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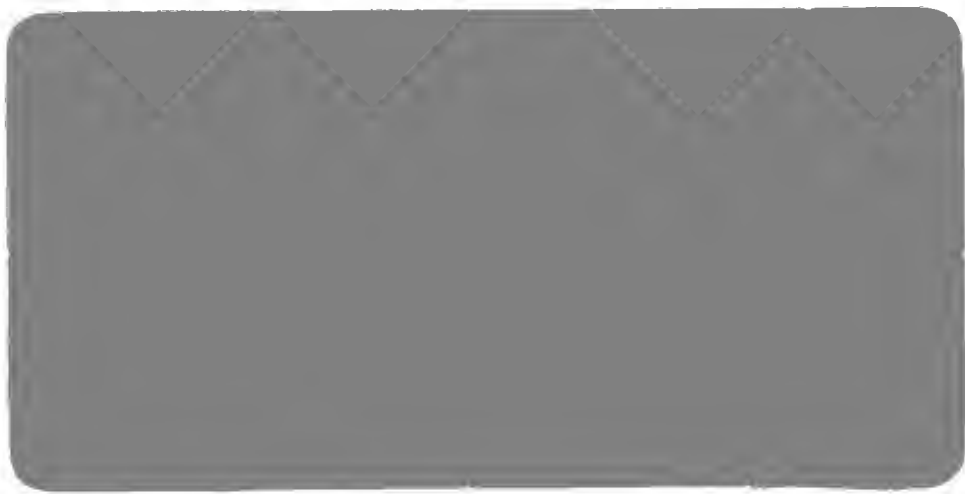
Faculty Working Papers

SIMPLIFIED BAYESIAN ANALYSIS OF THE VALUE OF
INFORMATION IN THE MARKETING OF NEW PRODUCTS

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Business Administration
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College of Commerce and Business Administration
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FACULTY WORKING PAPERS

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SUMMARY:

While Bayesian concepts on the value of information are now universally found in statistics and marketing research textbooks and most market researchers have heard of these procedures, their formal use in determining the value of information is limited. In this paper, a Bayesian perspective is used to suggest that for a typical decision maker whose time has high economic value and who makes many kinds of similar decisions, formal Bayesian procedures may be unnecessary and possibly inefficient. More simple rules may be used to decide whether or not to do research, and the decision on how much research to do can be made by the research group based on previous decisions with modifications.

QUESTION 10

1/10/20

1. The following table shows the number of people who visited the museum in each month.

Month: Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec

Number of people: 120, 150, 180, 200, 220, 250, 280, 300, 280, 250, 220, 180

2. The following table shows the number of people who visited the museum in each month.

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Number of people: 120, 150, 180, 200, 220, 250, 280, 300, 280, 250, 220, 180

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QUESTION 11

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Number of people	120	150	180	200	220	250	280	300	280	250	220	180

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SIMPLIFIED BAYESIAN ANALYSIS OF THE VALUE OF INFORMATION IN THE MARKETING OF NEW PRODUCTS

Introduction

While Bayesian concepts on the value of information are now universally found in statistics and marketing research textbooks and most market researchers have heard of these procedures, their formal use in determining the value of information is still limited. In this paper, we attempt to explain why this is so, using a Bayesian perspective. This then leads to suggestions for a series of simplified Bayesian decision rules on value of information for testing of new products.

Several surveys of business firms have suggested that although firms are aware of Bayesian methods they do not often use these methods formally when making decisions on how much research is necessary and how much to spend. In a recent paper, Albaum and his colleagues obtained information on a mail questionnaire from 105 market research directors from the list of the Fortune 500 (1). Only 11 percent of the responding companies reported that a formal calculation of value of information had been made at least once in the past year. Formal procedures were used on only 4 percent of all research projects. Similarly, Greenberg, et.al. found that 12 percent of 269 firms in the 1973 American Marketing Association Directory of Marketing Services and Membership Directory used any form of Bayesian Analysis. (5)

Albaum et. al. did indicate that formal procedures were most likely to be used for new product development among the small sample of firms that used any formal Bayesian methods. (1, p.183) We have also conducted a small telephone survey of market researchers at 40 firms from the top 100 of the Fortune 500, asking specifically about the use of Bayesian methods in new product development.

