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A Simulation Analysis of Alternative Pricing Strategies for Dynamic Environments

Researchers of the strategic implications of the well-known demand (e.g., adoption and diffusion) and supply (e.g., experience effects) dynamics have typically sought analytical solutions. Their success in this has been achieved partly by limiting the richness of the dynamics considered. This paper describes a simulation modeling capability, SIMSTRAT, which trades off analytical solutions for richer, more realistic representations of supply and demand. We present the model and then the results of our initial investigations using SIMSTRAT. When joined with new computer graphics capabilities, the model is successful in identifying conditions conducive to skim- and penetration-pricing strategies.

I. Introduction

The implicit assumption of the classical economic model of price determination is that the firm maximizes short-run profits. However, one of the key implications of strategy research of the past decade is that short-run profit maximization is not an appropriate criterion for many market situations. Instead, market share has been proposed as the key to long-term profitability (see, e.g., Buzzell, Gale, and Sultan 1974; Abell and Hammond 1979). This proposition has had a strong impact on both marketing practice and research. Hopkins (1981) reports that 88% of industrial firms surveyed spell out market share goals in detail. The emphasis on market share in practice has been reflected in the theoretical side also, where numerous market share forecasting and maximizing models have been published.

Long-term profitability has also become a research interest in its own right: more than a dozen papers have appeared in major journals since 1975. The impetus to this activity has been the recognition of the existence of intertemporal effects in the environment. For example, on the demand side, a consumer's purchasing in a given time period may preclude purchasing in the future because of the durability of the good or personal inventory loading. On the supply side, added current production early in new product introduction may reduce the cost of future pro-

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duction as the firm becomes more adept through experience. In such situations, the solution of a series of short-run maximization problems does not lead to a long-run maximization.

Our interest in this paper is the determination of preferred pricing strategies in market situations with dynamic supply and demand conditions. Our primary purposes are

1. by review of the relevant literature, to bring together the results of studies using varied analytical tools and specifications of the demand and supply dynamics;
2. to present the SIMSTRAT simulation model we developed to overcome some of the limitations in the types of environments considered by the analytical models; and
3. to demonstrate the utility of the SIMSTRAT model by presenting the results of our initial investigations using the model. We address two questions. First, under what circumstances does solution of a series of short-run maximization problems imply seriously suboptimal long-run profits? Second, when short-term profit maximization does not make sense, are there simple pricing rules that do?

The organization of the paper follows these three points. Section II traces both the economics and marketing literature on strategic pricing over the last decade. This review shows the current state of knowledge and the prospects for future contributions. Section III presents the structure of the SIMSTRAT model as a preliminary to the application of the model reported in Section IV. Section V concludes with a statement of important open research questions and our future research plans.

II. Strategic Pricing Literature

Prior to 1980 there are only two papers giving analytical results for dynamic demand or cost conditions. Rosen (1972) establishes the conditions for long-term profit maximization in a perfectly competitive market with dynamics on the cost side. Spremann (1976), on the other hand, addresses a monopolist operating under dynamic demand but stable cost conditions. Using optimal control, he generalizes the Dorfman-Steiner (1954) conditions for optimal price and advertising to the case of demand being a function of an index of past sales, in addition to current price and advertising.

The first paper to consider the interaction between supply and demand dynamics, and the most influential early paper is Robinson and Lakhani (1975). Using dynamic programming, they determine the optimal price path for a case of diffusion demand and experience curve costs. For their chosen case, the discounted profit level yielded by the optimal price path is six times greater than that yielded by a sequence of short-run profit-maximizing decisions. Consequently, while limited

TABLE 1 Major Strategic Pricing Papers

Stage 1—Monopoly, specific functional forms:
Bass (1980)
Dolan and Jeuland (1981)
Jeuland and Dolan (1982)
Bass and Bultez (1982)
Dolan (1980)
Stage 2—Monopoly, general functional forms:
Clarke, Darrough, and Heineke (1982)
Kalish (1983)
Stage 3—Competitive:
Teng and Thompson (1980)
Spence (1981)
Simon (1982)
Eliashberg and Jeuland (1982)

to one particular result and offering no possibility of generalization, the result is so striking that the paper is a key stimulus to future developments.

Much of the work since 1980 is directed to finding analytical solutions for the optimal price path under demand and supply conditions similar to those considered by Robinson and Lakhani. Table 1 catalogs the work in three stages.[1] These stages represent progression from the monopoly problem with very particular specifications of the relevant dynamics, to the monopoly problem with general specifications, to explicit consideration of competition. We now review the main contributions from each stage.

Stage 1 begins with Bass's (1980) considering only cost dynamics. In particular, he uses the experience curve productivity model for costs. However, the firm is assumed to maximize short-term profits at each decision point and the demand curve shifts only as a function of time, not as a function of previous sales. Dolan and Jeuland (1981) and Jeuland and Dolan (1982) are the first to achieve analytical results on the interaction of demand and cost dynamics. Unlike Bass, their monopolist's objective is to maximize discounted profits over some given time horizon. Optimal price paths for experience-curve costs and a number of dynamic demand situations are given. In support of the notion of modeling the firm as a short-run profit maximizer, Bass and Bultez (1982) provide a number of examples in which the short-run profit-maximizing strategy yields long-term profit near that achieved by the optimal strategy. A key to these cases, however, is that demand shifts are modeled exogenously as a function of time rather than endog-

1. The papers are not in chronological order of publication. Some are working papers and consequently bear the date of their first appearance. Others are published and bear publication dates, rather than the date of their first appearance as a working paper. Consequently, the dates in table 1 are only to help the reader identify the full citation in the references.

enously as a function of previous sales levels. Dolan (1980) compares exogenous and endogenous demand dynamics and shows this to be the main determinant of the extent of suboptimality of myopic behavior.

