Explaining Capacity Overshoot and Price War: Misperceptions of Feedback in Competitive Growth Markets*

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Abstract

Companies consistently get into trouble in rapid growth markets. Frequently they grow too fast, overshoot when the market saturates, then get into price wars and suffer huge losses due to low prices and excess capacity.

The companies that grow most aggressively sometimes lose the most, contrary to the new conventional wisdom that you have to be the largest player to benefit from increasing returns and positive feedbacks that confer success to the successful. How can the prevalence and persistence of this dynamic be explained? Is it just bad luck or is there a systematic explanation. And how can firms do better?

To explore these issues, we designed an experiment involving over 270 subjects (MBA and short course Executives). Subjects played the role of a management team for one firm in a simulated duopoly market, with a rapidly growing demand for the new product. As in the real world, market potential and the course of the product lifecycle were highly uncertain. Subjects made quarterly capacity, pricing and marketing decisions over a simulated ten year period. Performance was measured by cumulative net income.

The results showed that subjects systematically made pricing decisions that were not only far from the "optimal" price, but were often in the opposite direction from the optimal change. Subject performance was very poor, compared to a benchmark performance computed using simple behavioral decision rules. Subjects did not substantially modify their policies under different market structures or different competitor strategies. Neither did they modify their policies over trials - little learning took place.

The poor performance is explained in terms of flaws in the subjects' mental models - their "misperceptions of feedback". We close with discussion of implications for improved senior management strategies in new product markets.

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Introduction

The traditional "learning curve" perspective applied to the growth of new product markets suggests that early entrants can achieve sustainable competitive advantage through rapid investment in capacity and by pricing aggressively to pre-empt competition (Moore, 1996). Recently, aggressive strategies designed to gain dominant market positions have been reemphasized as theories of so-called 'increasing returns' based on positive feedback (due to network externalities, complementary assets, economies of scale and scope, and others) have gained considerable attention (e.g. Arthur 1994). However, previous work based on simulated markets has shown that aggressive strategies are suboptimal when the market is dynamically complex (Paich and Sterman 1993, Sterman et al, 1995). In recent years, the dynamic complexity of markets has increased dramatically, through shrinking product life-cycles, the acceleration of globalization and intensified competition.

Frequently, competing firms chase market share with the perception that "early dominance will lead to near monopolies as customers become locked in and reluctant to switch to competitors" (Wall Street Journal, 12 December 1996, p. A1). Many cases of "boom and bust" suggest that overcapacity, price wars and bankruptcies are chronic dysfunctional behaviors in industries which experience rapid growth and sudden saturation. These markets include consumer durables (such as bicycles and chain saws), consumer electronics (such as video games, personal computers, CB radios and VCRs), toys and games, fashions, and fads (such as wine coolers and fashion watches).

One characteristic of industries prone to profit-destroying boom and bust is the dynamic complexity of the strategy formulation problem. The existence of network effects, scale and scope economies, high fixed costs, and the strong role of complementary assets (e.g. software for PCs) does create positive feedbacks that favor an aggressive strategy aimed at market share dominance through rapid growth and low prices. But at the same time, short and unpredictable product lifecycles, rapid growth, intense competition, and long delays in adjusting capacity favor more conservative strategies. In addition to the tension between these opposites, the forces at work interact strongly. Hence managers have new dynamically complex issues to face, specifically relating to strategies on product pricing and capacity acquisition, for which their mental models and prior experience are inadequate, if not simply wrong.

The misperceptions of feedback (MOF) hypothesis (Sterman 1989a and 1989b) suggests that decision makers systematically misperceive dynamic environments that include multiple interacting feedback loops, time delays and nonlinearities. These misperceptions result in decisions that are far from optimal, and, in contrast to the economic view of decision making, leave a great deal of "money on the table". The misperception hypothesis has been supported by several experimental studies in the fields of system dynamics and behavioral decision theory (e.g. Diehl 1992, Kleinmuntz and Thomas 1987, Brehmer 1990 and 1992, Smith et al 1988, Funke 1991).

This paper applies the MOF perspective to the critical issue of pricing strategy. This paper presents the results of several experiments that test the MOF theory in the context of pricing decisions made in a rapidly growing market. The experiment required the subjects to make price and capacity decisions in a simulated market for a new product. The results show that many subjects made pricing decisions that were consistently in the opposite direction from the optimal change. Subjects systematically lowered price when it should have been raised and raised price when it should have been lowered. Other subjects changed price in the correct direction, but the magnitude of the change was much smaller than optimal.

In addition, the paper demonstrates that the incorrect price decisions can be interpreted as the result of the subjects' misperception of the feedback structure of the environment. The greater the dynamic complexity of the market environment, the worse performance is relative to the benchmarks (i.e., over and above changes in intrinsic task difficulty). The subjects' decisions would have been reasonable if the environment were simpler and did not include important feedbacks among price, orders, order backlog and lead-time. In fact, the subjects' decisions were close to optimal for the simple environment in which the subjects presume the market is in equilibrium. Unfortunately, the environment was not as simple as the subjects presumed. Price strategies that would have been effective in a simplified environment close to equilibrium were dysfunctional in the actual, disequilibrium environment of rapid growth markets.

The Misperceptions of Feedback (MOF) Hypothesis

The MOF hypothesis holds that decision makers systematically misperceive environments characterized by interacting feedback loops, time delays and nonlinearities. This misperception of feedback results in decisions that are far from optimal and are often much worse than decisions generated by simple, naive decision rules. The source of the misperception is the combination of the complexity of environment and the bounded rationality of the decision maker. Systems comprised of multiple feedback loops and time delays are too complex to be analyzed completely. Consequently, boundedly rational decision makers resort to simplification strategies that may ignore important feedback relationships but make the decision problem more tractable. The analysis of several experiments has shown that decision rules that would have been successful in simplified settings yield very poor outcomes in the actual environment.

Earlier work (Paich and Sterman, 1993) designed an experiment using business school subjects involved in a decision making task portraying new product dynamics in a simulated duopoly market structure. The experimental treatments were the strength of the key feedback processes (the strength of word of mouth and product durability) in a simulated market. Over a number of repeated trials, performance relative to potential was poor and was severely degraded when the feedback complexity of the environment was high. However, the behavior of the simulated competitor in the original experiment was quite simple. The competitor set price using a "cost-plus" strategy with a constant markup. In this study, the simulated market structure has been modified to include four different pricing strategies for the competitor ("cost plus", "margin oriented", "share oriented", "tit for tat"). These pricing strategies provide a more realistic range of competitor behavior and allow us to test the robustness of prior results.

