September 2004

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DECISION ANALYSIS
Vol. 1, No. 3, September 2004, pp. 177–189
ISSN 1545-8490 | EISSN 1545-8504 | 04 | 0103 | 0177

DOI 10.1287/deca.1040.0023

Value of Information in Portfolio Decision Analysis

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It can be time consuming to use decision analysis to allocate resources over a portfolio of projects. It may be possible to attain most of the value added by decision analysis in significantly less time. This paper defines and compares different analytic strategies in terms of the resulting value added for a range of simulated portfolios. A portfolio consists of a set of candidate projects or investments of uncertain value. The value of each project may be estimated with or without the additional information provided by decision-analytic methods. Projects are then completely prioritized and funded in order of the ratio of their expected net present value to their cost, or partially prioritized and funded whenever this ratio exceeds a predefined threshold level. The portfolio funded under the various analytic strategies is compared against a strawman alternative of random funding decisions. The value added through disciplined prioritization often exceeds the additional value added through the more costly step of developing refined estimates of project values. Intermediate approaches, including threshold approaches and the application of triage rules to determine which projects to analyze, are found to be useful but not robust.

Key words: portfolio management; project selection; decision analysis; resource allocation; budget allocation
History: Received on July 25, 2002. Accepted by Robert T. Clemen and Don N. Kleinmuntz on April 22, 2004, after 6 revisions.

1. Introduction

Portfolio decision analysis has been one of the major applications of decision analysis to business and government. It is used to aid in the allocation of resources across portfolios of capital investment opportunities (projects). At its simplest, this approach consists of applying decision-analytic techniques to the candidate projects in a portfolio one at a time to estimate the cost and value (or expected value or multiattribute utility, etc.) for each project. Projects are then ranked, or *prioritized*, in decreasing order of one of several essentially equivalent measures: the common term "bang for the buck," "productivity index" (Cooper et al. 2001), and "profitability index" or "benefit to cost ratio" (Kleinmuntz and Kleinmuntz 2001), the latter (abbreviated as BCR) defined as the expected value of the proceeds resulting from a project divided by its costs. The existing budget is then used to fund the higher-ranking projects until it is exhausted.

The research question that was the impetus for this paper is the following: How much of the benefit from portfolio decision analysis is due to the improved value estimates and how much is simply a result of the discipline of using an objective ranking (prioritization) to determine which projects get funded? Improvement of value estimates is time intensive, requiring expert interviews and development of financial models. Prioritization alone, on the other hand, can be done with models that do something as technically simple as sorting (e.g., Kirkwood 1997).

Several management studies (e.g., Rzaza et al. 1990, Clemen and Kwit 2001) have estimated the value added by the decision-analytic process, and in particular by portfolio analysis efforts. These studies typically compare the value of the new portfolio of funded projects with the expected net present value (ENPV) of the portfolio of projects that would have been funded without doing the analysis. Some studies (Adams et al. 2000, Sharpe and Keelin 1998) graphically compare the efficient frontier for portfolio value versus cost with the value and cost for the entire set of possible portfolios. Increases in value due to decision analysis estimated in these and other studies have ranged from 15% to over 100% of the value of the original portfolio that would have been selected. This increase in value far exceeds reasonable estimates of the cost of the analysis. Clemen and Kwit (2001), for example, found that different portfolio analysis efforts at Eastman Kodak took between 21 and 358 analyst hours.

Value-of-information techniques have been used to study the sources of value in decision analysis (Matheson 1968, Watson and Brown 1978), and a related approach will be used here. The intent is to explore a set of problems currently faced by decision analysts advising portfolio managers. Because it is impractical to calculate the value of all different information acquisition strategies, we shall simulate portfolios using parameters based on empirical data. We then record the cost and expected value of the portfolios, assuming they are managed under each of several analytic strategies. The different analytic strategies are modeled as different levels of information that may be available at the time funding decisions are made. Parameters used to simulate the portfolios are varied to consider different questions and to test the robustness of results.

Section 2 introduces a model used to simulate portfolios that are managed with one of several analytic strategies. Section 3 explains the parameter values used in the simulations. Section 4 describes the possible analytic strategies. The strategies range from a minimum-value ("strawman") strategy in which resources are allocated to projects without making use of relevant information, to a maximum-value ("gold standard") strategy in which projects are prioritized based on perfect information. In between are several strategies that make use of partial information about some or all projects. Section 5 presents the results of this simulation for each of the strategies, along with analysis of specific questions that arise. The most important statistic will be the expected value of the simulated portfolio under each strategy. From this, the value added by each strategy is calculated in absolute terms and as a percentage of the maximum potential value added. These results are used to identify circumstances where the simplest strategies, especially threshold-based rules, perform almost as well as more time-intensive and costly strategies. Section 6 summarizes the findings and their implications for portfolio decision analysis, as well as limitations of the model and directions for future research.

2. Model

Process

We will compare different strategies employed to prioritize simulated portfolios of projects where each project has resolvable uncertainty. We use a simple structure for project values and portfolio value, so that we may focus instead on the complications that arise from having a large number of uncertain projects.

We consider a process in which portfolio managers receive and manipulate a wide range of information about projects and, with this information, formulate estimates of project values. At some point, the manager may engage a decision analyst to refine those estimates via structured assessments and model building. This analysis, we assume, reveals perfectly the subjective expected value of the proceeds of the project based on the best possible estimates. The manager can then prioritize the projects with some level of precision and discipline and allocate a budget among them.

