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Credit risk measurement

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Abstract

Focused on globalizaing of economics and still actual financial crisis credit risk becomes one of the most discussing topic in business world. Every investment decision should be accompanied by analysis of the possibility of default. Through the years there were developed many credit risk measures, so research and quantification of them are a subject of interest of many economic publications and studies. So nowadays there are many approaches which can be used by investors to monitor credit risk and it can be calculated through various models and methods. The aim of the article is to present the basic ones as well as the most often used models based on them such like CreditMetrics, CreditRisk or KMV model. There is given a comparison of these models in dimension as risk definition, risk source, recovery rate, types of model etc. Then we also describe pros and cons of them. Eventually we apply the CreditMetrics model for a single bond.

Keywords: risk; credit risk; model; CreditMetrics;

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1. Introduction

Risk and particularly financial risk can be defined as a potential financial loss of a subject i.e. not an existing financial loss, but possible future losses resulting from the financial commodity instrument or financial commodity portfolio. Grublova (2010) said: focusing on the various sources of risk we can put financial risks into the following categories:

- Market risk— risk of loss due to unexpected changes in market prices as well as negative progress of interest rates , stock, commodity prices and exchange rate.
- Liquidity risk— the risk of loss that occurs when the costs of adjusting financial positions will increase substantially or a firm will lose access to financing.
- Operational risk—the risk of loss due to fraud, systems failures, trading errors (e.g., deal mispricing), and many other internal organizational risks.
- Business risk - the risk of loss caused by the situation in the economy in which the subject operates
- Credit risk— the risk of losses due to situation that counterparty to a financial transaction will fail to fulfill its obligation as well as the risk of changes in value associated with unexpected changes in credit quality.

According to Adamko, Spuchlakova and Valaskova (2015); the reason for measuring credit risk is the need to create a sufficient amount of capital to cover this type of risk. Size of a debtor affects the use of credit risk models. Therefore, banks have used them in assessing credit risks of large companies and nowadays they are also used in assessing small businesses, too. Basic attributes, which affect the amount of credit risk, are:

Default is a situation that counterpart is unable to pay anytime during the maturity. Furthermore the definition of default depends on the type of credit risk model: the mark-to-market models, credit event is a change in credit quality (upgrade or downgrade); default-mode model considers only two states (default or non-default) i.e. counterparty fulfills its obligations or not.

Credit exposure is the amount of liability that is available to the creditor in case of failure.

Default probability reflects the probability of the occurrence of default state in a given time period. This probability may be based on historical data or methods of market value (market prices of equities and financial derivatives).

Recovery rate is the percentage of debt that can be repaid by an obligor classified in the lowest rating category (usually classified in default category).

2. Credit risk models

Most widely used method for measuring an event of default is generally credit rating reflecting the counterparty's ability and willingness to repay its obligations (focusing on client credit-worthiness). There are two approaches to determining the credit quality of the counterparty: scoring models and credit ratings. Adamko, Kliestik and Misankova (2014) wrote that rating is based on an expert valuation of the counterparty's ability to meet its obligations through selected indicators. Scoring models are the types of econometric models in which the dependent variable is the probability of default and the independent variable is the variance of that likelihood.

The models measuring credit risk, based on estimation of basic parameters such default, recovery rates, credit exposure etc., can be distinguished by a number of attributes (for example measuring techniques and range of applications).

The most common measurement techniques include:

- An econometric method (credit scoring system) is based on the identification of certain key factors that determine the probability of default, and combine them to calculate your score.

- Neural networks use data econometric models to construct models that simulate the human learning process.

- Expert systems are subjective expert judgments on the basis of the key factors that determine the decision to grant the loan.

- Optimization models are aimed at finding the optimal weights for the creditor and debtor to minimize the creditor errors and maximize the profit.

In terms of range of application credit risk models are divided into two categories: partial and complex models. Partial models are focused on the individual loan products with model parameters varying by product type. On the other hand, portfolio approach evaluates the overall risk by the position of the portfolio.

According to Kollar, Bartosova (2014): portfolio credit risk models are subdivided into several types: such as top-down, bottom-up; by definition: the risk models focused on state of default or the market value of assets or models based on conditional and unconditional probabilities. A comparison of the most commonly used models of credit risk is shown in Table 1.