Model Structure

We used an interactive computer game for the experiment, the "B&B Enterprises Management Flight Simulator" (Sterman 1991; Graham et al 1992 discuss design principles and give examples). The flight simulator embodies a model representing a firm, its market, and its competition. Subjects manage a new product from launch through maturity, making price, capacity, and marketing decisions each quarter year through a ten-year simulation.

Market Sector

The market model is based on well known diffusion models in the tradition of Bass (1969), Kalish and Lilien (1986), Mahajan and Wind (1986), Homer (1987), and Mahajan, Muller, and Bass (1990). The essence of these models is the feedback structure through which potential purchasers become aware of and choose to buy the product. Adoption increases the customer base, generating word of mouth which leads to additional sales (a positive feedback), but also depleting the pool of potential customers (a negative feedback). The customer base follows an s-shaped pattern, while sales rise exponentially, then peak and decline to the rate of replacement purchases as the market saturates. Key features of the market sector include:

- Product price affects the number of potential adopters. The elasticity of industry demand is less than unity, quite typical for many goods (Hauthakker and Taylor 1970).
- The greater the aggregated marketing expenditures of the firm and the competition, the larger the fraction of potential customers who purchase each quarter. Diminishing returns set in for high marketing expenditure levels.
- Demand is also generated by word of mouth. Word of mouth is driven by recent purchasers (people who are still excited by the product and have not yet come to take it for granted). The strength of the word of mouth effect (the number of purchases generated per quarter by each recent purchaser) was a treatment variable in the experiment.
- A fraction of the customer base re-enters the market each quarter to replace worn or obsolete units. The repurchase fraction was a treatment variable in the experiment.
- Total orders for the product are divided between the firm and the competition in proportion to the attractiveness of each product. Attractiveness depends on price, availability (measured by delivery delay), and marketing expenditure. Firm demand is highly but not infinitely elastic – price is important to consumers but availability and marketing can differentiate the two products.

Firm sector

While many diffusion models implicitly equate shipments with orders, the model here explicitly represents the supply side of the market. The key assumptions of the firm sector are:

- Product is built to order. Customer orders flow into a backlog until they are produced and shipped. The firm will ship the current backlog within one period unless capacity is inadequate, in which case the backlog and delivery delay rise, reducing the attractiveness of the firm's product and the share of orders it receives.
- Subjects set a capacity target each quarter. Actual capacity adjusts to the target with a

delay representing the time required to plan for, acquire, and ramp up new production facilities. Capacity adjustments follow a distributed lag with a mean of four quarters. Some investments can be realized sooner than four quarters (purchasing equipment), while some take longer (building new plant). For simplicity the delay is symmetrical in the case of capacity reduction.

- The firm benefits from a learning curve which reduces unit costs as cumulative production experience grows. A standard "80%" learning curve is assumed – each doubling of cumulative production reduces unit variable costs by 20%. The competitor's learning curve has identical strength. Learning is assumed to be fully appropriable.
- Profit is revenue less total costs. Total costs consist of fixed and variable costs, marketing expenditures, and investment costs. Revenues are determined by the quantity shipped in the current quarter and the average price received for those units. Customers pay the price in effect when they booked their order, even if the price has changed in the interim.
- Fixed Costs are proportional to current capacity. Unit fixed costs are constant. Variable costs are proportional to output. Unit variable costs fall as cumulative production increases. The fraction of revenue spent on marketing is a decision made by the subject each quarter.
- Investment costs represent administrative, installation, training, and other costs of increasing capacity. Symmetric decommissioning costs are incurred whenever capacity is decreased. Investment costs are proportional to the magnitude of the rate of change of capacity.
- Subjects may lose as much money as they like without facing bankruptcy. The task is therefore more forgiving than reality since losses leading to bankruptcy in real life can in the game be offset by subsequent profits.

Competitor Structure and Strategy

The subject's firm faces competition from another firm which has launched a similar product at the same time. The playing field is level – the structure and parameters for the firm and its competitor are identical. But while the subjects make price and target capacity decisions for their firm, the competitor's price and target capacity decisions are simulated.

The competitor sets target capacity to meet expected orders and maintain normal capacity utilization. Expected orders are determined by the current order rate and the expected growth rate of orders. Extrapolative expectations are assumed: the recent growth rate of orders is projected four quarters ahead – the length of the capacity acquisition lag – to account for the growth in demand likely to occur while awaiting delivery of capacity ordered today. The forecast of future demand is adjusted in proportion to the balance between desired production and capacity. If desired production exceeds current capacity, additional capacity is ordered to reduce the backlog, and vice-versa. The decision rule for competitor capacity acquisition is extensively used in simulation models and is well supported empirically and experimentally (Senge 1980, Sterman 1987a, 1987b). The competitor price decision varies according one of four competitor scenarios (C1-C4) as follows:

Competitor Scenario 1 - "cost plus"
Competitor 1 is a simple base case. Costs are the only determinant of competitor price. The competitor here is totally unresponsive to subject decisions, the competitive situation, or market forces. The competitor sets price at a constant mark-up over cost. Competitor price falls as costs move down the learning curve. A poor outcome for subjects in scenario 1 cannot be blamed on a sophisticated or wily competitor.

Competitor Scenario 2 - "share oriented"
Competitor 2 represents an aggressive market-share oriented player. The competitor's goal for market share is 75%, and the competitor will aggressively cut mark-up whenever actual share is less than this goal. If share exceeds the goal, mark-up is raised only slightly. Likewise, the competitor will cut price dollar for dollar when the subject's price is less than its own (but not below unit variable cost). If the subject's price is higher than its own, however, mark-up is raised less than proportionately to boost share. Finally, mark-up is cut aggressively when there is excess capacity, but raised only weakly if capacity is inadequate. In scenario 2 the competitor prices low from the beginning to gain share and is extremely likely to retaliate to any move by the subject to lower price. Scenario 2 is the most difficult, for several reasons. First, by pricing low, the competitor increases the size of the market and growth of demand during the boom phase, often leading to a bigger bust as the market saturates. Secondly, the aggressive competitor retaliates strongly to any move by the subject to lower her price, often engaging subjects in a price war they did not intend to fight.

