The Current Models of Credit Portfolio Management: A Comparative Theoretical Analysis

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ABSTRACT: The present paper aimed at studying the current models of credit portfolio management. There are currently three types of models which consider the risk of credit portfolio: the structural models (Moody's KMV model, and Credit- Metrics model), the intensity models (the actuarial models) and the econometric models (the Macro-factors model). The development of these three types of models is based on a theoretical basis developed by several researchers. The evolution of their default frequencies and the size of the loan portfolio are expressed as functions of macroeconomic and microeconomic conditions as well as unobservable credit risk factors, which would be explained by other factors. The present study developed three sections to explain the different characteristics of those three models. The purpose of all the models is to express the default probability of credit portfolio.

Keywords: Risk management, Credit risk, Default probability, Structural models, KMV model, CreditRisk+, Credit Portfolio View

JEL Classification: G13; G21; G28

INTRODUCTION

The problem of evaluation of the failure probability of any borrower is the main concern to the bankers as soon as lending some money. The quantitative modeling of the credit risk for a debtor is rather a recent model which is used besides the modeling of the credit risk associated with instruments of a portfolio of credit- such as the loans, the pledges, the guarantees and the by-products (which constitute a recent concept).

A certain number of models were developed, including the applications of property developed for the internal custom by the financial institutions, and the applications intended for the sale or for the distribution (Hickman and Koyluoglu, 1999).

The big financial institutions recognize the necessity of applying these models as there is a variety of approaches and rival methods. There are three types of models of credit portfolio in use at present (Crouhy et al., 2000):

✔ The structural models: there are two models of management of credit portfolio which...
are supplied in the literature: Moody's KMV model (Portfolio Model) and Credit -Metrics model by JPMorgan.

- The actuarial models CSFP (Credit Suisse First Boston): this model (CreditRisk+) is developed in 1997.

The main idea for this study is to answer the following question:

How the default probability is defined by the credit portfolio models?

The organization of this paper is as follows. In section 2, the structural models are presented and the strengths and the weaknesses of each model are defined. The presentation of the econometric models is given in section 3. The section 4 presents the development of the Credit Risk + models and the final section is the research conclusion.

The Structural Models

The structural models of management of credit portfolio were presented by Merton (1974) and then, developed by Leland (1994), Leland and Toft (1996), Anderson and Sundaresan (1996) and Jarrow (2011). The structural model is defined by these two conditions:

- The process of management of the assets of the company has to be known on the market in which it operates.
- The structure of the liabilities of the company has to be known by all the actors operating on the market.

In practice, it is necessary to use parameters estimated implicitly to examine the models of management of credit portfolio because the values of the assets of the company are not observable. Nevertheless, the majority of the empirical evidence does not retain the structural models. The implicit prices obtained from the structural models does not seem to match the structure of maturity of the efficiencies on the assets of the company (Jarrow et al., 2003; Eom et al., 2004; Ericsson and Reneby, 2005; Schaefer and Strebulaev, 2008; Li and Wong, 2008; Jarrow, 2011) and to allow the forecasts of defect of the borrowers (Patel and Pereira, 2007; Bharath and Shumway, 2008).

The analysis of the model of Merton (1974) shows that the value of the firm follows a process of distribution and the defect occurs when the value of the firm falls below the nominal value of the debt on the date of maturity. In this respect, this model serves to determine a threshold of defect.

Merton's model developed by adding the other variables such as: the interest rate (Longstaff and Schwartz, 1995), the optimal permanent capital (Leland and Toft, 1996), the variable time of the threshold of default (Collin-Dufresne and Goldstein, 2001), the unfinished accounting information (Duffie and Lando, 2001) and the risk of the events of defect (Driessen, 2005).

The structural models are based on the theory of the options and the structure of the capital of the company (Hamisultane, 2008). The bankruptcy of a company took place when the value of assets is situated below the value of its debt. The structural models or the models of the value of the firm are based on the approach of Merton (1974) which supposes that the failure of a company appears in case the market value of its assets is lower than a certain threshold of its debts.

Generally, the models of credit portfolio management resting on the approach of Merton are the model KMV (Kealhofer, McQuown and Vasicek) of Moody and the Credit-Metrics model of JPMorgan (1997). The distinction between both structural models was described in the table 1.

<table>
<thead>
<tr>
<th>The KMV approach</th>
<th>The Credit-Metrics approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ The conduct of the value of the asset.</td>
<td>✓ The indication of own capital.</td>
</tr>
<tr>
<td>✓ Companies are decomposed into systematic components and that no-systematic.</td>
<td>✓ Companies are decomposed systematic components and that no-systematic.</td>
</tr>
<tr>
<td>✓ The systematic risk is based on the industry and the country of debtor.</td>
<td>✓ The systematic risk is based on the industry and the country of debtor and can be sensitive to the size of the asset.</td>
</tr>
<tr>
<td>✓ The correlation of defect ensues from the correlation of assets.</td>
<td>✓ The correlation of the defect ensues from the correlation of the efficiencies on own capital.</td>
</tr>
</tbody>
</table>

Source: Smithson (2003)
The structural models are also called models of the asset volatility. The structural models are rooted in Merton’s knowledge. In Merton's model, the correlation of defect has to be a function of correlation of assets. The estimation of a structural model requires the implementation of the market value of the assets of the company and its volatility.

In practice, the value of assets and their volatility are not observable for the most part of companies. The structural models lean strongly on the existence of assets quoted on the stock exchange so that the necessary parameters can be estimate.

The KMV Model

The KMV model of credit portfolio management was elaborated for the first time in 1993. This model allowed the development of several models of quantification of the credit risk: Credit Monitor, Credit Edge and Private Firm Model for the individual credit risk and Portfolio Manager for the credit risk of a portfolio.

The model KMV rests bases on the notion of default distance which is calculated by basing itself on the barrier which engages the defect. As soon as, the distance in the defect is calculated, it transformed into the probability of failure (Expected Default Frequency: EDF).

The KMV model which was developed by the Moody’s-KMV company is based on the theory of the prices of Merton options. It is about an abstract frame used to estimate the default probability of a company. The KMV model supposes that the company is in situation of defect when the value of its asset is less than the value of its debts. The Figure 1 explains the relation between the estimated own capital and the value of the asset. According to Merton's basic idea, in the KMV model the value of the own capital of the company is considered as being an option to buy. So, the value of the asset is considered as being the underlying asset and the debt represents the price of exercise (Chen et al., 2010).

![Figure 1: The relation between the market value of the assets of the company and the value of the debt (Merton, 1974).](www.SID.ir)
In the Figure 1, \( V_A \) indicates the initial investment of the shareholders of the company; \( X \) indicates the point of default which corresponds to the sum of the long-term debt and half of the current liabilities. When the value of assets \( (V_A) \) is superior to the debt \( (X) \), the shareholders will choose to gain profits staying after payment of the debts \( (V_A - X) \) and these will be chosen by default, what is shaped with a net value raised in the Figure 1. In this case, the investor executes the option to buy.

If the value of assets is lower than the debt \( (V_A < X) \), the shareholders will choose by default the transfer of the active total for the benefit of the creditors, what is coherent with a constant value of own capital indicated in the Figure 1, and it means that the option to buy is not executed (Caouandte et al., 1998; Kealhofer and Bohn, 2001; Saunders and Allen, 2002; Bohn and Croasbie, 2003).

