New Methods for Estimating Business Markets

R. V. Brown
G. L. Lilien
J. W. Ulvila

ABSTRACT. Market research, in business markets and elsewhere, is performed to provide information about the market. The low level of research expenditures in business markets reflects both the low quality of information available and the difficulty involved in evaluating the quality and value of that information.

This paper treats three methods for addressing industrial marketing research problems: Decomposed Error Analysis (DEA), to assess the likely accuracy of research; Analysis of Plural Estimates (APE), an approach to combine research methods; and Partial Conditioning of Consequences (PCC), an approach to determine the economic value of research. A short case is included with each method illustrating the value of that method in practice.

INTRODUCTION

One does market research to gather information about the market. Better information leads to better decisions: a firm might choose to

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R. V. Brown is Principal with Decision Science Associates, Inc. of Manassas, VA, 5631 Sudley Road, Manassas, VA 22110. G. L. Lilien is Director of Research, Institute for the Study of Business Markets, 113 Business Administration, Bldg II, Pennsylvania State University, University Park, PA 16802. J. W. Ulvila is Principal with Decision Science Associates, Inc. of Manassas, VA, 5631 Sudley Road, Manassas, VA 22110.

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ignore a valuable market, to enter an unprofitable market, to over- (or under-) price its product because of poor information about the market. U.S. businesses and other institutions spend more than two trillion dollars a year purchasing goods and services. Could better quality market research help this market operate more efficiently? Clearly the answer is yes.

The accuracy of market research studies for industrial products is poor. Studies show that over 70 percent of new industrial product budgets are spent on products that fail (Booz, Allen, 1982). Studies of new industrial product failures consistently show that inadequate market knowledge, brought about partially by ineffective market research, is a key contributor to that failure (Cooper, 1975, 1984a,b; Cooper and Kleinschmidt, 1986; Lilien, 1987; Lilien and Yoon, 1986; Maidique and Zirger, 1984).

Contrast the spending on industrial market research with that of consumer market research. Over $10 billion a year is spent on consumer market research in the U.S. This money is spent quite successfully, as evidenced by the relative reliability of sales and market forecasts and agreement between independent market estimates (Urban and Katz, 1983). On the other hand, industrial market research, serving a marketplace with more than twice the sales of the consumer market, accounts for market research spending of less than 10 percent of the consumer sum.

Industrial marketers would spend more on market research if they could be sure that they would see value from that investment: information is as valuable for businesses that sell to businesses as it is for those that sell to consumers. Users of industrial market research simply do not have appropriate tools at their disposal to perform the research that is needed. With a few significant exceptions, the use of large samples with standardized measurements based on classical statistics, which is both effective and the norm in consumer market research, fails in industrial market research and is rarely attempted.

What are the distinguishing characteristics of the estimation problem that lead to the failure of the consumer approach to industrial market research?

- Industrial populations are diverse in organizational size, structure, and activity as well as in target variables (such as product demand). This diversity cannot be accommodated by classical techniques.
- Individual firms or institutions are too complex and variable for standardized measurement–the answer to the estimation problem may well depend on finding the right individual within the organization or institution.
- The sampling unit itself is often difficult to define. Is the appropriate unit: a fast food outlet? a set of fast food outlets managed by the same individual in a single geographic area? the organization that manages all of the outlets in the U.S.? the corporation that owns the fast food organization (and which may operate many other business as well)?
- Sampling frames are incomplete, non-comparable and poorly documented, and structural data on the institutional population are inadequate for sample stratification.
- The user of research–typically the supplier of industrial products–is faced with many distinct estimation tasks, any one of which cannot justify much expense.
- Existing and potential information is complex and fragmented, and no single approach (e.g., a sample survey) captures the bulk of the information available, or is conclusive on its own.
- Much of the available information is in the form of diverse judgments, including those of the decision maker.

The main impact of these features is that judgment is unavoidable in planning and interpreting industrial market research. However, faced with choosing between an unstructured judgmental inquiry and a standardized questionnaire administered to a probability sample, the responsible researcher will typically take the former, in spite of the appreciable benefit the latter confers–of eliminating researcher bias and providing demonstrable (if not necessarily high) measures of accuracy. In fact, "industrial market research" normally consists of inexpensive informal discussions with industry representatives. Even inquiries into new markets are largely opportunistic. No matter how intelligent, creative, and well-informed such inquiries may be, the point of diminishing returns is soon reached, which accounts for low expenditures on industrial market research.

The reliance on informal, qualitative and ad hoc research has significant weaknesses. Coverage may be seriously incomplete if the inquiry is limited to familiar customers. The researcher also opens himself to the charge that he has deliberately distorted the conclusion to serve some private interest (like inflating the development budget for a new product) by using subjective judgment. He cannot systematically and "scientifically" defend the research strategy he has adopted, but, without a rationale for the research strategy and some way of measuring accuracy, it is difficult to improve on his approach. Substantial and valuable techniques may be developed by researchers, but the expertise cannot easily be transferred.

Significantly, even the rare textbooks in industrial market research have not changed much in recent years (Wilson, 1968; Cox, 1979). A recent ISBM/DSC survey of 200 companies selling to business elicited significant needs for more cost-effective market estimates and estimation methods (Lilien, Brown and Searls, 1991a, 1991b). This paper describes methods for improving industrial market research practice in three areas. Decomposed error analysis (DEA) is a method to determine and describe market survey errors. It can be used to help choose among survey techniques, examine ways of reducing errors, or estimate the accuracy of a survey. Analysis of plural evaluation (APE) is an approach to combining market estimates. It helps reconcile inconsistent results of different estimates, specifies the error of combined results, and helps allocate limited resources among different estimating methods. Quantifying the cost of surprise (via partial conditioning of consequences or PCC) is a method to determine the economic value of proposed market research by considering the decisions that the results of the research will influence and the prospect of reducing expensive mistakes.

In the sections that follow, we outline each of these methods and illustrate the value of that method in a case situation. This paper is illustrative and non-technical, but the methods described here (most of which have been developed or enhanced by the authors) are developed further in the appendix and described in detail in the references.

HOW ACCURATE ARE MARKET RESEARCH ESTIMATES? DECOMPOSED ERROR ANALYSIS (DEA)

Case 1: Evaluating Proposed Business Surveys

The marketing research manager of a large manufacturer of personal computers wished to quantitatively estimate the structure and trends of his business market. He had available a number of subscription services from which to choose, each using a different method of estimation. He had narrowed his choice down to two:

- phone/personal sample survey of 8000 businesses which gathered data on office equipment purchases and related behavior at 1-2 yearly intervals, and
- a vendor survey of shipment data solicited from all PC vendors.

How could he choose between these two methods? He used decomposed error analysis or DEA.

Decomposed error analysis. DEA was developed in the 1960s in response to practical problems of error appraisal encountered in the conduct of industrial market research (Brown, 1969). DEA gives a measure of uncertainty about a target variable (i.e., quantity of interest) whose estimate is subject to several sources of error. It can be used (with some adaption of technique) both to evaluate estimates already made or estimating approaches still to be implemented. We are considering the latter case here.

Computationally, DEA uses the statistical theory of the distribution of functions of random variables to infer the accuracy of an estimate. DEA identifies the components of that uncertainty and combines them appropriately. Those components include sampling fluctuations, mismeasurement, non-response, selection, or frame bias, to name a few.

DEA has three steps: modeling the generation of uncertainty in an estimate; decomposing it into more measurable parts; and properly combining those survey of yearly demand for his company's product, within a given budget. The executive must decide whether to use a large sample (say 1,000) mail questionnaire or a small sample (say, 80) of more expensive personal interviews. Total error can be decomposed broadly into mismeasurement, or measurement error, and sample unrepresentativeness, or representative error.