Dolan and Jeuland's results are significantly generalized in stage 2 by Clarke, Darrough, and Heineke (1982) and Kalish (1983). Dolan and Jeuland consider only the case in which current cost is a function only of accumulated output. They do not consider the impact of the rate of output. Clarke et al. (1982) describe the optimal price path for such situations.[2] Kalish (1983) does not model the output rate effect on cost but studies the demand side in depth, showing exactly what conditions on the demand function are required to obtain certain characteristics of the optimal price path.

With the work of stages 1 and 2, we have a good understanding of the pricing strategies appropriate for a monopolist facing any of a broad array of combinations of demand and supply conditions. The beginnings of work on the competitive case comprise stage 3.

Teng and Thompson (1980) were the first to advance into the oligopoly area studying both price and advertising decisions. Spence (1981) uses calculus of variations to derive results for very simple cost and demand models using both open-loop and closed-loop equilibrium concepts. His main result is that the value of market share is a nonlinear function of the rate of cost decline, the value being low for both very fast and very slow learning rates. Eliashberg and Jeuland (1982) use equilibrium concepts to focus on demand rather than cost dynamics. An alternative to the equilibrium determination approach is Simon's (1982) reliance on managerial judgments for estimates of competitive price levels. To date, results are limited to very specific situations based on equilibrium conditions.

While stage 3 does represent progress on the competitive problem, it is also evidence of the limitation of present analytical tools. For example, Eliashberg and Jeuland (1982) must revert to the no-cost dynamics and zero discount rate case to achieve analytical results, despite their facility with sophisticated optimization procedures. From this review, the following major points emerge:

1. optimality conditions for a monopolist facing dynamic demand and/or cost conditions are now well established;
2. derivation of the monopolist's optimality conditions for even simple demand and cost functions has required sophisticated mathematical procedures; and
3. work on the long-avoided competitive problem has begun, but the problem is formidable and progress on analytical solutions has been slow.

2. Haley (1981) examined the implications of such a cost function before Clarke et al. (1982), but only for stable demand situations.

The search for analytical solutions is warranted and no doubt will continue. However, based on the observations made above, a parallel research track, employing a fundamentally different research tool, is also appropriate at this point. Our focus is on pricing strategies for an innovating firm that will face competition at some time. Our purpose is to determine preferred strategies given differing demand, supply, and competitive conditions. We wish to accommodate even richer representations of those conditions than those which caused mathematical difficulties in previous work. Since this desire outweighed our natural preference for finding "optimal" as opposed to "good" strategies, we employ simulation techniques.

We now present a large scale computer simulation, SIMSTRAT (*sim*ulation of *strat*egies). This model yields the profit implications of any well-defined pricing rule, given a very broad range of market conditions. The use of simulation limits us to comparative results, that is, the relative performance of one strategy versus another. In this paper, we report on three strategies: (i) the "myopic" strategy of maximizing current period profits each period, (ii) the "skimming" strategy of initially setting price above the myopic price, and (iii) the "penetration" strategy of initially setting price below the myopic price. As long as there are no intertemporal linkages on either the supply or demand side, the myopic strategy is optimal. However, with the introduction of linkages either skim or penetrate can perform better. Simple examples of conditions favoring each follow.

1. Skimming: durable goods (no repeat purchase), no cost dynamics. For example, if there are two customers valuing the good at \$10 and \$6.00, respectively, with unit cost of \$1.00, the myopic strategy is to price at \$6.00, generating total contribution of \$10. A skimming strategy of price equal to \$10 until the first customer buys and then dropping to \$6.00 yields \$4.00 in additional contribution.

2. Penetration: as shown in Dolan and Jeuland (1981), if demand is stable over time, but costs follow an experience curve, a penetration-type strategy is preferred.

A key characteristic of these examples is that there is only one dynamic element at work so it is easy to see which way one is pushed from the myopic strategy. When there is more than one dynamic force, sorting out the effects can be very complicated. The following section presents the SIMSTRAT model which permits examination of the pricing strategy question in markets with complex dynamics. We then present results of our initial use of the model in Section IV.

III. SIMSTRAT Model Structure

Our structure is similar to the problem studied analytically by Spence (1981) and Eliashberg and Jeuland (1982); that is, we consider an innovating firm which will have a monopoly for a predetermined period. At an exogenously determined time, a competitor enters and a duopoly condition holds for the remainder of the planning horizon.

The two main sections of SIMSTRAT describe consumer activity and firm activity. Both the consumer and firm sections have static and dynamic elements.

Consumer Model

The static part of the consumer logic is the consumer's choice rule. The dynamic part is that each consumer is described by three attributes, whose values change over time:

1. *TNEXT*: time at which consumer's current inventory of the good is expected to be depleted;
2. *RPL* (reservation price leader): value consumer places on one unit of the leader's good; and
3. *RPE* (reservation price entrant): value consumer places on one unit of the entrant's good (N.B., $RPE = 0$ prior to entry).