The shareholders receive \( \max (V_A - X, 0) \) in the date of maturity \( T \). According to Merton’s model, the evolution of the market value of the assets of the company follows a process of geometrical distribution of the following shape:

\[
\frac{dV_A}{V_A} = \mu dt + \sigma_A dW_t
\]

Where \( W_t \) the process of Wiener Standard is, \( \mu \) is the average of the efficiency of assets and \( \sigma_A \) is the standard deviation of the efficiency on assets. The market value of the company is given by basing itself on the purchase price of a European option to buy supplies by Black and Scholes (1973):

\[
V_E = V_A N(d_1) - e^{-rT} X N(d_2)
\]

Where \( N(\cdot) \) indicate the function of distribution of the normal law with (Huang and Yu, 2010):

\[
\begin{align*}
 d_1 &= \frac{(\ln \left( \frac{V_A}{X} \right) + (r + \frac{1}{2} \sigma_A^2) T)}{\sigma_A \sqrt{T}} = \frac{1}{\sigma_A \sqrt{T}} \left[ \ln \left( \frac{V_A}{X} \right) + (r + \frac{1}{2} \sigma_A^2) T \right] \\
 d_2 &= \frac{(\ln \left( \frac{V_A}{X} \right) + (r + \frac{1}{2} \sigma_A^2) T)}{\sigma_A \sqrt{T}} = d_1 - \sigma_A \sqrt{T}
\end{align*}
\]

In the KMV model, there is a hypothesis which rests on the structure of the capital of the company. So, this capital has to consist only by actions, current liabilities and in the long term and convertible prices. Really, the value of the company \( V_A \) and the volatility of assets \( \sigma_A \) are not observable (Hull, 1997; Chen et al., 2010). These two values are deducted by using the values of the options \( V_E \).

So it is noted that:

\[
V_E = f(V_A, \sigma_A, X, c, r) \\
\sigma_E = g(V_A, \sigma_A, X, c, r)
\]

Where \( c \) is the coupon paid on the long-term debt, \( r \) is the interest rate without the risk and \( \sigma_E \) is the volatility of share prices.

By applying the Lemma of Itô to these two functions and by arranging the terms we obtain:

\[
\sigma_E = \frac{\frac{V_A}{V_E} \frac{dV_E}{dV_A}}{\sigma_A}
\]

With \( \frac{dV_E}{dV_A} = N(d_1) \) which is deducted from the equation which measures the value of the \( V_E \) which is defined by the following expression:

\[
V_E = V_A N(d_1) - e^{-rT} X N(d_2)
\]

Thus:

\[
\sigma_E = \left( \frac{V_A N(d_1)}{V_E} \right) \sigma_A
\]

Further to this transformation, we obtain a system of equation to two unknowns \( V_A \) and \( \sigma_A \):

\[
\begin{align*}
V_A N(d_1) - e^{-rT} X N(d_2) - V_E &= 0 \\
\sigma_E V_E - V_A N(d_4) \sigma_A &= 0
\end{align*}
\]

If the expressions of \( V_A \) and \( \sigma_A \) are determined, then we can arrive at the writing of the following formulation of the distance of defect (DD):
According to the KMV model the distance of defect is defined in the following way (Crosbie and Bohn, 2003):

\[ DD = \frac{\ln \left( \frac{V_A}{X} \right) + \left( \mu - \frac{1}{2} \sigma^2 \right) T}{\sigma_A \sqrt{T}} \]

From the distance of defect, the value of the default probability is deducted as follows:

\[ P_{KVM} = \text{Prob}(V_A(T) < X) = N \left[ \frac{\ln \left( \frac{V_A}{X} \right) + \left( \mu - \frac{1}{2} \sigma^2 \right) T}{\sigma_A \sqrt{T}} \right] = N(-DD) \]

Then we can obtain the frequency planned by default (Expected Default Frequency: EDF) such as:

\[ EDF = N(-DD) \]

However, the default probability does not correspond to the normal law. KMV Company tries to obtain the empirical value of the EDF rather than the theoretical value of the models (Zheng, 2005). Fortunately, KMV Company possesses an enormous base of historical data concerning the default of the companies. By basing itself on these data KMV defined tables which associate with the various possible values of the distance of default (DD) on a temporal horizon considered a default probability definite and noticed empirically.

To protect itself against the risk which results from potential losses bound to the evolutions of the portfolio, Kealhofer, McQuown and Vasicek (1993) based on the determination of a random size \( L \) relative to the losses of the portfolio which is defined in a general way and on a horizon \( H \) as follows:

\[ L = V_{H_{ND}} - V_H \]

Where \( V_{H_{ND}} \) indicates the value of the portfolio \( H \) in the absence of the losses and \( V_H \) indicates the market value of the portfolio \( H \). The development follows by KMV shows us that the distribution of \( L \) can be approached by an inverse normal distribution.

In the table 2, we resume all forces and weakness relative to the KMV model.

### Table 2: The forces and the weaknesses relative to the KMV model

<table>
<thead>
<tr>
<th>The forces</th>
<th>The weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ The default probability is connected with the information of the market.</td>
<td>✓ A hypothesis which is not realistic because she supposes that the debt of the company consists by bonds with zero-coupon and shares.</td>
</tr>
<tr>
<td>✓ Contrary to CreditMetrics models and CreditRisk+ models the debtors are specific. We can distinguish them by basing itself on their default probability, on their own structure of capital and on their own assets.</td>
<td>✓ KMV supposes that the price of assets follows one moment Geometric Brownian. This modeling by a continuous process excludes all the early defaults.</td>
</tr>
<tr>
<td>✓ The threshold of defect is determined in an empirical way.</td>
<td>✓ This method is difficult because it depend a several data which are in most of the time unobservable or with difficulty accessible.</td>
</tr>
</tbody>
</table>

Source: Hamisultane (2008)
The Credit Metrics Model

Credit-Metrics was thrown for the first time in 1997 by JP Morgan's bank. Credit-Metrics is considered as being an evaluation tool, for a portfolio, its variance of the values provoked by the changes of the quality of credit of the transmitter of the bonds (the credit migration) and leaves the defect of the counterpart. Unlike the approaches developed by the other models of management of a portfolio of credit, the probability of default in Credit-Metrics is given by rating agencies for the big companies and by methods of scoring and mapping for small and medium-sized firms (Paleologo et al., 2010).

Credit-Metrics belongs to the structural models since it rests on the model of Merton (1974) for the definition of the thresholds of the migration of credit (Jarrow, 2011). According to Hamisultane (2008), Credit-Metrics makes it possible to calculate CreditVaR of a portfolio. The methodology of this model is based on the probability of moving of a quality of credit to the other in a given horizon of time (analysis of the migration of credit). The calculation of CreditVaR by Credit-Metrics rests on the following four stages (Crouhy et al., 2000; Hamisultane, 2008):

1. Determination of the risk isolated from each credit of the portfolio.
2. The construction of the matrix of the probabilities of transition from a notation to another.
3. The valuation of the assets of the portfolio according to the scenarios of transition from a notation to the other one.
4. The calculation of CreditVaR.

The evaluation of a portfolio Value-at-Risk due to the credit (CreditVaR) by Credit-Metrics is given the following Figure 2 (Crouhy et al., 2000):

<table>
<thead>
<tr>
<th>Exposure</th>
<th>Value at Risk due to Credit</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Portfolio</td>
<td>Credit Rating</td>
<td>Seniority</td>
</tr>
<tr>
<td>Market volatilities</td>
<td>Rating migration likelihoods</td>
<td>Recovery rate in default</td>
</tr>
<tr>
<td>Exposure distributions</td>
<td>Standard Deviation of value due to credit quality changes for a single exposure</td>
<td>Models (e.g., correlations)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Joint credit rating changes</td>
</tr>
<tr>
<td></td>
<td>Portfolio Value at Risk due to Credit</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2: The evaluation of a portfolio
In the model Credit-Metrics, there are three categories of estimation to be used according to the nature of the composition of the portfolio. We are going to try, in what follows, to present the various principles of the model according to the composition of the portfolio.

A. The Portfolio in an Obligation

According to Hamisultane (2008), the system of rating used by CreditMetrics is the one rating agency. So, the broadcasting issuers of debt securities are noted according to a ladder of seven categories going from AAA to CCC according to the financial solidity of every company (Crouhy et al., 2000). The notation AAA is tuned to the healthy companies financially whereas those who are characterized by a bad financial situation are noted by CCC.

The notations offered by the agencies of rating are regularly published. These notations present information relative to the broadcasting issuers of debt securities. The agencies of rating include these notations in indicating tables, either the rate of historic default of broadcasting issuers according to their notation on a horizon of well determined time, or the evolutions of these notations in the time. These tables recapitulating the notations tuned to the broadcasting issuers of debt securities are defined by "the matrices of transition".