Figure 1 illustrates the tradeoffs involved here. The estimate of the total error is the hypotenuse of the triangle, and components are the other two sides. As the diagram shows, measurement error dominates representative error in the mail survey (Diagram A). Doubling or halving representative error will have a negligible effect on total error. In contrast, reductions in measurement error, even at the cost of relatively large increases in representative error, have substantial effect on total error. (Note that representative error has components, other than random sampling fluctuations, that are not reduced by sample size–leading to the difference in representative error between the two studies shown in diagrams A and B.)

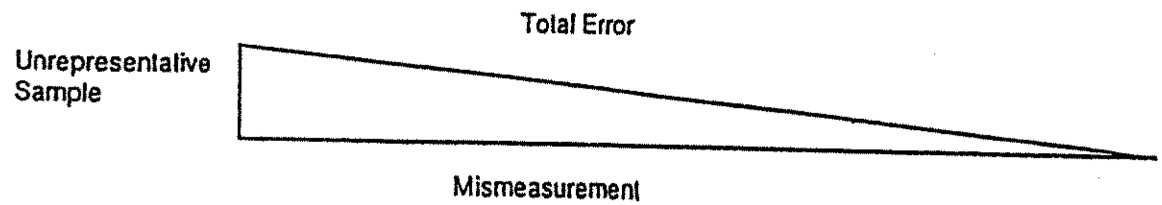
Consider the problem of what fraction of a population is likely to buy a product. If that fraction of the population is p, there are at least two sources of error: (1) the sample may not be representative of the population, and (2) the people who say they are going to buy may not do so accurately. If we call s the fraction that actually buys in our sample, it may differ from s', the fraction of our sample that says it will buy.

Sampling or sample representativeness error is the difference between the fraction of the population that would buy and the fraction of the sample that would buy, (p-s). Measurement error is the difference between the fraction of the sample that actually would buy, and the fraction of the sample that said that it would buy, (s-s'). Total error is then:

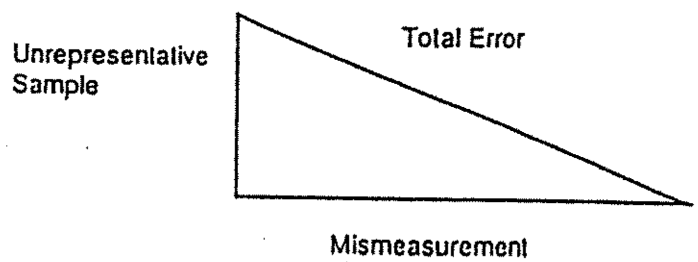
$$\begin{array}{cccccc} \text{Total Error} & = & \text{Representative Error} & + & \text{Measurement Error, or} \\ p\text{-}s' & = & p\text{-}s & + & s\text{-}s'. \end{array}$$

FIGURE 1. Comparing Errors in Two Surveys

A: MAIL SURVEY (n = 1000):



B: PERSONAL INTERVIEWS (n = 80):



CONCLUSION: Strategy B is more accurate in spite of the unrepresentative sample because mismeasurement dominates sample error.

DEA is not limited to considering these two broad sources of error. Figure 2 shows a case where representative error is itself decomposed into:

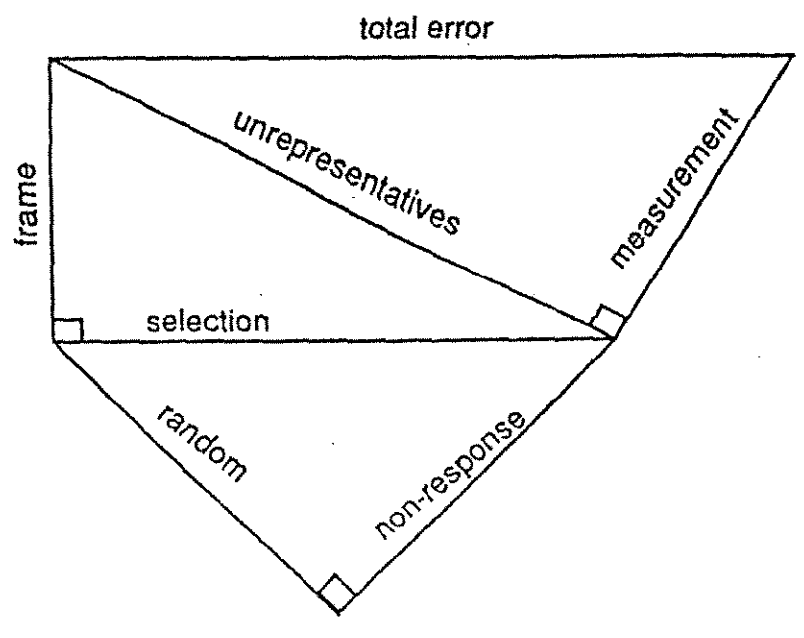
- Frame Error–because the sample is drawn from a list where the fraction, f, does not identically correspond to the target population, p, and
- Selection Error–because the sample achieved does not exactly match the frame (list).

Selection error is further decomposed into:

- Non-Response Error–because the sample selected, d, including "non-respondents" differ from respondents achieved in sample, s, and
- Random Sampling Error–because the sample selected, d, differs from the frame, f, it was selected from, due to random fluctuations. This is the usual "statistical" error affected by sample size.

This more complicated DEA is represented by a series of right triangles, which shows the contribution of each error component

FIGURE 2. Assessing Total Error from Its Individual Components



and the potential reduction in total error from reducing any component error.

In this case, total error is equal to frame error plus random error plus non-response error plus measurement error (Figure 3) or

$$\begin{array}{ccccccccc} \text{Total Error} & = & \text{Frame Error} & + & \text{Random Error} & + & \text{Non-Response Error} & + & \text{Measurement Error} \\ p\text{-}s' & = & p\text{-}f & + & f\text{-}d & + & d\text{-}s & + & s\text{-}s'. \end{array}$$

