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ON COMPENSATORY DEMAND FUNCTIONS IN MARKETING SIMULATIONS

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ABSTRACT

Given the usual pedagogical environment in which simulations are used, the potential for teaching the wrong things through their use is very great, especially since it appears that most marketing simulations can be coaxed into anomalous behavior. It is argued in this paper that a major reason for this potentially anomalous behavior is the use of a compensatory demand function which, while possessing a desired level of algorithmic simplicity, does not adequately portray marketplace behavior. A general approach to a solution to this problem is suggested.

INTRODUCTION

The widespread use of computerized simulations as pedagogical aids in schools of management is seen as a positive sign that professors are interested in innovative ways to move beyond the traditional lecture format. Marketing has been a part of this trend to simulations in the classroom. The number of marketing simulations is increasing (albeit slowly), and presumably this reflects an increasing number of adoptions.¹ But it is important to recognize the large potential for teaching the wrong things when using simulations. Shubik singles-out a marketing case to illustrate this point [12: p. 31]:

A flagrant example of potential misuse has been in the modeling of advertising in business games. Even a brief glance at the literature on how advertising affects sales is sufficient to indicate that there is little substantiated theory on advertising, yet in many of the business games played both at universities and in business training programs, advertising has been thrown in as an ad hoc modification on demand with teaching results which could be damaging were it not for the basic skepticism of most of the players. It is important that players be warned against learning false or unsubstantiated principles.

While Shubik's point is well taken concerning the lack of a theory of advertising, the modeling of the impact of advertising (and of other marketing mix elements) often does not even reflect the state of the art. While the lack of a comprehensive theory of the behavior of sales in response to marketing tactics is a handicap, still every effort must be made in designing these simulations to insure that sales behavior at least appears plausible.

DEMAND FUNCTIONS IN MARKETING SIMULATIONS

Broadly speaking, there are two approaches which might be taken to modeling the relationship between the demand for an individual firm's products and the firm's marketing mix: compensatory, or noncompensatory. This suggestion of a primary dichotomy of would-be demand functions borrows

its terminology from psychological studies of human information processing [4]. Compensatory functions are those in which a change in one element can be offset by a change in another element. Noncompensatory functions, on the other hand, do not permit such trade-offs to be made. Both models may assume several different forms, a thorough discussion of which lies outside the scope of this paper.² A linear non-interactive compensatory function is typified by the familiar equation form:

And of course non-linearity and interactions may be added to this compensatory form through the use of exponents other than one, and the addition of one or more multiplicative terms. Noncompensatory functions were formulated originally as conceptual aids to the study of decision making and were not mathematically specified. More recently several of the noncompensatory forms have been defined mathematically [6].

$$Y = b_1X_1 + b_2X_2 + \dots + b_nX_n \quad (1)$$

If the commercially available marketing simulations are examined, one finds that almost all have compensatory demand functions. Eight simulations were considered for illustrative purposes for this paper. Of this group, all but one featured a compensatory demand function.

MARKETING REALITY AS TRANSLATEE BY COMPENSATORY DEMAND FUNCTIONS

Considering the nature of compensatory demand functions, it is evident that the marketplace impact of a given set of tactical decisions will be profoundly affected by the fact that these functions, by design, freely permit tactical element trade-offs to be made. Given a compensatory non-interactive demand function, it is possible, for example, to generate a reasonable level of demand with distribution set to zero if the other controllable elements are sufficiently high. Thus a product may sell well if enough is spent on advertising, price is (perhaps) low enough, and quality high enough, in spite of the fact that it is ostensibly not available.

¹ For an estimate of the overall market for business simulations, and an overview of the problems in estimating this market, see [1].

² The interested reader is referred to [13] for an overview of and literature references to these models.

³ The simulations reviewed were [2; 3; 5; 7; 8; 9; 10; 11]. The simulation with a noncompensatory demand function is Markstrat [10]. It is this simulation's reasonable behavior, regardless of the vagaries of student Input, which inspired this paper.

