Journal of Applied Finance & Banking, vol. 9, no. 4, 2019, 167-178
ISSN: 1792-6580 (print version), 1792-6599 (online)
Scienpress Ltd, 2019

Study of endogenous and exogenous factors impact's on the default probability of listed companies on the Casablanca Stock Exchange

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Abstract

This paper aims to study the impact of endogenous and exogenous factors on the default probability through the structural approach (Internal Ratings-Based IRB). The study is conducted using data from listed companies on the Stock Exchange of Casablanca (BVMC); it covers the period from the beginning to the end of 2017. In this paper, we propose a numerical method, based on Monte Carlo simulation, to estimate the default probabilities using the Black & Scholes (1973) model. Our focus was on determining the most influential factors among the internal or external ones that impact the default probability of the listed non-financial companies on BVMC.

JEL classification numbers: D81
Keywords: Default probability, credit risk, IRB approach, Monte Carlo simulation.

1 Introduction

Computing the default probability (DP) is a cornerstone in credit risk analysis and management. In fact, DP is an important entry in many approaches of credit risk management; at the portfolio level, in pricing and credit risk hedging. The default of a company is usually associated with its bankruptcy.

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Article Info: *Received*: January 29, 2019. *Revised*: February 23, 2019
Published online: May 10, 2019

Due to the fact that the DP is the major variable of the IRBF approach, this paper is dedicated to computing the DP. In practice, predicting the failure of a company can only be assessed when there is a probability even if it is small. In the event of default, it will cause financial losses to the lender; so identifying DP is a critical issue (Kollar b., 2014) [1]. People and businesses have predicted the DP for decades (Allen & Saunders, 2002) [2]. It can be modeled in different ways and using different models. These models evaluate probability by using market data and can basically be divided into two groups based on assumptions they make. Thus we can distinguish between structural and reduced models (Lehutová, 2011) [3]. In the other hand, hybrid models have also been developed to try to combine the assumptions of the two previously mentioned models (Cisko & Kliestik, 2013) [4].

The roots of structural models go back to the work of Black and Scholes (1973) [5] and Merton (1974) [6]. Geske (1977) [7] extended Merton's assumptions by considering that several default options for coupons, sinking funds, subordinated debt, security covenants or other payment obligations could be treated as composite options (Majerčák & Majerčáková, 2013) [8].

The overall objective of our work is to evaluate and analyze the impact of internal and external factors on credit risk of the listed companies on the BVMC. In order to achieve our objectives, we have formulated two hypotheses:

Hypothesis 1*: *A same variation in the DP will result from the same variation of the factors across listed companies on the BVMC.

Hypothesis 2: The standard deviation of assets is the major factor influencing the probability of default for firms listed on the BVMC.

To verify these hypotheses we apply risk assessment methods to a sample of 12 listed companies over the period from January the 2nd to December the 31st of the year 2017.

The remaining of this paper will be organized on two sections. The first will be devoted to the theoretical approach of measuring credit risk. The second part will focus on the evaluation of credit risk of listed companies on the BVMC.

2 Theoretical credit risk assessment models

Credit risk is one of the most important risks faced by credit institutions. Its mastery rests on setting up clear identification, assessment and hedging procedures. Credit risk can be handled using various methods among which we find the structural approach (IRBF).

2.1 Basle requirements for credit risk

The recent subprime crisis has once again shown that credit risk remains the major risk for financial institutions. "At the heart of a global and complex crisis, credit risk has been a powerful catalyst" (Zelenko & De Servigny, 2010) [9]. In this perspective, the relative weight of credits is a primary criterion for judging the health of the banking sector. Credit risk is one of the indicators of financial stability on which the International Monetary Fund (IMF) and the World Bank (WB) rely to assess the fragility of the financial sectors. Therefore, effective credit risk management seems essential for the long-term survival of banking institutions and for global financial stability.

In July 1988, the Basle Committee developed the international solvency ratio, known as the COOKE ratio (Basle I) . It defines the capital requirements that banks must meet according to the taken risks. This ratio relates regulatory capital to weighted assets which must be at least 8%.

Due to the evolution of credit risks, the Cooke ratio scheme showed its limits. In 2004, the Basle Committee proposed a new set of recommendations that defines a more effective measure of credit risk, through a system of internal ratings that is specific to each institution (Internal Rating Based) as well as the new solvency ratio, namely McDonough's ratio. This latter considers also the operational risk.

