

Portfolio risk reduction: Optimising selection of resource projects by application of financial industry techniques

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Key Words: exploration ranking, portfolio theory, uncertainty, chance of success, EMV, project optimisation

SUMMARY

The resource industry seeks to forecast accurately the likely outcome of an exploration program - in particular minimum and maximum and average size of a success; also the chance of achieving a success.

Commonly such predictions are employed on a project-by-project basis. When a group of projects are combined in a portfolio, a higher level of evaluation is possible by quantifying the correlation coefficients among the projects. The outcome is that the portfolio total is not necessarily the sum of the individual parts. Combining the best individual projects usually does not produce the most efficient (lowest uncertainty) portfolio. Including some 'risky' projects (larger uncertainty) can lower the overall uncertainty of the portfolio.

Ranking projects by common measures such as Expected Monetary Value or Expected NPV are not the best approach to building a portfolio.

The approach in this paper draws on financial portfolio theory. This is routinely employed in the financial industry, which faces a similar challenge of forecasting outcomes (from investments). It is suggested that combining the better elements of resource and financial evaluations produce a more definitive prediction of the outcome of an exploration program.

Analysing projects within a portfolio structure reduces the uncertainty in the range of deposit success-case sizes that may be encountered. It allows selection of the most efficient group of projects. This maximises the expected NPV value for the total portfolio, while at the same time minimising the uncertainty in the range of NPVs that could occur.

Furthermore, if projects are selected with low correlation coefficients with each other ('diversification'), then the chance of obtaining one success is increased, compared to projects that are more positively correlated.

INTRODUCTION

The resources industry, when considering how best to short-list which exploration projects to undertake, naturally desires to accurately predict the likely result of *each* project. This paper considers not only this challenge, but more so the overall economic consequence when a *group* of exploration projects is combined in a portfolio.

We seek to define the most 'efficient' portfolio, where exploration returns are maximised and uncertainty is minimised. Combining the best individual projects usually does not produce the most efficient portfolio. Counter-intuitively, including some

larger uncertainty projects may actually lower the overall economic uncertainty.

Before exploration of a project is commenced, or continued after additional data is obtained, success-case predictions are made of deposit average size; additionally predictions may include minimum and maximum sizes. This range for the deposit size may be two-three orders of magnitude, which can be disturbing to those unfamiliar with the estimation process. In addition to these predictions, the chance of achieving a 'geological' success, or other similar measure, is estimated.

The financial industry, when making an investment, faces a similar challenge to the resources industry in forecasting the likely result - instead of deposits, the focus is size of investment returns. While methodologies of both industries have a number of similarities, there are some significant differences. This paper reviews the methodologies of both industries. Amalgamating the better predictive elements from both industries produces more accurate predictions for the resources industry.

The 1990s have seen a small, but growing, number of technical papers discussing the application of financial techniques to the resources prediction. The focus is how to *optimally* combine resource projects in a portfolio - how can we reduce the uncertainty in the predicted range of the overall result. In addition, and counter-intuitively, how to increase the chance of one success by judiciously selecting the optimum portfolio.

ECONOMIC EVALUATION OF PROJECTS

Resource Deposit - Range of Sizes

The first steps in the evaluation of a project determines the size (big/small) of a resource deposit (or size of returns from an investment); then estimate the chance that it could be in this range of sizes.

This process is achieved by firstly predicting the *type* of distribution (eg normal, lognormal, other) controlling the deposit/investment; secondly the range for the sizes of the deposit/investment (eg from low, median, mean or highside values). While debate continues with respect to the type of distribution controlling the range of sizes, there is interestingly considerable support for a lognormal observation for both geological deposits (eg Steinmetz 1992, McCray 1975, Singer and Orris 1994) and for investments (eg Lewis et al 1980, Grinold and Kahn, 1999). It is pertinent to note that financial portfolio theory, proposed by Markowitz in the 1950s, assumed a normal distribution for investment returns (Bernstein, 1996).

Generally, the resource estimation process breaks out several factors that independently contribute to the size of the deposit (eg source and reservoir space). The type of distribution for each factor is determined, either from empirical data or analogues. Next, appropriate assumptions are made for each distribution e.g. its minimum, average or maximum size. These separate distributions are then combined, either by Monte Carlo or serial multiplication,

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to estimate the range of sizes of the deposit. From this, the probability can be determined of achieving any given subset of this range.

It is important to distinguish between most-likely and mean values. These are not the same value, unless the overall distribution is normal. If only one number is required to quantify this distribution, the mean value is selected. This value is the *mean* deposit size, which after economic analysis becomes the *mean* NPV.

