Improving Business Valuation with the Use of Simulation Techniques

Ondřej Nowak, Jiří Hnilica

Abstract **—** This paper discusses the intricacies related to business valuation under uncertainty. It shows that under common practice only point estimates are employed which often proves to be misleading and incorrect. The paper further emphasizes that such pure deterministic analysis ignore valuable information regarding what is already known about an uncertain factor and its expected behavior. The suggestion is to integrate uncertainty and risk analysis in the valuation model using probability distributions and the Monte Carlo Simulation. This approach offers not only potential for the quantification of expected behavior of uncertain variables but also simple solutions to common problem areas, including the integration of expert opinions, nonrecurring events and non-linear dependencies among model variables.

Keywords**—** Business Valuation; Risk Analysis; Monte Carlo Simulations; Capital Budgeting.

I. Introduction

MODIGLIANY-MILLER theorem [15] states that with well-functioning markets, neutral taxes and rational investors, who can „undo" the corporate financial structure by holding positive or negative amount of debt, the market value of the firm (debt plus equity) depends only on the income stream generated by its assets. It follows, in particular, that the value of a firm should not be affected by the share of debt in its financial structure or by what will be done with the returns – paid out as dividends or reinvested (profitably) [14]. A corollary of this capital structure "irrelevance" proposition says that a company's investment decision should also not be influenced by its risk management policy – by whether a company hedges its various price exposures or chooses to leave them unhedged [2].

This notion is based on the idea that if investors can build their own portfolios according to their needs and pay the same price for firms financed in different ways, there is no reason for them to pay more for companies that hedge their positions when investors can carry out the same activity themselves. Irrelevance of risk management on the company value follows analogous arguments to the claims on the irrelevance of capital structure, where investors can adjust returns of their portfolios in order to quickly "synthesize" an indebted company from the company financed by equity only and vice versa.

Many researchers [23], [26], [10], [17], however, present both theoretical arguments and practical evidence arguing that correctly applied risk management practices due to the real market imperfections that firms face in fact increase company value. Empirical field studies on that topic [6], [18], [5], [24], [25] further imply that companies behave as risk averse and their value is not only affected by current performance, but also reflects the long-term prospects including sustainability, risk management and ultimately the stability of expected free cash flows in time.

This stability, in general, can be perceived as harmony between the supply of internally generated funds and the investment demand for funds. Because external financing is costly, this imbalance shifts investment away from the optimal level. Risk management can reduce this imbalance and enable companies to better align their demand for funds with their internal supply of funds [7].

Even though employed risk management practices and long term prospects of the company are important factors driving its value, reflecting these aspects in the valuation model remains a challenging task.

A. Equations in the Business Valuation

Company valuation methods build on the present value of the future free cash flows, that we expect the company to generate:

$$PV_{FCF} = \sum_{t=1}^{T} \frac{FCF_t}{(1+r)^t}, \tag{1}$$

where PV_{FCF} is the present value of free cash flows, FCF_t is the free cash flow generated by the company in year t, r is the required return and T is the lifetime of the company in years. Since all these parameters are subject to risk, it is not always clear how to estimate their values correctly [16]. This generally accepted valuation approach is based on neoclassical microeconomic principles of an asset valuation under risk, and therefore the expected values of input variables should be considered as:

Manuscript received May 17, 2012. The authors would like to express their gratitude for the financial support of the Ministry of Education of the Czech Republic - the paper is one of the outcomes of the research project MSM6138439905 New Theory of Economy and Management in Organizations and their Adaptation Processes.

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$$PV_{FCF} = \sum_{t=1}^{T} \frac{E(FCF_t)}{[1+E(r)]^t} \tag{2}$$

There is a significant amount of literature dedicated to the determination of the discount rate r. Much less focus is, however, given to the determination of (central) value of free cash flows. Estimation of $E(FCF_t)$ is far from trivial, since the probability distribution of free cash flows is necessary for the calculation. The situation is further complicated by the fact that the free cash flows are not estimated directly, but based on estimates of the individual components of free cash flows. There are a great deal of possible decompositions of free cash flows; valuation practitioners usually tend to relationship:

$$FCF = EBIT(1-t) + D - I - \Delta NWC\,, \tag{3}$$

where EBIT is Earnings Before Interest and Tax, t is tax rate, D depreciation, I investments and ΔNWC is change in net working capital. The decomposition of free cash flow can continue further, since EBIT has its components such as the product selling price P, quantity of the product sold Q, variable cost per item sold V and fixed costs F:

$$FCF = [(P-V)Q - D - F](1-t) + D - I - \Delta NWC\,. \tag{4}$$

Even the quantity of the product sold is often estimated indirectly on the basis of market capacity and market share, which is further complicated by the fact that in most cases there is no single product but a whole portfolio of products. Therefore EBIT can be estimated for each product separately. Similarly, net working capital can be broken down to multiple components.