The results indicated that 85 percent of the respondents had heard about Bayesian procedures, but that only 25 percent had ever found any use for formal Bayesian statistics in new product marketing. These figures are biased upward, since researchers at smaller companies would be even less likely to use Bayesian procedures, but they indicate how little formal procedures are used.

It is clear, however, that the factors that are taken into account in a formal Bayesian procedure are also very important to these firms in determining how much to spend on marketing research on new products. Slightly more than four out of five respondents in our survey mentioned uncertainty about the success of the new product as a basis on which the decision to spend for research was made; 70 percent mentioned the size of the initial investment on the product and the potential profits and losses; 55 percent mentioned breakeven points.

Earlier studies had suggested that non-use of Bayesian procedures was caused by lack of awareness of these methods, but the data from our small survey indicate that most researchers have, at least, heard of these methods. Some researchers have suggested that formal Bayesian procedures are avoided because they place too much psychological stress on the decision maker by forcing very specific prior distributions about a new product, (1, 2, 3) Brown suggests a non-psychological, purely Bayesian alternative explanation. It is simply that the cost of the formal Bayesian procedure is greater than the benefit derived. (3,4)

The benefit of the formal procedure is in optimizing the size of the sample based on the decision maker's priors and clarifying the decision as to whether any research is required. Even moderate differences from optimum, however, may have relatively low costs. Selecting a sample that is 20 percent larger or smaller than optimum would decrease the net value of information

only slightly. Thus, if a formal Bayesian decision process takes a week's effort by several persons, as Brown suggests, the decision maker might well decide, either explicitly or implicitly that the economic value of alternative uses of his and his subordinates' time is well in excess of the possible gains in net value of information. (3,4)

The other major factor encouraging informal procedures which has not been widely recognized is that many new products are perceived as being similar to existing products. In these cases, both formal and informal procedures suggest doing the same amount of research on the new product as was done earlier on similar products, adjusting for price-level changes. Even if the products are perceived as being somewhat different, it may be more efficient to modify existing procedures than to start from scratch each time. The remainder of this paper considers these simplified decision rules.

As a base, we shall use the framework of Schlaifer and discuss two action problems with linear costs. (6,7) The actions are whether to market or not to market a new product. We omit discussions of partial roll-outs and different promotion strategies for purposes of simplicity. We assume that the new product is one of a long line of other products on which market research has been done (or not done) and that reasonably optimum solutions for the sample sizes of these earlier products were determined, using either formal or informal procedures. That is, the firm is satisfied with the results and costs of previous sample surveys. While it is possible that, on all major factors that determine optimum marketing research expenditures, the new product may be identical to some earlier product, or products, the more general case is that some of the factors are similar while others differ.

The remainder of the paper discusses the effects of differences in key parameters. To simplify the discussion, it is first assumed that research was conducted previously and will also be conducted for the new product. The decision whether or not to do research is discussed separately.

Uncertainty Constant

For a large sub-class of new products, the decision maker may feel as certain (or uncertain) as he has felt about earlier products. To put it more formally, assuming a normal prior distribution, the prior mean is about the same distance from breakeven and the prior variance is the same as it has been for earlier products.

In this case, no new information is required from the decision maker and the market research group can decide on an optimum sample size on the basis of the cost of a unit of observation and the unit profit of the new product.

a) Costs of Data Collection and Unit Profit Constant

In this simplest case, all is as before and the optimum solution is to choose a sample just the same size as earlier at the same cost. This is the case where "doing what we've always done" makes perfect sense.

b) Costs of Data Collection and Unit Profit Increase (Decrease) Proportionately

Inflation is an obvious reason why the costs of data collection and unit profits might increase proportionately. Since the optimum n when sampling is conducted is proportional to $\left[\frac{k}{c}\right]^{1/2}$ (1)*

where k is the unit profit and c is the variable cost of data collection, it is again obvious that in this situation the optimum sample size remains unchanged. Note that while the optimum n remains unchanged, the total cost of the project increases.

c) Costs or Unit Profits Change

As may be seen in formula (1), changes in an optimum sample size would be directly proportional to the square root of the relative change in unit profit and inversely proportional to the square root of the relative change in unit cost of data collection.