To quantify the uncertainty (range of sizes) for the deposit/investment, the standard deviation can be computed. [In the financial world, the standard deviation is called the 'risk' of an investment. Note this meaning of risk is quite different to the resource industry, which expresses risk as the geological chance-of-failure].

Resource Project Geological Chance-of-Success

The next step for the resource industry is to quantify the *geological chance-of-success* that the deposit will fall in the defined range. This chance is determined from the serial multiplication of a number of geological factors controlling the size of the deposit. In the simplest case, each of these geological chance factors is independent. An additional complication does occur when some of these factors are dependent. [The financial industry does not have this level of analysis - it assumes that the chance is 100% of being in the range. This assumption is one area where the financial estimation accuracy could be improved, if it were to follow the resource approach].

Additional sophistication is possible by quantifying commercial chance-of-success, given a minimum commercial size. The commercial chance is lower than the geological chance, continually altering with economic and market conditions. The geological chance is constant until new geological data is obtained.

Project Ranking Methodology

Usually there is a cap on exploration funds, such that an explorationist has to choose from a subset of the available projects. Furthermore, it is not only required to rank projects, but also to predict the likely economic outcome after addressing a group (portfolio) of projects.

The evaluation of a group of projects begins with determining each project's Expected Value (EV) and Expected Monetary Value (EMV).

These are defined as:

$$EV = \text{Mean NPV} * \text{geological chance-of-success.}$$

$$EMV = (\text{Mean NPV} * \text{geological chance-of-success}) - (\text{Failure NPV} * \text{geological chance-of-failure}).$$

The failure NPV is usually the cost of the exploration program, or the cost of contributing additional funds once a project is underway.

Commonly projects are ranked by EMV, with the best projects regarded as those with the highest positive EMV (Newendorp 1975; Downey 1977). The EMV value incorporates the risk weighting of the estimated value of projects. When a company chooses to participate in a project that has a negative EMV, the company is *speculating* (= gambling), as opposed to a positive EMV project where it is *investing*.

The focus of this paper will show that ranking projects by EMV alone is not the optimum solution for a portfolio.

ILLUSTRATIVE EXAMPLE

To illustrate the concepts of this paper, consider the exploration data for two projects summarised in Table 1:

Project	Success Mean NPV (\$m)	Geol. Chance of Success	Failure NPV (\$m)	Geol. Chance of Failure	EV (\$m)	EMV (\$m)	Standard Dev. (\$m)
A	\$10	30%	\$2.0	70%	\$3.0	\$1.6	\$10
B	\$25	13%	\$2.0	87%	\$3.3	\$1.5	\$15

Table 1. Summary data for projects A and B.

Both projects have the same exploration cost (\$2m). Project A has a much higher chance of success, offset by a lower success case NPV. Project A has a slightly more positive EMV, whereas project B has a higher Expected Value. Project B has the higher uncertainty, as expressed by the standard deviation.

Assume there is a budget cap of \$2m (the failure NPV). What should an explorationist do?

- Invest \$2m in project A, because it has the higher chance of success, *or*
- Invest \$2m in project B, because it has a higher EV, and if successful a higher NPV, *or*
- Through a joint venture, split the \$2m between A & B - if so, which ratio is optimum?

Let's also assume we are desperate for at least one success. What difference does this make in how we should choose between these projects?

Financial Industry Diversification

The financial industry, when deciding on which investments to combine in a portfolio, generally cross-plots two measures of an investment - expected returns and uncertainty.

The expected returns are computed by the multiplication of possible returns and individual probability. Say four returns are estimated with associated probabilities (-10% & 0.3), (7% & 0.2), (12% & 0.4) and (20% & 0.1). The expected value is 5.2%.

The uncertainty is quantified as the standard deviation of the returns. In the above case, the uncertainty is 12.7%, assuming a normal distribution. The financial industry usually selects those investments that have a higher return, for a given uncertainty. The above analysis is appropriate when there is only one investment. When more than *one* investment is combined in a portfolio, the standard deviation is measured from the *covariance* of the investments. This is not the weighted average of the individual standard deviations. Covariance is a mathematical measure of the similarity between two distributions, as opposed to variance of a single distribution about a mean value.

Grinold and Kahn (1999) give the standard deviation for a portfolio with two projects as:

$$\sigma_p = \sqrt{(\%_A \sigma_A)^2 + (\%_B \sigma_B)^2 + 2(\%_A \%_B C_{AB})}$$

where $\%_x$ = percentage of project X in the portfolio and C_{AB} is the covariance between the two investments A and B.