In 2010, After the Subprime crisis, the Basle Committee focused on strengthening the regulation, control and risk management of banks through issuing the recommendations under the name of Basle III. This latter sets-up harmonized global liquidity standards by developing two minimum standards for liquidity financing. The first is the liquidity coverage ratio (LCR) which promotes the resilience of banks in the short-term through the provision of high quality liquid assets in order to overcome a severe crisis that would last for one month. The second ratio is the long-term net stable funding ratio (NSFR), with a 1-year horizon, to provide a sustainable maturity structure.

2.2 Probability of default on the basis of share prices

Generally, the default probabilities are estimated from the issued data by rating agencies which list the evolution of default rates according to a time horizon. Unfortunately, the frequency of ratings' review is low. For this reason, analysts have turned to the stock price, since it is available on the financial market.

This ability to obtain information facilitates proportionally and indirectly the calculation of values and the volatilities of assets, since the two variables (volatility and value of assets) are not observable. To solve this complexity, we used the model of (Black & Scholes, 1973) [5]. Let's note:

V_0 : The value of the firm's assets

dV_0: Variations in the firm's assets

μ : The average value of the firm's assets

σ_v : The volatility of the firm's assets

V_E: The value of the firm's shares

dV_E: The variations of the firm's shares value

σ_E: Stock volatility

dB: A Wiener process

D: The value of the debt to be repaid at the date "T"

Let the value of the assets vary according to the following equation:

$$dV_0 = V_0(\mu * dt + \sigma_v * dB) \tag{1}$$

The market value of the shares and the market value of the assets are ultimately linked by the Call formula (equation 2):

$$V_E = V_0 N(d_1) - De^{-rT} N(d_2) \tag{2}$$

Where : $d_1 = \frac{\ln\left(\frac{V_0}{D}\right) + \left(r + \frac{\sigma_V^2}{2}\right)T}{\sigma_V \sqrt{T}}$ and $d_2 = d_1 - \sigma_v \sqrt{T}$.

The " r " denotes the risk-free rate and N (.) is the standard normal cumulative distribution function.

To compute V_0 and σ_v (they are not directly observable) we use the equation (2). The V_E is known since the company is listed; this offers the first condition on V_0 and σ_v. The lemma of Itô (1940) offers the second constraint imposed on the two variables. We can establish that the volatilities of stocks and assets are linked by equation (3):

$$\sigma_E V_E = \sigma_v V_0 N(d_1) \tag{3}$$

The solution of the two nonlinear equations (2) and (3) makes it possible to determine the value and the volatility of the assets.

3 Data and Methodology

The nature of this study requires us to use quantitative research methods for data collection and analysis. In fact, the management of credit risk, and in particular the assessment of DP, is based on the measurement and, therefore, quantification.

Methods involve the forms of data collection, analysis, and interpretation that researchers propose for their studies (Creswell, 2009) [10]. Calculation procedures are particularly important in the context of DP.

The inputs of DP analysis are usually past performance, probabilistic beliefs of specialists. The results of this analysis are only logical consequences and reprocessing of these inputs. The data used in this study are in the form of financial time series.

The target sample is composed of Moroccan non-financial companies listed on BVMC's three compartments. Our final sample is made up of 12 non-financial Moroccan companies.

We used the annual financial statements of the five previous financial years from 2013 to 2017, with a daily change in the stock price over the period from the beginning to the end of 2017.

Within the structural models, initiated by Black-Scholes (1973) [5] and Merton (1974) [6], the value of the debt is evaluated using the theory of options. Thus, the company's stock and its debt appear as derivatives on the total value of its assets.

The structural approach to credit risk (also called the firm's model) is generally used for the determination of DP. This probability depends on the quality of the initial credit, the longevity of the debtor and, above all, its current and future financial capacity.

The basic hypothesis of the Black-Scholes-Merton model is that the assets of a firm X_0 follow a stochastic process in continuous time (Geometric Brownian Motion) and that the defect is realized if X_0 crosses the fault barrier.