$$\begin{aligned} &E(FCF) = \\ &= E\{[(P-V)Q - D - F](1-t) + D - I - \Delta NWC\}. \end{aligned} \tag{5}$$

Due to the existence of various types of dependencies it is not possible to build the estimation of E(FCF) only on the average values of its input variables. Considering for example non-zero correlation between price and quantity sold and non-zero correlation between variable costs and the quantity sold, (5) needs to be further extended to the expression:

$$\begin{aligned} &E(FCF) = (1-t)[E(PQ) - E(VQ) - E(D) - E(F)] + \\ &+ E(O) - E(I) - E(\Delta NWC) = (1-t)[E(P)E(Q) + \\ &+ \rho_{PQ}\sigma_P\sigma_Q - E(V)E(Q) + \rho_{PQ}\sigma_P\sigma_Q - E(D) - \\ &- E(F)] + dE(D) - E(I) - E(\Delta NWC). \end{aligned} \tag{6}$$

The more complex the relations between input variables, the more difficult the analytical solution becomes to the estimation of the central value of free cash flows. The central value of free cash flows $E(FCF_t)$ is the result of an aggregation of many random variables that are often mutually (and not only linearly) dependent and whose probability distributions are not usually known in advance and therefore must be estimated, including their interdependencies.

Further it is important to acknowledge that the structure of inputs for the E(FCF) in years to come will most probably differ. We can expect important future events like changes in the capital structure, changes in the project portfolio or even M&As. The outcome of such events is uncertain and traditional models are very limited in capturing the potential variability. Outputs of deterministic models can be considered accurate strictly under the assumptions that management had already made all decisions remaining for the rest of the company's life and all relevant uncertainties and potential scenarios have been quantified via the simple probabilistic calculus.

Generally all the estimates are uncertain numbers with the occurrence rather on an interval with varying density of expectations than on a few discrete data points. Deterministic models working with a single point estimate are usually using only one number out of such an interval thus ignoring important and valuable information about the uncertainty [8]. This number can be the mean, the most likely or any other statistically justifiable value. Limiting ourselves only to single points however makes us lose information concerning not only the variance (degree of uncertainty or risk), but also the shape of the probability distribution, which might not be symmetrical or unimodal [21].

Distinguishing the expected and most likely value is an integral part of business modeling, because the two values can differ significantly which can result in wrong input for the valuation model. This is usually a case of asymmetric distributions where mean, modus and likeliest value do not overlap.

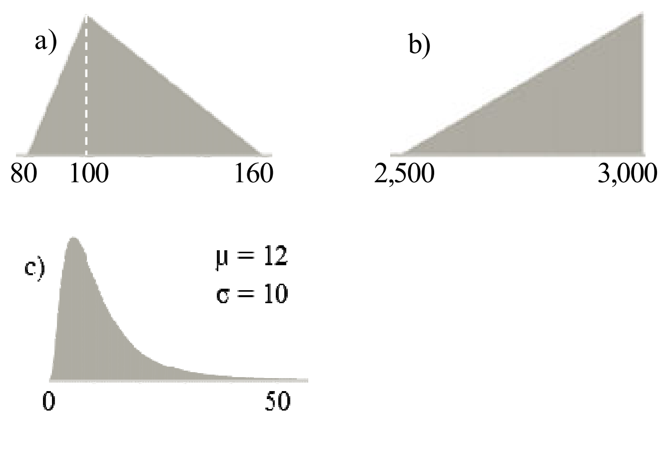

Fig. 1 asymmetric probability distributions

For triangular distribution in Fig. 1 a) the mode is 100, its median is 111 and mean 113.3. Positively skewed asymmetric distributions will usually have mean > median => mode. For another triangular distribution in Fig. 1 b), the most likely value is 3,000, which is also the highest value of the distribution. The mean of the distribution is, however, 2,833 and the median 2,853. This is an example of negatively skewed distribution which will usually have mean < median <= mode. Lognormal distribution in Fig. 1 c) is again positively skewed and its mode is 5.44, its median is 9.22 and the mean 12.

The theoretically correct approach for traditional modeling is to insert the expected (mean) values of uncertain variables into the model. Their true occurrence, however, is recognizable only after identification of all possible scenarios and their potential impact upon occurrence.

Scenario analysis also lies in the background of the portfolio theory introduced by Harry Markowitz [13] and William Sharpe [22], which implies that when two assets offer the same average profitability, the market will place greater value on the one with less risk. Their work introduced two distinct portfolio effects, which are diversification and statistical dependence. Savage [20] describes that accounting principles are improperly applying these phenomena thus creating numerous inconsistencies. For example a portfolio of homogenous random events is perceived as an addition of single events without the statistical context. Hence, it is sometimes impossible to book the expected value of such a portfolio.

Since in reality an occurrence of one factor often influences occurrences of other factors, capturing interdependency among factors within a financial model is a crucial part of valuation practice. The simplest approach is to use correlations under the assumption that the interdependencies are linear. However, in reality non-linear dependencies are much more frequent than linear and thus linearity assumption may generate false outcomes. Non-linearity e.g. implies that the value of a calculation based on average assumptions is not the average value of the calculation. This is technically known as Jensen's inequality [20].