We assume the proceeds follow a known distribution. Detailed data on actual portfolios are scarce, especially portfolios that have been subjected to decision analysis. Furthermore, there is wide variation in the characteristics of portfolios that would be encountered in practice. I therefore calibrated the model by querying industry experts, analyzing proprietary data, and considering published examples. A typical observation is that, "in [the] Pharma[ceutical industry], distributions of NPV are generally pretty skewed to the right. Indeed it is that fear of missing out on the mass to the right that makes people reluctant to kill projects." My own experience and that of other informants agrees with this, as does my analysis of proprietary data of actual portfolios and of examples from the literature (Cooper et al. 2001, Exhibit 3.2, p. 32). There seems to be convergence among the different sources, with general agreement that the distribution on project values is skewed to the right, with some mass to the left of zero (once costs are subtracted), and ranging as high as 10 to 20 times project costs.

Notation

We shall use the following notation for the model.

R_i: proceeds per unit of funding resulting from project i if it is funded

r_i: $\log(R_i)$
y_i: manager's estimate of r_i
μ: mean value of r_i
σ: standard deviation of r_i
ε: error in manager's estimate of r_i
τ: standard deviation of ε_i
V_i: the value of project i
F_i: binary variable indicating whether project i is funded
V: the total value of the portfolio that is funded
C_i: the cost of project i
c_i: $\log(C_i)$
T: a threshold level used for some strategies

Model Structure

We assume $r_i \sim \mathrm{N}(\mu, \sigma^2)$, i.e., project returns (R_i) follow a lognormal distribution having the desired characteristics. Before decision analysis begins, the manager forms an estimate y_i, generated about r_i. Specifically, $y_i = r_i + \varepsilon_i$, where the distribution of the error term is known to be $\varepsilon_i \sim \mathrm{N}(0, \tau^2)$ and errors are independent and identically distributed (i.i.d.) and uncorrelated with r_i. This structure results in a multiplicative error model—commonly seen in mathematical finance—where errors in the estimates about R_i are proportional to R_i; i.e., the manager receives a similar level of information quality for each project. For each project i that is analyzed, we assume that the actual value of r_i is revealed immediately before a single point in time at which project-funding decisions are made; otherwise r_i is revealed (by nature) after the funding decision.

To simplify the analysis, each project is assumed to have the same cost, arbitrarily set at \$1.00. Even though project costs really vary, we do not give up much by excluding this feature from the model because cost estimates tend to have less uncertainty and are more easily obtained than value estimates (e.g., Table 17.1, p. 149, in Martino 1995). The main impact of the assumption of identical costs will be to exclude knapsack-type problems where combinations of borderline projects are partly chosen to exhaust the available budget exactly.

Because its cost is \$1.00, the BCR of project i is equal to R_i. Thus, $V_i = R_i - 1$, the value of project i, and $V = \sum V_i F_i$, which is equal to $\sum R_i F_i - \sum F_i$.

3. Input Assumptions

Before simulating portfolios, we need to assign reasonable parameter values for a base case. The parameters will later be varied one at a time.

For the distribution on r, we assume $\mu = 1$ and $\sigma = 1$. This implies that the average BCR is $\exp(\mu + \sigma^2/2) \approx 4.5$, so that approximately 1 out of 6 projects has a BCR below 1.0, and approximately 1 out of 40 projects has a BCR above 20. These figures are consistent with the sources mentioned above.

The standard deviation of the error (τ) was based on responses to the following question: Consider a typical portfolio manager's unassisted estimates on proceeds per dollar of investment. Then consider the distribution of estimated values that would be revealed by the best possible analysis based on information available within the company. What is the distribution of the latter set of values above or below a given estimated value? I queried several experts and also examined a set of proprietary data in which estimates prior to decision analysis were compared with postanalysis estimates and, where available, actual market values. From these sources, $\tau = 1.0$ seems reasonable for the base case.

The parameter values used in the simulation are meant to be representative, but actual values depend very much on the specific situation. Late-stage projects, which have lower remaining costs, are likely to have higher BCRs. At the other extreme, where there are low barriers to requesting funds, the set of candidate projects may have lower BCRs and higher variance. Specific managers may be more or less knowledgeable about the projects in the portfolio than these numbers indicate.

An important implicit assumption in this analysis is that companies do not necessarily fund all projects with positive expected value. A likely reason for this is the presence of other constraints that are not explicit in our model. Capital is constrained—R&D departments have a budget and companies have competing uses for capital (and, due to problems of asymmetric information, cannot simply go to the market for more capital). Above a certain percentage of projects funded, the company cannot support them all. The market may be too small, or sales force, factories, and even R&D staff may be constrained. Furthermore, capital can be tied up for years in development, so a project that delivers \$2.00 for \$1.00 still utilizes that \$1.00 for a long time and may yield a low return on investment. Managerial attention is also limited, and a smaller portfolio that retains most of the potential value may be preferable because, ultimately, it will be better executed.

All of these factors influence the R&D budget. The number of candidate projects and the proportion of projects that can be funded within the available budget varies widely depending on context. For illustrative purposes, we arbitrarily assume a base case with 50 projects and a budget (\$15.00) sufficient to fund 30% of the candidate projects. If monetary values are in millions, this base case represents a midsized R&D department.

4. Strategies for Analysis and Funding

We consider four basic strategies and then some variations on them. Each strategy consists of a rule for information-acquisition decisions, i.e., for determining which projects will undergo a thorough analysis, and a rule for making funding decisions based on the information available. The strategies are:

S1: Random Funding. Projects are selected and funded in random order until the budget constraint is reached, i.e., if the index i indicates the order in which projects are considered,

$$F_i = 1 \quad \text{if } \sum_{j=1}^{i-1} C_j F_j \le B - C_i$$

and $F_i = 0$ otherwise.

This strategy generates the baseline portfolio for comparison with portfolios generated by other strategies. For this strategy, expected value increases at a linear rate with expenditure at the rate of the average BCR of all the projects. The value of this strategy for a given budget will be calculated using this closed-form solution, rather than simulation. The rationale for assuming project managers use a random process even when they have some information is that, without a disciplined value-maximizing process, the decision-making process may preclude the disciplined use of that information. Political and organizational pressures, conflict avoidance, or a historical pattern of haphazard first-come–first-served funding could all lead to this situation. Problems of this type are commonly cited as reasons for using a decision-analytic process. Nevertheless, this extreme case is mainly used as a basis for comparison.