The matrices of annual transition summarize all the changes of notation, on a horizon of time of one year, of a sand of broadcasting issuers is presented in the table 3.

According to Grundke (2009), this table must be carefully analyzed. So, by taking as an example the line corresponding to the BBB rating presented in the table above, we can deduct the probability of default in the table 4.

<table>
<thead>
<tr>
<th>Rating</th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
<th>Default</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>90.81%</td>
<td>8.33%</td>
<td>0.68%</td>
<td>0.06%</td>
<td>0.12%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>AA</td>
<td>0.70%</td>
<td>90.65%</td>
<td>7.79%</td>
<td>0.64%</td>
<td>0.06%</td>
<td>0.14%</td>
<td>0.02%</td>
<td>0.00%</td>
</tr>
<tr>
<td>A</td>
<td>0.09%</td>
<td>2.27%</td>
<td>91.05%</td>
<td>5.52%</td>
<td>0.74%</td>
<td>0.26%</td>
<td>0.01%</td>
<td>0.06%</td>
</tr>
<tr>
<td>BBB</td>
<td>0.02%</td>
<td>0.33%</td>
<td>5.95%</td>
<td>86.93%</td>
<td>5.30%</td>
<td>1.17%</td>
<td>0.12%</td>
<td>0.18%</td>
</tr>
<tr>
<td>BB</td>
<td>0.02%</td>
<td>0.14%</td>
<td>0.67%</td>
<td>7.73%</td>
<td>80.53%</td>
<td>8.84%</td>
<td>1.00%</td>
<td>1.06%</td>
</tr>
<tr>
<td>B</td>
<td>0.00%</td>
<td>0.11%</td>
<td>0.24%</td>
<td>0.43%</td>
<td>6.48%</td>
<td>83.46%</td>
<td>4.08%</td>
<td>5.20%</td>
</tr>
<tr>
<td>CCC</td>
<td>0.22%</td>
<td>0.00%</td>
<td>0.22%</td>
<td>1.30%</td>
<td>2.38%</td>
<td>5.00%</td>
<td>64.85%</td>
<td>19.79%</td>
</tr>
<tr>
<td>Default</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Source: Standard & Poor’s CreditWeek (1996)

<table>
<thead>
<tr>
<th>Initial rating</th>
<th>Potential rating in a one year</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>BBB</td>
<td>AAA</td>
<td>0.02%</td>
</tr>
<tr>
<td></td>
<td>AA</td>
<td>0.33%</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>5.95%</td>
</tr>
<tr>
<td></td>
<td>BBB</td>
<td>86.93%</td>
</tr>
<tr>
<td></td>
<td>BB</td>
<td>5.30%</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>1.17%</td>
</tr>
<tr>
<td></td>
<td>CCC</td>
<td>0.12%</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>0.18%</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Source: Grundke (2009)
After a period of one year, and settling on the asset of initial notation BBB, we can deduct that the probability that this active rest BBB after a period of one year is 86.93%, that to become AAA is 0.02% and that to be lacking is 0.18%.

The use of this model is based on three main hypotheses (JP Morgan and Co. Inc, 1997; Glasserman and Li, 2005; Hamisultane, 2008; Grundke, 2009; Figlewski et al., 2012):

- The absence of multiple transitions: for a horizon of time given the number of transitions is in most of a single transition.
- The stability of the matrix of transition in time: for every class of notation, two companies in different sectors or in different countries have the same probability to migrate from a notation to the other one.
- The matrix of transition is of type Markov: for period given the probability to migrate of a class of notation in another class is independent from what took place for the last periods. These hypotheses are emitted for the simplification of the calculations of the matrix of transition for the posterior periods.

Credit-Metrics determines the current value of the bond by using the curve of the rates with zero coupons to proceed with the calculations of CreditVaR. In that case, the transmitter of debt securities is not in situation of bankruptcy. By continuing in the same context of analysis that is the use of the notation BBB as the example, the following table of the Forward rates can be used:

It is supposed in this case which a noted transmitter BBB has emitted a Bond for 100 Euro over 4 years with a rate without annual risk of 6%. The current value of the bond is given by the equation below:

\[
V = 6 + \frac{6}{(1 + 4.1\%)} + \frac{6}{(1 + 4.67\%)^2} + \frac{6}{(1 + 5.25\%)^3} + \frac{106}{(1 + 5.63\%)^4} = 107.55
\]

By basing itself on the formula above, being able to us determine the various possible values of fire of type BBB according to his possible migrations towards other notations (Crouhy et al., 2000; Hamisultane, 2008). The possible values of a bond rated BBB according to the possible migrations are presented in the table 5.

In case the company had a bankruptcy, the value of the bond is determined by using the average recovery ratio calculated by CreditMetrics on historical data (Carty and Lieberman, 1996; Gordy, 1998).

Further to the representative table of the various values of BBB according to the possible migrations, the subtraction the distribution of the variations of the price of the obligation is given in the table 6.

The analysis of this table shows that CreditVaR in 1% (at a level of 99% confidence) is equal to the last value of the variation of the value of the bond which corresponds to the notation CCC. Thus, CreditVaR is equal to -23.91.

### Table 5: One-year forward zero-curves for each credit rating (%)

<table>
<thead>
<tr>
<th>Category</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
<th>Year 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>3.60</td>
<td>4.17</td>
<td>4.73</td>
<td>5.12</td>
</tr>
<tr>
<td>AA</td>
<td>3.65</td>
<td>4.22</td>
<td>4.78</td>
<td>5.17</td>
</tr>
<tr>
<td>A</td>
<td>3.72</td>
<td>4.32</td>
<td>4.93</td>
<td>5.32</td>
</tr>
<tr>
<td>BBB</td>
<td><strong>4.10</strong></td>
<td><strong>4.67</strong></td>
<td><strong>5.25</strong></td>
<td><strong>5.63</strong></td>
</tr>
<tr>
<td>BB</td>
<td>5.55</td>
<td>6.02</td>
<td>6.78</td>
<td>7.27</td>
</tr>
<tr>
<td>B</td>
<td>6.05</td>
<td>7.02</td>
<td>8.03</td>
<td>8.52</td>
</tr>
<tr>
<td>CCC</td>
<td>15.5</td>
<td>15.02</td>
<td>14.03</td>
<td>13.52</td>
</tr>
</tbody>
</table>

Source: CreditMetrics, JP Morgan
Table 6: Distribution of the bond values, and changes in value of a BBB bond, in 1 year

<table>
<thead>
<tr>
<th>Rating</th>
<th>Probability: p (%)</th>
<th>Price of the obligation (bond) V ($</th>
<th>Difference with regard to V: ∆V</th>
<th>Difference with regard to the average μ</th>
<th>μ² * p (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>0.02</td>
<td>109.37</td>
<td>1.82</td>
<td>2.28</td>
<td>0.0010</td>
</tr>
<tr>
<td>AA</td>
<td>0.33</td>
<td>109.19</td>
<td>1.64</td>
<td>2.10</td>
<td>0.0146</td>
</tr>
<tr>
<td>A</td>
<td>5.95</td>
<td>108.66</td>
<td>1.11</td>
<td>1.57</td>
<td>0.1474</td>
</tr>
<tr>
<td>BBB</td>
<td>86.93</td>
<td>107.55</td>
<td>0</td>
<td>0.46</td>
<td>0.1853</td>
</tr>
<tr>
<td>BB</td>
<td>5.30</td>
<td>102.02</td>
<td>-5.53</td>
<td>-5.06</td>
<td>1.3592</td>
</tr>
<tr>
<td>B</td>
<td>1.17</td>
<td>98.10</td>
<td>9.45</td>
<td>-8.99</td>
<td>0.9446</td>
</tr>
<tr>
<td>C</td>
<td>0.12</td>
<td>83.64</td>
<td>-23.91</td>
<td>-23.45</td>
<td>0.6598</td>
</tr>
<tr>
<td>Default</td>
<td>0.18</td>
<td>51.13</td>
<td>-56.42</td>
<td>-55.96</td>
<td>5.6358</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>107.09 ($)</td>
<td><strong>Variance</strong> = 8.9477</td>
<td><strong>Standard deviation</strong> = 2.99 ($)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: CreditMetrics, JP Morgan

B. The portfolio in Two Obligations

In the case of a portfolio consisted of two bonds, the analysis is based on the level of correlation of the migrations. In fact, in a portfolio consisted of several assets the migrations of the various credits are correlated. Credit-Metrics tries to estimate these correlations. If there are no good data to be used, Credit-Metrics used the correlations between the values of the assets of the broadcasting issuers of the credits which are approached by the correlations between the equity prices of these broadcasting issuers to calculate the correlations between the migrations of the credits (Treacy and Carey, 2000; Altman and Rijken, 2004; Gordy and Howells, 2006; Xing et al., 2012).