B. *Taxation and the value of the company*

Business valuation models often lack the influence of tax liabilities on free cash flows and therefore the value of the company as described by Smith and Stulz [23], Ross [19], and Leland [11]. The basic provisions of the corporate tax code (a zero tax rate on negative taxable income) yield a convex tax function. This implies that the riskier the project is (i.e. the larges potential variation in expected free cash flows) the more significant the difference in expected tax liability from the low risk scenario.

This phenomenon is illustrated on Fig. 2. Assume, for illustration, that there are two projects with only two possible scenarios with expected values of earnings before tax either Z_1 or Z_2 with equal probabilities for the first project, and either Z_3 or Z_4 with equal probabilities for the second project. Expected value of tax liability is $E(T_A)$ for the first project and $E(T_B)$ for the second. Clearly the riskier situation leads to a higher expected value of tax liability and therefore lower expected value of free cash flows.

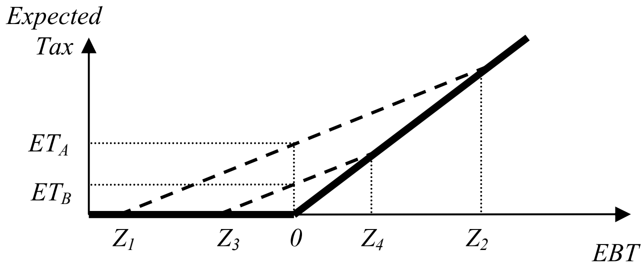

Fig. 2 Risk and expected tax liability [23]

Legislation in some countries allows for subtracting losses from previous years from the tax base in the current year. Though this is an important risk factor influencing both free cash flows and earnings after tax, its projection in MS Excel calculation is often challenging. Especially in the case of valuation of start-up companies it is typical that expected earnings in initial years are negative.

Tax liabilities are not a linear function of earnings before tax due to the existence of potential tax deductions such as losses from previous periods. Their estimation should therefore not be based on a simple calculation of expected values, but rather on a simulation which enables accounting for various possible scenarios.

II. Applying the Simulation Approach

There are several methods for incorporating the uncertainty into the financial model, but due to its simplicity and flexibility, the Monte Carlo simulation is the most popular. This approach calculates numerous scenarios of a model by repeatedly drawing values from a user-predefined probability distribution and inserting them in the model. The output of the simulation is a distribution of a monitored variable (e.g. company value), which however should not be understood as a probability distribution, but rather as a distribution of our ignorance (or uncertainty) concerning the model output.

Replacing uncertain numbers with distributions allows for an integration of a wide range of improvements into financial modeling. Separately analyzing each uncertain variable, approximating its potential occurrence with a corresponding shape of the distribution and observing their joint influence on model outputs provides useful insight into what is beyond the average scenario.

A. *Quantifying Uncertain Variables*

Representing uncertainty by a distribution is a crucial part of capturing possible scenarios and their outcomes. Fig. 3 serves as an example of a complicated shape for which a single value does not provide appropriate representation of the underlying phenomenon. Distribution shows frequencies of a water level in an urban area. It is easily readable that the water level is low and stable during dry seasons while it increases with much wider range in wet seasons. The risk of floods in the area increases with water level, however, the relationship between the water level and damages caused by floods is non-linear as there is probably a flood control system which reduces damages to zero until a threshold of an extreme event is reached.

It is therefore highly probable that the damage would be zero not only for the average water level, but also for most above average events. No single value will be able to provide the full story and its employment will always result in a great simplification and loss of information. The description of real world events requires capturing as many potential scenarios as possible, because each will probably result in a different outcome.

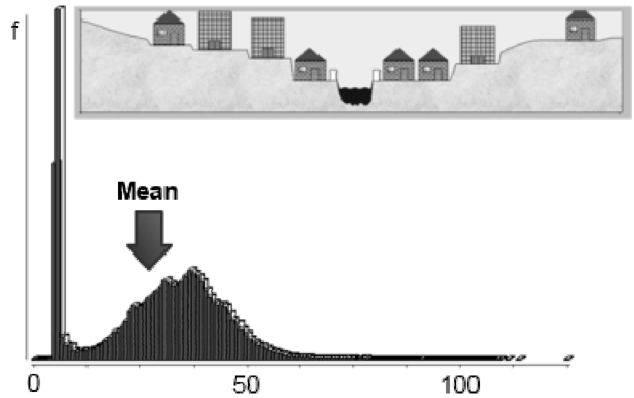

Fig. 3 Distribution of potential water levels [21]

There are essentially two sources of information used to quantify the variables within a risk analysis model: available data and expert opinions [28].