S2: Apply Threshold Rule Without Resolving Uncertainty. Projects are considered one at a time in random order, and project i is funded if y_i meets or exceeds a predetermined threshold level, until the budget is exhausted. If there is additional money in the budget left after all of these projects are funded, remaining projects are funded in random order until the budget is exhausted. If projects are indexed in the order they are considered, the decision rule can be expressed in terms of a first pass where $F_i' = 1$ if $y_i \ge \log(T)$ and

$$\sum_{j=1}^{i-1} C_j F_j' \le B - C_i$$

and $F_i' = 0$ otherwise, and a final funding decision where $F_i = 1$ if $F_i' = 1$ or if

$$\sum_{j=1}^{i-1} C_j (F_j' - F_j) \le B - \sum_{j=1}^{n} C_j F_j' - C_i,$$

and $F_i = 0$ otherwise.

Note the inefficient use of funds with thresholds may be asymmetric in practice. If funds remain after the threshold is applied, it might require relatively little additional effort to ratchet the threshold down and then fund another round of projects. On the other hand, if the threshold were too low, it would be hard to raise the threshold and take funds away from projects that had already been funded. When this is practical, only part of the results for S2 obtained in this paper would apply.

S3: Prioritize Without Resolving Uncertainty. Projects are ranked in order of y_i, and funded in descending order until the budget constraint is reached, i.e., the decision maker solves $\text{Max}_{\{F_i\}} \text{E}(V \mid y_1, \ldots, y_n)$ s.t. $\sum C_i F_i \le B$.

S4: Resolve Uncertainty Then Prioritize. Projects are ranked in order of r_i and funded until the budget constraint is reached, i.e., the decision maker solves $\text{Max}_{\{F_i\}} \sum R_i F_i$ s.t. $\sum C_i F_i \le B$.

The expected value of the portfolio funded under strategy S is denoted $V(\text{S})$. These values are related to value of information in the following sense.

Strategy S1 corresponds to a state of no information or, equivalently, no prioritization, while S2 corresponds to a state of partial information and partial prioritization. S3 corresponds to a state of the same partial information as in S2 plus complete prioritization. An alternate description of the situation in S3 is that the funding decision for a single project also incorporates information about the value of other projects to set the proper threshold level for the budget. With the intended interpretation of our model, the increase in value from S1 to S3 arises due to the use of a disciplined process to prioritize projects rather than to the acquisition of the partial information used (which the manager is assumed to have acquired without any help). S4 corresponds to complete prioritization with perfect information about project values.

Note that although none of these strategies contains special provisions for the case where the expected value of the marginal project is less than zero, real managers would not fund such projects. This simplifying assumption will lead to underestimates on the order of 1% for $V(\text{S4})$ at the highest two budget levels considered (at which point the efficient frontier starts to slope downward), and makes no difference for the other strategies.

Variations on these strategies are possible, e.g., perfect information and partial prioritization. This strategy, discussed briefly in the next section, has similar characteristics to S2. It may be an interesting option for a company that wants decentralized resource allocation, but it does not illuminate any new issues. We shall also consider briefly the strategy of ranking projects by ENPV instead of BCR when project costs in the model are allowed to vary.

5. Simulation Results

Computer Simulation Mechanism

The performance of different strategies is compared in terms of several measures across 500 simulated portfolios using the assumptions from §3. Each portfolio is simulated by generating random values and errors for each of the candidate projects in the portfolio. In this section, numerical results are reported for the base-case portfolio and selected variations (e.g., doubling and halving of various parameters) to illustrate the magnitude of benefit a typical manager might expect from different strategies. Where more complete sensitivity results are needed, the value of the various strategies is graphed against ranges for the possible parameter values.

The results of an Excel spreadsheet simulation for S3 and S4, each using the same 500 iterations, are given below. These are compared with the expected values from S1 and later S2. Figures for cost and BCR are given to make the presentation of these results consistent with the presentation of results for the richer sets of assumptions considered later. Ranges given for these numbers are 95% confidence intervals on the estimates of averages, approximated as the mean $\pm 2/\sqrt{499}$ times the standard deviation across the 500 simulated portfolios.

Base-Case Results on Value of Prioritization and Value of Information. A reasonable lower bound on portfolio value is $V(\text{S1})$, which averaged \$52.00 (±\$2.00) (all values are rounded to the nearest dollar) for the given budget of \$15.00. This is consistent with the theoretical expected value of \$52.00, i.e., the available budget multiplied by the average BCR of all projects, less cost. There is substantial improvement when projects are prioritized rather than funded at random, as the average of $V(\text{S3})$ was \$112.00 (±\$3.00). As might be expected, further improvement is possible when portfolio decision analysis includes resolution of uncertainties about project value estimates followed by prioritization, and $V(\text{S4})$ averaged \$137.00 (±3). The standard deviation over the 500 iterations for $V(\text{S3})$ is \$36.00, and for $V(\text{S4})$ it is \$35.00. These are similar, but the standard deviation as a percentage of V is substantially higher for S3 than for S4.

We do not yet consider S2 separately, because $V(\text{S2})$ is close to $V(\text{S3})$ if the threshold is set correctly.