If $TNEXT > 0$, the consumer is "out of the market" and does not purchase regardless of the price posted by either firm. If $TNEXT \leq 0$, the consumer is "in the market" and considers purchase of any good for which his valuation (the *RP*) exceeds or equals the corresponding price. If the value minus price is nonnegative for both goods, the consumer buys a unit of the good offering the greatest surplus, that is, the greatest difference between current value and current price.

The dynamics of the consumer logic are embodied in the updating of the three parameters describing the consumer. For each time period in which no purchase is made, *TNEXT* is decreased by one, denoting use of the current stock. If a purchase is made, *TNEXT* is set equal to *REP*, a variable representing the time required to exhaust the just purchased stock (*REP* is specified in the model as an input constant or a draw from some distribution).

With respect to reservation prices, the initial valuations of the leader's good are an input to the simulation (the *RPL*s for time = 0). Two switches, which are set "on" or "off" for each simulation run, govern the dynamics in RPLs. The first switch covers consumers who have yet to try the product. If the "diffusion switch" is on, the reservation price of the consumer is increased. This could be as a result of risk reduction due to favorable word of mouth, or from perceived social pressures. This effect is tied to the market penetration ratio. The change in *RPL* from time t to time $t + 1$ is given by:

$$RPL(t + 1) - RPL(t) = AD \cdot [PENR(t + 1) - PENR(t)] \cdot RPLO \tag{1}$$

where

$AD > 0$ = an input value reflecting the degree of influence of adopters on nonadopters;

$PENR$ (t) = percentage of population having tried the product by time t; and

$RPLO$ = consumer's initial reservation price for leader's good.

Thus, the reservation price for nontriers increases from $RPLO$ to $RPLO$ $(1 + AD)$ linearly with the number of triers in the population. The value of AD would be very small for inexpensive, frequently purchased items and larger for expensive products[3] especially if quality is difficult to judge before use.

Once a consumer has purchased, the diffusion-type mechanism of equation (1) no longer applies. The model logic provides for maintenance of RPL at its level at the time of purchase or, if desired, for decreasing the RPL to the price at which the purchase was made. The second option has some empirical support from the work of Doob et al. (1969). They show that in field experiments for certain goods, a low initial sales price created a reference point such that subsequent sales were lower than in the case where the low initial sales price was not used. Thus, the price paid provides a value reference point for the consumer.

When the entrant appears, each consumer must be assigned a value for the entrant's good. For each consumer, we generate the entrant's reservation price from the leader's by

$$RPE = RPL \cdot (1 + RAN \cdot DF), \tag{2}$$

where

RAN = a random number selected from a uniform distribution on $[-.5, +.5]$, and

DF = an input value defined on $[0, 2]$ that captures the extent of customer heterogeneity in the valuation of the relative merits of the leader's and entrant's goods.[4]

3. The range of conceivable values for AD is difficult to state. However, AD values exceeding one seem reasonable for a product such as a personal computer. "Retailing Boom in Small Computers" (1982) reports research by Texas Instruments showing "the sale of the first home computer on the block will spawn six more computer sales in short order, five of which will be the same brand as the first." Consequently, the word-of-mouth and demonstration effects are quite significant.

4. For example, if $DF = 0$, then there is perfect correlation between RPE and RPL across users. If $DF > 0$, such is not the case, as the table shows:

Customer	*RPL*	*RAN* (Random Number)	*RPE* $DF = 0$	*RPE* $DF = 1$
1	2	+.2	2	2.4
2	4	+.4	4	5.6
3	6	−.3	6	4.2

When consumers' preferences are similar DF would be low. It is also possible to add a constant to all RPEs if either good is inherently better. We have not, however, used that option in runs reported here.

Each consumer is assigned a different random number, so $RPL - RPE$ has expected value zero, but a positive variance as long as $DF \neq 0$.

The total market is represented by N segments, each of which is treated as described above. There may be more than one consumer in a segment, but all consumers within a segment behave identically throughout the entire simulation. Thus each segment is treated like an individual consumer and appropriate weights are applied for different segment sizes in all calculations. By varying the number of consumers in the various segments different distributions of reservation prices can be produced, for example, normal distribution, skewed toward high or low reservation prices.

Firm Model

The second major part of SIMSTRAT is the firm logic. The dynamics are in a firm's cost. Total unit cost is made up of two components, one of which is subject to experience-curve cost declines and one which is fixed. Specifically, for each firm i,

$$TC_i(t) = FC_i + VCO_i \cdot \left(\frac{ACV_i(t)}{ACVO_i}\right)^{-B_i}, \tag{3}$$

where

$TC_i(t)$ = total per unit cost at time t,
FC_i = fixed component of per unit cost, not subject to experience,
VCO_i = initial value of the variable component of per unit cost (i.e., at the end of pilot production period),
$ACV_i\,(t)$ = accumulated volume at time t,
$ACVO_i$ = pilot production volume, and
B_i = firm's experience rate.

Within any period, unit cost is a constant and there are no capacity constraints. In economic terms, the short-run average cost curves are horizontal and shift downward over time because of experience.

The other key portion of the firm modeling is the definition of the pricing rules. Fundamentally different rules are used in the monopoly and competitive periods. In the monopoly period, the leader uses a simple pricing rule employing perfect, but only current, information on cost and demand. We assume the leader has perfect information about reservation prices for all segments in the market. The leader then computes the myopic price, MP, which maximizes current period profit.