3.1 Modeling

The frequency of changes in the rating of financial assets has led financiers to consider continuous stochastic processes to model share price variations. The fluctuation of financial asset prices, both upwards and downwards; can be modeled using a geometric Brownian motion or Weiner process. Equation (1) admits as a solution:

$$V_t = V_t * \exp\left(\left(\mu - \frac{\sigma^2}{2}\right) * t + \sigma B_t\right) \quad (4)$$

As a result, the return on assets between "t" and "t+dt" is:

$$\frac{V_{t+dt}}{V_t}=\frac{V_t * \exp\left(\left(\mu-\frac{\sigma^2}{2}\right)*(t+dt)+\sigma B_{t+dt}\right)}{V_t * \exp\left(\left(\mu-\frac{\sigma^2}{2}\right)*t+\sigma B_t\right)} \quad (5)$$

Moreover, since B_{t+dt} and B_t and are standard Brownian motions, the difference $B_{t+dt}-B_t$ follows a normal distribution with a standard deviation $\sqrt{dt}$. This brings us to:

$$\frac{V_{t+dt}}{V_t}= \exp\left(\left(\mu-\frac{\sigma^2}{2}\right)*dt+\sigma * \varepsilon(0,\sqrt{dt})\right) \quad (6)$$

From equation (6), we can draw:

$$V_{t+dt}= V_t * \exp\left(\sigma * \varepsilon(0,\sqrt{dt})+\left(\mu-\frac{\sigma^2}{2}\right)* dt\right) \quad (7)$$

A first step before starting the study is to identify the statistical and stochastic properties of the sample. These properties condition the models and estimation methods.

3.2 Calculation method

To calculate the DP, Monte-Carlo method will be used. This method allows generating default scenarios that are required for the calculation of DP. The default occurs if

$$V_{t+dt_{(i)}} < D \qquad with\ i=1,2,3,\dots,n \quad (8)$$

For “n” scenarios :

$$PD=\frac{number\,(V_{t+dt_{(i)}}<D)}{n} \qquad \text{with } i=1,2,3,\dots,n \quad (9)$$

According to Oubdi & Touimer (2017) [11], the two parameters "dt" and "n" are chosen so that their variations do not affect the calculated DP. From our tests we can conclude that the pair (0.005, 10000) remains optimal.

3.3 Descriptive statistics of the sample

The choice of the concept of failure is not sufficient. We must add a temporal horizon. A credit rating cannot be given without specifying a time horizon. We know that every business can go bankrupt one day. The whole question for credit evaluation is: when? This is why there is often an aspect of implicit anticipation in the creation of a credit rating. This anticipation is linked to the choice of a time horizon that makes it possible to determine a palette of reasonable scenarios for the evolution of the variables of interest. It is not simple to make short-term expectations neither to make long-term ones. It is possible, however, to predict short-term bankruptcy more accurately than long-term bankruptcy because credit risk is increasing over time. Serious credit rating agencies issue both short-term (12-month) credit notes and long-term credit ratings. Insofar as short-term forecasting uses a narrower range of changes in interest variables, short-term rating scales contain fewer steps than long-term ones. Thus, banks need to estimate the probability of default of one year for each risk category. This is why, in our case, we choose a time horizon from January the 2nd to December 31st. Table 1 summarizes the descriptive statistics of the companies in our sample.

Table 1: Descriptive statistics

Value label	AFRIQUIA GAZ	C MINIERE TOUISSIT	DLM	DOUJA PROM ADDOHA	FENIE BROSSETTE	MANAGEM
Mean (Stock return) %	**-0,08**	**2,92**	**5,82**	**-8,16**	**-2,58**	**1,85**
S.D (Stock return) %	**1,95**	**2,01**	**1,56**	**1,84**	**3,37**	**2,20**
Debt in MAD	**20 582 524,41**	**224 420 000,00**	**50 664 502,31**	**44 600 000,00**	**10 066 594,08**	**1 649 994 720,00**
Market Value in MAD	**9 526 783 750,00**	**2 502 535 495,30**	**231 208 000,00**	**14 815 319 377,72**	**210 214 265,44**	**13 079 281 598,33**
Shapiro-Wilk*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Anderson Darling*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Lilliefors*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Jarque-Bera*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Skewness (Pearson)	**0,41**	**-0,93**	**0,46**	**0,899**	**0,421**	**0,601**
Skewness (Fisher)	**0,412**	**-0,936**	**0,463**	**0,904**	**0,423**	**0,604**
Kurtosis (Pearson)	**3,744**	**6,417**	**1,139**	**7,499**	**1,679**	**4,157**
Kurtosis (Fisher)	**3,845**	**6,572**	**1,186**	**7,677**	**1,737**	**4,266**
ADF**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
PP**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**