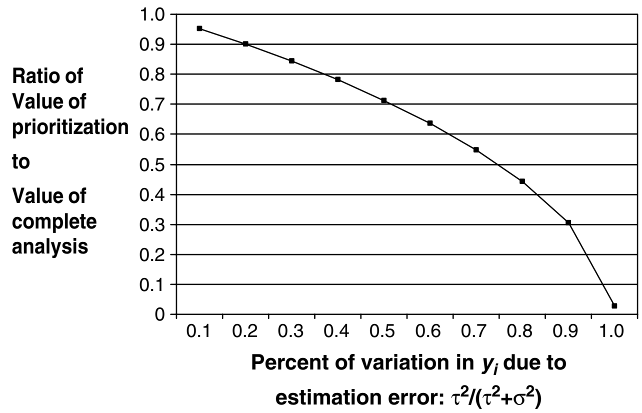
Because the portfolios selected by S1, S3, and S4 all have the same cost, the differences in value can be interpreted as the value added by the analytic strategy. This value added has two parts: The increment in value from prioritization alone (from random funding to funding that is prioritized based on estimated values), $V(\text{S3}) - V(\text{S1})$, is \$61.00 (±3), and the increment from resolution of uncertainty and prioritization, $V(\text{S4}) - V(\text{S3})$, is \$24.00 (±1). The standard deviation on this difference is \$11.00, which suggests that perfect information may occasionally contribute more value than prioritization. For the base-case parameters, on average about 71% of the increase in value comes from prioritization of projects alone, and 29% comes from the additional step of resolving uncertainty over project value.

Sensitivity of Base-Case Results to Level of Uncertainty. In the base case, the variation in estimated values is caused in equal parts by error and by variation in the actual project values. When the standard deviation of the error is half as large relative to the standard deviation of estimated project values as in the base case, which happens when $\tau \approx 0.38$, the results are more extreme. The value of prioritization, $V(\mathrm{S3}) - V(\mathrm{S1})$, increases to \$81.00 while the additional value of perfect information, $V(\mathrm{S4}) - V(\mathrm{S3})$, decreases to \$5.00, i.e., 10% of the requested funding and 33% of the budget. These increases in value would justify Howard's (1973, p. 81) suggestion "to spend at least one percent of the resources I am allocating on making sure that I am getting a good allocation of those resources." The case is much stronger with respect to prioritization than with respect to improving of estimates. In still more extreme cases, where there is even less uncertainty or where the budget is sufficient to fund most projects, the value of resolving uncertainty about project values approaches zero.

Value of perfect information is higher, naturally, when there is more uncertainty to be resolved. When τ is large, prioritization without additional information is essentially a random process and adds no value. At the other extreme, when values are known with certainty, the value of resolving uncertainty is zero and all the potential value lies in prioritization. Figure 1 shows $[V(\mathrm{S3}) - V(\mathrm{S1})]/[V(\mathrm{S4}) - V(\mathrm{S1})]$ when the percent of variation in y_i due to estimation error ranges from 0% to 100%. The percentage shown on the x-axis is calculated as $\tau^2/(\tau^2 + \sigma^2)$, which goes from 0% to 100% as τ varies from 0 to ∞.

All other parameters are unchanged from the base case; $V(\mathrm{S1})$ and $V(\mathrm{S4})$ do not depend on the parameter τ. This ratio, as with all other such ratios presented here, is calculated from the simulation data by dividing the average value of the numerator by the average value of the denominator, rather than the average value of this ratio calculated for each of the 500 iterations. Note, we are using the ratio of the

Figure 1 Importance of Prioritization vs. Accuracy of Project Value Estimates

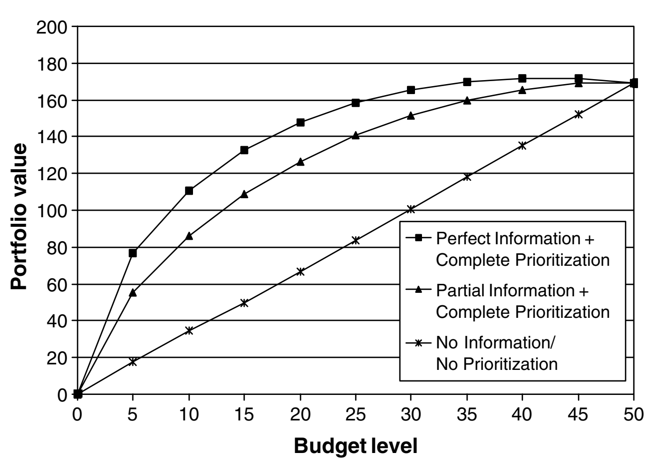


expected values, $E[V(\mathrm{S3}) - V(\mathrm{S1})]/E[V(\mathrm{S4}) - V(\mathrm{S1})]$, which provides a biased estimate for the expected ratio $E\{[V(\mathrm{S3}) - V(\mathrm{S1})]/[V(\mathrm{S4}) - V(\mathrm{S1})]\}$.

This graph shows the average increase in value (over random funding) from prioritization alone as a percentage of the maximum increase possible with perfect information and prioritization. Even when $\tau^2 = 3$, so that 75% of the variation in y_i is due to estimation error, the increased value from prioritization and estimated project values is still half the entire increase in value arising from both prioritization and perfect information.

Sensitivity to Budget Level. To this point, the budget has been fixed at \$15.00. When the budget is varied, the results persist. Figure 2 shows the value

Figure 2 A Comparison of the Opportunity Curves Under Different Analytic Strategies



versus cost frontier for the portfolio prioritized using estimated values and for the portfolio prioritized using actual values. It is apparent that as the budget increases, the value added by perfect information and prioritization decreases as a percentage of the budget. Intuitively, the benefit of the analysis is in picking out the best projects to replace randomly selected projects, and as the budget increases, there are fewer good projects left to do the replacing. As the budget ranges from $5.00 to $45.00, the value added by prioritization ranges from 64% to 86% of the value added by perfect information and prioritization. The reason this effect occurs is that the value of information about marginal projects (i.e., those for which additional information and prioritization are more likely to change the funding decision) is higher at the low end of the budget where the variation in value (in absolute rather than percentage terms) among the marginal projects is greater.

