3 firms to quickly drop out of the market.

Table 1A. **Model parameters.**

Parameter	Definition	Values Used in Simulation
α	fraction of consumers who are "unswitchables" (even if their preference is unavailable); 0 = lowest loyalty, 1= complete loyalty.	.2
ε	the rate of error in implementing marketing budget rules. This error has a mean of 0 and a distribution that is triangular. It is calculated as (1 - epsilon + epsilon), where epsilon is a random variable distributed evenly between 0 and epsilon. For epsilon = .5 the average absolute error is approximately 17%. For epsilon = .25, the corresponding mean absolute error is approximately 8.5%.	0, .25, .5

Table 1B. **Budget rules.**

Budget Rules	Definition (starting values of marketing (t=0) = 6.6)
%R	marketing is a (varying) percentage of last period's sales
MC	equal to average budget of competitors.
ML	market learning, optimizes current profits adjusted for current competitive spending and brand availability.

Table 2. **Summary Statistics for 50 Runs of each of the 27 Separate Simulations**

	A			B			C		
	Avg. Error = 0% (Epsilon=0)			Avg. Error = 8.5% (Epsilon=.25)			Avg. Error =17% (Epsilon=.5)		
No. Firms Surviving at t=50 (Each run the number of firms with share>.001 at t=50 is stored. This statistic reports the 50-run average of that number.)									
Assortment	MC	ML	%R	MC	ML	%R	MC	ML	%R
Full	5.00	5.00	5.00	5.00	4.94	5.00	5.00	4.88	4.98
Broad	5.00	5.00	5.00	5.00	2.96	3.02	5.00	2.54	2.08
Limited	5.00	5.00	5.00	5.00	2.42	1.10	5.00	2.04	1.04
Num.Survivors Std Dev. (The standard deviation of the above number over the 50 runs.)									
Assortment	MC	ML	%R	MC	ML	%R	MC	ML	%R
Full	0.00	0.00	0.00	0.00	0.31	0.00	0.00	0.62	0.14
Broad	0.00	0.00	0.00	0.00	1.08	0.84	0.00	0.94	0.80
Limited	0.00	0.00	0.00	0.00	0.53	0.30	0.00	0.34	0.20
Avg Industry Mktg/Sales, t = 41-50 **(The M/S ratio is the sum of all firms' marketing divided by market size. Each run the average M/S for t 41-50 is stored. This statistic reports the average of that number over 50 runs.)**									
Assortment	MC	ML	%R	MC	ML	%R	MC	ML	%R
Full	33.00	34.65	33.00	33.33	34.02	34.85	33.70	33.19	39.29
Broad	33.00	29.02	33.00	31.04	28.71	34.52	30.13	25.38	37.34
Limited	33.00	29.12	33.00	30.87	26.98	34.54	32.19	23.89	34.39
Industy Mktg/Sales Std Dev. t = 41-50 (The standard deviation of the t=41-50 avaerages. This number emphasizes run-to-run differences, but supresses within-run variations.)									
Assortment	MC	ML	%R	MC	ML	%R	MC	ML	%R
Full	0.00	0.00	0.00	9.40	2.21	2.16	26.23	2.66	6.50
Broad	0.00	0.00	0.00	10.09	11.37	2.22	13.49	12.41	6.91
Limited	0.00	0.00	0.00	8.66	4.83	4.32	18.52	5.16	7.43
Industry Mktg/Sales Minimum, t = 41-50 (Each run the minimum M/S from t=41-50 is stored. This statistic reports the average of these within-run minimums.)									
Assortment	MC	ML	%R	MC	ML	%R	MC	ML	%R
Full	33.00	1.64	33.00	30.74	2.31	33.45	27.49	1.47	35.30
Broad	33.00	0.36	33.00	28.17	22.93	32.52	25.01	18.44	32.42
Limited	33.00	1.31	33.00	28.00	23.95	31.91	26.95	18.43	29.25
Industry Mktg/Sales Maximum, t = 41-50 **(Each run the maximum M/S from t=41-50 is stored. This statistic reports the average of these within-run maximums.)**									
Assortment	MC	ML	%R	MC	ML	%R	MC	ML	%R
Full	33.00	61.68	33.00	36.29	62.30	36.29	40.21	64.70	43.45
Broad	33.00	61.01	33.00	34.20	34.04	36.49	36.12	32.17	42.82
Limited	33.00	55.59	33.00	33.89	29.97	37.42	37.86	29.71	40.20

Table 3. **Summary results of simulation supported in Table 2, regression coefficients of treatment variables on dependent measures (standard error of coefficient in parentheses)**

Simulation Variables	Number of surviors at t=50	Average M/S-ratio t = 41-50
Base Case*	6.56 (0.50)	34.85 (1.43)
Epsilon (error)	-2.84 (0.95)	0.57 (2.75)
Assortment: Broad	-1.05 (0.48)	-2.69 (1.37)
Assortment: Limited	-1.50 (0.48)	-3.41 (1.37)
Budget: Market Learning	-1.17 (0.48)	-3.78 (1.37)
Budget: %Revenue	-1.42 (0.48)	2.01 (1.37)
R-squared	0.58	0.55

*Base is Budgeting Rule of Match Competition, Epsilon = 0, and Assortment = Full.

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