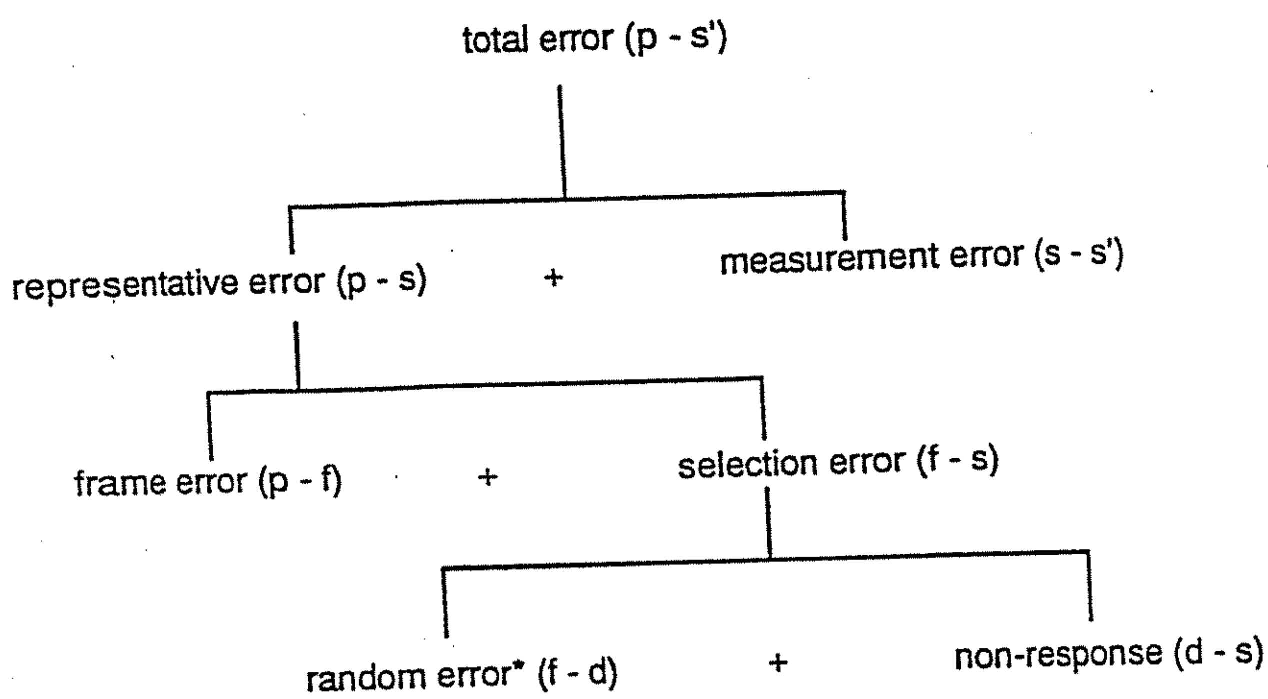
In many industrial market research cases, a target variable can be decomposed using DEA, and separate error assessments can be made for any components that might be affected by the design choice. Even if the decision appears to affect only one type of error (e.g., sample size affects random error), there are often indirect effects on other variables (e.g., a larger sample may require economizing on interviews, thereby increasing measurement error). DEA has been used to assess errors in marketing research on products as diverse as telecommunications equipment, parking spaces, office equipment, and personal computers.

To get back to our personal computer manufacturer, he analyzed the errors to which each service was subject, for one of many market features addressed by the services. This was the installed base of PCs in business use in the U.S. at the end of 1988. He used DEA, as shown in Figure 4 (but with some simplification for ease of presentation). This is an adaptation of the linked-triangle approach illustrated in Figure 2, but the sources of component error are defined a little differently.

For the *user survey*, the error in estimating number of PCs in business use at the end of 1988 is decomposed into error in estimating the population of user establishments and error estimating installed base per establishment. The latter is further decomposed into unrepresentativeness of establishments sampled and error in measuring establishments. (Further decomposition of representative error into random, frame and non-response error was performed but is not shown here.)

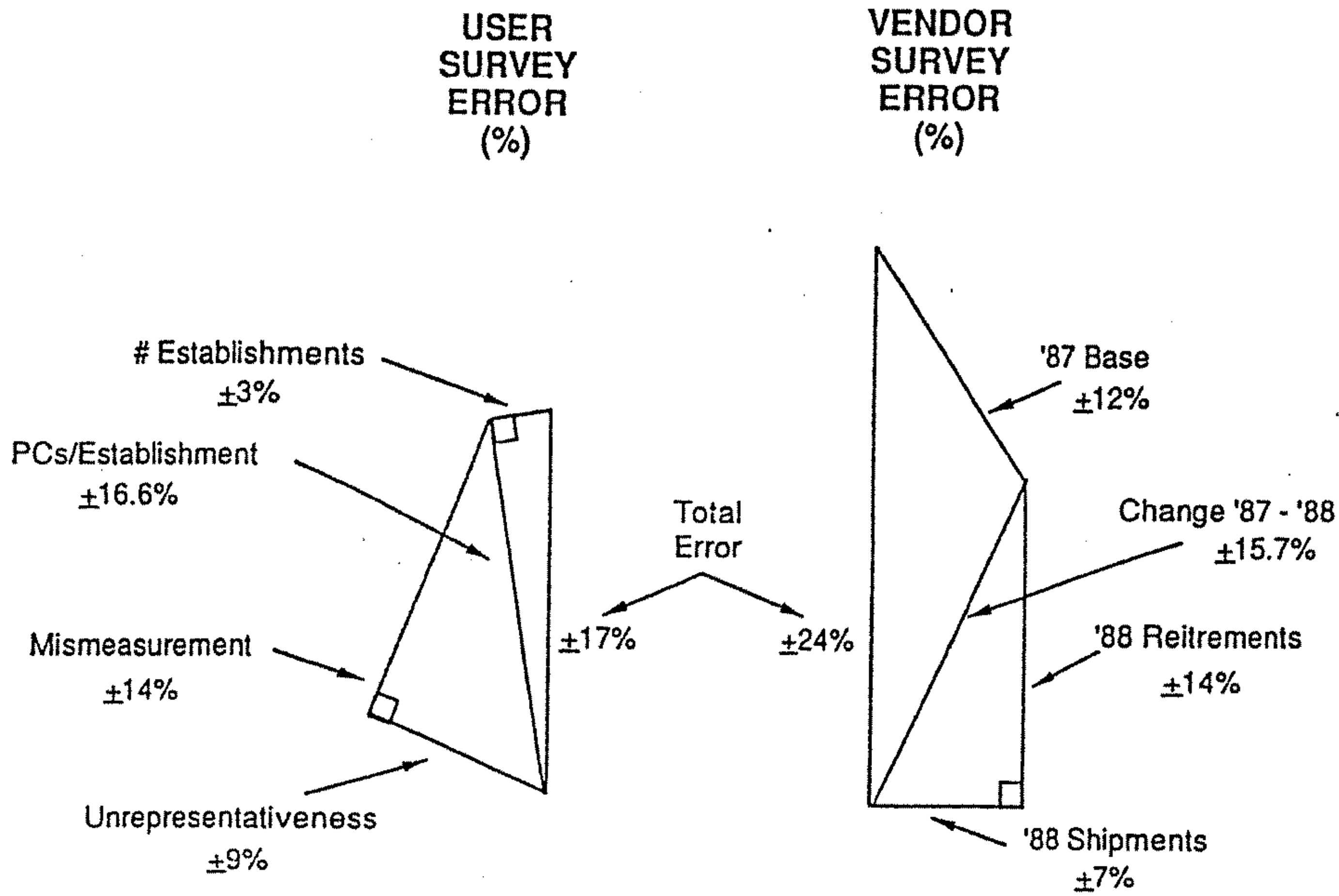
The length of each corresponding line is a judgment of proportional error by a market research specialist, based on any information available from the survey organizations and on general experience with surveys of this type. These are the errors remain-

FIGURE 3. Splitting Total Error into Components



* generalizable for complex sampling schemes

FIGURE 4. Probable Errors in Estimating 1988 Installed Base from Two Sources



ing after judgmental allowance has been made for any assessed biases (tending to underestimation in this case). For example, he judged that errors in estimating the population of establishments would be small compared to the error in estimating the number of installed PCs per establishment, and have negligible impact on total error. The conclusion shown here is that the true installed base would be within ± 17% of the user survey estimate (adjusted for bias).

More specifically, he judged that, due to mismeasurement, the true numbers of PCs per establishment could still (with 90% probability) be 14% more or less than those reported by the same businesses (with adjustment for bias). Together with a similar assessment of ± 9% for residual error due to sample unrepresentativeness (including random error), the total error in PCs per establishment works out at ± 16.6% (see Appendix A.1). When combined with an assessed error of ± 3% in the total number of establishments, we get the total error in number of PCs is about ± 17%.