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Interactive compensatory demand functions are more difficult to manipulate into anomalous behavior. One often seen method of implementing an interactive compensatory function is that of multiplicatively combining indices which represent a team's spending deviation from the mean for that element, where the mean is defined as one. The following is such a function:

$$DI_1 = \prod_{j=1}^n I_{ij} \quad (2)$$

where: DI_1 = the demand index for firm 1

I_{ij} = the expenditure index for element j for firm 1

n = the number of controllable elements.

This approach handles situations such as the previous example of zero distribution very well (if the indices are not constrained). However, there are marketing mixes which are quite reasonable which will be penalized by this form of demand algorithm. Deviations in indices from the mean produce asymmetrical demand movements, such that a drop below unity in any index will produce a relatively larger decrease in demand than will be offset by a corresponding upward shift in another index. On the other hand, if all indices are greater than or equal to one, an increase in an index has a powerful upward impact upon the demand index. This can be illustrated by the following set of index numbers:

I_1	I_2	I_3	I_4	DI_1 (equation 2)
1.0	1.0	1.0	1.0	1.00
1.0	1.0	0.8	1.2	0.96
1.0	1.0	0.2	1.8	0.36
1.0	1.0	1.3	0.7	0.91
1.0	1.0	1.5	1.0	1.50

Consider that I_1 is product quality, and I_4 price, where an increasing index number indicates increasing quality, or decreasing price. The second and third sets of indices are examples of a lower quality, lower price strategy. Neither of these sets of decisions is as effective in generating sales volume as is the first set of indices. In fact, before the third set of indices yields a demand index of one, the price index must be equal to five. In a similar fashion, we see that a high quality, high price strategy produces less demand perhaps not unreasonable. The last example illustrates the direct impact of an above average element when the others are one. Thus we see that a demand function such as this one rapidly punishes those whose marketing mixes deviate by much from the mean, and provides pressures for "me too" strategies, and spending "wars." But rather than look at hypothetical sets of indices, let us consider the results of an experiment using actual marketing simulations.

Of the seven simulations examined for this paper which have compensatory demand functions, all but one have interactive compensatory formulations. Of this group (i.e. those with interactive compensatory functions), one was used to provide illustrative data; the selection of this particular simulation was based only upon its availability. In the following table the results of several trials are reported. The price shown is the mean price of a team's product mix; all

other factors not shown in the table are held constant across all five teams.

	Mean Price	Total Sales-force	Total Advertising	Total Sales (in units)	EPS
Trial 1					
Team No. 5	\$330	0	\$12,550,000	312,086	\$-9.16
Each Other Team	\$330	1600	\$12,550,000	682,437	\$- .22
Trial 2					
Team No. 5	\$397	0	\$12,550,000	217,920	\$-8.61
Each Other Team	\$330	1600	\$12,550,000	672,535	\$- .72
Trial 3					
Team No. 5	\$330	0	\$0	147,132	\$.72
Each Other Team	\$330	1600	\$12,550,000	723,673	\$ 1.34

The output of this simulation, summarized in the table above, describe a strange circumstance. The product is not available⁴, yet sales are not too bad. The impact reduced demand makes in this instance may be eased a bit by increasing price 20% (trial 2), and the EPS discrepancy considerably reduced by eliminating advertising (trial 3). Since this particular simulation does not include advertising carryover effects, trial 3 is especially interesting. Admittedly these results were obtained with a knowledge of this simulation's operation, but the fact remains that the simulation should not behave in this fashion. This simulation performs in this manner because the marketing mix elements are constrained to non-zero lower limits, in an attempt to produce reasonable behavior in what the authors apparently believe to be a reasonable operating range. But artificially defining operating ranges, either through index limits or by non-linearities, does not eliminate the fundamental problem: a compensatory demand function.