Competitor Scenario 3 - "margin oriented"
Competitor 3 represents a margin oriented competitor. The competitor's goal for market share here is an equitable 50%. If actual share is less than this goal the competitor cuts mark-up only slightly, preferring to give up share if necessary rather then sacrificing margin. If share exceeds the 50% target, the competitor in this scenario will raise mark-up to boost profitability even if such action pushes share down again. Similarly, when the subject's price is lower, the competitor lowers mark-up only slightly, but will raise mark-up aggressively when it finds its product selling for less. The competitor also raises mark-up when capacity is insufficient to meet demand, but only cuts mark-up slightly when there is excess capacity. Essentially, the competitor seeks a collusive equilibrium in which both firms split the market at the collusive rather than competitive equilibrium price. The competitor's response to disequilibrium is to signal its desire to achieve the collusive equilibrium by keeping prices high even at the cost of market share or capacity utilization. This competitor can be exploited by the subjects. If the subject wants to build up her market share, she may easily undercut the competitor without provoking strong retaliation. If she wants to increase her own margins, she may do so easily without losing market share. Most important, however, by encouraging higher prices for both the competitor and the subject, scenario 3 slows the growth of demand and smoothes out the transition from boom to bust. A strategy like scenario 3 is in fact the optimal strategy for this environment.

Competitor Scenario 4 - "tit for tat"
Competitor 4 responds aggressively to imbalances in both directions. The target market share here is 50%. The competitor adjusts mark-up strongly in the face of imbalances in

either direction in market share, relative price and demand/supply balance. Scenario 4 puts the player in an environment where the competitor makes strong moves. The direction of these moves depends to a great extent on the subject's own decisions. The game may evolve to an implicitly collusive equilibrium in which both subject and competitor price high, smooth the industry life cycle, and reap large profits, or it may degenerate into a price war, severe boom and bust, and large losses for both.

It is important to note that the model of competitor behavior used here does not presume the competitor is omniscient. The competitor price is set without recourse to any complex game-theoretic reasoning, nor does the competitor rely on information the player does not have. On the contrary, the competitor is modeled as an entity with bounded rationality, who uses simple but realistic rules of thumb in setting price (see for example Morecroft 1985 for models and empirical evidence supporting the decision rules for price used here). The competitor uses only its own costs, market share, capacity, and backlog, along with subject's price, in making its price decision (in scenario 1 the competitor utilizes cost information only). In fact, the subject knows and can utilize far more information about the competitor and the market.

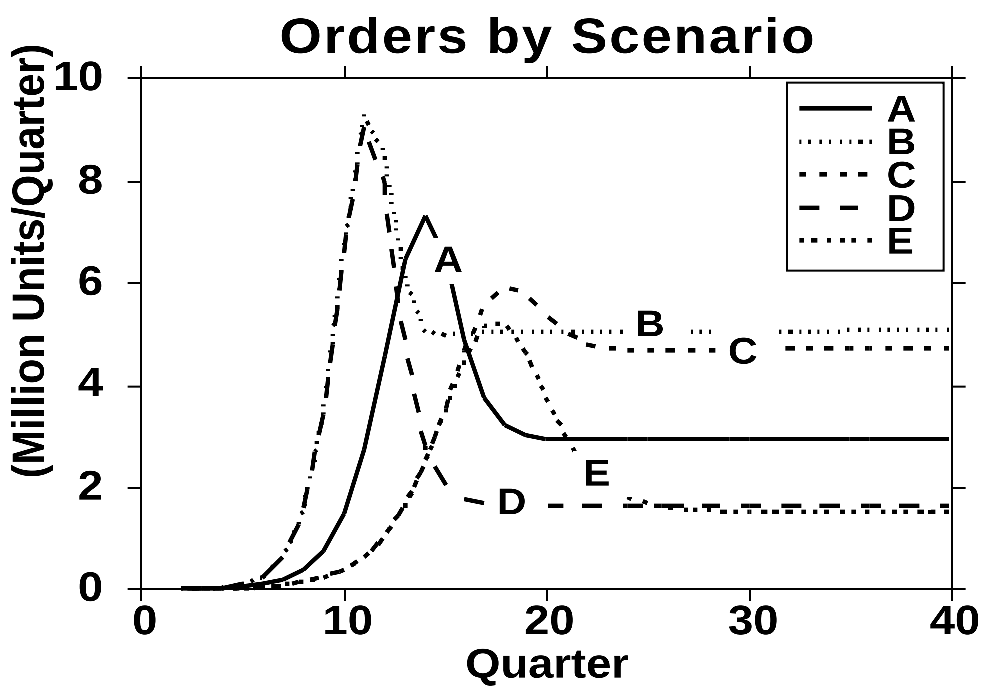
Experimental Design

The experiment was repeated six times over a three year period at a major US management school. Most of the subjects were second-year full-time MBA students, taking a *System Dynamics for Business Policy* elective. One group of subjects were mid-career executives. Each subject played the game five times, providing the equivalent of 50 years of simulated experience. Overall, there were 271 subjects making a total of 1352 trials. After trials were eliminated due to incorrect sequences of trials, repetition of trials etc., the dataset was reduced to 1119 trials for 253 subjects (226 MBAs and 27 Executives). The five game tasks were assigned as homework to be done individually over two weeks. Subjects were given a full written briefing guide (Sterman, 1992) together with an in-class demonstration of the software. Subjects were allowed to take as long as they wished to make each of the 40 quarterly decisions for each game, and to suspend play between trials as required. There was no time pressure (other than the overall due date).

The experimental design used a Graeco-Latin square, with five market scenarios (M1-M5) and four competitor scenarios (C1-C4). The five market scenarios had different replacement fraction (r) and word-of-mouth (w) factors according to Figure 1. The stronger the word of mouth, the faster the growth and sooner the saturation of the market. The smaller the repurchase fraction, the lower the equilibrium replacement demand and the steeper the bust when the market saturates.

Figure 1 Experimental Treatments - Five Market Scenarios M1-M5 (labeled A, B, C, D, E) and the Resulting Market Dynamics

Repurchase Fraction/ Base Case Value \ Strength of Word of Mouth/ Base Case Value	0.5	1	2
0.5	E		D
1		A	
2	C		B



Note: Assumes no capacity constraints and constant margin pricing. Actual demand patterns also depend on subject decisions.

Task Sequences

Five task sequences are used to complete the Latin Square with five trials. Each sequence of tasks involves each one of the five market scenarios (M), and each one of the four competitor scenarios (C) just once. The fifth competitor scenario is chosen at random for each sequence. A total of 20 scenarios (five market scenarios by four competitor strategies) are thus available, of which each subject plays just five, according to the sequences shown in Table 1. For example, a subject playing sequence 3 will face market scenario 3 and competitor scenario 1 in trial 1, followed by market scenario 1 and competitor scenario 4 in trial 2. Hence, each subject plays each of the five market scenarios just once, and plays each of the four competitor scenarios at least once. The market scenario and competitor strategies used in each trial were not revealed to the subjects.