For the *vendor survey*, the total error in estimating PCs installed was decomposed into errors in the estimate for the previous year (± 12%) and the net increase over the intervening year. The latter, (at ± 15.7%) was derived from errors in shipments (± 7%) and retirements (± 14%). The judgments needed here were complicated by the observation that estimates of the 1987 base and of the increase between 1987 and 1988 are likely to suffer from some of the same errors. That is the errors are judged to be positively correlated. This is reflected in the angle between the corresponding lines not being a right angle, but obtuse, in fact 120°. This corresponds to a judgment that the correlation is about halfway between none and complete (see Appendix A.1.). This results in an error for the vendor survey of ± 24%.

Thus, based on these judgments, the user survey promised to be more accurate than the vendor survey. The geometry permits a simple comparison of these accuracies by comparing the lengths of the corresponding lines. This visual inspection will probably give all the insight needed to determine if any plausible change in judgmental inputs would change the implied conclusion.

ARE TWO ANSWERS BETTER THAN ONE? COMBINING ESTIMATES USING ANALYSIS OF PLURAL EVALUATION (APE)

Case 2: Combining Existing Estimates

We return to case 1 from a slightly different perspective. We suppose that the marketing research manager has, in fact, had both of the surveys he was considering done and has now received results. The user survey produces an estimate that 14 million PCs were installed in 1988, and the vendor survey an estimate of 24 million. How should he combine his sample survey and vendor survey estimates to get a "best" estimate of market size?

Analysis of Plural Evaluation. APE addresses the general question of how best to combine multiple, inconsistent estimating approaches. As with DEA, it can also be used before or after the fact: either to plan a multiple approach or to pool the resulting estimates (as in the above case).

The approach addresses a key issue in industrial marketing research, where the approach is typically "singular." That is, all resources available for primary research are devoted to a single survey, model, etc. which produces a single estimate. Although good sense often suggests that some combination of several approaches would be appropriate, few techniques are available to guide "plural evaluation" or to analyses of the inconsistent results that plural evaluation generate.

Underlying the methodology of plural evaluation (Brown and Lindley, 1982; 1986) is the principle that combining several approaches to the same problem generally leads to more confidence in the results. This principle has long been part of the "folk wisdom" of market researchers, and has great intuitive appeal.

Moreover, it has support from Bayesian statistical theory (Brown and Lindley, 1986). Whatever one assumes about the error (variance) of individual estimates, the *projected* variance of the appropriately combined estimate is always less than that of any single estimate. (However, after the fact, estimates received may prove so different that the original estimate errors may need to be re-evaluated upward and with them, assessed error of the combined estimates.)

Generally, the variance reduction is greater when the correlation between the estimates is small. This observation, together with experienced intuition, suggests two broad guidelines for the use of plural evaluation: first, some plural evaluation is better than none; and second, the greatest gain is achieved from combining analyses that are as different as possible (Brown and Lindley, 1986). It is interesting to note that this principle applies in as widely varying domains as stock selection strategies (Farrell, 1982) and advertising copy generation (Gross, 1972).

The above argument implies that the greatest accuracy is achieved by combining many dissimilar evaluations, but, practically, cost and time constraints must limit the number of analyses considered. Resources devoted to a second analysis may come at the expense of accuracy in the first, and two similar analyses may be cheaper than two dissimilar ones due to shared set-up costs.

Analysis of plural evaluation (APE) addresses such questions. The methodology has application to two classes of practical market research problem: interpreting the results of plural research; and planning a plural research strategy.

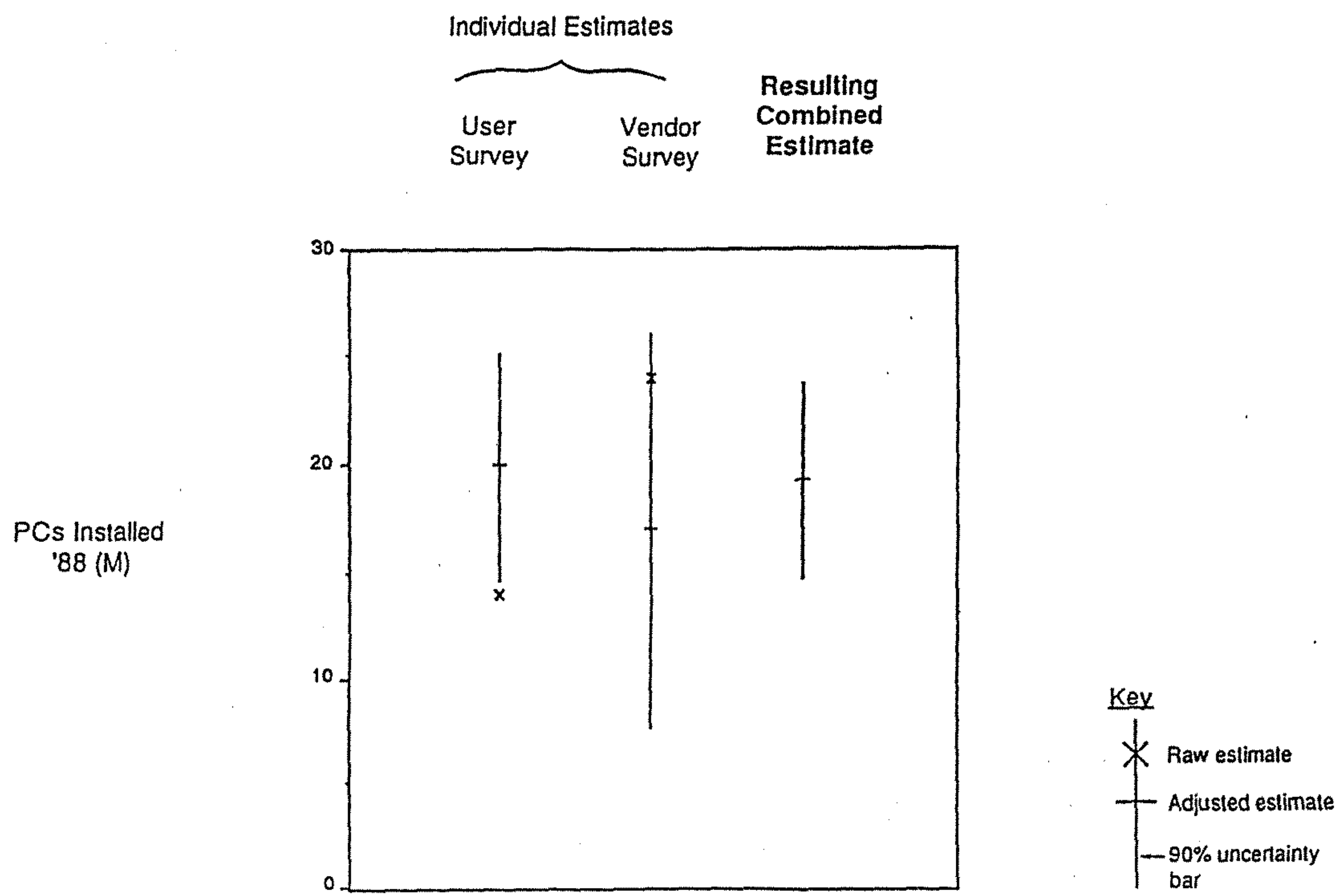
Analysis of Plural Estimates from Case 2

Well-established classical algorithms exist for approximately pooling conflicting individual solutions. A Bayesian counterpart allows for the incorporation of judgment. To return to our PC case, Figure 5 shows how estimates of PCs installed from the contending user and vendor surveys were pooled using an algorithm which takes into account bias and accuracy for each survey (see Appendix A.2).

Note that the *after-the-fact* accuracies assessed here do not correspond exactly to those projected *before* the surveys were undertaken due to information which the surveys brought to light lowering confidence in *either* survey.