The correlation coefficient ρ_{AB} , however, is a more direct way to determine the portfolio standard deviation. The correlation coefficient ranges between 1.0 (perfect correlation) to -1.0 (perfect 180° phase correlation), and is about 0.0 when there is little correlation. Financial investments can have a correlation coefficient predicted from the analysis of the time series of prior returns of the investments, as well as crystal-ball gazing on the myriad of economic factors that control the returns (eg economic stability, balance-of-payments, inflation, etc).

Camina and Janacek (1984) show the correlation coefficient is given by

$$\rho_{AB} = \frac{C_{AB}}{\sigma_A \sigma_B}$$

$$\text{so } \sigma_p = \sqrt{[(\%_A \sigma_A)^2 + (\%_B \sigma_B)^2 + 2(\%_A \sigma_A)(\%_B \sigma_B)\rho_{AB}]}$$

Mathematical inspection shows the portfolio standard deviation $\sigma_p \leq \%_A \sigma_A + \%_B \sigma_B$. The equality holds only if the two investments are perfectly correlated (when $\rho_{AB} = 1$). Since this is very rare, *combining investments in a portfolio reduces the standard deviation (uncertainty)*. This is the underlying mathematical basis of the argument for financial *diversification* of ‘not putting all your eggs in one basket.’ The resource industry commonly applies this approach in the exploration phase by selecting projects that are geographically widely separated.

The standard deviation for the portfolio of varying proportions of projects A and B is graphed in Figure 1 for correlation coefficients ranging from 1.0 to -1.0. In this example, for say a correlation coefficient of 0.0, the minimum standard deviation is \$8.3m. This demonstrates being in a portfolio lowers the individual standard deviations (project A \$10m, project B \$15m).

Portfolio theory aims to maximise the Expected Value while minimising the uncertainty. For a correlation coefficient say 0.0, the optimal solution is EV \$3.1m and uncertainty \$8.3m for A:B 70%:30% (Figure 2). Thus splitting the budget in this manner provides a better solution than investing the whole budget in Project A (EV \$3.0m and uncertainty \$10m), even though A might be preferred on an EMV basis alone.

Efficient portfolios are those that show the highest expected value for a given level of uncertainty. Markowitz (1952, 1957) introduced this concept to the financial world, for which he was later awarded the Nobel Prize for Economics. Figure 3 shows that both projects A and B *on their own* are inefficient - for their individual levels of uncertainty, there are better solutions (portfolios) that have higher Expected Values.

The power of investment diversification is explored by Grinold and Kahn (1999):

- Given a portfolio of N projects, each with uncertainty s and uncorrelated returns, the uncertainty of an equal-weighted portfolio of these projects is:

$$\sigma_p = \frac{\sigma}{\sqrt{N}}$$

Thus combining the projects in a portfolio reduces the overall uncertainty from σ to σ/\sqrt{N} .

- Assuming the correlation between all pairs of projects is r, the uncertainty of an equally weighted portfolio is:

$$\sigma_p = \sigma \sqrt{[(1 + \rho(N-1)) / N]}$$

In the limit that the portfolio contains a very large number of correlated projects, this becomes:

$$\sigma_p \rightarrow \sigma \sqrt{\rho}$$

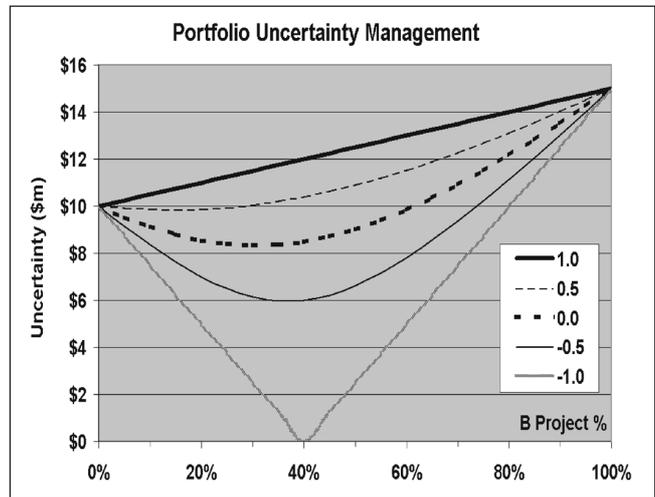


Fig. 1. Combining projects in a portfolio reduces resultant uncertainty, depending on correlation coefficient.