1) Determining Variability from Data

The observed data may come from a variety of sources: surveys, computer databases, history or research. Before making use of the data, the analyst should be satisfied with their reliability and representativeness. Anomalies in the data should be checked out where possible and proved outliers should be discarded. There are several techniques available to interpret observed data for a variable in order to derive a distribution that realistically models its true variability and our uncertainty about that true variability.

If there is not enough information about the analyzed data set, or for any other reason the assumption about the shape or type of probability distribution cannot be established, non-parametric distribution fitting methods may be used. In these cases, for each scenario the Monte Carlo simulation draws randomly from the underlying data set (an empirical distribution).

However, it can also be assumed that the analyzed data come from a known theoretical distribution. A typical example is the normal distribution, whose frequent occurrence is likely attributable to the central limit theorem, which predicts that the sum of a large number of independent random variables, each with finite mean and variance, will be approximately normally distributed. In these cases parametric distribution fitting methods are used. The empirical distribution of underlying data is then used only to determine the degree of fit to a theoretical (parametric) distribution. Various theoretical distributions can be analyzed to find the one that best fits the observed data. Compared to non-parametric fitting methods mentioned above this approach leads the simulation to abandon the original data set and draw data from the theoretical distribution. This however sometimes means ignoring gained empirical experience.

The shape of the probability distribution is closely related to the uncertainty regarding the estimation of values of its parameters, which is known as Second Order Distribution Fitting. With some simplification, methods for estimating the probability distribution of parameter values can be categorized into the three following groups: classical statistics, Bootstrap method and Bayesian statistics. All three methods are very useful, but require more effort and their applicability varies according to circumstances [9], [28].

2) Modeling Expert Opinions

In some situations proper data are not available and that is when expert opinions are often more suitable. When applying simulations, the potential of covering expert opinions is much larger as it is possible to create a distribution of all estimates. Thus no important information regarding collected estimates, including the uncertainty of them being correct, would be ignored. Each expert can further be assigned a weight of his or her estimate in order to distinguish between the qualities of various expert respondents. Such a weighting implies the probability of the estimate of the expert is correct, which may for example be derived from his or her reputation or an existing track record.

Furthermore it is easier to cooperate with each expert, because his or her subjective uncertainty concerning the estimate can be captured by a distribution. Thinking hard about the factors that could interfere with an expected base case scenario makes an expert consider both an upside and downside potential variability of the situation. Requiring an expert to also define the worst and the best case scenarios allows for an understanding of the range of potential outcomes. Only then is it possible to realize what can be expected if everything goes wrong and vice versa. That is crucial for a business valuation process as the potential variability of partial uncertain variables within the model add up to a total uncertainty about the value of the company.

The most comprehensible approach to this matter is usually by asking an expert about his or her pessimistic, realistic and optimistic estimates. The three values can then be used as parameters for a triangular or betaPERT distribution. The two distributions have achieved a great deal of popularity among risk analysts, since they both offer considerable flexibility in their shape, intuitive nature of their defining parameters and speed of use.

However, for both distributions, minimum and maximum values are the absolute boundaries for the estimated variable, which can lead to underestimating the low probability extreme values and their impact on the value of the company. Generally, an analyst will never be able to define the absolute worst case scenario - it is basically beyond any possibilities to identify all the factors influencing the variability and the extent of their influence. Reasoning of this phenomenon is widely discussed in Taleb's book Black Swan [27].

It is therefore often more suitable to perceive the potential variability on some confidence interval. Phrasing the question of the pessimistic and optimistic estimates in a way that it opens the model to occurrences of potential tail events is an important aspect of its robustness. Asking, what is the worst scenario that can happen in 99 cases out of 100, can be a good method to start with, because it simply leaves the 1% of tail events undefined. Statistics will effectively fill this gap with probability distributions.

B. *Modeling Dependencies*

Often we are dealing with the question of to what extent within the model does the behavior of one variable determine the expected occurrence of others. Our brain is able to work with similar relationships intuitively based on our empirical experience; however their proper implementation to the valuation model may be complicated. This is not just an infamous problem of distinguishing correlation from causation, but also the issue of mathematical interpretation of the inner dynamics within the model.

Working with linear dependencies expressed by correlations is usually the easiest method. However, it is important to keep in mind that their application is correct only if there is a presumption that the dependence is "approximately" linear. It is inappropriate to use correlations otherwise.