A SUGGESTED SOLUTION

Obviously this paper is directed towards noncompensatory demand functions as a solution to the problem discussed. As noted earlier, some forms of noncompensatory (usually called configural) functions have been mathematically specified. Perhaps then all that needs to be done is to substitute one equation for another. For example, a conjunctive function (one of the configural forms) requires some minimum level on all elements to produce a non-zero demand. However the mathematical approximations of these configural functions often rely simply on particular non-linear interactive functions to generate a response surface corresponding to, for example, the conjunctive model. Simply substituting one non-linear compensatory equation for another will not solve the problem. Since these equations are compensatory approximations of noncompensatory systems, they can undoubtedly be coaxed into anomalous behavior.

⁴ In this simulation, the salesforce is responsible for servicing all existing accounts and cultivating new ones.

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One approach to modeling demand which offers promise as a solution is that of a two stage demand function: configural screening followed by a compensatory function. For example, the Keiser and Lupul simulation [9], features this two stage process in its handling of the distribution function. Without adequate distribution, this simulation severely restricts sales. What is needed to accomplish a configurally-behaving demand function is not necessarily a pre-processing program as incorporated in the Keiser and Lupul game, but rather modeling each element of the marketing mix in terms of the state-of-the-art in marketing. For example, what does advertising do? Does it shift the demand function? In the economist's model this is advertising's impact on industry demand. But in marketing our view of the role of advertising is that of generating awareness and interest, affecting attitude and belief structures, and of interactively affecting responses to other marketing variables. At the very least, a product will not be too successful if the marketplace is unaware of it. Isn't this then the sort of process to model when attempting to simulate responses to marketing efforts? Such factors as brand awareness and product availability might be used as limiting (i.e. non- compensatory) factors in calculating sales potential.

- [11] Ness, Thomas E. and Ralph L. Day, Marketing in Action: A Decision Game (Homewood, Illinois: Richard D. Irwin, 1978).
- [12] Shubik, Martin, The Uses and Methods of Gaming (New York: Elsevier, 1975).
- [13] Wright, Peter, "Consumer Choice Strategies: Simplifying Vs. Optimizing," Journal of Marketing Research, Vol. 12 (February 1975), pp. 60-67.

REFERENCES

- [1] Biggs, William D. "Who is Using Computerized Business Games? A View From the Publishers' Adoption Lists," in Samuel C. Certo and Daniel C. Brenenstuhl (eds.), Insights into Experiential Pedagogy, Proceedings of the Sixth Annual ABSEL Conference, 1979, pp. 202-206.
- [2] Boone, Louis E. and Edwin C. Hackleman, Jr., Marketing Strategy: A Marketing Decision Game (Columbus: Charles E. Merrill, 1975).
- [3] Bush, Ronald F. and Bob Brobst, Marketing Simulation: Analysis for Decision Making (New York: Harper and Row, 1979).
- [4] Coombs, C.H., A Theory of Data (New York: John Wiley and Sons, Inc., 1964).
- [5] Doddridge, Ben F. and J. Rodney Howard, Operation Encounter: Marketing Decision Making in a Changing Environment (Pacific Palisades, California: Goodyear Publishing Company, 1975).
- [6] Einhorn, Hillel J. "Use of Nonlinear, Noncompensatory Models as a Function of Task and Amount of Information," Organizational Behavior and Human Performance, Vol. 6 (January 1971), pp. 1-27.
- [7] Faria, A.J., R.O. Nulsen, Jr., and J.L. Woznick, Compete: A Dynamic Marketing Simulation (Dallas, Texas: Business Publications Inc., 1979),
- [8] Hinkle, Charles L. and Russell C. Koza, Marketing Dynamics: Decision and Control (New York: McGraw-Hill, 1975).
- [9] Keiser, Stephen K. and Max E. Lupul, Marketing Interaction: A Decision Game (Tulsa: PPC Books, 1977).
- [10] Larreche, Jean-Claude and Hubert Gatignon, Markstrat: A Marketing Strategy Game (Palo Alto, California: Scientific Press, 1977).