The three strategies of interest in the initial SIMSTRAT investigations are (1) myopic strategy: price = MP; (2) skimming strategy:

$$\text{price} = Z \cdot MP + (1 - Z) \cdot (\text{maximum } RPL \text{ of consumers in market}); \tag{4}$$

and (3) penetration strategy:

$$\text{price} = Z \cdot MP + (1 - Z)\,(\text{unit cost}). \tag{5}$$

The weights Z, $0 < Z < 1$ are varied across simulation runs, but held constant over the entire monopoly period for any given run.

The policy followed during the monopoly period not only determines the leader's profits during the monopoly period, but also influences both his cost position and market demand for the beginning of the competitive period. Because of the endogenous dynamics built into the system (through *TNEXT, RPL, RPE*, repurchase cycle, and cost changes) the myopic policy is not always to be preferred over skimming or penetration strategies.

The major conceptual problem in formulating the model is price determination in the competitive period. We use two procedures, both of which accord the first firm a leadership role. The first rule is a Stackelberg leader-follower solution in a myopic game. In this situation, the leader declares his price first, then the entrant selects his price to maximize his own profits given the leader's price. For his part, the leader knows the entrant's decision rule a priori. Thus, the leader's initial price declaration is the short-term profit-maximizing price conditional on the decision rule of the entrant.

The second rule mirrors a price leadership situation, similar to that observed in markets such as steel, cigarettes, and turbine generators (see Sultan 1975; Scherer 1979). The leader declares a price. So as not to set off a round of price cutting, the entrant does not undercut the leader; rather he matches the leader's price. This behavior is quite common in situations in which the leader dominates the entrant in terms of cost advantage, distribution, or marketing power. It can also occur in other situations in which both firms recognize that each is better off if they are not so aggressive in trying to gain share. Again, we grant the leader knowledge of the entrant's decision rule (i.e., match price) and the leader selects his current period profit-maximizing price in the light of it.

Thus, in both situations, the leader solves a short-term maximization problem. In the Stackelberg leader-follower model, the entrant solves a myopic optimization problem as well. However, he solves no explicit optimization problem in the price leadership model. Implicitly, his objective is to seek long-term profits through the avoidance of price competition.[5]

5. While it may seem at first that the entrant is behaving irrationally in a "match price" model, such is not the case. In many demand situations, the match price model succeeds in holding market prices higher, resulting in greater profits for the entrant than the short-term optimizing mode of the Stackelberg model. A specific example of this is given in table 3.

TABLE 2 SIMSTRAT Input Parameters

Market characteristics:	
N	Number of segments in the population
REP	Time interval a unit of good lasts, specified as either a constant or a draw from distribution
AD	Diffusion-effect parameter (in eq. [1])
DF	Product-valuation heterogeneity parameter (in eq. [2])
Individual segment characteristics (for each of *N* segments):	
S(*I*)	Number of customers in segment *I*
RPLO(*I*)	Initial valuation of leader's good
Leader firm:	
FC	Fixed component of unit cost (in eq. [3])
VCO	Initial value of variable component of unit cost (in eq. [23])
ACVO	Pilot production volume (in eq. [3])
B	Experience rate (in eq. [3])
Z	Weights to be used in skim and penetrate strategies (in eqq. [4] and [5])
Entrant:	
TENT	Time of entry
FC, VCO, ACVO, B	As for leader firm
FPS	Entrant pricing strategy (0 if Stackelberg model, 1 if match price model)
Model Control Parameters:	
TEND	Number of periods to simulate
DISC	Discount rate applied in calculation of present values

Model Structure Summary

Table 2 summarizes the inputs to the simulation model. The inputs basically describe the market situation, individual segments, and the firms. A sample model output is shown in table 3. The output shows the prices for leader and entrant for each time period, unit sales to new and repeat customers, and the discounted profit over the 10-period duration. Note that for the specific parameter values of the example, both leader and entrant do much better if the entrant matches the leader's price, rather than attempts to maximize short-run profits.

IV. Simulation Results

Our initial SIMSTRAT investigations are directed to resolution of the following currently open questions: (1) Under what conditions is myopic pricing behavior inferior to simple long-term pricing policies? and (2) When myopic behavior is not appropriate, what simple pricing rule is better? The first question has been addressed by Robinson and Lakhani (1975), Dolan (1980), and Bass and Bultez (1982). Robinson and Lakhani and Dolan have examples where being myopic is quite suboptimal. Bass and Bultez provide examples of cases where myopic is pretty near optimal. This literature indicates that the key parameters may be the experience rate and the extent of influence of adopters on nonadopters. On the second question, Baumol and Quandt (1964) examine the performance of simple pricing rules but not in a dynamic environment. Our treatment differs from these efforts in terms of the number of environmental factors and the complexities of demand (particularly repeat purchase) and competition considered.

In this section we proceed as follows. First, for a given market situation, we compare the performance of skim and penetration policies with that yielded by myopic profit maximization in terms of profit levels and prices charged over time. Then, in succession, we change the experience rate and the adoption/diffusion (*AD*) parameter to observe the effects on the preferred price path. We then check for interaction effects by varying both parameters simultaneously. Three-dimensional graphics prove quite valuable in detecting the nature of the effect.

Having examined the effects of the two variables most often addressed in the literature to date, we then present results of simultaneous variation of other factors as well. We look at one case in detail and use analysis of variance to summarize results of many other investigations. We conclude that the extent of suboptimality of the myopic rule is substantial, both in terms of degree and frequency of occurrence, and is the result of a highly interactive process of the market variables.