Table 1 Five Sequences of Market Scenario, M (1-5) and Competitor Scenario, C (1-4) used in 5 Trials. Notation M, C.
Cr is a competitor scenario randomly selected from C1-C4.

	Trial 1	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**
Sequence 1	M2,C4	M4,C3	M3,Cr	M1,C2	M5,C1
Sequence 2	M4,Cr	M3,C2	M1,C1	M4,C5	M2,C3
Sequence 3	M3,C1	M1,C4	M5,C3	M2,Cr	M4,C2
Sequence 4	M1,C3	M5,Cr	M2,C2	M4,C1	M3,C4
Sequence 5	M5,C2	M2,C1	M4,C4	M3,C3	M1,Cr

The design is reasonably well balanced, with an average of 45 subjects in each of the 25 cells.

Benchmark Decision Rules

The potential cumulative net income over 40 quarters varies considerably for each of the 20 scenarios, due to the variance in total industry sales generated by the different market competitor scenarios. Hence a benchmark rule is needed to compare subject performance in the 20 different scenarios. The subject's cumulative net income for each game of 40 quarters is divided by the benchmark cumulative net income for the particular scenario, giving a "performance relative to benchmark".

$$\text{Performance Relative to Benchmark} = \frac{\text{Subject cumulative net income}}{\text{Benchmark cumulative net income}}$$

The functional form of the benchmark decision rules for Target Capacity and product Price are formulated following examination of subject logs, and reference to the literature:

$$\text{Target Capacity} = \text{Target Market Share} * \text{Expected Industry Demand} *(1+\text{Expected Demand Growth})^{\alpha_1} * (\text{Current Backlog/Capacity})^{\alpha_2}$$
$$\alpha_1 \geq 0,\ \alpha_2 \geq 0 \qquad (1)$$

$$\text{Price} = \text{Unit Costs} * (1+\text{Gross Margin}) * (\text{Current Backlog/Capacity})^{\beta}$$
$$\beta \geq 0 \qquad (2)$$

where Target Market Share = 0.50 and Gross Margin = 0.25

The target capacity rule seeks to capture 50% of expected demand, where demand is forecast by extrapolating current industry sales at the current growth rate. Target capacity is increased (decreased) relative to the demand forecast when capacity is insufficient (excessive) relative to desired production.

The benchmark pricing decision rule assumes cost-plus pricing with a constant gross margin and an adjustment for the demand/supply balance. Price simply follows costs down the learning curve, with a markup sufficient to cover marketing expense, investment costs, and provide a reasonable profit (at normal capacity utilization).

The behavioral benchmarks are simple, even naive, rules. They utilize only four cues (costs, industry sales, backlog, and current capacity) rather than full information. The rules naively extrapolate demand growth even though the subjects know the product will go through a life-cycle of growth, saturation, and decline (the benchmark rule's forecast of demand is guaranteed to miss the peak in the market). They do not use pricing to clear the market, control profitability, or signal intentions. There is no game-theoretic reasoning. There is no explicit consideration of investment costs, no anticipation of market saturation and no response to competitor price or capacity, much less the competitor's strategy. The rules cannot learn. They are much less sophisticated than the decision making typically presumed in economic models and strategy texts. Subjects should be able to outperform the benchmark performance quite easily.

The decision parameters α_1, α_2 and β were chose to maximize average cumulative net income per scenario over all 20 market and competitor scenarios, subject to the constraint that cumulative net income is not negative (i.e., no losses) in any single scenario. The global maximum of cumulative profits was generated by:α_1=0.50, α_2=2.375, β=2.50, implying a modest response to growth in industry demand, and strong adjustments of capacity and price to the demand/supply balance.

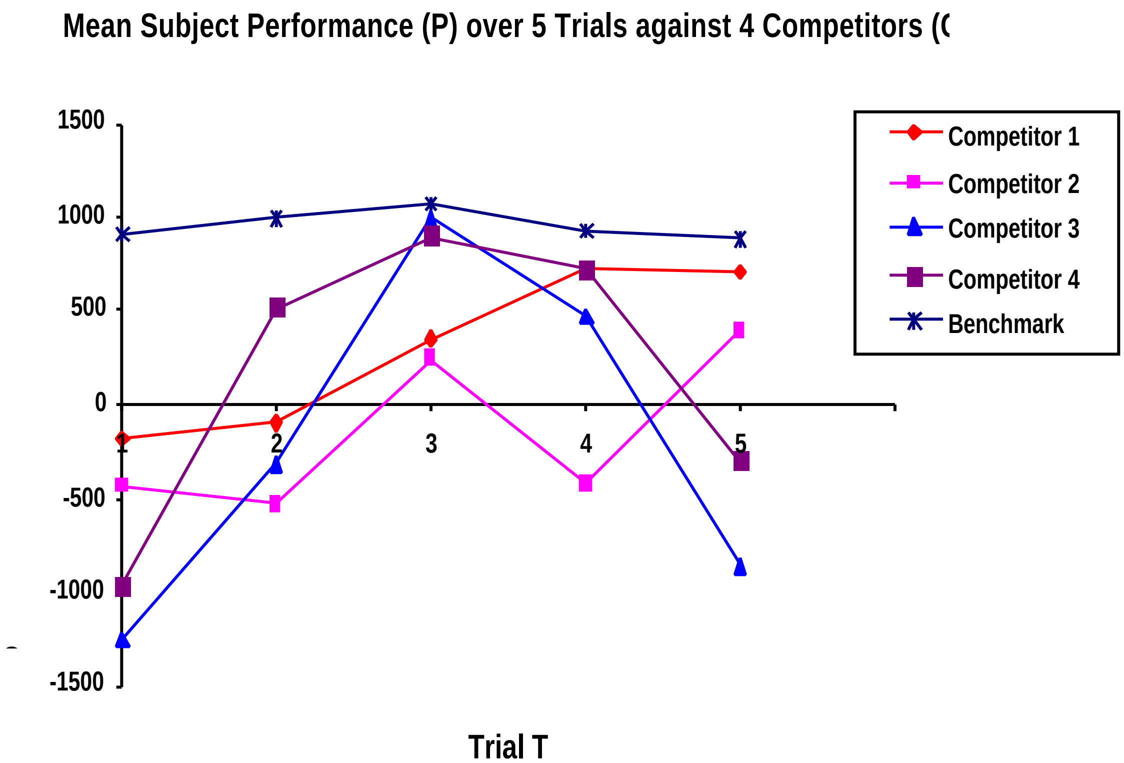
As expected, these parameters yield the lowest cumulative net income of $18.9m for M=2, C=2 (the most rapid product lifecycle coupled with the most aggressive competitor strategy). The highest is $1722m for M=4, C=4. The total cumulative net income over 20 scenarios is $19,170m, the average per scenario being $959m. This scenario generates the highest total cumulative net income over all 20 scenarios, and hence is used for calculating the benchmark profits.