1) *Correlations*

In financial modeling, two basic types of dependencies are pursued. The first is the already mentioned dependence between model input variables that can be for example product price and the quantity sold. This type not only affects the overall reliability of the estimate (i.e. the total variance of the distribution), but also the mean value of free cash flows - and thus the value of the company. The reason is the general validity of the theorem on the product of the mean values of two random variables P and Q:

$$E(PQ) = E(P)E(Q) + \operatorname{cov}(P,Q). \tag{7}$$

The second type of dependence, almost always ignored in the models, is the autocorrelation of time series, i.e. correlation between values of a single input variable at different points in time. An example is the quantity sold in successive years, for which it will certainly be the case that

$$\rho(Q_{t+1}, Q_t) \neq 0. \tag{8}$$

Generally the mean value of the sum of random variables is the same as the sum of their mean values. Therefore this kind of dependency will not affect the estimated value of the company. However, this is not the case of the reliability of our estimate, since the definition of the variance of company value estimate is as follows:

$$D(PV) = \sum_{k=1}^{T}\sum_{l=1}^{T} \operatorname{cov}\left(\frac{FCF_k}{(1+r)^k}; \frac{FCF_l}{(1+r)^l}\right). \tag{9}$$

In reality the time dependence (i.e., different than zero covariance between variables in time) between FCF_k and FCF_l is more frequent than independence. Moreover, it is usually a direct dependence, which means that the stronger the dependence the lower the reliability of our estimate, as the variance increases. In practice it is impossible to capture the fact in MS Excel, simply because the above formula for calculation of the covariance works at the level of free cash flows and not of its individual input variables.

To observe the uncertainty concerning the value of the company under different levels of correlation among model input variables see Fig. 4. While the central value of the distribution (representing the value of the company) remains identical in all three scenarios, variance of the distribution is clearly decreasing with the decreasing correlation due to the effect of diversification [13].

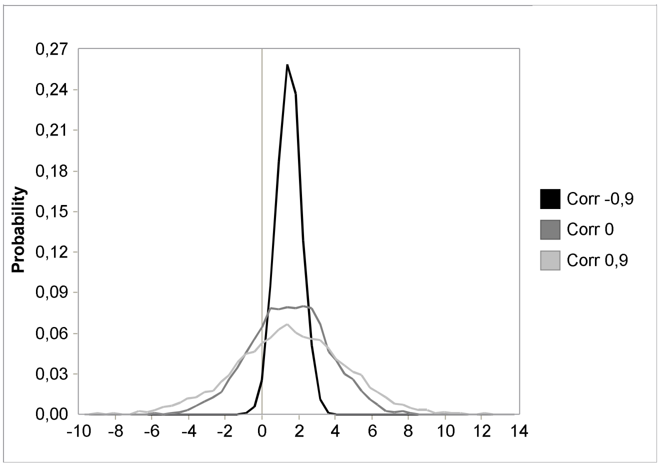

Fig. 4 Correlations and variance of an output distribution (created in ModelRisk software)

Since in the case of business valuation the occurrence of positive correlations is more likely (see above), the resulting distribution of the value of the company will have a larger variance than if interdependences are completely ignored. Not including interdependencies in the valuation model implies that there are none and therefore the correlations are actually equal to zero, which is an implausible assumption, directly leading to an underestimation of uncertainty.

2) Modeling Non-linear Dependencies

A flexible way of capturing non-linear dependencies between random variables X and Y (i.e., input variables of the model) is linking their parameters – in our case parameters of probability distributions. During the simulation only the occurrence of the first variable determines the conditions of the other. For example, assuming that both X and Y come from a uniform distribution U [a, b], then the dependence of random variable Y, can take the form

$$Y \approx U[f_1(X); f_2(X)], \tag{10}$$

where f represents a function (e.g. see Fig. 5). Both coordinates of this chart are obtained by the Monte Carlo simulation, which will always generate a random value of X first. This will be used as an input parameter for the second random variable Y with parameters U [cX + d, eX + f]. Therefore for each scenario, only the occurrence of a random variable X determines the interval at which the coordinates of Y lie. Similarly any kind of distribution or combination of distributions can be used.

Modeling dependencies between random variables is not limited to the same type of stochastic process or the type of probability distribution. In all cases, however, it is necessary to validate the dependence with statistical analysis first (see Fig. 5).

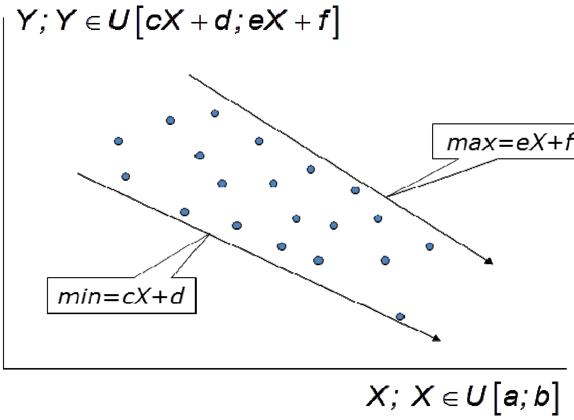

Fig. 5 Modeling dependencies between random variables [9]

C. Modeling Nonrecurring Events

Business is always exposed to the risk of nonrecurring events that may significantly affect a company's cash flows. In terms of financial planning these risks have a binary character, because it is expected that a particular event either occurs or not. However, under both scenarios events may unfold differently. Such risks may include competition entering the market, a change in the legislation, a change in the tax code or natural disasters. All of them may have a major impact on business, its processes and cash flows, and therefore their proper integration into the valuation model is essential.