The conclusion, that there were between 15 and 24 million PCs installed in 1988, could have been gauged approximately by eye (as

FIGURE 5. Combining Two Estimates of Installed PCs



with the earlier DEA example), by locating the final estimate between the two adjusted means, but closer the one with the shorter uncertainty bar (the user survey). The final uncertainty bar is a little shorter than that of the better estimate on its own.

The basis of the error evaluations for the user survey shown on the left of Figure 5 is shown in Figure 6. Both the reported estimates for number of establishments (part A) and the average installed PCs per establishment (part B) are judged to require significant adjustment upward, based on the limited information on research method available. For example, in part B the true numbers of installed PCs per establishment ("actual respondents") is expected (cross-hatch) to be about a third higher than those reported in the achieved sample, due to measurement error. Non-response and frame error account for small additional upward adjustments (as well as increasing the residual error), as shown in the larger triangle at the left of Figure 4. The accumulation of adjustments for PCs per establishment is driven by the following assumptions:

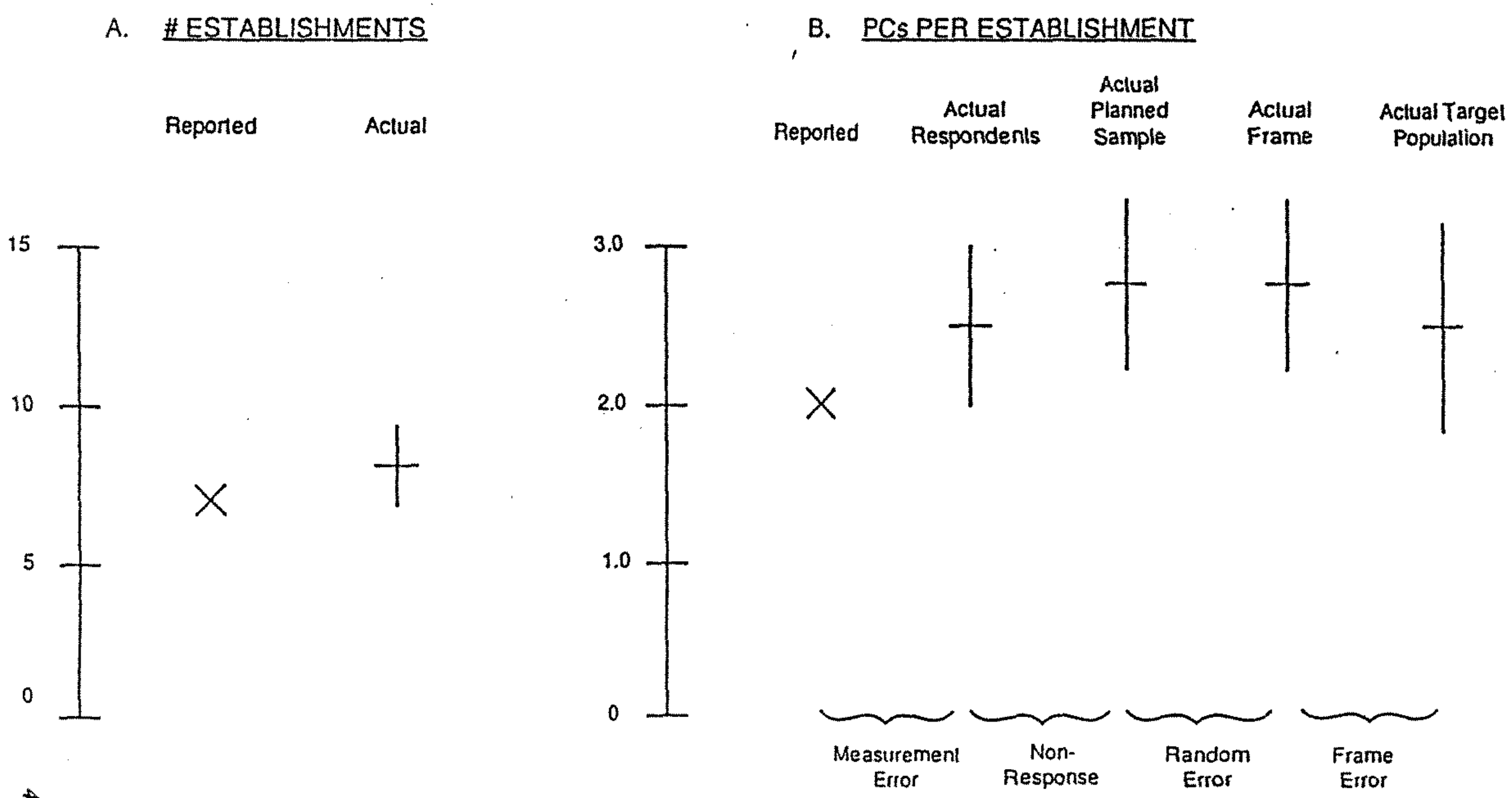
- respondents tend to under-report equipment installed in phone interviews (measurement error);
- large users of PCs are least likely to respond (non-response error);
- sampling fluctuations cause negligible bias (random error);
- however, small users are most likely to be missing from the sampling lists used (frame error).

The uncertainty bars are based on the linked triangle approach of Section 2, updated to reflect new knowledge gained as a result of conducting the survey. It should be reiterated that these error assessments could change significantly, based on more complete knowledge of the survey methods used.

Planning Plural Research

Plural research is common and sound practice in industrial market research, since there are usually a variety of possible estimation approaches that depend on different sources of information, but which may be unreliable individually. For example, demand for an

FIGURE 6. User Survey Estimate of Installed PCs Adjusted for Potential Errors



industrial component may be estimated from manufacturers times sales per manufacturer; from users times demand per user; and from new equipments sold times components per equipment plus equipments in use times replacements per equipment. Often, there are a number of sources of information about the quantity of interest. Common sources include desk research, opinion of salesmen, and sample surveys. Combining different sources of information typically leads to improved accuracy of estimate.

Consider the problem of allocating resources between various approaches. (We assume here that, for a given method, accuracy will generally increase as more resources are allocated to that method.) A distinctive feature of estimating business markets is that many contending approaches–sampling and other–are available for any given estimate, none of them capable of producing high accuracy on its own. Multiple approaches are, therefore, indicated, but the best balance is difficult to determine.

In a sample survey, both error and cost depend on sample size. There are typically three components of cost: a fixed cost, a variable cost proportional to the number of interviews, and a sliding cost which increases with the number of interviews, but less than proportionately. Information can be considered the inverse of error (more precisely the reciprocal of variance). Until the fixed cost of mounting a survey has been incurred, virtually no information is obtained. It does not then increase proportionately to sample size because of the non-random errors, which do not depend on sample size.

With desk research, information typically increases rapidly for a little effort but soon reaches a point where additional effort provides little or no new information. Figures 7a and 7b show one view of how information increases with resources for survey research and desk research, respectively.

These graphs can be combined to show the best use of a given research budget–that is, the split between the two methods that gives the most information within budget. The method is shown for two different budgets, a small one (Figure 7c) and a large one (Figure 7d). The method involves seven steps.

1. Draw the graph of information versus cost for survey research, as shown in Figure 7a.

2. Construct the mirror image of the graph of information versus cost for desk research by reversing the direction of the cost axis (i.e., cost starts at zero and increases to the left).
3. Overlay the mirror-image of the desk research graph on the survey research graph with the origin of the mirror-imaged desk research at the budgeted total cost.
4. Construct the graph for total information by adding the two graphs vertically.
5. *Find the point with the greatest total information.*
6. Read the budgets for survey research and desk research on the cost axis. The survey budget is read left to right and the desk research budget is read right to left.