Table 1. Comparison of Selected credit risk models (Sivak, 2014)

	CreditMetrics	CreditRisk+	KMV
Type of model	Bottom-up	Bottom-up	Bottom-up
Definition of risk	Market value of assets	Losses due to default	Losses due to default
Characterization of credit events	Credit migration	Actuarial random default rate	Distance to default, structural and empirical
Risk source	Assets valued at market value	Default probability and default rate	Value of assets
Correlation of credit events	Multivariate normal assets returns	Independence assumption or correlation with expected default rate	Multivariate normal assets returns
Recovery rate	Random (beta distribution)	Constant within band	Constant or random
Volatility of credit events	Constant or variable	Variable	Variable
Numerical approach	Simulation or analytic	Analytic	Analytic and econometric

3. Credit Metrics for a single bond

Credit Metrics model was created by JP Morgan in 1997 and since 1999 it has been part of the risk management of many financial institutions. Kollar & Kliestik (2014) wrote that the aim of the model is to determine the volatility of asset values in the portfolio within a given time period using standard deviation. The risk of default is considered not only, but also the risk that the value of assets changes due to changes in the rating. The calculation of credit risk by Credit Metrics is based on several assumptions:

- All assets in the same rating category have the same probability of default and the same forward yield curve.

- The current default probability is equal to the average default probability calculated from historical data.

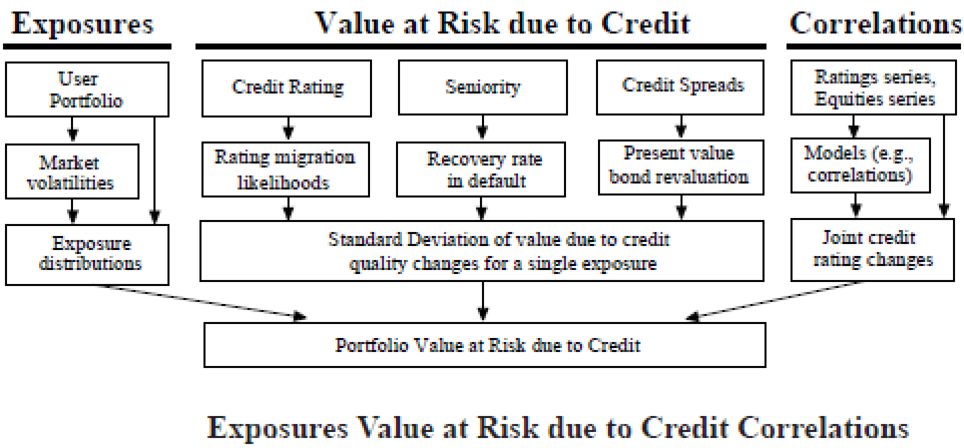

Figure 1 CreditMetrics framework

Model framework is shown in Figure 1.

The calculation algorithm is divided into four steps. Parts *Exposures, Correlations* and *Portfolio value at risk due to Credit* analyze portfolio credit risk. Part *Value at Risk Due to Credit* is used for analyzing the credit risk of individual financial instruments such as bonds and loans and this framework we use to evaluate credit risk of single assets. According to Kollar, Valaskova and Kramarova (2015): algorithm of evaluating credit risk of single assets consists of four steps according to the framework outlined above:

1. Credit rating determines likelihood of the bond defaulting or migrating to any possible credit quality state at the risk horizon.

2. The seniority of the bond determines its recovery rate in the case of default.

3. Credit spreads aid revaluation of bond to present value.

4. Calculating of credit risk according to standard deviation.

Table 2. Transition Probabilities of Single A-bond Over Next Year, According to S & P's for Five Years Maturity

Year-end rating	Probability of state (%)
AAA	0,09%
AA	2,27%
A	91,05%
BBB	5,52%
BB	0,74%
B	0,26%
CCC	0,01%
Default	0,06%

The next step of the analysis is to estimate recovery rates depending on the seniority of the debt. The table shows the average recovery rate and standard deviations. In the case of bond classified as Senior Secured recovery rate is 53.10% so that only 96.84$ should be paid if the default happened.