Subject Performance

Figure 2 compares subject performance to the benchmark in all five trials, and against all four competitors. On average, performance is extremely poor. Performance does improve over the five trials against competitors 1 and 2. Against competitors 3 and 4, initial improvement for the first three trials then worsens for trials 4 and 5. In all five trials, and against all four competitors, the mean subject performance is below the benchmark performance.

Table 2 and Figure 3 show how the mean subject performance relative to the benchmark (PRB) varies over the five trials, and against three competitor scenarios. Competitor scenario 2 is omitted in Figure 3 because large outliers distort the scale.

Figure 2 Mean Subject Cumulative Net Income (P) in 5 Trials (T) against 4 Competitor Strategies (C)



A PRB=1.0 would mean the subjects achieve the same cumulative net income as the benchmark decision rule. Similarly, PRB=0.5 means 50% of benchmark profit, whereas -0.5 means a negative cumulative net income of magnitude equal to 50% of the benchmark profit. Large negative values indicate the subjects sustained huge losses. Though performance relative to the benchmark does vary from trial to trial, the variation is not significant. Subjects do *not* learn to improve performance over the five trials. Performance relative to the benchmark does depend on the particular competitor scenario, with competitor 2 generating significantly worse scores than competitors 1, 3 and 4. The mean subject performance relative to benchmark in all five trials and against all four competitors, is below the benchmark score of 1.0.

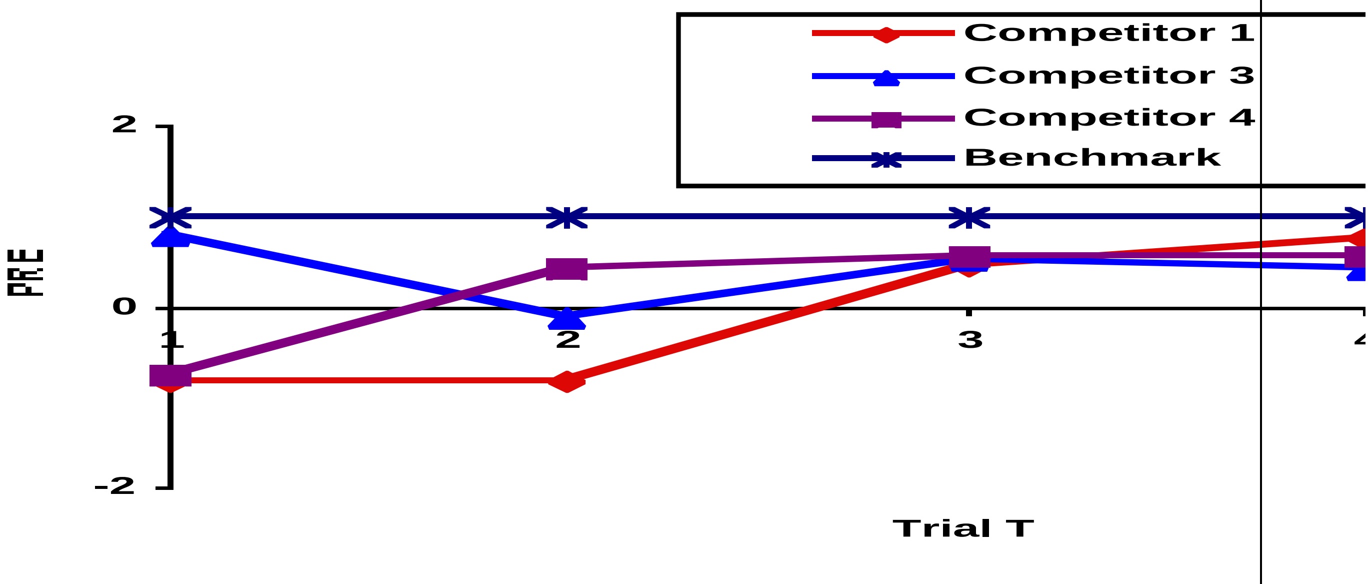
Table 2 Summary Results for Mean Subject Performance Relative to Benchmark (PRB): mean (standard deviation in parentheses).

			Trial T			
	T=1	**T=2**	**T=3**	**T=4**	**T=5**	**Overall**
Competitor C						
C=1	-0.822	-0.809	0.443	0.745	0.669	-0.059
	(8.00)	(3.93)	(0.533)	(1.39)	(0.554)	(4.521)

C=2	-0.754	-4.5114	-16.199	-11.415	0.712	-6.241
	(4.45)	(11.5)	(28.7)	(23.1)	(0.841)	(17.9)
C=3	-0.801	-0.125	0.527	0.423	-1.767	-0.341
	(7.56)	(3.46)	(0.712)	(1.68)	(11.9)	(6.58)
C=4	-0.753	0.406	0.542	0.551	0.039	0.149
	(3.67)	(0.602)	(0.495)	(1.09)	(2.48)	(2.12)
Overall	-0.784	-1.302	-3.142	-2.368	-0.156	-1.544
	(6.25)	(6.68)	(15.0)	(12.5)	(6.41)	(9.98)

The percentage of subjects who score above the benchmark performance (over all trials) is 17.9%. This does vary across trials, from - 4.8%, 11.5%, 19.1%, 26.5% and 3.1% for trials 1-5 respectively. Clearly some subjects do appear to improve relative to the benchmark performance, but the mean subject score for each trial is still well below the benchmark. This percentage does not vary much against competitors - 16.2%, 19.2%, 17.4% and 18.2% for competitors 1-4 respectively.

Figure 3 Mean Subject Performance Relative to Benchmark as a Function of Trial T (1-5) and Competitor Scenario C (1,3,4).