Model Results: Base Case Environment

Our "base case environment" has 50 consumer segments ($N = 50$), each with two consumers [$S(I) = 2$]. It takes 4 time periods to consume the good ($REP = 4$), the number of adopters influences nonadopters' reservation prices only slightly ($AD = 0.5$), and consumers are fairly homogeneous in their perceptions of the relative merits of the two goods ($DF = 0.5$). On the cost side, the leader has an 80% experience curve ($B = .3218$) for the portion of costs subject to experience. The fixed and initial variable costs per unit are \$2.00 and \$13 respectively ($FC = \$2.00$, $VCO = \$13$). Pilot production volume is 100 ($ACVO = 100$). On entry in period 5, ($TENT = 5$), the entrant is in the same position as the leader was at the beginning of the simulation. Profits are discounted at the rate of 5%, ($DISC = 5\%$).

Figure 1 shows the discounted contribution generated by skim pricing policies in the monopoly period as a function of the weight on the myopic price in the $P = (Z \cdot MP) + (1 - Z) \cdot$ (maximum reservation price) equation. One curve shows results for the Stackelberg leader-follower model, the other results for the price-matching behavior of the follower. The results for penetration strategies are not shown because, in this situation, penetration is less profitable than myopic for all levels of Z. Figure 1 shows that if the entrant strategy is a price-matching one, the best skimming strategy weights the myopic price .7 and the max-

TABLE 3 **Sample Model Output**

A. Inputs

Market	Individual Segment	Leader Firm	Entrant	Model
$N = 50$	$S(I) = 2$	$FC = \$2$	$FC = \$2$	$TEND = 10$
$REP = 2$	$RPLO(I) = \$I$	$VCO = \$13$	$VCO = \$13$	$DISC = 5\%$
$AD = 1.5$	. . .	$ACVO = 100$	$ACVO = 100$	. . .
$DF = .5$	. . .	$B = .3$	$B = .3$	. . .
		$Z = 1$	$TENT = 3$	

B. Stackelberg Leader-Follower Price

	Leader					Follower				
	Price	Cost	New Sales	Repeat Sales	Contribution	Price	Cost	New Sales	Repeat Sales	Contribution
1	31.8	12.0	40.	0	790.	0	0	0	0	0
2	29.3	8.2	28.	0	592.	0	0	0	0	0
3	29.3	7.4	0	0	0	24.7	12.	42.	0	534.
4	14.8	7.4	8.	22.	223.	14.4	8.1	22.	0	139.
5	7.9	6.9	6.	24.	30.	9.2	7.5	2.	14.	27.
6	7.9	6.6	0	30.	41.	9.2	7.2	0	22.	44.
7	7.9	6.3	0	20.	32.	9.0	6.8	2.	18.	44.
8	7.9	6.1	0	30.	53.	9.0	6.6	0	22.	53.
9	7.9	6.0	0	20.	39.	9.0	6.4	0	20.	53.
10	7.9	5.9	0	30.	61.	9.0	6.2	0	22.	61.
Cumulative sales	. . .		82.	176.	1861.	. . .	. . .	68.	118.	955.
Total sales	. . .	. . .	. . .	258.	. . .	. . .	. . .	. . .	186.	. . .
Discounted profit	. . .	. . .	. . .	1570.	. . .	. . .	. . .	. . .	731.	. . .

C. Follower Matches Price

	Leader					Follower				
	Price	Cost	New Sales	Repeat Sales	Contribution	Price	Cost	New Sales	Repeat Sales	Contribution
1	31.8	12.0	40.	0	790.	0	0	0	0	0
2	29.3	8.2	28.	0	592.	0	0	0	0	0
3	29.3	7.4	0	0	0	29.3	12.0	24.	0	415.
4	29.3	7.4	2.	30.	701.	29.3	8.9	20.	0	408.
5	21.5	6.9	6.	4.	146.	21.5	8.0	2.	20.	296.
6	21.5	6.7	0	32.	472.	21.5	7.4	2.	20.	309.
7	21.5	6.4	0	10.	151.	21.5	7.0	0	22.	318.
8	21.5	6.3	0	32.	485.	21.5	6.7	0	22.	324.
9	21.5	6.1	0	10.	154.	21.5	6.5	0	22.	329.
10	21.5	6.0	0	32.	494.	21.5	6.3	0	22.	334.
Cumulative sales	. . .	. . .	76.	150.	3984.	. . .	. . .	48.	128.	2733.
Total sales	. . .	. . .	. . .	226.	. . .	. . .	. . .	. . .	176.	. . .
Discounted profit	. . .	. . .	. . .	. . .	3019.	. . .	. . .	. . .	. . .	1923.

NOTE.—In B and C, leader is myopic optimizer.

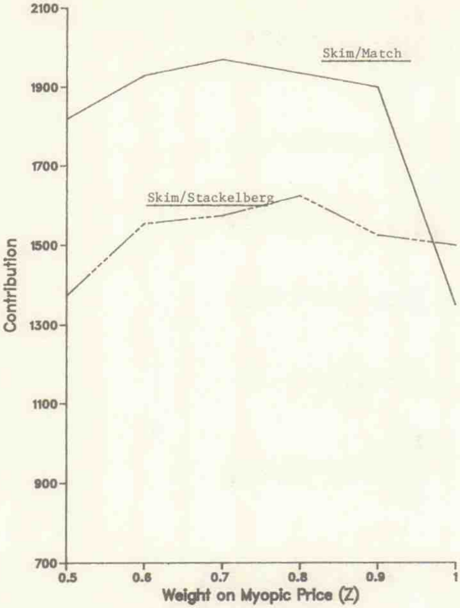

FIG. 1.—Discounted contribution for skim strategies

imum reservation price in the market .3.[6] If the entrant is a myopic Stackelberg follower, the best weight on the myopic price is .8 (meaning higher prices). Figure 2 shows the associated price paths for the two skimming strategies and the myopic price path.