$$n_2 = n_1 \left[\frac{k_2}{k_1} \cdot \frac{c_1}{c_2} \right]^{1/2} \quad (2)$$

*Proof:

$$n = h \sqrt[3]{(k\sigma/c)^2} \propto h \left[\frac{k}{c}\right]^{2/3} \quad (1, p. 543)$$

$$h \approx \sqrt{\frac{1}{2Z} P' (D_{\infty})} \propto \sqrt{1/Z} \quad (1, p. 543)$$

$$Z = \frac{\sigma_p}{\sigma} \left[\frac{k\sigma}{c}\right]^{1/3} \propto \left[\frac{k}{c}\right]^{1/3} \quad (1, p. 538)$$

$$h = \propto \left[\frac{c}{k}\right]^{1/6}$$

$$\text{So } n \propto \left[\frac{k}{c}\right]^{4/6 - 1/6} = \left[\frac{k}{c}\right]^{1/2}$$

Changes in k unrelated to inflation would occur if the new product is either more or less expensive than the older products to which it is compared. Changes in c would occur if either a different sample design, data collection procedure or different organization were to be used.

Uncertainty Changes, Data Collection Costs and Unit Profits Constant

a) Changes in Distance From Breakeven

It is assumed here that the decision maker has the same known prior variance as on the earlier products to which comparisons are made, but that the prior mean is either nearer or farther from the breakeven point than previously. In this situation, if sampling is justified,

$$n_2 \approx n_1 \left[\frac{P'_N(D_2)}{P'_N(D_1)} \right]^{1/2}$$

since $h \approx \left[1/2 Z P'_N(D) \right]^{1/2}$ (1, p. 543)

where $D = \frac{|\bar{x}_p - x_b|}{\sigma_p}$

and \bar{x}_p is the prior mean

x_b is the breakeven point derived by estimating fixed costs and selling price

σ_p is the prior standard deviation*

and $P'_N(D)$ is the height of the unit normal integral at value D.

Table 1 gives the ratio of sample sizes n_2/n_1 for various values of D_2 and D_1 .

*For methods of estimating σ_p see (7, p. 100).

TABLE 1

RATIO n_2/n_1 FOR VALUES OF D_1 and D_2

		D_1									
		0-.2	.4	.6	.8	1.0	1.2	1.4	1.6	1.8	2.0
D_2	0-.2	1	1.04	1.09	1.17	1.28	1.43	1.63	1.89	2.24	2.71
	.4	.96	1	1.05	1.13	1.23	1.38	1.57	1.82	2.16	2.61
	.6	.92	.95	1	1.07	1.17	1.31	1.49	1.73	2.05	2.48
	.8	.85	.89	.93	1	1.09	1.22	1.39	1.62	1.92	2.32
	1.0	.78	.81	.85	.91	1	1.12	1.27	1.48	1.75	2.12
	1.2	.70	.73	.76	.82	.90	1	1.14	1.32	1.57	1.90
	1.4	.61*	.64*	.67	.72	.79	.88	1	1.16	1.38	1.67
	1.6	.53*	.55*	.58*	.62*	.68	.76	.86	1	1.19	1.43
	1.8	.45*	.46*	.49*	.52*	.57*	.64	.73	.84	1	1.21
	2.0	.37*	.38*	.40*	.43*	.47*	.53*	.60*	.70*	.83	1

*Optimum solution may be to do no research.

For other values of D_1 and D_2 use the relation: $\frac{n_2}{n_1} = \left[\frac{P'_N(D_2)}{P'_N(D_1)} \right]^{\frac{1}{2}}$

Table 1 is limited to values of D_1 and D_2 of 2.0 or less. For larger values, it is unlikely that market research would be conducted except in very special cases. As expected, if D_2 is smaller than D_1 , which means that the firm is now nearer to breakeven, a larger sample is required. If D_2 is larger than D_1 indicating the new product is farther from breakeven, less sampling is required. For the largest values of D_2 near to 2.0 where the ratios are small, it may be that no market research would be conducted, although ratios are given in Table 1. These cases are designated by * in Table 1, but see the discussion below on whether or not any research should be done.

b) Changes in Prior Variance, D Constant

In this situation, the decision maker is more (or less) certain about his prediction of product success, but the normalized distance from breakeven is unchanged. (This implies that the absolute distance from breakeven changes as much as the prior standard deviation.) The more realistic case where both D and the prior standard deviation change is discussed next.