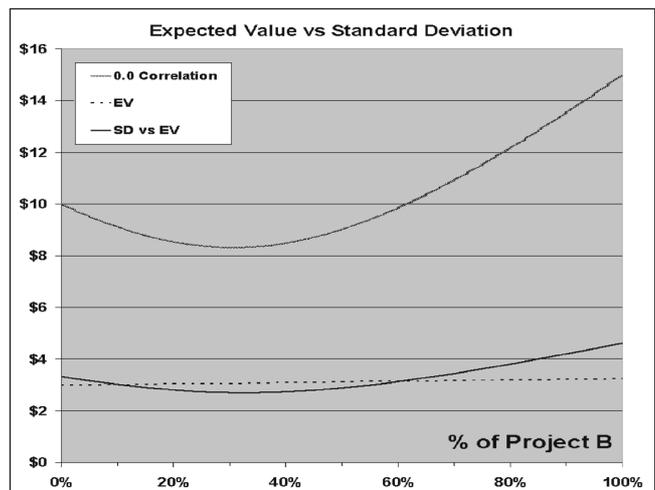


Fig. 2. Optimum solution of lowest uncertainty relative to Expected Value is 30% project B & 70% project A.

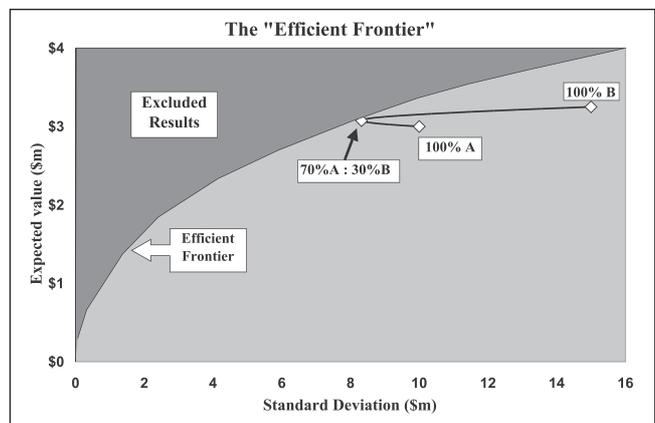


Fig. 3. Neither projects A nor B are optimum on their own. The most efficient combination is 70%A : 30%B, which is on the ‘Efficient Frontier.’ It is not possible to have results above the Efficient Frontier.

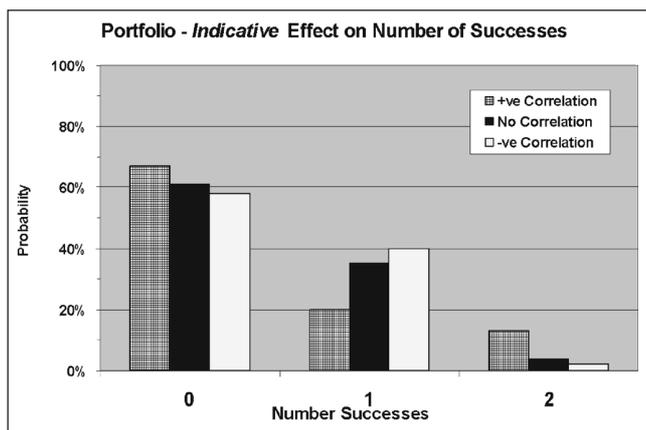


Fig. 4. Indicative effect of strong correlation coefficient on number of success (positive correlation increases chance of none and two successes; negative correlation increases chance of one success).

DISCUSSION

The application of financial portfolio theory to resource projects requires discussion of two matters:

- how does the prediction of the number of successes alter when projects are grouped in a portfolio
- how to quantify the geological correlation coefficient.

Effect on Number of Successes

In answer to does it make a difference if we are desperate for at least one success, notice the *indicative* effect of positive and negative correlations on the number of successes (Figure 4 - actual probability values depend on the individual correlations and chances of success). In essence, positive correlation reduces the effect of diversification, whereas negative correlation increases the effect.

Consider the situation where the two projects are *positively* correlated. The following qualitative discussion analyses the probabilities. If project A is successful, the probability of success for project B will now be greater than 13%. Thus the probability of two successes is increased if the correlation is positive. Now, since the probability of success for project A is less than 50%, it is more likely that A will fail. Given a positive correlation, the chance of success for B is now less than 13%. Hence for positive correlation, the probability of no successes is increased, compared with the probability if the projects are not correlated. Overall, we note that if there is positive correlation, the chance of *one* success is decreased.