According to Iscoe et al. (1999), to be able to divert the correlations of the migrations of the credits of the correlations of the values of assets, it is necessary to have a model linking the quality of a credit to the value of assets. The solution proposed by Credit-Metrics is to use an extension of the model of Merton (1974) which incorporates the migrations of the credits. In this aligned, we suggest taking into account the probability of migration of a bond rated initially by BB. These probabilities are given by the table 7.

By basing itself on the model of Merton (1974), we can suppose that the efficiency on a bond modeled as follows:

\[ r = \mu + \sigma \varepsilon \]

With, \( \varepsilon \) a term of error is such as \( \varepsilon \sim N(0,1) \), \( \mu \) is the average efficiency on the bond and \( \sigma \) is the standard deviation of the efficiencies of this bond. Then, the default probability of an issuer of the bond is given by the following expression:

\[ \text{Pr } \{ \text{default} \} = \text{pr } \{ r < Z_{\text{def}} \} = \text{pr } \{ \mu + \sigma \varepsilon < Z_{\text{def}} \} \]

Thus,

\[ \text{Pr } \{ \text{default} \} = \text{pr } \{ r < Z_{\text{def}} \} = \text{pr } \{ \sigma \varepsilon < Z_{\text{def}} \} \]

If \( \mu = 0 \)

\[ \text{pr } \{ \text{default} \} = \left( \varepsilon < \frac{Z_{\text{def}}}{\sigma} \right) = \Phi \left( \frac{Z_{\text{def}}}{\sigma} \right) \]

Where \( \Phi \) indicates the cumulative function of the normal law.

By using the table 8, we can establish the table according to who summarizes the distribution of the probability of migration affected in conformance with BB rating.

With, \( 1 - \Phi \left( \frac{Z_{\text{AA}}}{\sigma} \right) \) represent the probability so that the bond of BB rating can pass in the notation AAA and \( Z_{\text{AA}} \) indicates the threshold from which BB passes to AAA.

The transformation graphic of the data above is presented in the figure 3.
Table 7: Transition matrix based on actual rating changes

<table>
<thead>
<tr>
<th>Initial Rating</th>
<th>Rating at year-end (%)</th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
<th>Default</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>90.81</td>
<td>8.33</td>
<td>0.68</td>
<td>0.06</td>
<td>0.12</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AA</td>
<td>0.70</td>
<td>90.65</td>
<td>7.79</td>
<td>0.64</td>
<td>0.06</td>
<td>0.14</td>
<td>0.02</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>A</td>
<td>0.09</td>
<td>2.27</td>
<td>91.05</td>
<td>5.52</td>
<td>0.74</td>
<td>0.26</td>
<td>0.01</td>
<td>0.06</td>
<td>0</td>
</tr>
<tr>
<td>BBB</td>
<td>0.02</td>
<td>0.33</td>
<td>5.95</td>
<td>86.93</td>
<td>5.30</td>
<td>1.17</td>
<td>0.12</td>
<td>0.18</td>
<td>0</td>
</tr>
<tr>
<td>BB</td>
<td>0.03</td>
<td>0.14</td>
<td>0.67</td>
<td>7.73</td>
<td>80.53</td>
<td>8.84</td>
<td>1.00</td>
<td>1.06</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>0.11</td>
<td>0.24</td>
<td>0.43</td>
<td>6.48</td>
<td>83.46</td>
<td>4.07</td>
<td>5.20</td>
<td>0</td>
</tr>
<tr>
<td>CCC</td>
<td>0.22</td>
<td>0</td>
<td>0.22</td>
<td>1.30</td>
<td>2.38</td>
<td>11.24</td>
<td>64.86</td>
<td>19.79</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: Standard & Poor’s CreditWeek (1996)

Table 8: The distribution of the probability of migration of BB rating

<table>
<thead>
<tr>
<th>Rating</th>
<th>Probability from the transition matrix (%)</th>
<th>Probability according to the asset value model</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>0.03</td>
<td>$1 - \Phi(Z_{AA}/\sigma)$</td>
</tr>
<tr>
<td>AA</td>
<td>0.14</td>
<td>$\Phi(Z_{AA}/\sigma) - \Phi(Z_{A}/\sigma)$</td>
</tr>
<tr>
<td>A</td>
<td>0.67</td>
<td>$\Phi(Z_{A}/\sigma) - \Phi(Z_{BBB}/\sigma)$</td>
</tr>
<tr>
<td>BBB</td>
<td>7.73</td>
<td>$\Phi(Z_{BBB}/\sigma) - \Phi(Z_{BB}/\sigma)$</td>
</tr>
<tr>
<td>BB</td>
<td>80.53</td>
<td>$\Phi(Z_{BB}/\sigma) - \Phi(Z_{B}/\sigma)$</td>
</tr>
<tr>
<td>B</td>
<td>8.84</td>
<td>$\Phi(Z_{B}/\sigma) - \Phi(Z_{CCC}/\sigma)$</td>
</tr>
<tr>
<td>CCC</td>
<td>1.00</td>
<td>$\Phi(Z_{CCC}/\sigma) - \Phi(Z_{Def}/\sigma)$</td>
</tr>
<tr>
<td>Default</td>
<td>1.06</td>
<td>$\Phi(Z_{Def}/\sigma)$</td>
</tr>
</tbody>
</table>

Source: Crouhy and al. (2000)

Figure 3: Generalization of the Merton model to include rating changes (Crouhy and al., 2000)
Thus:
\[ Z_{\text{def}} = \Phi^{-1}(1.06\%), \sigma = 2.30\sigma \]

The values of the other thresholds are calculated according to whom corresponds itself aside type of the normal distribution of the random on the assets of the notation BB (Gupton et al., 1997; Crouhy et al., 2000; Nickell et al., 2000; Bangia et al., 2002; Albanese and Chen, 2003; Albanese et al., 2003; Rosch, 2005; Feng et al., 2008).

It is supposed now that a second issuer presents a rating A where the random on assets follow a normal distribution with a parameter \( \sigma' \). In that case, the values of thresholds relative for two bands who rated BB and A are presented in the table 9.

By taking into account the table above, we can calculate the probability of migration joined in the following way:

\[
P(Z_{\text{BB} < Z < Z_{\text{AA}}}) = \int_{Z_{\text{BB}}}^{Z_{\text{AA}}} \int_{Z_{\text{A}}}^{Z_{\text{BB}}} f(r, r', \sigma, \sigma')drdr' 
\]

With \( r \) and \( r' \) indicate respectively the random on the assets who are rated by BB and A and \( f(r, r', \sigma, \sigma') \) represent the joint density function by the Gaussian distribution which depends on the coefficient of correlation \( \rho \).

The joint density function of the Gaussian distribution of two variables \( X \) and \( Y \) is presented by the form below:

\[
f(x, y) = \frac{1}{2\pi \sigma_x \sigma_y \sqrt{1-\rho^2}} \exp \left( -\frac{1}{2(1-\rho^2)} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} - \frac{2\rho xy}{\sigma_x \sigma_y} \right) \right) 
\]

According to Hamisulfane (2008), for \( \rho = 20\% \) the matrix of joint transition which considers the correlation banding both entities BB and A who is presented in the table 10.