Value label	**MED PAPER**	**RES DAR SAADA**	**SODEP Marsa-Maroc**	**SOTHEMA**	**TAQA MOROCCO**	**TOTAL MAROC**
Mean (Stock return) %	**-4,70%**	**-5,68%**	**0,003%**	**-0,50%**	**0,00%**	**-2,03%**
S.D (Stock return) %	**3,95**	**1,97**	**1,53**	**1,60**	**1,43**	**2,04**
Debt in MAD	**8 591 759,86**	**839 199 000,00**	**6 355 416,53**	**22 379 636,97**	**398 692 810,36**	**57 142 857,16**
Market Value in MAD	**83 685 112,22**	**4 691 457 534,78**	**10 403 107 023,12**	**2 364 465 600,00**	**19 735 400 841,38**	**14 103 255 040,00**
Shapiro-Wilk*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Anderson Darling*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Lilliefors*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Jarque-Bera*	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
Skewness (Pearson)	**-1,442**	**-0,204**	**0,088**	**0,813**	**-0,282**	**-0,424**
Skewness (Fisher)	**-1,45**	**-0,205**	**0,089**	**0,818**	**-0,284**	**-0,426**

Kurtosis (Pearson)	**16,471**	**4,43**	**8,227**	**7,848**	**1,752**	**4,155**
Kurtosis (Fisher)	**16,831**	**4,545**	**8,419**	**8,032**	**1,812**	**4,264**
ADF**	**< 0,0001**	**0,001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**
PP**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**	**< 0,0001**

** H_0: The financial series of price changes follows a Normal law. The tests performed are with a level of significance alpha = 0.05. The results of the "p-value" are shown in the table.*
*** H_0 : The series has a unit root.*

It is worth noting that the number of data points is 250 and the average of the price variations is almost zero. This is mainly due to the luck of transparency of the companies. Indeed, many companies meet only minimum requirement in terms of financial communication according to the Moroccan Authority of the capital market (AMMC, May 2017). The second problem of attractiveness is the classification of listed companies according to the activity sector rather than the performance.

The Shapiro-Wilk, Anderson Darling, Lilliefors and Jarque-Bera tests reject the null hypothesis of normality for all values (since the calculated "p-value" is below the level of significance alpha = 0, 05). The non-normality of financial series is a well-known fact in finance, especially for financial assets (Goodhart & O'Hara, 1997) [12].

The analysis of the thick tails (Fat tails) confirms the non-normality and that the distribution of the prices does not follow a Gaussian as predicts the EMH (Efficient Market Hypothesis). Finally, the D'Agostino [13]and Jarque-Bera tests, based on the asymmetry and kurtosis coefficients, accept the hypothesis of non-normality. Given that the calculated p-value of the financial values is less than the level of significance alpha = 0.05, therefore one must reject the null hypothesis H_0, and retain the alternative hypothesis H1 (The series is stationary).

4 Results and discussion

The table 2 reports the estimates of the two parameters σ_V & V_0 using equations 3 and 4 with a risk-free rate of 2.37%[3] .

[3] According to Bank Al Maghrib, the risk-free rate over the period of study is 2.37%.

Table 2: Calculation of volatility and market value of assets listed on the BVMC

Name	σ_v	V_0
AFRIQUIA GAZ	1,95%	9 546 884 203,68
C MINIERE TOUISSIT	1,85%	2 721 699 273,55
DELATTRE LEVIVIER MAROC	2,03%	280 685 870,73
DOUJA PROM ADDOHA	1,83%	14 858 874 785,04
FENIE BROSSETTE	3,22%	220 045 086,19
MANAGEM	1,96%	14 690 631 197,02
MED PAPER	3,59%	92 075 641,37
RES DAR SAADA	1,68%	5 511 001 352,39
SODEP-Marsa Maroc	1,53%	10 409 313 587,15
SOTHEMA	1,58%	2 386 321 075,42
TAQA MOROCCO	1,40%	20 124 755 723,67
TOTAL MAROC	2,03%	14 159 059 533,70

Now we will study the DP using Monte Carlo simulation method. This method consists in using the strong law of large numbers to estimate the DP. Table 3 summarizes the results obtained on the 10,000 simulations with 200 steps in time (See methodology section for more details).

Table 3: The probability of default of companies in the sample

Company	DP
AFRIQUIA GAZ	1,49%
C M TOUISSIT	34,64%
DLM	59,32%
DOUJJA ADOHA	1,37%
FENIE	74,93%
MANAGEM	46,53%
MED PAPER	88,02%
SAADA	44,03%
MARSA MAROC	0,00%
SOTHEMA	1,56%
TAQA	1,85%
TOTAL	4,45%

At the first glance, it is impossible to infer the most important factor impacting the DP. In order to measure the relationship between DP and structural factors, we have to test for each factor.