Now consider the situation where projects are *negatively* correlated. If project A is successful, the probability of success for project B will now be less than 13%. Thus the probability of two successes is decreased if A is successful, compared with independent or positively correlated projects. However, since the probability of success for project A is less than 50%, it is more likely that A will fail. Given a negative correlation, the chance of success for B is now more than 13%. Hence for negative correlation, it is *more likely that there will be one success* than if the projects are independent or positively correlated, since the chance of project A occurring is the same regardless of correlation. The increase in probability of one success comes from a reduction in the chance of none and two successes.

The basis of economic diversification is to seek projects that have the lowest correlation. The result, all other things being equal,

will increase the chance of one success. This helps if total failure (no successes) could affect job security!

A methodology for calculating the probability of the outcomes, given the various independent probabilities and correlation coefficients, is yet to be developed.

As noted in the Introduction section, there is not universal acceptance for the type of distribution controlling a resource deposit. Common types of distributions used include normal, lognormal and triangular. The financial methodology discussed above assumes a normal distribution. If the resource distribution is lognormal, though, then the standard deviation will be over-estimated because of the high-side outliers.

Another difficulty associated with analysing a portfolio occurs when the projects have different distributions within and between each project.

Geological Correlation Coefficient

To maximise the expected return of a portfolio, ideally each project's correlation coefficient must be determined with *every* other project. Determining the coefficient includes considerations such as:

- resource size (affects the duration of the project)
- dependent / independent factors in the chance-of-success
- similarity of geological areas
- future capital and operational costs
- future resource prices
- market similarities
- country (political) risk.

For X projects in a portfolio, we require X estimates of the standard deviation and $X(X-1)/2$ correlations (Grinold and Kahn, 1999). Thus for 10 projects in a portfolio, required are 45 correlation coefficients. These are not an easy matter, nor quick, to define. Therefore, implementation of efficient portfolio theory requires a decision on how rigorous does the analysis need to be. Options could include:

- painstakingly determining each of these correlations, or
- grouping similar projects to reduce the number of correlations, or
- applying a variation of the 'structural risk model covariance' approach of Grinold and Kahn (1999), or
- Ball and Savage (1999) have developed an approach using Monte Carlo and linear programming techniques.

Compromises may need to be made in the process. The important issue is to ask the right questions when constructing the portfolio - realising that selecting the best individual projects are unlikely to produce the most efficient portfolio.

To adapt financial portfolio theory to resource projects, determining the correlation coefficient should focus on the likely time series of the annual profit-returns for a project. More investigation is required on how best to determine these correlation values. It is suggested that the geological correlation coefficients could range from near zero to low positive numbers.

CONCLUSIONS

Accurate forecasting of the likely result of an exploration program is essential - in particular forecasting the average size of a success, the minimum and maximum sizes, together with the chance of achieving at least one success.

Although such predictions are common in the resource industry, a higher level of evaluation is obtainable if efficient portfolios are sought. Quantifying the correlation coefficients among resource projects, while problematical, should be mandatory if a company wishes to maximise its expected return while minimising the economic uncertainty of an exploration program.

Intuitively, the procedure of spreading exploration projects over a variety of areas is commonly employed now. This paper suggests the efficiency of the given selection of projects can be quantified. Additionally, it is possible to decrease the chance of failure and increase chance of one success, albeit at the expense of achieving more than one success.

A mathematical issue with the method proposed in this paper is the assumption that the controlling distribution is normally distributed (Bernstein, 1996). A lognormal distribution, because of the outliers on the high side, has a larger uncertainty (standard deviation) than a uniform distribution with the same mean value. A lognormal distribution, skewed to the upside, has most-likely values that are smaller than the mean.

The computed uncertainty of a lognormal distribution will overestimate the most-likely uncertainty of each project, so that the portfolio uncertainty also is overestimated. However, the basic premise of the effect of diversification still holds.

During the 1990s, there has been increasing application of financial theory to resource projects (eg see Capen in Steinmetz, 1992); MacKay (1996) reviews the growing use of portfolio theory; Ball and Savage (1999) have proposed an approach based on Monte Carlo and linear programming.

Some financial analysts continue to criticise aspects of the Markowitz theory, disputing aspects such as efficient markets. The mathematical basis of diversification, though, is a separate issue and has held up. It is now the mantra of financial investors. While diversification does not guarantee a success, it does increase the chance of one success. Diversification power is now being unleashed on the resource industry, as companies seek an edge in an increasingly competitive world.

ACKNOWLEDGEMENTS

The ramifications of correlation on the probability of success were assisted by discussions with Koya Suto and Nigel Fisher.

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