Sensitivity to Population Mean and Standard Deviation. The overall predicted increases in portfolio value are over 100% for the base case, and this number declines to the lower end of the reported range (around 20% when the budget is $40.00) as the budget increases. It is encouraging that these numbers are not far from the reported increases in practice, but it is necessary to check that the results are not overly dependent on the original parameter values.

The ratios between the values from the various strategies do not depend at all on the population mean—all the effects simply scale up. The assumed value of the population standard deviation is important. As σ increases (while τ increases in the same proportion, so that the percent of variation in y_i due to estimation error remains unchanged), the distribution of project values is more skewed, which makes prioritization relatively more important. The value added by prioritization as a percentage of the total potential value added is over 80% at $\sigma = 2$, and over 90% at $\sigma = 3$.

The model assumes that the estimates of r_i are unbiased, that is, the error associated with the estimate has a mean of 0. On the other hand, if portfolio managers were systematically optimistic, perhaps persuaded by overly optimistic project managers, the mean could be positive. This would not change the end result under processes using complete prioritization, assuming the bias was the same for all projects. If thresholds were used, however, such a bias could lead to overspending, etc. A common solution to this problem is to set in some way a higher threshold, often in the form of a hurdle rate well in excess of the cost of capital. If biases vary depending on the project manager and the portfolio manager is not able to identify them, the effect is to add noise to the process and effectively increase the size of the error in the portfolio manager's estimates.

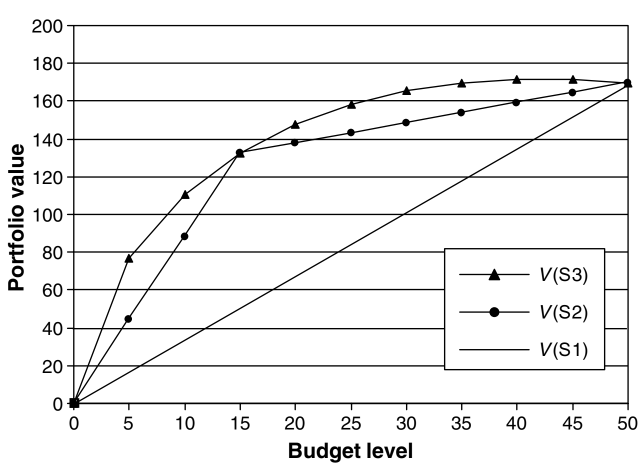
Effect of Relaxing Cost Assumptions. The assumption of identical project costs does not significantly affect the results for the strategies considered. Another strategy seen in practice is S3′, ranking projects in order of ENPV. The problem with this strategy is the role of project magnitude as a driver of project value. For example, a project with a cost of $2.00 and a benefit of $4.00 would be selected before two smaller projects each with a cost of $1.00 and a benefit of $2.50. We can estimate how much that matters using the data from Figure 1. In two small sets of portfolio data I collected, C_i were roughly lognormal with c_i having standard deviation approximately 2. Assuming this is correct, the proceeds of project i, R_iC_i, follow a lognormal distribution, and this strategy is equivalent to prioritizing projects in order of $y_i + c_i$. Using this value, we can compare $[V(\text{S3}') - V(\text{S1})]/[V(\text{S4}) - V(\text{S1})]$, the percent of potential value added by S3′, to that for the original S3. The effect of ignoring cost variation is the same as adding that variation to the variation of the estimate. Where $\tau = 0$, $\tau^2 + \text{var}(c_i) = 4$, and thus 80% of the variation in the estimate $(y_i + c_i)$ is due to noise, $[V(\text{S3}') - V(\text{S1})]/[V(\text{S4}) - V(\text{S1})] = 44\%$ (instead of 100%); for $\tau = 2$, the ratio would be 32% (instead of 44%). For the base-case value of $\tau = 1$, the "rank by ENPV" strategy would lie between S1 and S3 (40% instead of 71% of the potential value added). We can see that in the face of substantial cost variation, ranking by ENPV makes poor use of available information, and decision-analytic practice has rightly rejected it.

Effect of Relaxing Assumption of Lognormal Distribution. The assumption of a lognormal distribution matters, of course, but other distributions yield similar results. For example, an earlier version of this model assumed that actual values were uniformly distributed between 0 and 4, that the manager had a noninformative prior and that estimated values were equal to actual values plus a normally distributed error term with mean 0 and standard deviation 1. In that case, the value added by prioritization was about 75% of the value added by prioritization and perfect information. This figure was more stable than in the lognormal model. The relative value of prioritization was more sensitive to change in the standard deviation of the error, but the direction of the effect was the same.

Threshold Rules

For a given threshold, T, there is some budget level, denoted B_T, sufficient to fund all of the projects whose estimated BCR falls above the threshold, with no funds remaining to fund projects below the threshold. Thus, at $B = B_T$, S2 funds exactly the same projects as S3, and $V(\text{S2}) = V(\text{S3})$. As B ranges from 0% of requested funds to B_T, $V(\text{S2})$ increases at the constant rate of the average BCR of a project whose estimated productivity is above T, as shown in Figure 3. As B ranges from B_T to 100% of requested funds, $V(\text{S2})$ increases at the constant rate of the average BCR of a project whose estimated BCR is below T. When $B \neq B_T$, $V(\text{S3}) \geq V(\text{S2})$ but still $V(\text{S2}) \geq V(\text{S1})$, with equality at the endpoints where 0% or 100% of projects are funded regardless of the analytic strategy.