For the same information curves, Figures 7c and 7d show markedly different conclusions as to how to split resources between desk and survey research for two different budgets. If the budget is small (Figure 7c), most information will be obtained if the entire budget is devoted to desk research, while for a large budget (Figure 7d) most of the resources should be spent on the survey.

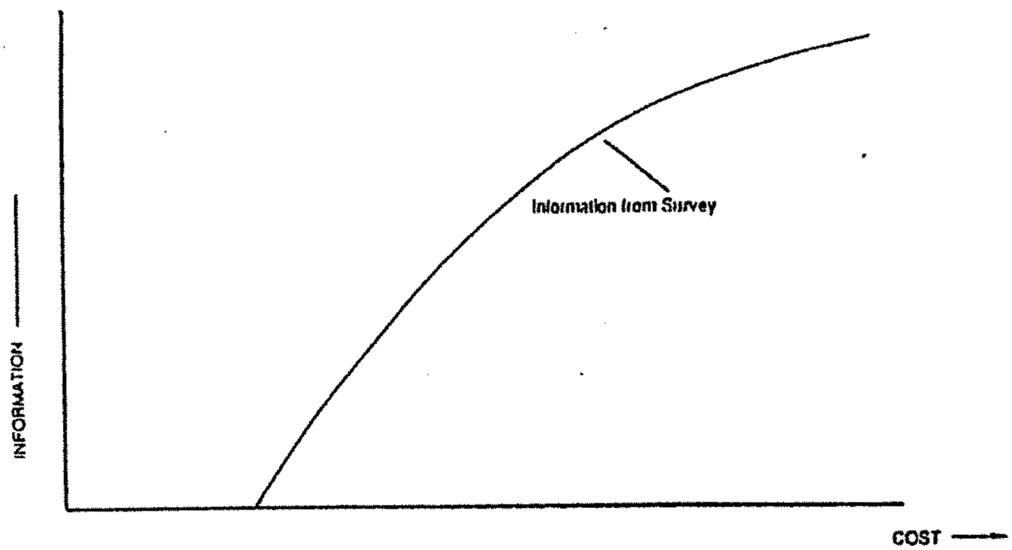
As with previous examples, the main conclusions can be derived by eye, without the need for confirming calculations.

HOW CAN YOU ECONOMICALLY JUSTIFY A MARKET RESEARCH PLAN? ECONOMIC EVALUATION VIA PARTIAL CONDITIONING OF CONSEQUENCES (PCC)

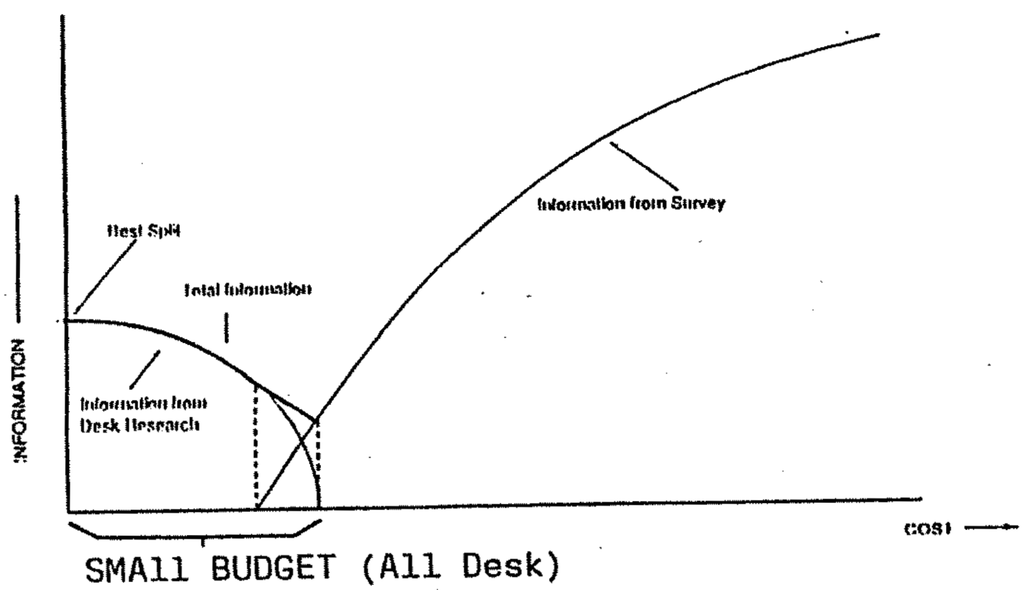
Case 3: Comprehensive Market Study Case

The president of an office equipment manufacturer was considering some major shifts in marketing strategy. His marketing research group had developed a comprehensive market research plan, which would cost up to $200,000 over the next months. Recent failure to meet profit goals had prompted him to cut back on marketing expenses generally, and the group needed a strong case to convince him to approve this plan, which would actually require an increase over the previous market research budget. In other words, the market research team needed a method to quantify the value of the research. PCC is such an approach.

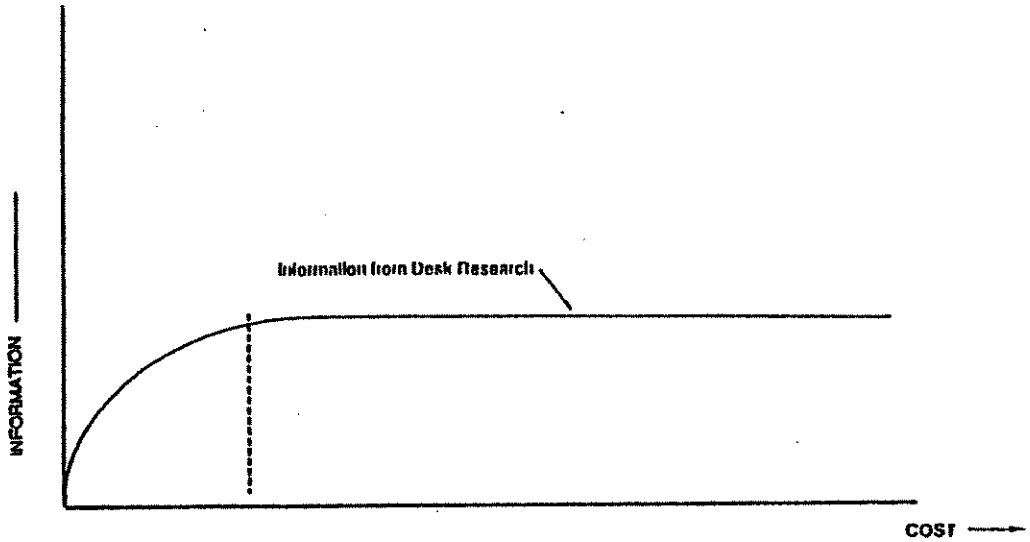
FIGURE 7. Allocating a Market Research Budget Between Two Studies