The last column of the table and the last line of this one represent the marginal probability for the entities BB and A which are equal to the sum of the joint probability by line or by the column. According to Crouhy and al. (2000) these marginal probabilities correspond to the probability of migration of BB and of A taken individually. The variation of the portfolio of both bands is calculated for each of the joint probability (Brady and Bos, 2002; Brady and al., 2003).

Table 9: Transition probabilities and credit quality thresholds for BB and A rated obligors

<table>
<thead>
<tr>
<th>Rating in 1 year</th>
<th>Rated-A obligor Probabilities (%)</th>
<th>Thresholds: ( Z_{(p)} )</th>
<th>Rated-BB obligor Probabilities (%)</th>
<th>Thresholds : ( Z_{(p)} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>0.09</td>
<td>3.12</td>
<td>0.03</td>
<td>3.43</td>
</tr>
<tr>
<td>AA</td>
<td>2.27</td>
<td>1.98</td>
<td>0.14</td>
<td>2.93</td>
</tr>
<tr>
<td>A</td>
<td>91.05</td>
<td>-1.51</td>
<td>0.67</td>
<td>2.39</td>
</tr>
<tr>
<td>BBB</td>
<td>5.52</td>
<td>-2.30</td>
<td>7.73</td>
<td>1.37</td>
</tr>
<tr>
<td>BB</td>
<td>0.74</td>
<td>-2.72</td>
<td>80.53</td>
<td>-1.23</td>
</tr>
<tr>
<td>B</td>
<td>0.26</td>
<td>-3.19</td>
<td>8.84</td>
<td>-2.04</td>
</tr>
<tr>
<td>CCC</td>
<td>0.01</td>
<td>-3.24</td>
<td>1.00</td>
<td>-2.30</td>
</tr>
<tr>
<td>Default</td>
<td>0.06</td>
<td></td>
<td>1.06</td>
<td></td>
</tr>
</tbody>
</table>

Source: Crouhy and al. (2000)
Table 10: Joint rating probabilities (%) for BB and A rated obligors when correlation banding asset random is 20%

<table>
<thead>
<tr>
<th>Rating of first company (BB)</th>
<th>Rating of second company (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AAA</td>
</tr>
<tr>
<td>AAA</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.00</td>
</tr>
<tr>
<td>BBB</td>
<td>0.02</td>
</tr>
<tr>
<td>BB</td>
<td>0.07</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
</tr>
<tr>
<td>Default</td>
<td>0.00</td>
</tr>
<tr>
<td>Total</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Source: CreditMetrics, JP Morgan (Lucas, 1995)

C. The Portfolio in Several Obligations

In case the portfolio consists further more than 2 bands calculates its joint probability will be more complicated. So, model Credit-Metrics propose the use of the simulations of Monte Carlo and the decomposition of Cholesky to generate trajectories correlated to the bond and build the distribution of the values of the portfolio on certain horizon of time (Gouriéroux and Monfort, 1995; Fishmen, 1997; Crouhy et al., 2000; Hamilton et al., 2002).

According to Hamisultane (2008) and Feng et al. (2008), to generate trajectories correlated to the variables which follow a normal distribution $N(\mu, \Sigma)$. The determination of these trajectories requires the respect for the following five stages:

**Stage 1:** The regression of the random $r_t$ of the band on the sectorial indications, for example, in the case of three bands and two sectorial indications.

$r_{1,t} = \alpha_1 + \alpha_{1, X} I_{1,t} + \alpha_{1, Y} I_{Y,t} + \nu_{1,t}$

$r_{2,t} = \alpha_2 + \alpha_{2, X} I_{1,t} + \alpha_{2, Y} I_{Y,t} + \nu_{2,t}$

$r_{3,t} = \alpha_3 + \alpha_{3, X} I_{1,t} + \alpha_{3, Y} I_{Y,t} + \nu_{3,t}$

In the second stage it is necessary to estimate the various parameters of three models.

**Stage 2:** The calculation of the variances and the covariance’s banding 2 bands i and j:

$\text{cov}(r_i, r_j) = \hat{\alpha}_{i,X} \hat{\alpha}_{j,X} V(I_X) + \hat{\alpha}_{i,Y} \hat{\alpha}_{j,Y} V(I_Y) + (\hat{\alpha}_{i,X} \hat{\alpha}_{j,Y} + \hat{\alpha}_{i,Y} \hat{\alpha}_{j,X}) \text{cov}(I_X, I_Y)$

And

$V(r_i) = \hat{\alpha}_{i,X}^2 V(I_X) + \hat{\alpha}_{i,Y}^2 V(I_Y)$

By using these two formulae, we can obtain the matrix of the variances-covariance’s $\Sigma$.

**Stage 3:** The decomposition of Cholesky of the matrix of the variances of the variances-covariance’s $\Sigma$ in the following way (Hamisultane, 2008):

$\Sigma = AA^T$

With A represent the lower triangular matrix and $A^T$ transposed by the matrix A.

**Stage 4:** The simulation of variables

$Z_{i,t} \sim N(0,1)$

In fact, the existence of the bond to be feigned allows the existence of $Z_{i,t}$. 

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Stage 5: The simulation of the values of the correlated variables \( V \sim N(\mu, \Sigma) \) by basing itself on a process of geometrical distribution:

\[
\frac{dV}{V} = \mu dt + a\sqrt{dt} Z
\]

Thus:

\[
\frac{dV}{V} = \begin{pmatrix}
\frac{dV^1_i}{V^1_i} \\
\frac{dV^2_i}{V^2_i} \\
\vdots \\
\frac{dV^n_i}{V^n_i}
\end{pmatrix}
\approx \begin{pmatrix}
\ln V^1_i - \ln V^1_{i-1} \\
\ln V^2_i - \ln V^2_{i-1} \\
\vdots \\
\ln V^n_i - \ln V^n_{i-1}
\end{pmatrix}
\]

\[
\mu = \begin{pmatrix}
\mu_1 \\
\mu_2 \\
\vdots \\
\mu_n
\end{pmatrix}
\]

\[
dt = \Delta t
\]

\[
A = \begin{pmatrix}
\beta_{11} & 0 & \cdots & 0 \\
\beta_{21} & \ddots & \ddots & \vdots \\
\vdots & \ddots & \ddots & 0 \\
\beta_{n1} & \cdots & \beta_n & 0
\end{pmatrix}
\]

\[
\sqrt{dt} Z \approx \sqrt{\Delta t} \begin{pmatrix}
Z^1_{1,1} \\
Z^2_{1,1} \\
\vdots \\
Z^n_{1,1}
\end{pmatrix}
\]

According to Crouhy et al. (2000), Nickell et al. (2000) and Bangia et al. (2002), the forces and the weaknesses of this model are presented in the table 11.

The Econometric Models (Credit Portfolio View of Mackinsey)

Credit Portfolio View is a model with multiple factors which is used to feign the common conditional distribution of the default probability and migration for various groups of estimation and in different industries (Crouhy et al., 2000). This model was developed by Wilson (1997) within McKinsey. The approach developed by this author bases itself on the hypothesis that the probability of defect and migration are connected to macroeconomic factors such as the level of the long-term interest rate, the growth rate of the GDP, the global unemployment rate, the exchange rates, the public spending, the savings.

Credit Portfolio View is based on the occasional observation which supposes that the default probability, as well as the probability of migration, is connected to economic cycles. When the economy is in situation of recession, then the cycles of credit are also lesser. If it is the opposite case (the economy is in situation of expansion) then the cycles of credit become stronger. In other words, the cycles of credit follow the tendency of economic cycles. Because the state of the economy is widely driven by macroeconomic factors, Credit Portfolio View proposes a methodology to connect these macroeconomic factors to the probability of default and migration.

Provided that the data are available, this methodology can be applied in every country, in the different sectors and in the diverse classes of borrowers of the obligors who react differently within the economic cycle.

The way that a model Credit Portfolio View works is as follows (Smithson, 2003):

\( \checkmark \) Simulate the state of the economy.

\( \checkmark \) Adjust the rate of default to the state of the simulation of the economy.

\( \checkmark \) Attribute a probability of default for every debtor on the basis of the simulations of the state of the economy.