Figure 3 As Funding Increases, Portfolio Value Under Partial Prioritization (S2) Increases at the Average Rate for the Projects That Meet the Threshold



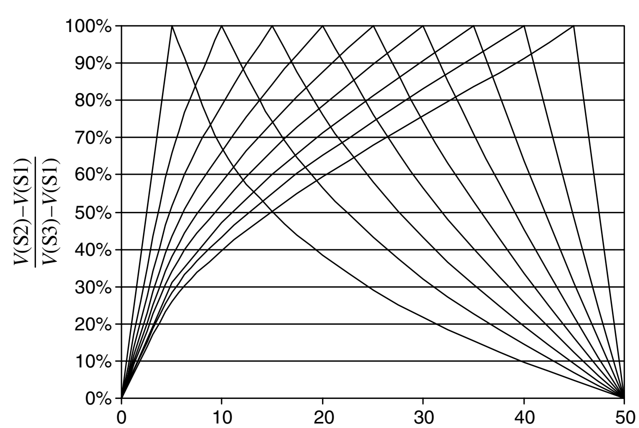
Note. After these are all funded, at the lower rate of projects that do not meet the threshold.

Sensitivity to Fit Between Threshold and Budget. In practice, it might be difficult to set T so that B_T is exactly equal to the desired budget level. For example, if the portfolio of potential projects is small and potentially idiosyncratic, or if the underlying business is not yet understood, it would be impossible to predict with precision the portion of projects that would be funded by the threshold rule. It is therefore important to know how much value is lost by employing the threshold rule instead of complete prioritization. If the loss is not great, it may still be preferable to use a decentralized threshold rule.

As B diverges from B_T, $V(\text{S2})$ grows closer to $V(\text{S1})$ rather than $V(\text{S3})$. Figure 4 shows the value added by partial prioritization, $V(\text{S2}) - V(\text{S1})$, as a percentage of the value added by complete prioritization, $V(\text{S3}) - V(\text{S1})$. Each curve corresponds to a different level of T, specifically, the levels of T where $B_T =$ \$5.00, $B_T =$ \$10.00, etc. It is apparent that the performance of threshold rules deteriorates quickly if the threshold is not well matched to the available budget.

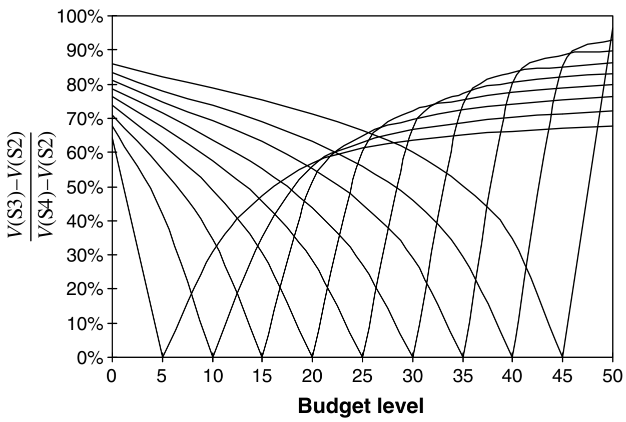
The portfolio manager can go from S1 to S2 with minimal quantitative analysis. Using S2 as a new baseline, we can ask what percentage of the possible value added by analysis would come from the first step of completing prioritization (S3), and how much would come from adding the additional step of obtaining more perfect information (S4), and

Figure 4 Percent of Prioritization Value Obtained When Using Threshold Rules Instead of Complete Prioritization (Partial Information Case)



Note. Each curve represents a different threshold level.

Figure 5 Additional Value of Complete Prioritization as a Percent of the Additional Value of Perfect Information and Complete Prioritization



Note. Curves are approximate. Each curve represents a different threshold level.

only then prioritizing projects. Figure 5 shows the improvement from complete prioritization as a percentage of the total possible increase in value from complete analysis, $[V(\mathrm{S3}) - V(\mathrm{S2})]/[V(\mathrm{S4}) - V(\mathrm{S2})]$, against the funding level. Again, each curve represents a different level of T. If $|B - B_T|$ is large ($\geq$10), then performing complete prioritization (or, equivalently, setting the threshold more appropriately for the budget and reevaluating projects against the new threshold) will bring much ($\geq$50%) or even most of the additional potential value from analysis. When $|B - B_T|$ is small then most of the remaining value of analysis will have to come from improved estimates of project value, especially at low budget levels.

If population parameters are known, the uncertainty on project value is known, and portfolios are not too small, T can be set so that on average $B_T = B$. For the current example, the budget can fund 30% of the projects. Approximately 30% of projects will have $r_i > 1.5$. Because of the additional noise present in the estimated values, a slightly different proportion of investments would be funded at that threshold under partial information. Therefore, a higher threshold—corresponding to the top 30% of the distribution on y_i ($\approx$1.75)—must be used.

Use of this threshold rule, in theory, eliminates the need for project-level managers to even communicate value estimates to the portfolio manager. This ought to cut costs of analysis tremendously. A decentralized threshold rule, however, would preclude changing the budget or threshold to some new level after seeing what projects are available. Furthermore, this approach assumes the threshold is set correctly even though it would not be possible to know the distribution of project values beforehand.

Without such flexibility, a possible drawback of using threshold rules is that the results are less predictable. This is because the combined cost of all projects whose BCR exceeds the threshold may be less or greater than the budget constraint. For the base case, the standard deviation of portfolio value under S2 was \$41.00 (\$43.00 when using actual rather than estimated values), which is about 20% greater than for S3. Unpredictable costs might cause greater organizational difficulties—the standard deviation of cost under S2 was \$5.00, or 1/3 of the budget level, while cost is fixed under S3 and S4.

Variable spending levels are not necessarily bad. If budget is not a constraint, the threshold rule could actually have the modestly desirable side effect of correlating spending with the availability of promising projects. The average expenditure for S2 was \$18.20 and $V(\mathrm{S2})$ averaged \$125.00, compared with \$124.00 for S3 interpolating from Figure 2 for the same budget level. When using actual values, rather than expected values, the average expenditure was \$15.56 and the increase in average value due to use of the threshold rule was almost \$2.00. The central limit theorem mitigates both effects, however. As the number of projects increases, the percentage by which the number of projects exceeding the threshold differs from its expected value approaches zero. Conversely, with fewer projects, the good and bad effects of using thresholds would tend to be larger.