A frequent mistake is ignoring the less likely events that have been identified as risks, but, despite their significant potential impact on business, the probability of occurrence is considered negligible. Another common approach is that even though the model includes both possible outcomes, they are reflected in a single average distribution, which is also inappropriate, since in reality the "average" situation will never occur.

Nonrecurring events are the kind of uncertainty impossible to be covered using deterministic modeling techniques. As an example of such event, consider the launch of a new technology creating its own market segment (e.g. iPad). At first there is an uncertainty concerning the revenues generated by the product of the company being valued, but there is also a risk of competition soon entering the market with a competing product, thus taking share on the revenues. Uncertainty of revenues generated by the product in the two scenarios can be represented by a bimodal distribution as shown in Fig. 6. The black line distribution shows an incorrect modeling approach where an average value of the two situations has been taken into account.

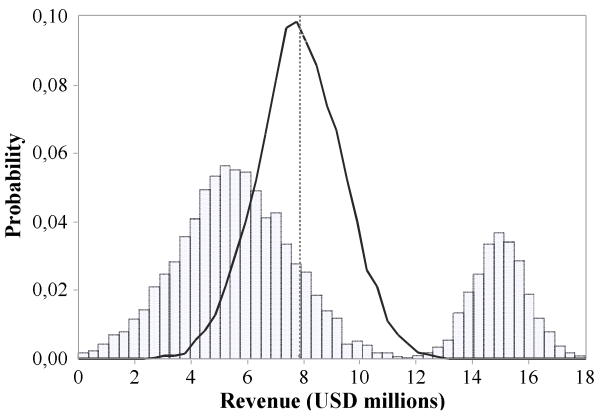

Fig. 6 Modeling nonrecurring events (created in ModelRisk software)

It is important to note that both distributions have the same mean value. In traditional models it is therefore impossible to distinguish whether a correct modeling technique has been employed.

III. Uncertainty plugged in Business Valuation

The structure of a simulation model is very similar to a deterministic model, with all functions and operations that link variables together, except that each variable is represented by a probability distribution instead of a single value. The objective is to calculate the combined impact of the variability in the model's parameters in order to determine a probability distribution of the possible model outcomes.

In this paper two important aspects of business valuation under uncertainty will be discussed as well as potential benefits offered by appropriate implementation of Monte Carlo simulation in the area. Challenges related to discounting the free cash flows will be addressed first, followed by the introduction of risk metrics, which are building on Value at Risk method.

A. Discount Rate in Company Valuation

Despite the widespread acceptance and use of the DCF approach to business valuation, there is a growing recognition of its important limitations [12]. DCF analyses are based on a static view ignoring flexibility and variability, and therefore tend to misvalue investments with non-linear payoffs. The major criticism is however pointed to the use of a single discount rate to discount free cash flows, regardless of differences in risk or financing. This approach may help understand the value of the company on average, but it fails to reflect the variety of uncertainties behind each factor within the model.

As discussed throughout the paper, a company cannot be valued without a clear understanding of the risk profile of its operating cash flows. Basic approaches in this matter are stress testing or what-if analysis, where the purpose is to estimate how the value of the company reacts to different potential economic scenarios. A crucial question regards the minimum level of free cash flows the company can be expected to generate under the worst possible economic scenario and whether the company will still be able to cover its debt obligations. In reaction to this information, managers may decide to lower some risk exposures or reduce leverage to lower the company's risk profile. This concept is related to the probability of the company's default, which is a very important aspect of its value [25].

Including a risk analysis of future cash flow, however, requires considering a theoretical shift from traditional DCF conventions. Calculations performed in a risk analysis spreadsheet model are usually presented as a distribution of company value because the cash flows are also expressed as distributions rather than their expected values. Theoretically, however, this is incorrect. Since a value of the company presents what the company is worth at the moment of valuation, it can have no uncertainty as there can be only one such number. The problem is that the risk has been double counted by first discounting at the risk-adjusted discounted rate and then showing the company value as a distribution.

The theoretically correct method for calculating the value of the company under these circumstances is to discount the cash flow distributions at the risk free rate. Such distribution is, however, difficult to interpret and incomparable with outputs of other models. Since there is no framework to cover this issue, it is recommended by practitioners to apply risk adjusted discount rate to produce a distribution of company value [28]. The mean value of the company will be more precise than the one calculated by the DCF approach, because it incorporates asymmetrical distributions, correlations and other phenomena described in this paper.

Bancel and Tierny [1] suggest dividing the expected free cash flow of a company into two parts: a relatively certain, or low risk, component; and an uncertain, or risky, component. While the risky component should be funded entirely by economic capital, the low risk component can be financed by debt, since there is a marginal probability of company's inability to finance it (see Fig. 7).