\( \checkmark \) The value of the individual transactions attributed to the debtors according to the probability of defect is determined on the basis of the simulations of the state of the economy.

\( \checkmark \) Calculate the loss of the portfolio by adding the results for all the transactions.

\( \checkmark \) Repeat all the stages quoted above certain number of times to map finally the distribution of the losses.

In the model Credit Portfolio View of McKinsey, the historic rates of default for the various industries are described according to the macroeconomic variables specified by the user of the model:

\[
\text{Probability of default } = f(\text{GDP, Unemployment Rate, } \ldots, \text{Exchange Rate})
\]
In the approach McKinsey, the rates of defect are commanded by a sensibility in a sand of the factors of the systematic risk, or the specific factors to the company. The table 12 summarizes the main characteristics of the model of McKinsey (Smithson, 2003).

Table 11: The forces and the weaknesses relative to the CreditMetrics model

<table>
<thead>
<tr>
<th>The forces</th>
<th>The weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ In the model CreditMetrics, both aspects of the credit risk are taken into account.</td>
<td>✓ The rating according to companies must be correct.</td>
</tr>
<tr>
<td>✓ The rating according to companies must be correct.</td>
<td>✓ The interest rates are supposed constant.</td>
</tr>
<tr>
<td>✓ The interest rates are supposed constant.</td>
<td>✓ The existence of a relation between the economic situation and the probability of defect. In that case, every economic cycle has to have matrices of transition appropriate for him.</td>
</tr>
<tr>
<td>✓ The existence of a relation between the economic situation and the probability of defect. In that case, every economic cycle has to have matrices of transition appropriate for him.</td>
<td>✓ The variability of the actions of a company can be used to deduct the variability of the price of the assets of the company.</td>
</tr>
</tbody>
</table>

Source: Crouhy and al. (2000), Nickell and al. (2000) and Bangia and al. (2002)

Table 12: The main characteristics of the model Credit Portfolio View

<table>
<thead>
<tr>
<th>Unit of analysis</th>
<th>Segmentation towards industries and on countries.</th>
</tr>
</thead>
<tbody>
<tr>
<td>The data by default</td>
<td>Empirical estimation of the rates of default according to the macroeconomic variables. (For example: the GDP, the unemployment rate)</td>
</tr>
<tr>
<td>The structure of correlation</td>
<td>Obtained from the correlations banding the chosen macroeconomic variables and the estimated factors of sensibility.</td>
</tr>
<tr>
<td>The engine of the risk</td>
<td>The adjustment of the ARMA model (Autoregressive Moving Average model) with the evolution of the macroeconomic factors. The shocks undergone by the system determine the standard deviation of the average of the rates of defect concerning the level of the segment.</td>
</tr>
<tr>
<td>The distribution of the rates of defect</td>
<td>Logistic (Normal distribution).</td>
</tr>
<tr>
<td>The horizon</td>
<td>The maturity of the marginal default rate year by year.</td>
</tr>
</tbody>
</table>

Source: Smithson (2003)

The Forecast of the Default Rate

In the Credit Portfolio View model, the probabilities of default are modeled as being a Logit function. In this modeling the independent variable is a specific speculative index in every country and which depends on macroeconomic variables. The Logit function allows that the values of probability of default are included between 0 and 1 (Crouhy et al., 2000; Hamisultane, 2008).

\[ P_{jt} = \frac{1}{1 + e^{-\gamma_{jt}}} \]

\[ Y_{jt} = \beta_{j,0} + \beta_{j,1}X_{jt,1} + \beta_{j,2}X_{jt,2} + ... + \beta_{j,m}X_{jt,m} + \epsilon_{jt} \]

And \( \epsilon_{jt} \sim N(0, \sigma_{\epsilon_{jt}}^2) \)

Where \( P_{jt} \) indicate the conditional probability of default for period t for the debtors of the industry j and \( Y_{jt} \) represent an indication stemming from a model in m factors. \( \beta_{j,0}, \beta_{j,1}, ..., \beta_{j,m} \) are coefficients to be estimated by the
method the Ordinary Last Squares (OLS). \( X_{j,t} \), \( X_{j,2,t}, \ldots, X_{j,m,t} \) are values of economic variables in the date \( t \) of the industry or the country \( j \). \( e_{j,t} \) represent a term of error which is normally distributed and independent of \( Y_{j,t} \).

The model of McKinsey so land us land us note, as it is a model of macro-factors \( X_{j,t} \) who are represented by variable macroeconomic who follow a Autoregressive model of order 2 (AR2):

\[
X_{ji,t} = Y_{j,i,0} + Y_{j,i,1}X_{j,i,t-1} + Y_{j,i,2}X_{j,i,t-2} + \omega_{j,t}
\]

And \( \omega_{j,t} \sim N(0, \sigma^2_{\omega,j}) \)

Where: \( Y_{j,i,0}, Y_{j,i,1}, \) and \( Y_{j,i,2} \) are a coefficients to be estimated and \( \omega_{j,t} \) is a term of error which is normally distributed and independent of \( X_{j,i,t} \).

In this frame, our objective is to resolve the system below:

\[
P_{j,t} = \frac{1}{1 + e^{\theta_{j,t}}} \\
Y_{j,t} = \beta_{j,0} + \beta_{j,1}X_{j,t} + \beta_{j,2}X_{j,t-1} + \cdots + \beta_{j,m}X_{j,m,t} + \varepsilon_{j,t}
\]

\[
X_{j,t} = Y_{j,i,0} + Y_{j,i,1}X_{j,i,t-1} + Y_{j,i,2}X_{j,i,t-2} + \omega_{j,t}
\]

Where \( E_t \) is the vector of the innovations such as:

\[
E_t = \begin{bmatrix} \varepsilon_t \\ \omega_{j,t} \end{bmatrix} \sim N(0, \Sigma)
\]

And

\[
\Sigma = \begin{bmatrix} \Sigma_e & \Sigma_{e,\omega} \\ \Sigma_{\omega,e} & \Sigma_{\omega} \end{bmatrix}
\]

With \( \Sigma_{e,\omega} \) and \( \Sigma_{\omega,e} \) Represent the matrices of correlation.

In case the parameters are estimated, then it is possible to feign the probability of default by basing itself on historical data. Credit Portfolio View uses tired matrices of transition of economic cycles.

The Conditional Matrices of Transition

By basing itself on the matrices of transition in the economic cycles which are proposed by the Credit Portfolio View, we can determine the situation of the economy (Crouhy et al., 2000). It needs to be noted that the matrices of transition in the Credit Portfolio View are different to those of the matrices of migration in the Credit-Metrics in this respect (Hamisultane, 2008).

Credit Portfolio View proposes a tool based on the following ratio: \( \frac{P_{j,t}}{\varphi SDP} \)

Where \( P_{j,t} \) represent the probability of default feigned for date \( t \) and for the sector \( j \) and \( \varphi SDP \) represent the historic default probability which is based on observed data.

If \( \frac{P_{j,t}}{\varphi SDP} > 1 \) then the economy is in period of recession and if \( \frac{P_{j,t}}{\varphi SDP} < 1 \) then the economy is in period of expansion.

Credit Portfolio View suggests employing this ratio to adjust the probability of migration. So, the matrix of transition multi-period is given by the following formula:

\[
M = \prod_{t=1}^{T} M(\frac{P_{j,t}}{\varphi SDP})
\]

Where \( M(.) \) can take two different values.

So, \( M(.) = M_L \) if \( \frac{P_{j,t}}{\varphi SDP} > 1 \) and \( M(.) = M_H \) if \( \frac{P_{j,t}}{\varphi SDP} < 1 \)

With \( M_L \) indicate the matrix of transition in the case of a period of recession and \( M_H \) indicates the matrix of transition in the case of a period of expansion.

We can simulate a lot of time the matrix of transition to determine the probability of default for any estimation and for any period. The methodology of Monte Carlo Simulation can be used to determine the distribution of the default probability for any period.