Using an appropriate threshold rule to make funding decisions based on estimated values can lead to outcomes nearly as good as fully prioritizing projects using the same estimates, in some cases better. Still, portfolio value is quite sensitive to errors in the choice of threshold. The more unusual the portfolio, the more difficult it would be to set an accurate enough threshold.

Triage Rules

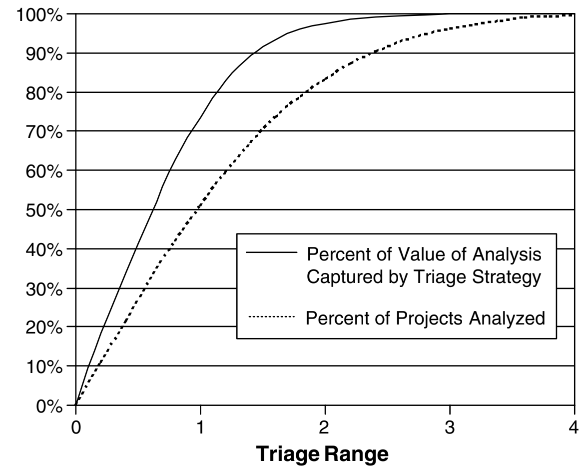
Perhaps it is not surprising that the value of information (that is, the results of the analyses of individual project values) appears to be a minor part of the total value added by decision analysis. Intuitively, a project with extremely high (low) value is likely to be included in (excluded from) the portfolio whether or not uncertainty about its value is resolved. Reacting to this phenomenon, Spradlin and Kutolski (1999) describe a triage strategy for deciding which projects in the portfolio to analyze. Here, the portfolio manager identifies favored (automatically included), equivocal (to be analyzed), and undesirable (automatically excluded) projects. Even though this strategy was used mainly to accommodate senior management preferences regarding the status of certain projects, it merits consideration as an alternative analytic approach.

Spradlin and Kutoloski's strategy can be thought of as a variation on the use of threshold rules. The latter now serves as a baseline. We now consider a new strategy, S5, using a "triage" rule characterized by a distance, d, around the threshold. Within this range, uncertainty about project values is resolved. Outside of this range, projects are automatically funded or not, without further resolution of uncertainty. We define S5 with the following decision rule: $F_i = 1$ if $y_i > \log(T) + d$, or if $y_i \geq \log(T) - d$ and $r_i \geq \log(T)$, and $F_i = 0$ otherwise.

Base-Case Results for Triage Rule and Sensitivity to Triage Distance. If $\log(T) = 1.5$ and the triage distance, d, is 1.0, then projects where $y_i < 0.5$ are refused funding without further analysis; projects where $y_i > 2.5$ are funded without further analysis, and projects where $0.5 \leq y_i \leq 2.5$ are analyzed further and then funded only if analysis reveals that $r_i \geq 1.5$. In this case, about 50% of projects are analyzed and the value of the portfolio is \$130.00. This represents about 70% of the added value of perfect information. This strategy has predictable limiting behavior. As the triage distance approaches zero (infinity), no (all) uncertainties are resolved so the triage strategy is simply a threshold strategy using partial (perfect) information. We now consider the initial example with different distances for the equivocal project bin.

Figure 6 shows variations of the base case with the upper curve $[V(\text{S5}) - V(\text{S1})]/[V(\text{S4}) - V(\text{S1})]$ representing the percentage of the value of perfect information provided by the "partial perfect information" of the triage policy. The lower curve represents the percentage of projects analyzed, i.e., the percentage

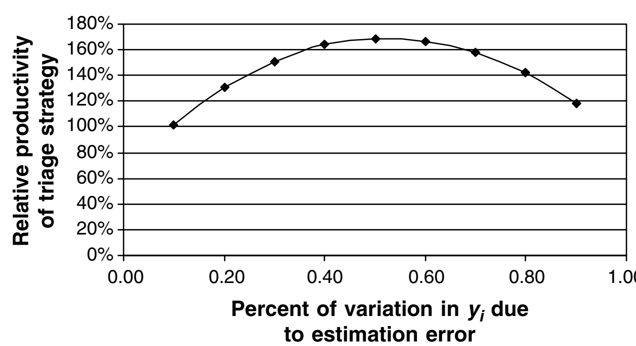
Figure 6 Triaged Analysis Value Added as Percent of Total Potential Value Added



of projects for which the estimated value fell within the indicated distance of the baseline threshold. The results validate the triage strategy. For $d \leq 1.2$, the value added per project analyzed is 140%, or more of the value added per project analyzed under the perfect-information strategy S4.

Sensitivity of Triage Rule Results to Level of Uncertainty. This result is sensitive to the level of uncertainty in estimates as shown in Figure 7. At low levels of uncertainty (low values of τ), there is not much efficiency to be gained. Von Winterfeldt and Edwards' (1986) principle of flat optima applies here, in that it makes less difference if a borderline project is mistakenly replaced by a different borderline project with a slightly lower value, even though this is more likely to happen than severe mistakes. At high levels

Figure 7 Triaged Analysis Value Added as Percent of Total Potential Value Added



of uncertainty, a project that is selected to be analyzed is not easily distinguished from other projects for which the value of information is also substantial. Thus, whether the triage approach is effective as a means of conserving analytic efforts depends on how much uncertainty remains to be resolved.