In this case:

$$n_2 = n_1 \left(\frac{\sigma_{P_1}}{\sigma_{P_2}} \right)^{1/2} \quad (3)$$

where σ_{P_1} and σ_{P_2} are the former and new prior standard deviations. This relation follows directly from Schlaiffer (1, p. 543)*.

* $\frac{n_1}{n_2} \propto \frac{h_1}{h_2}$; $\frac{h_1}{h_2} \propto \left(\frac{z_2}{z_1} \right)^{1/2}$ and $\frac{z_2}{z_1} \propto \frac{\sigma_{P_1}}{\sigma_{P_2}}$

This result may be somewhat counter-intuitive. It states that the ratio of the new and old sample sizes is inversely proportional to the square root of the ratio of the prior standard deviations if everything else is held constant. For example, if the current prior standard deviation is four times as large as before, the new sample would be only half as large. This reflects the fact that the relative gain in information declines more rapidly in this new case while the costs remain the same.

c) Changes in Prior Variance, D Variable

A more realistic situation is one in which the absolute value of the difference between the prior mean and breakeven remains the same, but the prior standard deviation changes. Then D varies inversely with σ_p . Even more generally, both σ_p and D vary but there is no relation between them. In all of these cases, the optimum solution for the new sample size may be found by combining the results of Table 1 with formula (3).

To illustrate how one would do this, assume that $\sigma_{P_2} = 2\sigma_{P_1}$, that is, the decision maker is less certain about the new product, but that there is the same absolute distance between his prior mean and breakeven, and that all other parameters are the same as before. Then $D_2 = \frac{1}{2} D_1$. The ratios in Table 1 are multiplied by $\sqrt{\frac{1}{2}}$ or .707 to give the final ratios of n_2/n_1 .

D_1	.2	.4	.8	1.2	1.6	2.0
D_2	.1	.2	.4	.6	.8	1.0
$r = n_2/n_1$ (from Table 1)	1	1.04	1.13	1.31	1.62	2.12
.707 r	.71	.74	.80	.93	1.15	1.50

Summary of Procedures for Adjusting of Sample Sizes.