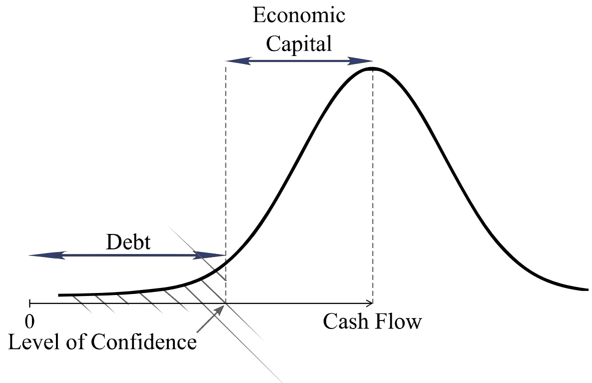

Fig. 7 Economic capital and firm-risk profile [1]

Management is therefore assumed to use economic capital to fund only the risky portion of the company's assets and cash flows. As shown in the figure, the relatively certain portion of the firm's assets is assumed to be funded entirely by debt, and the amount of economic capital is determined by the distance to default that has been selected based on a target risk that is accepted by management.

It is further indicated that there could be more than two levels of cash flows according to their levels of risk. It would be easier to estimate discount rate for each of the cash flow groups since it derives from their costs of financing. This would motivate management and analysts to pay closer attention to the risk profile of company cash flows. As a result, their valuation should be more reliable than the one calculated by the DCF approach relying heavily on average cash flows.

In further comparison with the DCF approach, this model takes into account more than just estimates of average cash flows and the weighted average cost of financing. It motivates management to produce a cash flow profile that consists of at least two scenarios. A useful valuation should depend heavily on estimates of risk and the market's required return for bearing risk. By setting explicit targets for risk and attempting to measure the cost of risk, managers should produce valuations that are both more accurate and more readily communicated to analysts, board members, and other third parties.

Second, this method assumes that corporate leverage is an important decision whose import for value should be reflected more directly in the valuation process. It provides for each period of time an estimate of the required economic capital that reflects the level of debt financing and the associated probability of default. The value of economic capital is equal to the present value of free cash flows to economic capital discounted at the cost of economic capital.

B. Value-at-Risk and its successors

Value-at-Risk can be defined as the worst loss that might be expected from holding a security or portfolio over a given period of time, given a specified level of probability, known as the confidence level [3]. While Value-at-Risk was first applied at the beginning of 1990s by financial institutions to measure the potential effect of market risk on the market value of portfolios of financial instruments, a number of companies have been interested in applying concepts of this methodology in the corporate environment.

The corporate environment usually refers to a setting that focuses on a company's shareholder value and on key corporate financial results such as earnings and cash flow. This can be contrasted with a financial environment wherein the focus is on the market value of portfolios of financial instruments. While the market values of portfolios are of interest to corporations, they are just a subset of the types of financial results that corporations care about. To corporate managers, financial results such as earnings and cash flow are generally more important since they directly drive shareholder value [4].

Employment of simulation provides a large set of market scenarios which can be used to generate a distribution of future financial results. These distributions can further be analyzed in order to identify any of the following risk measures.

The Cash Flow-at-Risk approach answers the question of how large a deviation between actual cash flow and the planned value can occur due to changes in the underlying risk factors. The Earnings-at-Risk approach is a similar view of the problem. Here the focus is not placed on financial accounting cash in-flows and out-flows, but instead on profits and losses as defined by relevant accounting principles.

Present Value-at-Risk measures the worst loss in the value of the company that might be expected over its lifespan, given a certain confidence level. For example, if the PV-at-Risk is $1 million at the 99 percent confidence level, it means that the chance of the value of the company being lower than $1million from its expected value is on average one in a hundred. This interpretation of PV-at-Risk therefore calculates the distance between the mean of the distribution and its first percentile.

Another possible definition of PV-at-Risk is the value of the first percentile itself, which will be interpreted as the lowest possible value of the company with 99% confidence. Interpretation of this second approach would be slightly more difficult as it still requires comparing the value of the percentile to the expected value of the company in order to express the uncertainty regarding its calculated estimate.

As original Value-at-Risk provides an aggregate measure of all risk factors relevant to portfolios of financial instruments, Present Value-at-Risk provides an aggregate measure of all risk factors influencing the value of the company. Hence PV-at-Risk offers a probability statement about the potential change in the value of the company due to the unfolding of uncertain factors over time.

IV. Conclusion

Company valuation based solely upon point estimates leads to many inaccuracies or outright blunders. Its shortcomings can be conquered by applying simulation approach which clarifies many important questions. Due to incorporating range estimates, asymmetrical distributions and dependencies among model variables, the value of the company is more precise than the one calculated by the DCF approach. Not to mention the contribution of the thinking exercise itself to the quality of the decision-making process. Simulation also provides a transparent interpretation of an uncertainty about this value and corresponding input variables, which is a significant improvement over a single value output of DCF model which lacks the understanding of where this value may be located on the real distribution of all possible scenarios and therefore shows nothing about the confidence with which we may rely upon the estimated final value.