The high probability of default of Med PAPER, the sole national paper manufacturer is justified primarily by the dumping strategy that was practiced by paper exporters from Portugal and Secondly by the waiver of a claim of 4.3 million MAD. From the historical data retrieved from annual financial statements closed since 31 December 2013, we can see that the net worth of this company is less than one quarter of the share capital. An EGM was held on June 20, 2014 and decided that the company would not be wound up early. The company was required at the latest by the end of December 2016 to reconstitute equity up to a value equal to at least one quarter of the share capital. An EGM was held on September 19, 2017 and gave power to the Board of Directors to regularize the company's net position by raising capital by capitalizing reserves, share premiums, merger premiums and amortization. The commitments made in the framework of the memorandum of understanding signed between the company and the CDG group on December 24, 2013, and the agreements with its banks, the effect of which has been recorded by the company during the 2017 financial year with the CDG Group and some of its banks.
For FENNIE, the high probability of default is explained by the decline in its turnover due to the gradual abandonment of low-margin trades, the difficulties of the sector.
Our study consists of identifying the variables that have the strongest influence on the DP by supposing a variation of each of them. This will allow as computing new DP for each change in variables. Table 4 summarizes the results.

Table 4: The variation of the probability of default according to each factor

Name	Δ Debts in MAD	Δ PD	ΔV_E in MAD	Δ PD	μ	Δ PD	$\Delta\sigma_v$	Δ PD
AFRIQUIA GAZ	4%	5,27%	-4%	4,42%	100%	-0,83%	0,80%	**8,90%**
C M TOUISSIT	4%	1,95%	-4%	2,05%	100%	-1,90%	0,80%	**1,06%**
DLM	4%	1,54%	-4%	1,33%	100%	-1,72%	0,80%	**1,06%**
DOUJJA ADOHA	4%	2,70%	-4%	4,93%	100%	-11,64%	0,80%	**5,66%**
FENIE	20%	0,58%	-4%	0,60%	100%	-0,14%	0,80%	**0,93%**
MANAGEM	4%	1,71%	-4%	1,80%	100%	-2,38%	0,80%	**1,38%**
MARSA MAROC	4%	36,36%	-4%	81,82%	100%	0,00%	0,80%	**90,91%**
MED PAPER	20%	0,22%	-4%	0,30%	100%	-0,37%	0,80%	**0,42%**
SAADA	4%	1,92%	-4%	2,19%	100%	-3,06%	0,80%	**1,13%**
SOTHEMA	4%	6,26%	-4%	6,41%	100%	-1,03%	0,80%	**4,86%**
TAQA	4%	6,50%	-4%	5,22%	100%	-0,65%	0,80%	**3,57%**
TOTAL	4%	5,13%	-4%	5,85%	100%	4,17%	0,80%	**7,52%**

From table 4, we can see that the variation of factors starts having a significant impact on DP at a threshold of 4% for the debt and the asset value for the companies AFRIQUIA GAZ, CM TOUISSIT, DLM, DOHHA , MANAGEM, MARSA MOROCCO, SAADA, SOTHEMA, TAQA and TOTAL . This threshold is only of 0.80% fpr σ_E, while it jumps to 100% for μ. Thus, we can infer that the standard deviation of assets is the major factor influencing the DP of listed firms on the BVMC (i.e H_1 is retained).

In order to have a significant variation in the probability of default for the two companies FENNIE and MED PAPER, the total debt factor must increase by 20%. Thus, the impact of variations in factor on DP varies across companies in our sample (i.e., H_2 is rejected).

For the sample as a whole, when the risk of default is very high, the variation in the probability of default according to the debt criterion is very small but with the same direction of variation. On the other hand, the value of the asset and the probability of default are negatively correlated with a weak correlation. This may be due, in one hand, to the value of the asset and, in other hand, to the debt level.

Finally, its influence of firms' asset mean on DP is negligible, while the volatility is found to be a key and significant element that strongly influences the probability of default.

5 Conclusion

The results of the research study were presented, analyzed and discussed. An initial analysis of the data shows the non-normality of the data in our sample. In fact, the unconditional density of financial series generally has thicker tails than the normal one since extreme values are relatively common.
The study of the DP shows that the credit universe offers an estimate of the risk in order to make a reasonable study of credit applicants' ratings.
For the study of the DP, according to the IRB model, the results show the trend that non-financial companies with low volatility have a lower default rate than companies with higher volatility.
On the other hand, the study of the weight of each factor indicates the tendency for debt and asset value to be less influencing than the volatility of the asset and that both parameters (debt and market value) have almost the same impact weight on DP. The assignment of the average asset factor to the probability of default is almost zero.

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