The forces and the weaknesses relative to the Credit Portfolio View model are presented in the table 13.
Table 13: The forces and the weaknesses relative to the Credit Portfolio View model

<table>
<thead>
<tr>
<th>The forces</th>
<th>The weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>✓ Credit portfolio View connects the probability of default and the matrices of transition with economic indicators. In other words, the probability of default is stronger in period of recession than in period of expansion.</td>
<td>✓ In the Credit Portfolio View model, we use macroeconomic data which cannot be available for a country or a business sector.</td>
</tr>
<tr>
<td>✓ This model determines only the probability of default of a country or a business sector and not an issuer.</td>
<td></td>
</tr>
</tbody>
</table>

Source: Hamisultane (2008)

The Model Csfp: Credit Risk+ Market Risk

Since 1990s, Credit Suisse First Boston (CSFB) has developed new methods of risk management. In 1993, the credit Swiss Group launched, in parallel of an important project which aims at modernizing its credit risk management and by using the expertise of CSFB, new one management tool of the credit portfolio in the future. In December, 1996, Credit Suisse Group presented the CreditRisk+ model as being a model of the credit portfolio management.

The structural models present an inconvenience concerning the default. These models suppose that the default cannot have arisen by surprise because the market value of assets is supposed to follow a continuous process of distribution. In this aligned, a process of Fish was used in the actuarial models the purpose of which is to model the unpredictable character of the emergence of the default what is developed in the model CreditRisk+.

CreditRisk+ is a model with intensity is which presents no hypothesis on the causes of failure of a company. It is model statistical of the default of credit risk which makes no claim about the causes of the default. This approach is similar to that of the management of the market risk, in which no attempt is made model the causes of the movements of market prices. This model does not consider the consequences of a deterioration of the quality of the quality of the counterparty.

The number of failures in a credit portfolio during the given period justifies itself by a process of Fish. CreditRisk+ uses a methodology based on techniques and quantitative methods.

The present model is based on an actuarial calculation to determine and present the distribution of the losses of a credit portfolio.

CreditRisk+ presents four hypotheses:

- ✓ Every individual credit presents only two possible states: failures or no failures.
- ✓ The default probability of an individual credit is low.
- ✓ The default probability for a big group of borrowers is very low.
- ✓ The number of default over a period is independent from that of any other period.

Based on these hypotheses, the probability distribution of the number $X$ of defaults over a given period (one month or one year for example) can be represented by using the law of Fish of average $\mu$ and of standard deviation $\sqrt{\mu}$:

$$\Pr(X = n) = \frac{\mu^n e^{-\mu}}{n!}$$

Where $\mu$ is the average of the number of default a year.

$$\mu = \sum P_A$$

With $P_A$ indicate the default probability of the obligor $A$.

The annual number of the defaults, $n$, is a stochastic variable of average $\mu$ and a standard deviation $\sqrt{\mu}$. According to CreditRisk+, the calculation of the distribution of the losses requires the use of an approach by bonds; that is issued in a portfolio are grouped and collected by edge of exposure.
The process of determination of the distribution of the losses of a portfolio is constituted by three stages:

1. The determination of the generative function of probability for every bond.
2. The diversion of the generative function of probability for the whole portfolio.
3. The determination of the distribution of the losses for the whole portfolio.

The distribution of the losses of default for a portfolio is diverted in two stages as the watch represents in the figure 4.

It was supposed that the distribution of fish allows moving closer to the distribution of the number of the events of defect. Then we should expect that the standard deviation of the default rate is approximately equal to the square root of the average.

In case of defect of an obligor, the counterparty incurs a loss equal to the quantity possessed by the obligor less a quantity of restoring. In CreditRisk+ the exposure for every obligor is adjusted by the rate planned by restoring, to calculate the loss of default. These adjusted exposures are exogenous in the model, and are independent of the market risk and minimize the risk.

To divert the distribution of loss for a diversified portfolio, the losses are divided into bands with the level of the exposure in every band.

To analyze the distribution of the resultant losses of the whole portfolio, presenting us the default probability expressed by the function defined in terms of variables auxiliary $z$ by respecting itself the following approach of the formulation of the generative function:

We considered $X$ a whole and positive random variable. The generative function of $X$ is the whole series:

$$ G(z) = \sum_{k=0}^{\infty} p(X = k)z^k $$

Where $P(X=k)$ is the probability that the random variable $X$ takes the value $k$. To obtain $P(X=k)$ from the generative function $G(z)$, we use the following formula:

$$ P(X = k) = \frac{1}{k!} \frac{d^kG}{dz^k}(0) $$

In that case, the generative function associated among default $X$ arisen among all the bonds of a portfolio is given by the expression below:

$$ F(z) = \sum_{n=0}^{\infty} \frac{\mu^n e^{-\mu}}{n!} z^n = \exp(\mu(z - 1)) $$

This function can be written as follows:

$$ F(z) = \prod_{A} F_A(Z) $$

Where $F_A(z)$ indicate the generative function of a portfolio constituted by a single bond of the issuer $A$.

Every portfolio consists of $m$ identical bond of exposure of indications $j$ ($j = 1, 2, m$). Every bond is characterized by:

$$ \epsilon_j = \mu_j \theta_j $$

Thus implies that: $\mu_j = \frac{\epsilon_j}{\theta_j}$

With, $\epsilon_j$ indicate the expected average loss expressed in multiple of a standard exposure $L$, $\mu_j$ indicate the expected number of defaults which is a known value and $\theta_j$ indicate the exposure expressed in multiple of $L$ in the band $j$.

In that case, the inputs of the model to be developed are: the individual exposure $L$ and the probability of default $P_A$ for the issuer (debtor) $A$. Then, the loss hoped for the debtor $A$ is expressed as follows:

$$ \lambda_A = L_A * P_A $$

$$ \epsilon_A = \frac{\lambda_A}{L} $$

The expression above is obtained when the expected loss is expressed in units of $L$. So, the expected loss $\epsilon_j$ for the bond $j$ is given then as follows:

$$ \epsilon_j = \sum \epsilon_A $$
In this perspective, the expected number of defects $\mu_j$ for each of the indicated bond $j$ is then given by:

$$\mu_j = \frac{\epsilon_j}{\overline{\theta}_j} = \sum_{\overline{\theta}_j=\theta_j} \frac{\epsilon_A}{\overline{\theta}_A}$$

Thus, the number of waited defects total $\mu$ for them $m$ bond is expressed as follows:

$$\mu = \sum_{j=1}^{m} \mu_j = \sum_{j=1}^{m} \frac{\epsilon_j}{\overline{\theta}_j}$$

The expression of the generative function of the included losses is obtained by:

$$G(z) = \sum_{n=0}^{\infty} P(Aggregate losses = n \times L)z^n$$

Then, if we put:

$$G(z) = \exp \left( -\sum_{j=1}^{m} \mu_j + \sum_{j=1}^{m} \mu_j z^{\overline{\theta_j}} \right)$$

Then, the generative function of the included losses can be written in the following way:

$$G(z) = \exp \left( \mu(p(z) - 1) \right) = F(p(z))$$

Where from, we can obtain the distribution of the losses of the total portfolio of an amount $(n\times L)$ as follows:

Figure 4: CreditRisk+ risk measurement framework (Crouhy et al., 2000)
\[ A_n = \frac{1}{n!} \frac{d^n G}{dz^n} (0) \]

Land us note in that case that, \( A_n \) can be calculated in continuous by basing itself on the following formula and under the hypothesis according to which \( \mu \) is constant.

Where from we obtain:

\[ A_0 = G(0) = \exp(-\mu) = \exp \left( - \sum_{j=1}^{m} \frac{\epsilon_j}{\theta_j} \right) = \sum_{\theta_j=\mu}^{n} \left( \frac{\epsilon_j}{\mu} \right)^{A_n-\theta_j} \]

The CreditRisk+ model considers that every sector is driven by a simple fundamental factor. This factor explains the variability of the rate of average defect measured for this sector. The fundamental factor influences the rate of defects planned in the concerned sector which is modeled by a random variable of average \( \mu \) and of standard deviation \( \sqrt{\mu} \) indicated for every sector.