Vertical Axis is PRB, Performance Relative to Benchmark

General Linear Model

To gain insight into the determinants of performance, we estimate a general linear model for the dependent variable Performance Relative to Benchmark (PRB), with independent variables Subject (SUB), Trial (T), Competitor (C), the log or the Word-of-Mouth Effect (logw), and the log of the Replacement Fraction (logr). Principal interactions of the main effects are also included. The additive error term ε is assumed to be a normally distributed random variable with zero mean. The linear model we are estimating is:

PRB = constant + SUB + T + C + logw + logr + logw*logr + C*T + T*logw

+T*logr + C*logw + C*logr + C*logw*logr + ε

The results of the analysis of variance are shown in Table 3.

The competitor scenario, and the determinants of the speed and severity of the product lifecycle (the replacement fraction, strength of word-of-mouth, and their interaction) are highly significant. Further, the interactions of competitor strategy with the determinants of the product lifecycle are also highly significant. The magnitude and sign of the WOM and replacement fraction are as expected. The stronger the word of mouth, the faster the growth of demand, higher the peak, and sharper the transition to decline. Subjects have more difficulty when the positive feedback driving growth is strong. Similarly, the smaller the replacement fraction, the worse the subject performance, since a small replacement purchase rate means a greater demand decline from peak to equilibrium. The worst performance arises when rapid growth is combined with a highly durable product. The greater the dynamic complexity of the market, the worse is subject performance relative to potential.

Table 3. Analysis of Variance for Dependent Variable PRB
$R^2 = 51\%$

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Sub	253	24743	18359	72	1.11	0.137
T	4	1048	280	70	1.08	0.367
C	3	7380	1646	548	8.43	0.000
logw	1	3807	687	687	10.56	0.001
logr	1	4452	1035	1035	15.89	0.000
T*C	12	6598	413	34	0.53	0.897
logw*logr	1	1130	776	776	11.92	0.001
T*logw	4	574	427	106	1.64	0.161
T*logr	4	2174	263	65	1.01	0.401
C*logw	3	1693	430	143	2.20	0.086
C*logr	3	1410	1793	597	9.18	0.000
C*logw*logr	3	2648	2648	882	13.56	0.000
Error	826	53791	53791	65		
Total	111	111454				

The coefficients of the significant main effects are:

Constant	-1.2239	
C1	1.4523	Competitor strategy “cost-plus”
C2	-3.8061	Competitor strategy “share-oriented”
C3	0.6996	Competitor strategy “margin-oriented”
C4	1.65	Competitor strategy “tit-for-tat”
logw	-1.5765	Word-of-mouth (WOM) effect (speed of growth)
logr	1.7407	Replacement fraction (severity of bust)
logr*logw	1.3306	Interaction of WOM and Replacement Fraction

Competitor strategy 2 generates by far the worse performance relative to benchmark (coefficient of C2 is -3.8) and is what we expect given the strategy of competitor 2. In fact, Bonferroni post-hoc tests show that only C2 is significantly different from the other competitor scenarios C1, C3, and C4.

We also tested for a “sequence effect” to see if the particular order in which the scenarios are being completed contributes significantly to performance. The trial sequence is, in fact, significant but post-hoc tests reveal that only sequence four is significantly worse than the others. This sequence included market scenario two and competitor scenario two which in combination are particularly difficult for the subjects. Sequence is therefore not included in subsequent statistical models.

Analysis of Subjects' Decision Rules

The general linear model and ANOVA show that the greater the dynamic complexity of the market and of the competitor strategy, the worse the subjects do relative to potential. Next we explore the nature of the decision rules subjects used to see if we can identify the sources of their poor performance and gain insight into the mental models they bring to the task. Behavioral decision rules are estimated for target capacity and price. These rules are generated from analysis of subjects' logs and written reports of their strategies. The rules we tested represent just two of many possible rules. But they do reveal how the weights on the cues that subjects use to make their decisions vary over trials and treatments (i.e., market scenario M and competitor scenario C).

A more complete description of the form of these decision rules is given in Paich and Sterman 1993, pp. 1450-1451. The postulated rules generalize the benchmark decision rules. We postulate that subjects select the share of the market they seek to capture, estimate future market demand from prior information, current demand, and recent demand growth, and invest to balance capacity with demand. Specifically:

$$C^*_t = S^* [D_0^{(1-\alpha 0)} D_{t-1}^{\alpha 0})](1 + g_{t-1})^{\alpha 1} (B_t / C_t)^{\alpha 2},$$
$$g_{t-1} = (D_{t-1} - D_{t-2}) \;/\; D_{t-2} \qquad (3)$$

where S^* is target market share (assumed constant), D_0 is the prior expectation of average industry demand, D is actual demand, g_t is the expected fractional growth rate of demand, B is the backlog (desired production), and C is current capacity.

The proposed decision rule for price P assumes subjects use markup pricing:

$$P_t = (UPC_t)\,(M^*_t),$$
$$M^*_t = M_0\,(UPC_t \;/\; UPC_0)^{\beta 1}\,(B_t / C_t)^{\beta 2}\,(CP_{t-1} \;/\; P_{t-1})^{\beta 3} \qquad (4)$$

where UPC = unit product cost (fixed plus variable) and M^* = gross margin. Gross margin depends on the subject's response to the demand/supply balance and the policy for passing cost reductions on to the consumer. As the firm moves down the learning curve, the subject must decide how much of the cost reduction to pass on to consumers. All cost reductions are passed into price when $\beta_1 = 0$, while $-1 <= \beta_1 <= 0$ indicates price falls less than costs. Positive values of β_1 indicate price falls faster than costs, perhaps indicating an attempt to build market share and move more rapidly down the learning curve than the competitor. We further expect that the gross margin will increase when backlog is high relative to capacity ($\beta_2 > 0$).

Re-arranging equations 3 and 4 and taking logs gives the following equations for estimation by regression:

$$\log(C_t^*) = a_0 + a_1\log(D_{t-1}) + a_2\log(1+g_{t-1}) + a_3\log(B_t / C_t) + \varepsilon_1 \qquad (5)$$

$$\log(P_t) = b_0 + b_1\log(UPC_t) + b_2\log(B_t / C_t) + b_3\log(CP_{t-1}) + \varepsilon_2 \qquad (6)$$

Each rule was estimated separately for all the 22 Executive subjects, and for a similarly sized random sample of 24 MBA subjects. The mean and variance of the performance relative to benchmark for the random sample of MBA subjects (mean=-2.49, s.d=12.2) are within 95% confidence limits of the population mean and variance (mean=-1.55, s.d.=10.23), and hence the sample is considered to be representative. The error terms are serially correlated, so the Cochrane-Orcutt procedure for first-order autocorrelation was used. Table 6 shows the regression coefficients mean and standard deviations.