The impetus to hold prices above the myopic level in the monopoly period comes from the durability of the good ($REP = 4$). The firm is constantly trading off contribution that could be made in a future period from returning customers with higher reservation prices, if the price is kept up, with decreasing price to sell new customers with lower reservation prices. Thus increasing sales by dropping price has a nega-

6. While we use the word "best" to describe some strategies, it should be noted that we mean best of the set we considered. Our best is not globally optimal, since, again, simulation restricts us to comparative results.

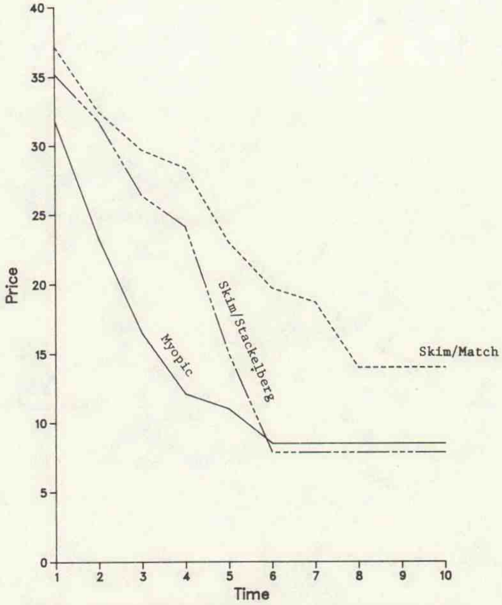

FIG. 2.—Price paths for leader for alternative entrant strategies

tive externality on next-period demand by taking consumers out of the market for long periods. This negative effect apparently outweighs the positive effect through $AD > 0$ and cost-decline incentives in this situation.

To examine this question, we separately increase AD and the experience rate to observe the effect on the optimal price path. Figure 3 shows the price path for the best skimming policy for the base case environment with a price-matching entrant ($Z = .7$) compared to best price paths for the base case with an increase only in AD (from .5 to 1.5) and for an increase only in the experience rate (from 80% rate to 70% rate). As might be expected, the effect of each change individually is to decrease the incentive to skim the market, and lower prices result.

With respect to the profit levels generated by the best strategy relative to the myopic, figure 1 shows the skim/match situation yielding a