6. Conclusion

Managerial Interpretation of Results

We have seen that a one-size-fits-all approach to portfolio analysis can waste effort. Instead, it is important to first understand the context, i.e., the parameter values, and only then pick a portfolio management policy. From the base-case results for the first four strategies, we see that, at the very minimum, managers should use some sort of disciplined process. It may be good enough to simply apply a threshold where projects with high BCRs are funded and projects with low BCRs are rejected. In such cases, setting the appropriate threshold might be a reasonable objective for analysis in support of the portfolio manager.

For various reasons, it may be difficult to choose such a threshold. In that case, explicitly ranking projects adds substantial value. In decision-analytic practice, the ranking of projects is often preceded by the formation of detailed estimates of project value. Such improved value estimates are also beneficial, but unless uncertainty is high, improved estimates are not nearly as important as the basic use of a disciplined process. It is important to distinguish between these two sources of value. Although a full decision-analytic approach improves value in both ways, at a more detailed level, the actions required to improve estimates are different than the actions required to ensure a disciplined process, and if one source of value or the other is dominant, scarce managerial resources can be allocated to that effort. Sensitivity analysis showed that even when uncertainty seems high and difficult to resolve, there is substantial value to adopting a decision process that incorporates a disciplined approach to prioritization.

Beyond the use of thresholds, two other time-saving approaches were considered. Managers would forfeit a lot of value by ranking projects in terms of ENPV instead of explicitly considering BCR, and this approach is not recommended. Managers who already use a disciplined approach may be able to save effort by analyzing in detail only those projects that appear to be close calls. It is reasonable to use this technique in extreme cases, but the efficiency gains are small enough that if it is worth making the effort to analyze the marginal project, it is likely that most projects should be analyzed.

General Implications

Costs of analysis have not been considered explicitly in this model, but the costs of analysis are significant. At the high end, a rigorous portfolio analysis could take two full-time-equivalent professionals working for one week to analyze each asset. Considering overhead and consulting rates, the cost of analysis can exceed \$1.00 million. Perhaps more prohibitive are costs of delay, disruption, and managerial attention, which provide even more motivation to streamline the portfolio analysis process. Identifying the sources of value in analysis should aid in defining the organizational equivalent of "fast and frugal" heuristics (Gigerenzer and Todd 1999). These would allow managers to focus attention on those aspects of the portfolio decision process where attention is truly needed.

Current decision-analytic processes along the lines of S4, facilitate prioritization by first generating transparent project valuations. Extensive information gathering and documentation is necessary to make the process reliable if the portfolio manager gets unpredictably biased input from project managers and champions, which is a well-documented danger (Bower 1970). The alternative is for the portfolio manager to attempt to remove bias and then prioritize without further involvement of individual project managers. Arguably, gathering information first improves organizational buy-in and honesty, but extensive decision analysis seems like a costly way to create trust. For example, Kleinmuntz and Kleinmuntz (2001) describe their success with an approach using less costly single-day group sessions. In their process, asset values are estimated without detailed models but the organizational benefits of a transparent process are still achieved.

Still, the traditional approach to portfolio management has been a popular application of decision analysis. It may be that the benefits of analyzing projects go beyond the improved value estimation and prioritization considered in this paper. For example, individual project value is often improved during a full-scale portfolio decision analysis (Allen 2000). Other costs and benefits of the portfolio are still managed qualitatively, commonly through efforts to "balance the portfolio." This is sensible given the fact that portfolio managers often face multiple constraints and objectives, but use results of portfolio analysis as an invaluable input. In the course of a rigorous portfolio analysis, managers may find that projects are synergistic in value, can share costs, or are correlated for some other reason. Such phenomena, though not investigated here, could conceivably increase the value of analysis, e.g., analysis that identifies and leverages synergies. Quality decisions about such projects require more coordination than merely considering, as in this model, whether another project has exhausted the budget.

Benchmarking studies such as those by Cooper et al. (2001) and by Matheson and Matheson (1998) have identified other best practices for portfolio management that reflect more of the complexity of this task. In addition, real portfolios often consist of projects in varying stages of development, with varying capital needs over time and varying levels of uncertainty, and the list of candidate projects itself may be fluid. These dynamic aspects of portfolio management add further complications not included here. Such considerations could limit the flexibility of the portfolio manager to take advantage of complete information about individual projects, or, alternatively, could allow the analyst to find additional nonobvious sources of value. When the value added by analysis, and the choices to be made regarding type of analysis are more subtle than in the current model, the implications of the current results must be tempered.

This paper has considered a simplified representation of portfolio decision making and demonstrated some value drivers, but clearly there is much more modeling to do along these lines. A streamlined version of the current model could be amenable to closed-form analysis rather than simulation. Such a model would be more easily extended in other directions to study such considerations in portfolio management as Bayesian learning, risk attitudes, and financial portfolios.

In sum, simple uncertainty resolution in portfolio decision analysis is clearly not always the primary source of economic value. Prioritization is necessary, as is some quantity of information. Additional information gathering may add value, but this depends on how much information the portfolio manager already has and how much new information is to be gathered with the analytic resources available. The simulation results in this paper provide explanations for some of the sources of value in portfolio management and corresponding observed practices, e.g., intuitive methods as opposed to full analytic for prioritization of early stage R&D. The payoff from spending time on portfolio decision analysis is already high, even with the brute force approach of analyzing all projects. The payoff could be higher if portfolio decision analyses plans are focused by taking advantage of knowledge about the general characteristics of a portfolio even before individual projects are assessed.

Acknowledgments

The author thanks Dana Clyman, Terry Reilly, Janet Wagner and George Wu and the editors and anonymous reviewers for their valuable comments on earlier drafts of this paper. William Leaf-Herrmann and Tom Spradlin who, in addition to offering their comments on the drafts of the paper, offered judgments about the model parameters based on their experiences. He also thanks numerous other individuals who have offered useful feedback after related presentations, and Strategic Decisions Group for engaging in this research by generously allowing him to review its data for purposes of calibrating the model.

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