Furthermore it is possible to determine the minimum level of free cash flows the company is expected to generate under the worst possible economic scenario. This information should reveal whether the company will still be able to cover its debt obligations and help management to decide if any adjustments in the capital structure of the company should be made. The urgency of which would be clearly readable from the risk analysis. The distribution of the value of company may also provide a hint on how the capital structure should be adjusted from the risk perspective.

References

[1] F. Bancel, and J. Tierny, "Valuing Companies with Cash Flow@Risk," *Journal of Applied Corporate Finance*, vol. 23, no. 2, 2011, pp. 85-93.

[2] M. J. Brennan, and E.S. Schwartz, Corporate Income Taxes, Valuation, and the Problem of Optimal Capital Structure. *Journal of Business*, 1978, vol. 51, pp. 103-114.

[3] Crouhy, M. et al.: *The Essentials of Risk Management.* McGraw-Hill, 2005.

[4] RiskMetrics Group: CorporateMetrics Technical Document, 1999.

[5] G. Dobrota, L. P. Paliu, and G. A. Babucea, Risk management at the level of economic agents within the context of sustainable development. *Proceedings of the International Conference on risk management, assessment and mitigation*. 2010, pp. 380-385.

[6] N. Duarte, Business Strategies on Innovation, Risk and Proactivity, *Proceedings of the 5th WSEAS International Conference on Economy and Management Transformation (Volume I)*. 2010, pp. 302-307.

[7] K. A. Froot, D. S. Scharfstein, J. C. Stein, A Framework for Risk Management, *Harvard Business Review*, 1994, vol. 72, no. 6, pp. 91-102.

[8] D. Hertz, Risk Analysis in Capital Invetsment. *Harvard Business Review*, 1964, vol. 42, pp. 95-106.

[9] J. Hnilica, and J. Fotr, *Applied Risk Analysis in financial management and investment decision making* (*Aplikovaná analýza rizika ve finančním managementu a investičním rozhodování*). Grada Publishing, 2009.

[10] R. G. Hubard, Capital-market imperfections and investment. *Journal of Economic Literature,* vol. 36, no. 1, 1998, pp. 193-225.

[11] H. E. Leland, Presidential address: Agency costs, risk management, and capital structure. *Journal of Finance*, 1998, vol. 53, no. 4, pp. 1213-1234.

[12] D. Laughton, R. Guerrero, and D. Lessard, "Real Asset Valuation: Back to Basics Approach," *Journal of Applied Corporate Finance*, vol. 20 no. 2, 2008, pp. 46-65.

[13] H. Markowitz, *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley & Sons, 1959.

[14] F. Modigliani, Introduction. In A. Abel (ed.). *The Collected Papers of Franco Modigliani*. Volume 3. Cambridge: MIT Press, 1980, pp. 11-14.
[15] F. Modigliani, and M. H. Miller, *The Cost of Capital, Corporation Finance and the Theory of Investment*. American Economic Review, Vol. XLVIII, June 1958, str. 268.
[16] McKinsey & Company, *Valuation: Measuring and Managing the Value of Companies*. John Wiley & Sons, 2010.
[17] S. C. Myers, Determinants of corporate borrowing. *Journal of Financial Economics*, vol.13, no. 2, 1984, pp. 147-175.
[18] B. Ozdincer, C. Ozyildirim, The Impact of the Long Term Performance of a Bank on Its Market Value. *International journal of mathematical models and methods in applied sciences*, vol. 2, no. 1, 2008, pp. 96-102.
[19] M. Ross, *Corporate hedging: What, why and how?* University of Carolina, Berkley, 1997.
[20] S.L. Savage, “Accounting for Uncertainty,” *The Journal of Portfolio Management*, 2002.
[21] S.L. Savage, and J. Danziger, *The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty*. New York: John Wiley & Sons, 2009.
[22] W.F. Sharpe, *Portfolio Theory and Capital Markets.* New York: McGraw-Hill, 1970.
[23] C. W. Smith; R. M. Stulz: The Determinants of Firms´ Hedging Policies. *Journal of Financial and Quantitative Analysis*, vol. 20, no. 4, December 1985, pp. 391–405.
[24] J. Strouhal, C. G. Bonaci, E. A. Matis, “Corporate Governance Lesson Taught by the Financial Crisis: A Research Note,” *International Journal Of Mathematical Models And Methods In Applied Sciences*, vol. 5, no. 3, 2011, pp. 688-695.
[25] R. Stulz, Managerial discretion and optimal financing policies. *Journal of Financial Economics*, vol. 26, no. 1, 1990, pp. 3-28.
[26] R. Stulz, *Risk Management and Derivatives*. Thomson South-Western, 2003.
[27] N.N. Taleb, *The Black Swan: The Impact of the Highly Improbable*. Random House, 2008.
[28] D. Vose, *Risk Analysis. A Quantitative Guide, Third Edition.* John Wiley & Sons, 2008.