Table 6 Mean and Standard Deviations of Estimated Parameters for Subjects' Capacity and Pricing Rules (Equations 5 and 6)

	MBA Subjects	**(N=91)**		**Exec subjects**	**(N=54)**	
Capacity Rule:	Mean	Std Dev	% Sig	Mean	Std. Dev	%Sig
a_0	8.399	5.107	73%	8.975	7.480	72%
a_1	0.374	0.348	62%	0.329	0.490	57%
a_2	0.316	0.949	39%	0.195	0.683	22%
a_3	0.214	0.436	53%	0.064	0.401	22%
ρ_1	0.570	0.330	71%	0.634	0.255	91%
R^2	0.821	0.192		0.828	0.156	
Pricing Rule:						
b_0	1.343	9.375	43%	-0.335	10.419	48%
b_1	1.038	4.260	52%	1.191	2.940	63%
b_2	-0.106	0.391	51%	-0.098	0.112	67%
b_3	0.0684	0.470	51%	0.137	0.361	39%
ρ_2	0.0631	0.392	78%	0.309	0.270	87%
R^2	0.876	0.131		0.902	0.131	

ρ_1 and ρ_2 are the first-order autoregressive coefficients.

"%Sig" column indicates the percentage of trials in which the parameter was significantly different from zero.

The estimated parameters for the MBAs and executives are very similar. The greatest difference is in the mean estimate for a_3, (0.214 for MBAs vs. 0.064 for the executives), indicating the executives paid less attention to the supply/demand balance than MBAs (only 22% of the estimated values for the executive group were significantly different from zero, compared to more than half for the MBAs). However, the difference in the mean estimate of a_3 between the two groups is not statistically significant.

The coefficient b_3 in the pricing rule is very small (0.0684 for MBAs and 0.137 for executives) with less than half significantly different from zero (47% MBAs, 39% Executives). Surprisingly, subjects appear to pay little attention to the competitor price when formulating their own pricing decision. This seems unlikely, apart from the case of Competitor 1 (cost-plus pricing). Eliminating Competitor 1 from the analysis, the parameter b_3 mean (s.d) is 0.247 (0.293) for MBAs, and 0.257 (0.198) for Executives. These values are much higher than those estimated with Competitor 1 included, and show that more attention is paid to the Competitor price when it varies.

Next, we investigate how subject decision weights change with experience and across market environments by estimating linear models for each estimated parameter in turn (a_0, a_1, a_2, a_3, b_0, b_1, b_2, b_3) with subject (Sub), trial (T), word-of-mouth effect (logw), replacement fraction (logr) and competitor scenario (C) treatments as explanatory variables (equation 7). EXEC is a dummy variable to distinguish between MBA and Executive subjects.

$$\text{Estimated parameter} = \text{constant} + \text{Sub} + \text{EXEC} + \text{C} + \text{T} + \text{logw} + \text{logr} + \varepsilon \tag{7}$$

Most of the estimated parameters do *not* change significantly with experience (trial), or as the market environment (word of mouth, replacement fraction and competitor strategies) change. The estimation of parameter b_3 (governing the response to competitor price in the pricing rule) does depend significantly on the competitor strategy C, with an overall R^2 of 47%. The competitor scenario effect has coefficients (significantly different from zero) for C1=0.48, C2=0.10, C3=0.18 and C4=0.26. The weight that subjects place on competitor price does vary significantly with the particular competitor scenario, but the adjustments are small. There is no clear pattern to the coefficients, and in estimating six terms in eight models we would expect at least one effect to be significant at the 5% level just as a matter of chance. Overall, the results show that subjects' decision rules are not sensitive to the dynamic complexity of the market or the competitor strategy. More important, there is no evidence of learning from experience: subjects do not modify their strategies over time.

Discussion

The results show, first, that performance relative to potential is poor on average. Second, performance relative to potential is significantly worse in dynamically complex environments. Third, the decision rules of the subjects are not responsive to the market environment or competitor strategy. Fourth, in general, subjects are not sufficiently responsive to the demand supply balance, either in adjusting their capacity or in adjusting prices. Finally, there is little evidence that subjects learned from experience, and no evidence that they learned from their experience how to do better in dynamically complex environments. These are sobering results, but consistent with prior work (Paich and Sterman 1993, Sterman 1994).

The pricing behavior of the subjects warrants special consideration. Recall from the analysis of the benchmark decision rule that the optimal value of b_2, the coefficient that relates the demand / supply balance to price, is 2.5, which implies that a 1% increase in the demand / supply balance causes a 2.5% increase in price. The average estimated value of b_2 for both the MBAs and the executives was -0.1; over 75% of the estimated coefficients were negative. A negative value for b_2 implies that the subjects *reduced* price in response to lower product availability, exactly the opposite of the optimal response. Those estimates of b_3 that were positive were generally much smaller than the optimal value.

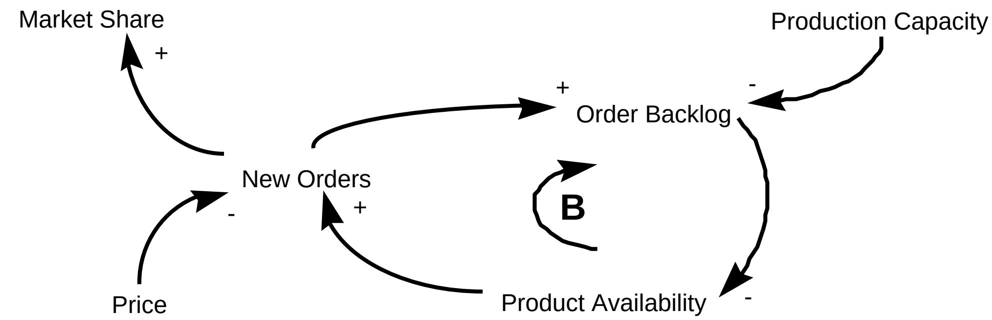
Apparently, the subjects in the experiment, focused on maintaining market share, reason that they must offset the reduction in product attractiveness caused by long delivery times by lowering prices. However, lower prices, by increasing product attractiveness, actually worsens the delivery situation. The result is a positive feedback, a vicious cycle of deteriorating customer service, lower prices, and still worse service. Furthermore, since in the real world customers have heterogeneous tastes, the effect of lower prices and long delivery times is to systematically drive away those customers who are delivery sensitive and price insensitive while attracting those customers who, for reasons of limited funds, are willing to wait longer to save a few dollars. Consequently, a firm that cuts price to maintain attractiveness as service deteriorates will find its customer mix changing to favor price sensitive bargain hunters. That is, the firm systematically increases the elasticity of its demand curve, increasing its vulnerability to price competition at the same time they invite a price war.