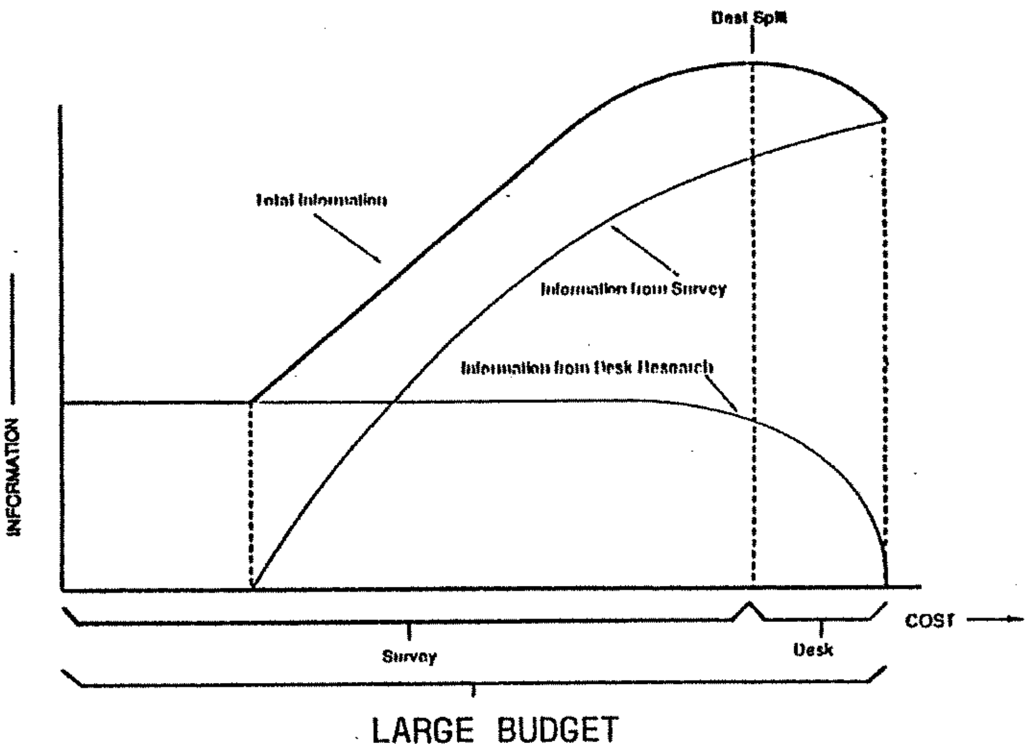
A: INFORMATION RESULTING FROM RESOURCES APPLIED TO SURVEY RESEARCH



C: ALLOCATION OF SMALL BUDGET BETWEEN THE TWO STUDIES



B: INFORMATION RESULTING FROM RESOURCES APPLIED TO DESK RESEARCH



D: ALLOCATION OF LARGE BUDGET BETWEEN THE TWO STUDIES

To determine the value of market research, one must account for the decisions that the results will influence. Standard decision analysis theory suggests: setting up a decision tree, noting the possible results of each research option and determining a single best final marketing, etc., decision for each result; and choosing the option with the highest expected utility (Raiffa, 1968). This type of analysis is almost never fully appropriate in practice. It requires that all relevant information that might be received before the final decision be modeled explicitly, and that the procedure for making the decision must be known currently with certainty.

Partial conditioning of consequences (PCC) treats future actions as probabilistic events, and the consequences of subsequent actions can be evaluated probabilistically, using less than all the information that will be learned (Brown, 1978).

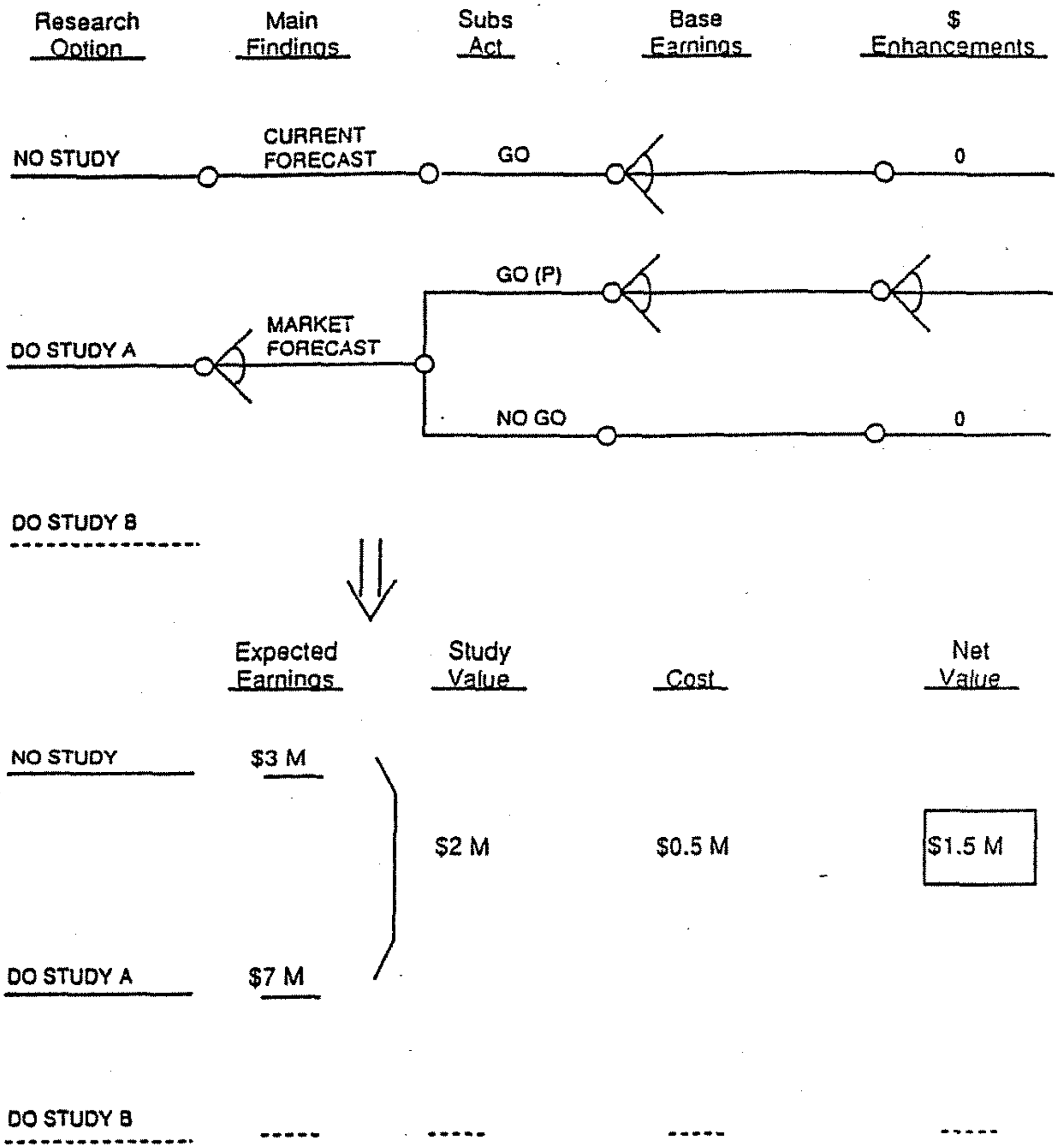
For example, Figure 8 shows a PCC model structure of a new product study, where several studies are under consideration and their prospective economic values are compared with the "no study" base. The model assumes that, based on a current forecast, the decision would be to launch the new product. The earnings resulting from that subsequent act are uncertain and represented by a fan in the figure.

This is the base case, against which to compare other options. For example, "do study A" will lead to a new market forecast, which constitutes the "partial conditioning information," which is uncertain (hence the fan following the study). The subsequent act is whether to "go" with the new product. In the PCC model, the probability of "go" is a function of the forecast.

The resulting earnings are broken into two components. One, called "base earnings," are those that would have accrued if the new product were launched as currently envisaged. The other amount, "dollar enhancement," are the additional earnings that result because the study has economic benefits beyond helping the "go–no go" decision; for example, the study may unearth an improved product, marketing strategy, or pricing strategy. (By definition, the "no study" option has no dollar enhancements.)