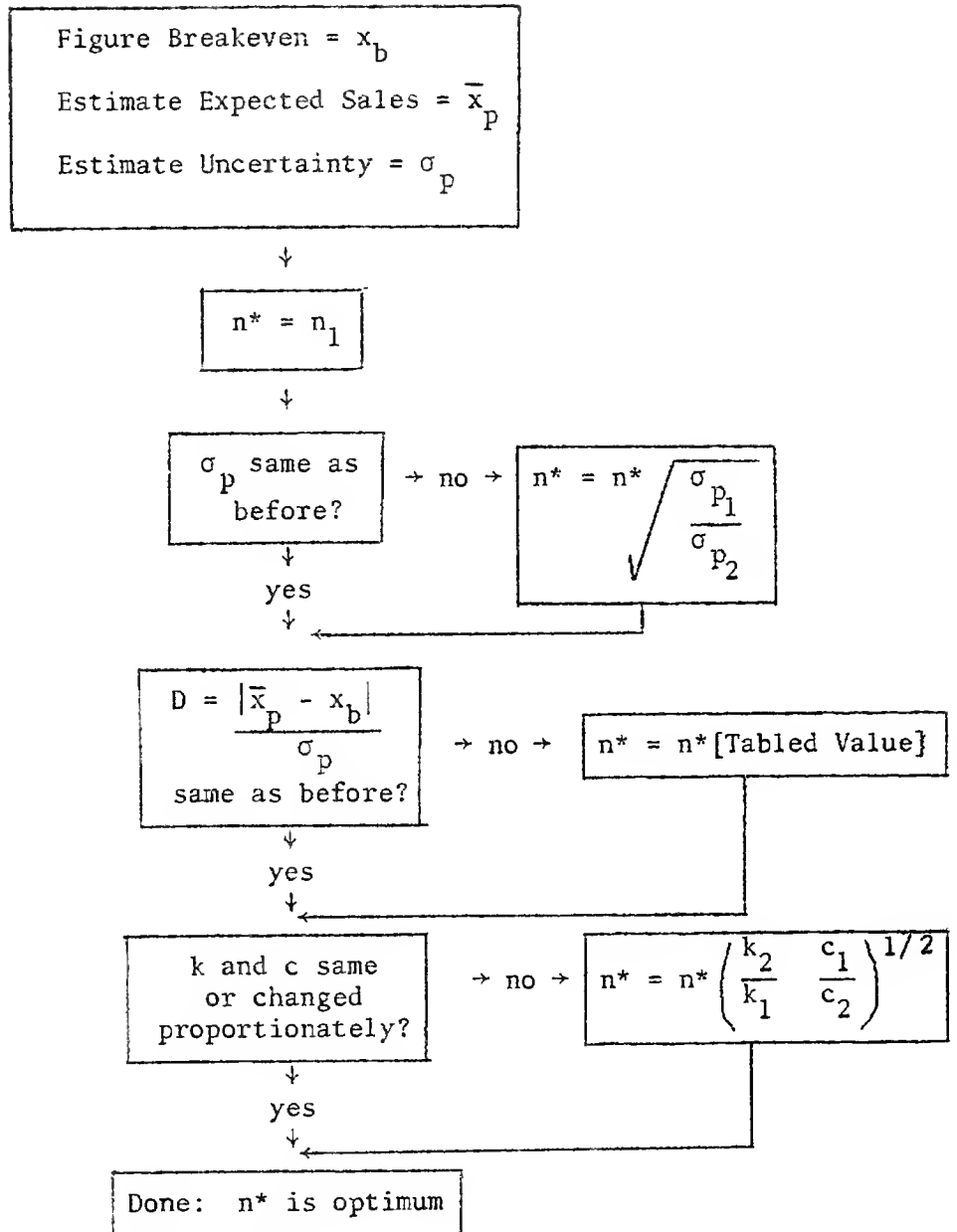
In the most general case where all parameters vary, a combination of formulas (2) and (3) and Table 1 would give the new estimate of sample size. Changes in sample size vary directly with the square root of the relative change in unit profit, inversely with the square root of the relative change in cost of data collection, inversely with the square root of the relative change in prior standard deviation and by distance from breakeven as described in Table 1. Figure 1 summarizes this general case in flow-chart form.

The Decision on Whether or Not to Do Market Research At All

Many products are introduced into the market without any market research. One explanation is that the decision maker is highly certain of the success of the product so that new information has little value.

In many cases where the decision maker is uncertain, however, research is not done because of the large fixed costs of doing research. These large costs are not, as one might think, the fixed costs of mounting a research project such as sampling, hiring and training interviewers and developing a questionnaire. These fixed survey costs rarely influence the final decision. Instead, the large fixed costs are in the time lost in conducting a survey. If a firm has a time lead on competitors in developing a new product, this lead may result in substantial additional profits. The time lost in doing the research may be translated into large potential losses in profit. To avoid these losses, the product is launched immediately without research. It is assumed that the potential losses if the product is a failure are low relative to the possible profits. This strategy is obviously more likely to be used where there is a small initial capital investment such as on a new flavor of a grocery product than on a new car model where the initial investment is very

Figure 1



large. Where the time spent in doing research could reduce profits sharply, there is no need for a formal Bayesian analysis or even the simplified analysis described above.

Where foregone profit is not a major concern, a simple rule may be followed. Unless the decision maker is very certain about the success or failure of a new product the firm should do research. This rule may result in some small losses from optimum because the firm does a small study when a formal analysis would suggest that no market research was required. The cost of the formal analysis, however, would frequently be greater than these small losses. This rule appears to be in agreement with the behavior of the large firms who participated in our survey.

Summary

A major argument for the use of formal Bayesian procedures is that they prevent muddy thinking about whether one should or should not do research and how much to do. In this paper, we have attempted to suggest that for a typical decision maker whose time has high economic value and who makes many similar kinds of decisions, formal Bayesian procedures may be unnecessary and possibly inefficient. More simple rules may be used to decide whether or not to do research, and the decision on how much research to do can be made by the research group based on previous decisions with modifications.

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