Table 3 Recovery Rates by Seniority Class

Seniority class	Mean (%)	Standard deviation (%)
Senior Secured	53,80%	26,86%
Senior Unsecured	51,13%	25,45%
Senior Subordinated	38,52%	23,81%
Subordinated	32,74%	20,18%
Junior Subordinated	17,09%	10,90%

Kliestik, Lyakin and Valaskova (2014) said; if we consider the same yield curve for all bonds of the same rating category, we can revalue the present value of the bond according to forward rates for every credit quality state in which bond could occur at the end of the year. Each forward rate is a discount factor of cash flow paid in each year; coupons are paid for first four years and face value and coupon is paid at the end of maturity. According to Duffie, Singleton (2003) the present value of the bond varies depending on the rating therefore the highest PV has AAA - Bond and present value decreases associating with decreasing rating. In case of default PV is determined by recovery rate.

Table 4 Forward rates and present value of bond by end of year

	forward rates				
Category	Year 1	Year 2	Year 3	Year 4	Present value of bond at the end of year ($)
AAA	3,60%	4,17%	4,73%	5,12%	188,60
AA	3,65%	4,22%	4,78%	5,17%	188,28
A	3,72%	4,32%	4,93%	5,32%	187,35
BBB	4,10%	4,67%	5,25%	5,63%	185,39
BB	5,55%	6,02%	6,78%	7,27%	175,67
B	6,05%	7,02%	8,03%	8,52%	168,76
CCC	15,05%	15,02%	14,03%	13,52%	143,50
Default	-	-	-	-	96,84

The last step of credit risk valuation of a single bond is volatility estimation due to a change in the rating categories. Kral & Kliestik (2015) wrote that there are two levels of risk that are traditionally used: standard deviation and quantile. The standard deviation is defined as a dispersion of individual values and using of mean hence increases the standard deviation which indicates increasing risk (in that case credit risk).

Table 5. 4Standard Deviation Calculation for Bond Initially Rated Single A

Year-end rating	Probability of state	New bond value	Probability weighted value	Difference of value from mean	Probability weighted difference squared	
AAA	0,09%	188,60	0,17	1,53	0,0021	
AA	2,27%	188,28	4,27	1,21	0,0334	
A	91,05%	187,35	170,58	0,28	0,0708	
BBB	5,52%	185,39	10,23	-1,67	0,1547	
BB	0,74%	175,67	1,30	-11,40	0,9619	
B	0,26%	168,76	0,44	-18,31	0,8715	
CCC	0,01%	143,50	0,01	-43,56	0,1898	
Default	0,06%	96,84	0,06	-90,23	4,8847	
		Mean	187,07		Variance	7,1688
				Standard deviation		2,68

In Table 5 we estimated the risk associated with counterparty default in absolute value is equal to 2.68. Also we must take into account the uncertainty associated with default and recovery rate. This uncertainty is determined by the standard deviation of 26.86%, which we can include in the calculation of credit risk according to the following formula:

$$\sigma = \sqrt{(96{,}84 - 2 * 26{,}86) - 187{,}07^2 * 0{,}00006} = 2{,}84$$

Incorporating of recovery rate uncertainty caused the increase in credit risk rate from 2.68 to 2.84 (5,91% increase).

4. Conclusion

Each credit risk models differ from each other in the way of construction, as well as the amount of input data, calculating difficulty, and usability of the results. Each model was created primarily due to regulatory requirements. Over time, the situation on the financial market has changed and nowadays banks and other financial institutions themselves initiate the creation of new models or improving existing ones.

The models presented in this paper have some advantages and also disadvantages. For example, Credit Metrics model is clear and logically organized, but the model requires a large amount of input data in form of a transition matrix, recovery rates or the value of the correlation of portfolio instruments. According to Saunders, Allen and Allen (2002): in the contrast to Credit Metrics, KMV model expresses particularly the risk of the entire company and requires few information for the calculation of credit risk of individual instrument. The model is applicable only to publicly-traded companies. This is certain limitations for usefulness of the model. On the other hand, the model can dynamically respond to changes in the market because it requires market observable input data and then may reflect the current market situation.

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