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Semi-deviation from a Benchmark Value as a Measure of Risk in Petroleum Development Projects

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"Variance is acknowledged by many as a questionable and many times inadequate measure of risk."

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Introduction

Risk is frequently associated with variability of outcomes. For this reason, variance and standard deviation are commonly applied measures of risk. However, this metric is acknowledged by many as questionable and many times inadequate (e.g. Markowitz, 1959; Estrada, 2007).

Two distributions with the same variance and different means have different risk perceptions. Moreover, when the distribution of outcomes is asymmetric, variance equally penalizes gains and losses. Hence, it is more precise to define variance as a statistical measure of uncertainty rather than risk (Walls, 2004). Nevertheless, it is still commonly applied to assess the level of risk of petroleum development projects.

An alternative metric is the coefficient of variation (CV), a standardized measure of dispersion that allows comparing alternatives with widely different means. With this metric, the standard deviation is normalized by the expect value (EV). The goal is to avoid considering projects with the same variability but different EV as being equally risky. However, this ratio makes no sense if the EV is less than or equal to zero, being only useful for random variables with strictly positive distributions.

Semi-variance was proposed as a more plausible and accurate estimate of risk (Markowitz, 1959). In this context, the prefix semi, which comes from the Latin, means partially and refers to a subset of overall project variance. Particularly, this metric denotes the downside variance of returns, i.e., risk is associated with the outcome falling below a predefined benchmark value. It is considered a more plausible measure than variance as: (1) investors generally do not dislike upside volatility; (2) it is more useful than variance when the underlying distribution of outcomes is asymmetric and just as useful when it is symmetric; and (3) it combines the information provided by two statistics: variance and skewness (Estrada, 2007). Additionally, as with the CV this metric avoids considering an alternative to have low risk for having low variability of outcomes because it can assess all alternatives on the basis of the same EV. However, unlike the CV, it can be applied to random variables that take positive, null or negative values.

The semi-variance assumes that investors are indifferent to upside volatility. Therefore, this metric has no value for investors that focus only on the upside, with no regard for the downside (Campbell et al., 2001). Nevertheless, this is usually not the risk definition when assessing petroleum development projects. The decision maker is frequently concerned with the chance of potential losses due to the high magnitude of investments.

Objective

The objective of this study is to illustrate the strength and effectiveness of the semi-standard deviation (square root of the semi-variance), or semi-deviation for short, as a measure of risk in petroleum development projects. To do so, the level of risk of a set of theoretical decision alternatives is assessed and compared by means of the standard deviation, coefficient of variation and semi-deviation bellow a benchmark value. To assess the quality of these metrics, the results are compared with the respective risk curves.

Measures of Risk

Three alternative measures of risk are assessed and compared: the standard deviation (σ), the coefficient of variation (CV) and the semi-deviation with respect to a benchmark B (S_B), defined by the following equations:

$$\sigma = \sqrt{E\{(X_i-\mu)^2\}}$$

$$CV = \frac{\sigma}{\mu}$$

$$S_B = \sqrt{E\{min[(X_i-B),0]^2\}}$$

where σ is the standard deviation, E is the expectation operator, X is a random variable, μ is the mean value, CV is the coefficient of variation, and S_B is the semi-deviation with respect to a benchmark value of return B.

The predefined benchmark B below which the variability of outcomes is assessed must be assigned by the decision maker and depends on the definition of loss. It is advised to compare all the decision alternatives with respect to the same benchmark value, and not on the basis of each alternative's mean value μ. By this, it is ensured that a decision alternative will not be considered as low risky for having low variability of outcomes.

To assess the level of risk of a set of alternative development projects, we propose the following steps to objectively finding this value: (1) calculating the EV of each decision alternative; (2) ranking the decision alternatives in decreasing EV; (3) assuming the project that maximizes EV as reference, and consequently as the benchmark value B.

Application and Results

A set of theoretical illustrative examples are presented in the following sections. The level of risk is measured by the three cited metrics and the results compared with the respective risk curves to assess the quality of the metrics under analysis.

Example 1 – Assessing the risk of alternatives with the same expected value

Let us consider two sets of decision alternatives, characterized by the same EV (5 units of the objective function): (1) alternatives A and B have different variability and symmetric distributions (Figure 1); (2) alternatives C and D have different variability and asymmetric distributions (Figure 2).

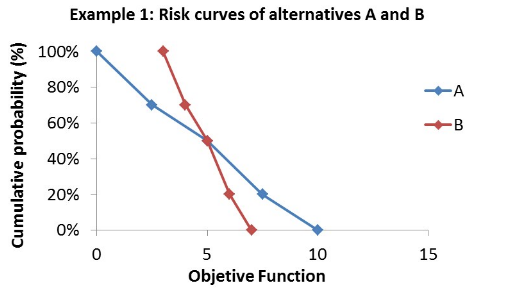

Figure 1 - Risk curves of alternatives A and B, characterized by the same EV, symmetric distributions and different variability.

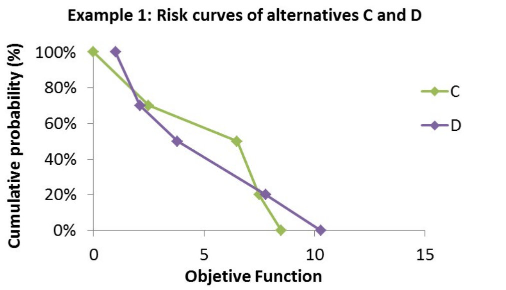

Figure 2 - Risk curves of alternatives C and D, characterized by the same EV, asymmetric distributions and different variability.