The standard deviation reflects the degree to which, in all the probability of default, the obligors in the portfolio are exposed are more or less that their levels of the average. By continuing this analysis, the model CreditRisk+ bases on the hypothesis that \( \mu \) is constant. So, by basing itself on the distribution of Fish of parameter \( \mu \) the probability of failures are underestimated. In that case, it is necessary to take into account the existence of an average number of variable failures.

The parameter \( \mu \) is considered as being a stochastic variable and depends on characteristics of the sector. In fact, and according to the CreditRisk+ model, a sector is considered as being a sand of credits the rates of failures of which are subjected to the same influences. In the CreditRisk+ model, every portfolio is divided into sectors indicated by \( k \) with \( 1 \leq k \leq K \).

In particular, for every sector \( k \), we introduce one random variable \( x_k \) which represents the average number of defaults in this sector. The average number of the defects is equal in \( \mu \).

The hope of \( x_k \) for the sector \( k \) is noted \( \mu_k \) and its standard deviation is equal \( \sigma_k \). In this frame \( \mu \) is calculated as follows:

\[ \mu_k = \sum_{j=1}^{m(k)} \frac{\epsilon_j^{(k)}}{\theta_j^{(k)}} \]

In the case that \( \mu \) is no constant; the generative function of the number of defaults is given by:

\[ F(z) = \prod_{k=1}^{k} F_k(z) \]

And

\[ F_k(z) = \int_{0}^{\infty} z^n \int_{0}^{\infty} \rho (n \text{ defaults}) f(x) dx \]

Where \( f(x) \) indicates the density of the variable \( x_k \).

The continuation of the calculations is conditioned by the presence of a nature of distribution given in \( x_k \). In the CreditRisk+ model, the choice is fixed to a distribution Gamma \( \Gamma \) of average \( \mu \) and of standard deviation \( \sigma_k \). Thus we obtain:

\[ F_k(z) = \int_{x=0}^{\infty} e^{x(z-1)} \frac{e^{-x} x^{\alpha_k-1}}{\beta_k^n \Gamma(\alpha_k)} \]

Where the Gamma function written as follows:

\[ \Gamma(\alpha) = \int_{x=0}^{\infty} e^{-x} x^{\alpha-1} dx \]

For every sector \( k \), we have two parameters of Gamma function to be estimated \( \alpha_k \) and \( \beta_k \). Thus:

\[ \alpha_k = \frac{\mu_k^2}{\sigma_k^2} \]

\[ \beta_k = \frac{\sigma_k^2}{\mu_k} \]
By substituting and by basing itself on the definition of the Gamma function, we obtain then:

\[
F_k(z) = \int_{x=0}^{\infty} e^{x(z-1)} \frac{x^{\alpha_k} e^{-x}}{\beta_k^\alpha_k \Gamma(\alpha_k)}
\]

\[
\iff \quad F_k(z) = \frac{\Gamma}{\beta_k^\alpha_k \Gamma(\alpha_k)(1 + \beta_k^{-1} - z)^{\alpha_k}}
\]

\[
= \frac{\beta_k^\alpha_k}{\beta_k^\alpha_k (1 + \beta_k^{-1} - z)^{\alpha_k}}
\]

After this simplification, the generating function of the distribution of the probabilities of default for the sector K is given by the following expression:

\[
F(z) = (1 - p_k) e^{\alpha_k z}
\]

Thus:

\[
P_k = \frac{\beta_k}{1 + \beta_k}
\]

After the determination of the number of defaults in a portfolio, one goes in what follows to present the generating function of the losses incorporated in a portfolio functions written is the following:

\[
G(z) = \sum_{n=0}^{\infty} p \text{ (Aggregate losses } = n \ast L)z^n
\]

So:

\[
G(z) = \prod_{k=1}^{K} G_k(z) = \prod_{k=1}^{K} F_k(p_k(z))
\]

Where the polynomial function \(P_k(z)\) is written as follows:

\[
P_k(z) = \frac{\sum_{j=1}^{m(k)} \left(\frac{e_j^{(k)}}{\theta_j^{(k)}}\right) z^{\theta_j^{(k)}}}{\sum_{j=1}^{m(k)} \left(\frac{e_j^{(k)}}{\theta_j^{(k)}}\right)}
\]

One can deduce the expression from the generating function \(G(z)\) which is written in the following way:

\[
G(z) = \prod_{k=1}^{K} \left[\frac{1 - p_k}{1 - p_k \sum_{j=1}^{m(k)} \left(\frac{e_j^{(k)}}{\theta_j^{(k)}}\right) z^{\theta_j^{(k)}}}\right]^{\alpha_k}
\]

In this respect, we can deduct the distribution of the losses of portfolios from the \(A_n\) which is given by:

\[
G(z) = \sum_{n=0}^{\infty} A_n Z^n
\]

In case \(G(z)\) verify the following relation:

\[
\hat{G}(z) = \frac{A(z)}{B(z)}
\]

Where \(A(z)\) and \(B(z)\) are two polynomials of the following shape:

\[
A(z) = a_0 + \cdots + a_n z^n
\]

\[
B(z) = b_0 + \cdots + b_n z^n
\]

Thus, the coefficients \(A(z)\) verify the relation of following recurrence:

\[
A_{n+1} = \frac{1}{b_0(n+1)} \left( \sum_{j=0}^{a_{n+1}} a_j A_{n-1} \sum_{i=0}^{b_{n+1}} b_i A_{n-1} \right)
\]

This relation is applied knowing that \(G(z)\) verify the following condition:

\[
\hat{G}(z) = \sum_{k=1}^{K} \left(\frac{P_k A_k}{\mu_k} \sum_{j=1}^{m(k)} \left(\frac{e_j^{(k)}}{\theta_j^{(k)}}\right) z^{\theta_j^{(k)}}\right)
\]
Generally, the CreditRisk+ model is based on mathematical techniques in the modeling of the distribution of the losses in the field of the banking activities and of the insurance. The behavior of common default of the borrowers is incorporated by treating the rate of default as being a common random variable for multiple borrowers. So, the borrowers are assigned among the sectors among which each has a rate of average default and a volatility of rate of default. The volatility of rate of default is the standard deviation which would be observed on a portfolio of infinitely diversified homogeneous credit.

The forces and the weaknesses relative to the CreditRisk+ model are presented in the table 14 (Hamisultane, 2008).

**CONCLUSION**

In this paper we developed a comparative theoretical approach’s concerning the model of management of credit portfolio. Then, we studied the four mains models of credit portfolio management. In the financial literature those models are grouped by three types of credit portfolio models (Crouhy et al., 2000). The structural models: there are two models of management of credit portfolio who are supplied in the literature: Moody's KMV model (Portfolio Model) and CreditMetrics model by JPMorgan. The Macro-factors model (Econometric model): The Credit Portfolio View model introduces in 1998 by Mckinsey. The actuarial models CSFP (Credit Suisse First Boston): this model (CreditRisk+) is developed in 1997.

The KMV model and Credit Portfolio View base their approach on the same empirical observation that default and migration probabilities vary over time. The KMV model adopts a microeconomic approach which relates the probability of default of any obligor, to the market value of its assets. The Credit Portfolio View model proposes a methodology which links macroeconomics factors to default and migration probabilities. The calibration of this model necessitates reliable default data for each country, and possibly for each industry sector within each country.

Structural models are based on option theory and capital structure the company. On econometric models, they link the probability fault of the company to the state of the economy. The probability of failure depends in these models of macroeconomic factors such as unemployment, the rate of increase GDP, the interest rate long-term. Moreover, in the CreditRisk+ models, the probability of default varies over time.

<table>
<thead>
<tr>
<th>Table 14: The forces and the weaknesses relative to the CreditRisk+ model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>The forces</strong></td>
</tr>
<tr>
<td>✅ The use of a minimum of data since the distribution of the losses depends only on one reduced number of parameters. This characteristic makes it possible the CreditRisk+ model to reduce and minimize the risk of errors due to the uncertainty of the parameters.</td>
</tr>
<tr>
<td>✅ The CreditRisk+ model uses models based on closed formulas what allows him a fast execution of calculations.</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Source: Hamisultane (2008)
REFERENCES