Suppose that analyzing the consequences of "do study A" (both components) produces expected earnings of $7 million, compared with expected earnings of $5 million for "no study," as shown in

FIGURE 8. PCC Evaluation of New Product Study



the lower diagram. If the cost of study A is $500,000, then the conclusion is that the study has an expected net value of $1.5 million. (This type of procedure was used by Urban and Katz, 1983, to assign a value of more than $400,000 to a typical, $50-$75,000 pre-test market research procedure for consumer packaged goods.)

Variants of this structure are appropriate for a wide variety of industrial market research valuations. In addition to new product decisions, the method has been applied to market penetration studies, pricing decisions, market positioning, and elsewhere.

To return to case 3, the market research staff developed a justification using PCC, tied to identifying "nasty surprises" that current uncertainties could yield. For each, they assessed how likely the surprise was to occur, with and without the proposed research, and what it would cost in terms of opportunities missed or unnecessary costs.

The company was currently prepared to redirect its marketing effort to target Fortune 2000 accounts. If it turned out that the company's best prospects lay, after all, with the smaller end-users, up to $180 million in lost sales could result. On current information there appeared to be 30% chance of some surprise of this kind, and the proposed market study would reduce this risk substantially. Another economic value was that the study was expected to show how to increase marketing productivity by 5%.

This PCC based analysis produced a persuasive case that the proposed research would be worth about $20 million in additional sales (beyond the current projection of $400 million), and added an expected profit of about $4 million. The analysis easily justified the market research cost proposed, even if conservative assumptions were made.

CONCLUSIONS

We started this paper with three observations:

1. market research expenditures in business markets are very low while good market information could be of substantial value;
2. business markets have many characteristics that often make consumer marketing research methods inappropriate; and
3. methods specific for industrial markets are not widely known.

We then presented three procedures that have been applied to address various problems that arise frequently in the industrial marketing arena:

1. Decomposed Error Analysis (DEA), an approach for determining how accurate different estimates (or research procedures) are likely to be;
2. Analysis of Plural Research (APE), a method for combining different sources of information or studies in such a way that accuracy is enhanced; and
3. Partial Conditioning of Consequences (PCC), an approach for assessing the value and justifying industrial market research studies.

These methods are well-developed and have been successfully applied. They are not cook-book methods, however, and, like good industrial research in general, require expertise to apply properly. We hope this paper will serve to encourage more industrial or business marketers to learn more about how these methods can help improve the quality of information used for their business decisions. And we hope that such tools will stimulate the development of better data sources to provide that information.

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APPENDIX

A.1 Decomposed Error Analysis

The total user survev error in Figure 4 is composed of the error in estimating the number of establishments and the error in estimating PCs per establishment, which is itself composed of mismeasurement error and unrepresentativeness. Since the user survey errors are uncorrelated and the arguments are multiplicative, the total error is calculated from the following:

$$TE=\sqrt{CE_1^2+CE_2^2}$$

where:

TE, is the total error expressed as a credible interval (e.g., 90% credible interval) divided by the mean and CE_1 and CE_2 are the component errors expressed as credible intervals divided by means.

This formula is strictly appropriate for distributions (such as normal distributions) with credible intervals equal to constant multiples of their standard deviations. It is a reasonable approximation for most distributions encountered in market research.

APPENDIX (continued)

Graphically, this relationship can be depicted by a combination of right triangles. In the example in Figure 4, mismeasurement error is ±14%, unrepresentativeness error is ±9% and the error in the number of establishments is ±3%. This gives

PCs/Establishment Error = $\sqrt{(.14)^2+(.09)^2}=\sqrt{.0277}=\pm16.6\%$

Total User Survey Error = $\sqrt{(.166)^2+(.03)^2}=\sqrt{.0286}=\pm16.9\%$.

The total <u>vendor survey error</u> in Figure 4 is composed of the error in estimating the '87 Base and the error in estimating the '87-'88 change, which is composed of errors in estimating '88 shipments and retirements. Estimates of '88 shipments and retirements are uncorrelated and can be combined using the formula above. In the example in Figure 4, the error in estimating '88 shipments is ±14% and the error in estimating '88 retirements is ±7%, so the error in estimating the '87-'88 change is $\sqrt{(.14)^2+(.07^2)}=\pm15.7\%$.

APPENDIX (continued)

The estimates of the '87 base and the '87-'88 change are correlated and are combined using the formula:

$$TE=\sqrt{CE_1^2+CE_2^2+2\rho CE_1\times CE_2}.$$

Where ρ is the correlation between the two component errors. In the example in Figure 4, the error in estimating the '87 base is $\pm 12\%$ and the correlation between this estimate and the estimate of '87-'88 change is 0.5. This gives

$$\text{Total Vendor Survey Error} = \sqrt{(.157)^2+(.12)^2+(2)(.5)(.157)(.12)}=\pm 24\%.$$

This combination is also depicted graphically in Figure 4 by a series of triangles, but they are not all right triangles. In cases where the errors are correlated, the angle, θ, between the component errors is determined by: $\cos\theta=-\rho$ or $\theta = \cos^{-1}(-\rho)$. In the example, $\theta=\cos^{-1}(-.5)=120°$. The angle θ will be obtuse if errors are positively correlated ($\rho>0$), acute if the errors are negatively correlated ($\rho<0$), and a right angle if the errors are uncorrelated ($\rho=0$). Table A shows the approximate relationship between ρ and θ. The correlation can be assessed directly, for example by visualizing 0.5 as "midway between complete and no correlation", or indirectly through standard statistical techniques.

APPENDIX (continued)

Correlation between errors	Approximate Angle between errors
-1	0°
-.5	60°
-.25	75°
0	90°
.25	105°
.5	120°
.7	135°
1	180°

Table A: Approximate Relationship Between Correlation and Angle

A.2 Analysis of Plural Evaluation

The resulting combined estimate in Figure 5 is a combination of two independent estimates, from a user survey and a vendor survey, of the same quantity, PCs installed in '88. The procedure for combining estimates is as follows. First, each individual estimate is adjusted to remove its bias, then uncertainty ranges are determined, then estimates are combined. The resulting combined estimate is calculated from the following:

$$RCE = AE_1 \times (U_2^2/(U_1^2+U_2^2)) + AE_2 \times (U_1^2/(U_1^2+U_2^2))$$

where RCE is the resulting combined estimate, AE_1 and AE_2 are the two adjusted estimates, and U_1 and U_2 are uncertainty ranges for the estimates. The example in Figure 5 illustrates the following situation:

	Raw Estimate (M)	Adjusted Estimate (M)	90% Uncertainty (M)
User Survey	14	20	15 to 25
Vendor Survey	24	17	8 to 26

This gives

$$\text{Resulting Combined Estimate} = (20)((26\text{-}8)^2/((25\text{-}15)^2 + (26\text{-}8)^2)) + (17)((25\text{-}15)^2/((25\text{-}15)^2 + (26\text{-}8)^2)) = 19.3$$

The size of the uncertainty range in the resulting combined estimate, U_R, is calculated from

$$U_R = \sqrt{U_1^2 \times U_2^2 \;/\; (U_1^2 + U_2^2)}$$

$$= \sqrt{(25-15)^2 \times (26-8)^2 \;/\; ((25-15)^2 + (26-8)^2)}$$

$$= 8.7$$

19.3 ± (8.7/2) or 14.9 to 23.7.

These formulas are appropriate for combining independent, normally distributed estimates with a "flat" prior distribution on the combined estimate. More complicated formulas are involved if the estimates are correlated, if the prior distribution is not "flat", or if the distributions are not normal. In particular, the Student's t, distribution can be used to accommodate unexpectedly discrepant estimates, which provide evidence that initially assessed confidence in each individual estimate is too high (Lindley, 1981; Ulvila and Brown, 1983).