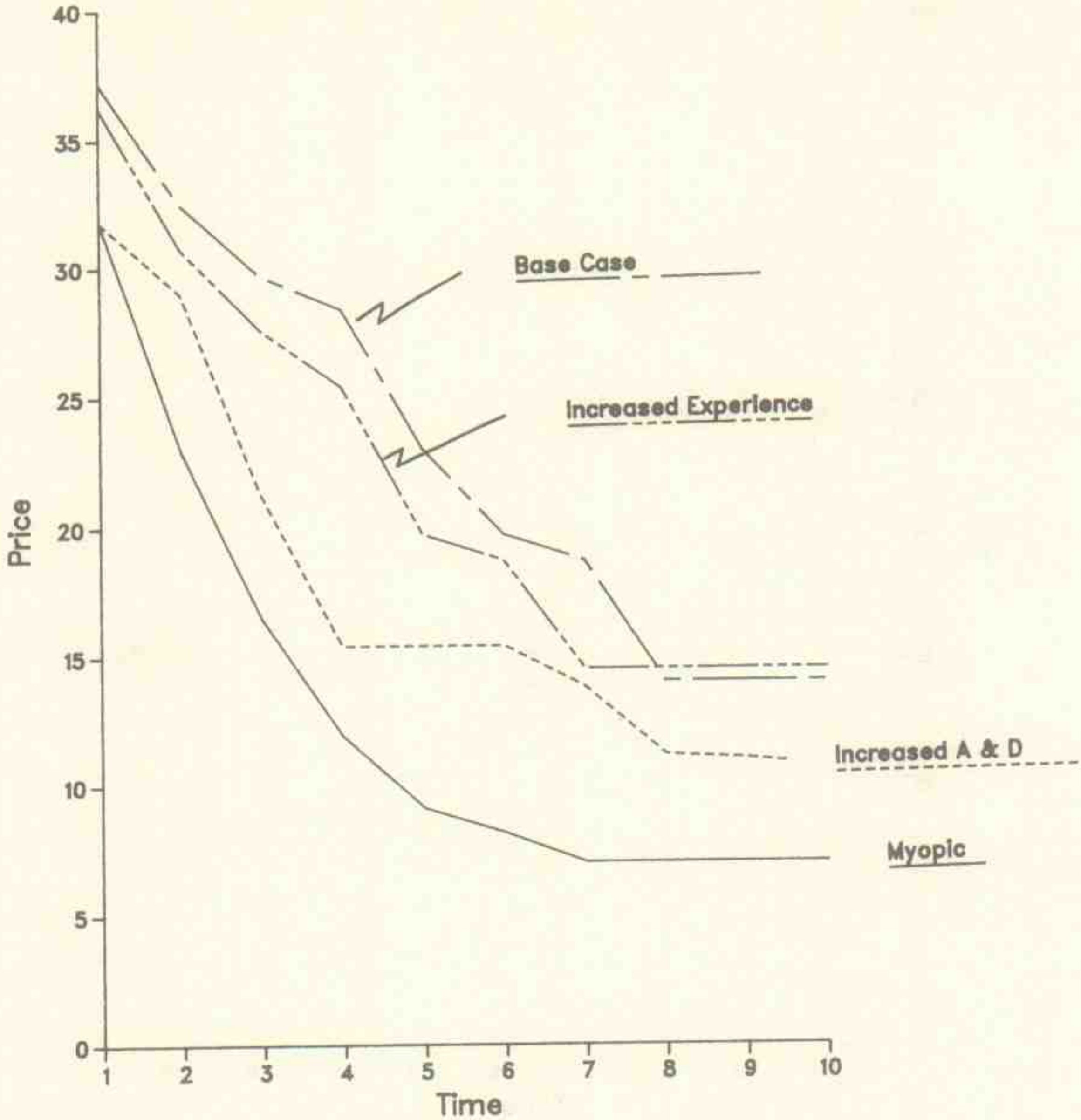

FIG. 3.—Price paths for leader with entrant matching

40% increase in profits by being best rather than myopic. The corresponding figure for Stackelberg follower behavior is 10%. Seeing the price path movements in figure 3, that is, toward the myopic strategy, one might hypothesize that the suboptimality of the myopic strategy decreases with increases in *AD* or experience. To test this proposition, we computed the "dynamic ratio" for all combinations of *AD* from 0 to 1.8 in increments of .2 and experience rates from 55% to 100% in increments of 5%. The dynamic ratio for any diffusion/experience pair is defined as:

$$\operatorname*{Max}_{Z} \frac{\Pi\,(S,\,Z)}{\Pi\,(M)}$$

where

$\Pi\,(S,\,Z)$ = the discounted contribution of the skimming strategy with weight Z applied to the myopic price

$\Pi\,(M)$ = the discounted contribution of the myopic strategy.

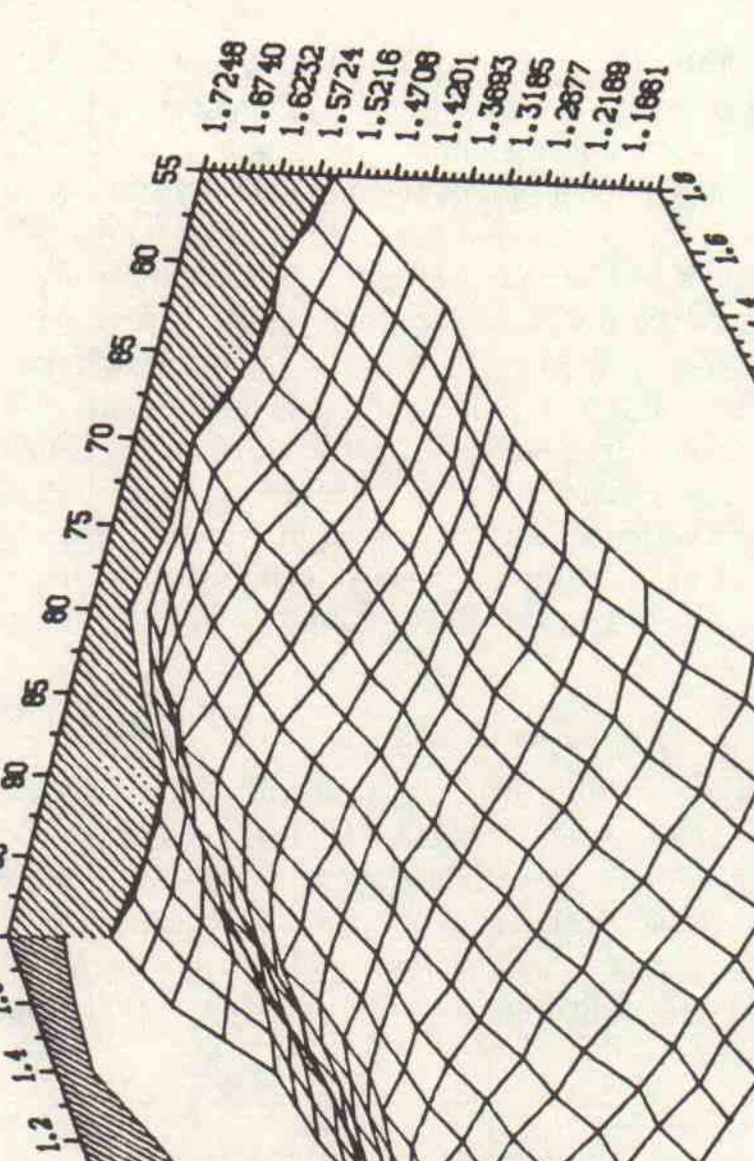

FIG. 4.—Dynamic ratio response surface: follower match

Thus, the dynamic ratio minus 1 is the fractional increase of the best skimming strategy over the myopic strategy. Since $Z = 1$ is a value considered in the search, the dynamic ratio never is less than one. Figure 4 is a three-dimensional plot of the dynamic ratio as a function of the diffusion and experience parameters.[7] The most immediate observation from figure 4 is the nonlinear effect of the experience rate. Second, the effect of the diffusion parameter is interactive with the level of experience as indicated by the ridge in the dynamic-ratio surface running from 90% at the zero-diffusion level back to 80% at high-diffusion levels. Further examination of response surfaces similar to figure 4 for different environments (i.e., changes in parameters other than diffusion and experience) reveals less regular and more dramatic changes in the shape of the response surface. Consequently, there are no easy generalizations to be made about the effect of individual variables.