Assessing alternatives A and B is straightforward, and the three metrics indicate that A is riskier than B (Figure 3). For alternatives with asymmetric distributions, as C and D, the analysis becomes more complex and the metrics provide contradictory levels of risk (Figure 4).

According to Figure 2, D is less risky than C, with higher chances of high outcomes, and lower chances of low

"The semi-deviation focuses on the downside volatility and allows comparing the level of risk of different decision alternatives on the basis of the same expected value."

outcomes. However, as the variability of D is slightly higher than C (σ_C = 3.2 and σ_D = 3.5 units of the objective function) and both alternatives have the same EV, the standard deviation and the coefficient of variation indicate that C is riskier than D. Conversely, the semi-deviation correctly identifies the riskiest alternative.

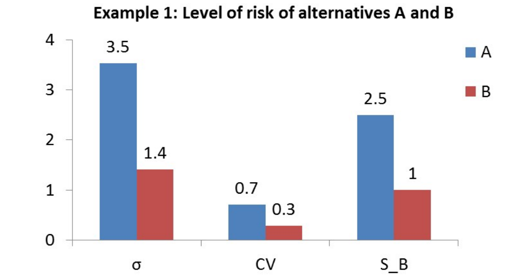

Figure 3 - *Level of risk of alternatives A and B, measured by the standard deviation (σ), the coefficient of variation (CV) and the semi-deviation below the maximum EV (S_B).*

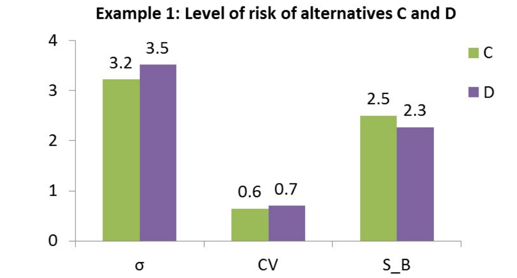

Figure 4 - *Level of risk of alternatives C and D, measured by the standard deviation (σ), the coefficient of variation (CV) and the semi-deviation below the maximum EV (S_B).*

Example 2 – Assessing the risk of alternatives with the same variability

Let us consider 5 decision alternatives (A to E), characterized by the same variability (σ = 3.5 units of the objective function), symmetric distributions but different EV, including positive (A and B), zero (C), and negative (D and E) values (Figure 5).

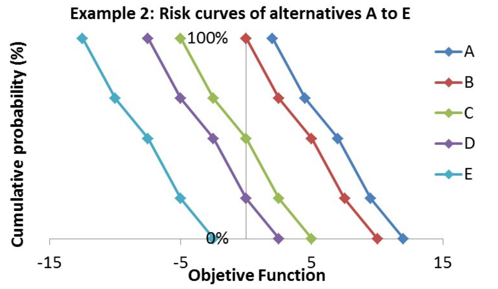

Figure 5 - *Risk curves of alternatives A to E, characterized by the same variability, a symmetric distributions and different EV.*

As this set of decision alternatives has the same variability, the standard deviation is unable to distinguish different levels of risk (Figure 6). The CV is only adequate to measure the risk of alternatives A and B, the ones taking strictly positive values. It is however inadequate for the remaining alternatives: (1) as C has an EV equal to zero, the calculation of the CV is mathematically undefined; (2) for alternatives D and E, negative values of risk are provided and have no meaning. Conversely, the semi-deviation correctly ranks the set of alternatives by level of risk (Figure 6).

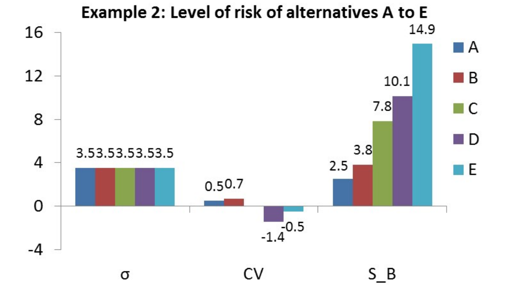

Figure 6 - *Level of risk of alternatives A to E, measured by the standard deviation (σ), the coefficient of variation (CV) and the semi-deviation below the maximum EV (S_B).*

Concluding Remarks

The purpose of this study is to illustrate the usefulness of semi-deviation as a measure of risk, when assessed with respect to a predefined benchmark value. Although several studies exist demonstrating its advantages, it is still not commonly applied to assess the level of risk of petroleum development projects.

The simple examples here presented show that the semi-deviation:

1) improves risk assessment considering alternatives with the same expected value and asymmetric distributions;
2) improves risk assessment considering alternatives with the same variability but widely different expected values, including distributions that take negative values;
3) avoids misinterpreting a decision alternative as having low risk due to its low variability of outcomes;
4) allows focusing on the downside scenarios, and does not penalize upside volatility;
5) allows comparing the level of risk of different decision alternatives on the basis of the same expected value;
6) gives flexibility to the decision maker by allowing him to include its definition of loss when calculating the risk.

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