The decision to lower price when product availability is poor has been observed in many real situations. For example, Apple Computer suffered severe shortages of innovative new products (Wall Street Journal August 11, 1995). The backlog of unfilled orders grew substantially and market share declined. However, Apple reduced price by as much as 40% on some of the items that were in short supply. In addition, IBM has made similar decisions in the PC market.

As another example, People Express Airlines fell victim to just this dynamic. Initially, People Express offered low fares and good service. But its very low fares led to rapid growth, causing staff shortages, rapid hiring, a decline in employee experience, and other operational problems resulting in a sharp decline in customer service. Consequently, the customer mix shifted from both business and discretionary (student, vacationer) passengers in the early days to a customer base almost exclusively made up of price-sensitive discretionary travelers. When competitors then cut prices to match People’s fares, People lost the only remaining dimension of product attractiveness in which it had an advantage and was soon forced to the brink of bankruptcy and a forced sale to Frank Lorenzo’s Texas International (Sterman 1988, Graham et al 1992).

The MOF hypothesis can account for the significant difference between subjects' responses to supply/demand imbalances and the optimal response. The MOF holds that in determining their choices decision makers ignore important feedback loops. In the model, an important feedback loop links product availability, market share, and orders. As shown in Figure 4, an increase in new orders increases the order backlog and reduces product availability. Lower availability reduces market share and orders. This causal chain creates a goal seeking feedback loop that balances supply and demand.

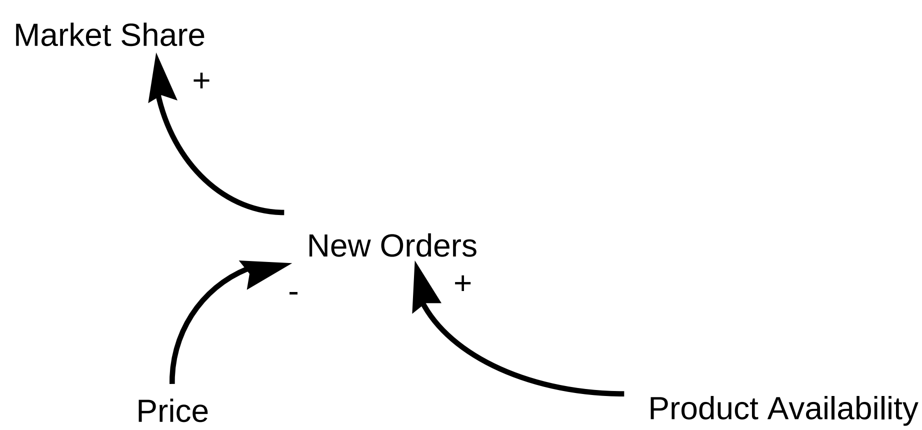
Figure 4 Feedback Structure of Simulated Model



The causal link between orders and product availability makes it optimal to raise price when availability falls. Assume that orders unexpectedly increase. Because capacity acquisition takes time, additional orders reduce product availability and market share. By itself, raising price would further reduce market share and orders. However, the reduction in orders caused by the higher price improves availability and pushes share back up. The higher price reduces orders to some degree, but not enough to offset the revenue gain from a higher price per unit. Consequently, raising price in response to lower availability significantly increases profit.

The MOF holds that decision makers could find it difficult to determine the policy implications of the feedback structure described in Figure 4. In this situation, the decision maker might use a simpler mental model of the situation that ignores the goal seeking loop. An example of a simplified mental model is shown in Figure 5. In the simplified mental model, product availability is not connected to the order backlog and does not depend on past pricing decisions.

Figure 5 Simplified Feedback Loop Structure of Simulated Model



The simplified mental model shown in Figure 5 has very different policy implications than the mental model shown in Figure 4. Assume that market share is determined by the same equation as in the full simulation and that the decision maker maximizes profit for a single period. For the model in Figure 5, it can be shown that the optimal response to lower product availability is always to lower price.

In other words, a decision maker who used the simplified mental model would decide to lower price in response to lower availability. In addition, for the specific parameters in the simulation model, the optimal value of the parameter b_2 is about -0.12 which is very close to the average estimated value for the subjects. The stated rationale for reducing price in response to poorer availability could be something like the following. Lower availability has reduced market share and, in order to compensate, price should be reduced. The lower price will induce customers to wait until the product is available, increase orders, and improve profitability. A price increase would "punish the customer" and ultimately reduce profitability.

One explanation for the subjects' pricing behavior is that they found an excellent solution to the wrong problem. The subjects' pricing strategy works well in the simplified environment described in Figure 5. The same strategy performs poorly in the actual environment described in Figure 4. A mental model that ignores the feedback connection between price and future availability generates decisions that are the opposite of the correct decisions.

In essence, if the system were in equilibrium (if capacity adjusted rapidly to demand), delivery delay would be independent of price, and a drop in market share could be offset by lower prices. But in the simulation as in the real world, capacity adjustment takes time, the firm is often in disequilibrium, and price is strongly couples to delivery delay. The subjects appear to assume implicitly that the market and firm are in equilibrium, despite the fact that evidence to the contrary was available to them at all times during the experiment. We conjecture that the emphasis on equilibrium and comparative statics in economic theory and course work may contribute to this error.

Our study did not collect concurrent verbal protocols or other real-time metrics of people's reasoning, so we cannot prove that they used a simplified mental model like the one described in Figure 5. We can say that a hypothetical decision maker who used the simplified mental model and attempted to maximize profit would have generated price decisions that were consistent with the subjects' actual price decisions. However, the subjects' actual decisions could have resulted from some other mental model. Follow up study would be required to answer the question definitively.

It is possible that factors not included in the model could make it optimal for real-world firms (computer manufacturers, for example) to reduce price in the face of product shortages. Price cuts could be necessary to maintain the loyalty of the dealer network or to promote an image of price competitiveness or fairness. Many real markets involve more competitors than our experiment, so the scope for collusive behavior is less. It is not obvious to what extent these factors would change the optimal response to supply/demand imbalance. Given the importance of pricing for both short-term and long-term profitability, this is an important topic for future research.

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