Model Results: Analysis of Variance

Figure 4 addresses the viability of skim strategies only for base case environment values of all parameters but *AD* and the experience rate. Our initial concern with these variables came from their citation in previous literature. However, changes in other variables have a strong impact as well. For example, changing three additional variables (*REP*, *TENT*, *DF*) produced the following dramatic drop in the dynamic ratio when the entrant is matching price:

	Base Case	Stronger Intertemporal Effects
AD	.5	1.5
Experience Rate (%)	80	70
REP	4.	2.
TENT	5.	3.
DF	.5	.8
Dynamic ratio	1.40	1.04

To investigate the question of magnitude of effects and interactions of variables on a broader scale, we ran the model through 162 scenarios produced by taking five variates at the following levels:

1. experience rate (*EXP*):
   level 1—no experience-curve declines,
   level 2—costs decline to 81% with doubled experience,
   level 3—costs decline to 67% with doubled experience;

7. More precisely, fig. 4 is a smoothed version of the plot of dynamic ratios. Random number generation sequences had some effect on the dynamic ratio of each run. Consequently, we averaged each run's dynamic ratio with that of the eight points adjacent to it to permit clearer identification of the trends. Dynamic ratios should not be confused with total contribution. For both skim and myopic, total contribution is monotonically increasing in both *AD* and experience. The dynamic ratio reflects the different comparative advantage under the alternative strategies.

2. diffusion effect (*AD*):
   level 1—none,
   level 2—AD = 1.0,
   level 3—AD = 1.5;
3. time of competitive entry (*TENT*):
   level 1—no entry,
   level 2—after 4 periods,
   level 3—after 6 periods;
4. number of time periods to consume good (*REP*):
   level 1—2 periods,
   level 2—4 periods,
   level 3—no repeat purchase; and
5. follower pricing strategy:
   level 1—Stackelberg leader-follower,
   level 2—price matching.

All other variables are as in the base case environment. A stochastic element in the simulations was introduced in the generation of entrant's reservation prices from the leader's. Each scenario was run with five different sets of randomly generated entrant's reservation prices.

Employing ANOVA to assess the results of the 810 simulation runs (162 scenarios × five replications), we found the following (overall dynamic ratio mean = 1.14):

A. Main effect F-ratios (significant, $P > .01$)

TENT	88.
REP	218.
EXP	N.S.
AD	5.97
Follower strategy	41.25

B. Two-way interactions (S = significant; N.S. = not significant)

	REP	*EXP*	*AD*	Follower
TENT	S	N.S.	S	S
REP		S	S	S
EXP			N.S.	N.S.
AD				N.S.
Follower				

In addition, two three-way interactions are significant. Variance in dynamic ratios explained by the variates is .981.

Due to the highly interactive nature of the results, one does not gain much by looking at individual main-effect estimates. Most striking from the results is the weakness of the widely discussed experience effect when varied over levels commonly found in empirical studies, namely, 70%–80%. (Note that fig. 4 extends well beyond this range.)

The time required for a consumer to reenter the market after a purchase, *REP*, has the strongest effect on the viability of skimming. This effect is strongly interactive with time of competitive entry.

This initial investigation shows the following:

1. In some market situations, dynamic pricing rules outperform myopic pricing rules substantially. Figure 4 shows dynamic ratios of up to 1.65. A key point is that the simple pricing rules evaluated here use no more information than required for the myopic price determination. In previous studies, myopic has been compared with optimal, where the data requirements to implement an optimal strategy exceed those of the myopic. Here, we show the dominance of rules as easily implemented as myopic.

2. The extent of suboptimality of myopic behavior is a complex, interactive function of market characteristics. Most striking from our results is the relative unimportance of the two variables most widely examined in previous work—the experience rate and diffusion effect. We find from other simulation runs that the relative magnitude of reservation prices and cost affect the importance of the experience effect. For example, when we increased the initial size of the cost component subject to experience to \$25 (from \$13) and kept reservation prices uniform on [0, 50], the experience rate effect became significant. This, and the nonlinear effect of experience shown in figure 4, are key areas of future investigation.

V. Summary

One important question to be answered here is the value of simulation analysis in a research program. Early investigations in an area are probably best confined to analytical investigations to yield an understanding of the basic structure of a system. However, if one ultimately wishes to develop a methodology useful to managers, movement away from conveniently functional forms to more realistic ones may be required.

The simulation methodology described here has a dual objective. First, we wish to have a means of investigating basic research questions such as those considered in analytical studies. Through a rigorously structured series of runs of the model, generalizations about the effect of specific variables on price paths should emerge. The interactive nature of the effects, as identified in our initial investigations, makes any analyses of this question difficult. However, simulation analysis is possible conceptually, and whether analytical investigations can achieve any interpretable results is an unanswered question. Our second objective is to produce a methodology useful to managers. For this purpose, the simulation's "if, then" mode of producing the expected profit impact of a given pricing strategy is probably preferable to any optimization efforts. While the study vividly pointed out the limitations of simulation (only comparative results, significant computer time even after the model development stage), the results show the potential contributions for the approach for both objectives.

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