Credit Scoring and Credit Control XI conference

Developing a Commercial Credit Risk Rating Model:

Case Study of a Petrochemical Company

Author:

Dennis W. Bams, Ali Ebrahimnejad

Department of Finance, School of Business and Economics, Maastricht University, P.O. Box 616, 6200 MD Maastricht, The Netherlands

Email: w.bams@maastrichtuniversity.nl

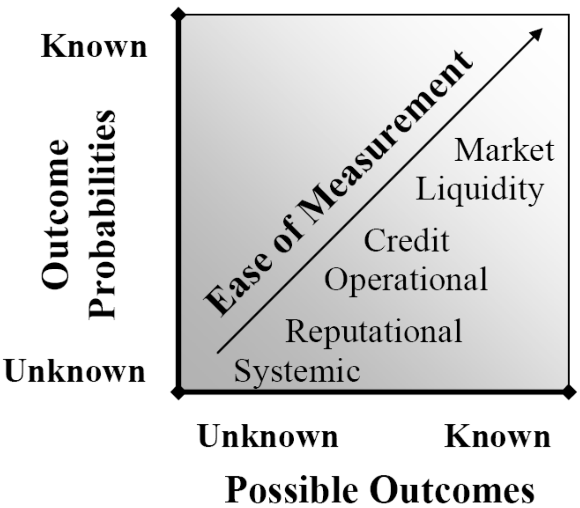
Abstract

This paper presents a model for credit risk assessment in the petrochemical industry. We first briefly describe the main models and approaches to credit risk assessment. Next we explain the methodology of credit risk assessment and credit granting at a major petrochemical company in Europe. Then we describe why the current available models are not suitable for the company and develop a model combining Z-score and an "A-Score" which is comprised of a number of non-financial factors selected based on qualitative expert judgment. We use Analytic Hierarchy Process (AHP) to weight the factors. Using expert judgment, we test and demonstrate that the model has strong predictive power for assessing the creditworthiness of the company's customers and that A-Score results in significant improvements to Z-Score in replicating the expert judgment.

I. Introduction:

Credit risk is “the risk that a counterparty will not settle an obligation for full value, either when due or at any time thereafter.” (BIS, 1996). As there is no clearcut measurement for distinguishing the obligors that will actually default from those who will not, there has been continuous effort and improvement for credit risk models. Furthermore, unlike risks such as market risk where variables such as stock price changes are observable daily, default is a rare event. For instance, the odds of a firm with AAA rating defaulting are approximately 2 in 10,000 per annum (Moody’s, 2003). This makes the task of credit risk measurement even more difficult. (Figure 1)

Figure 1. Ease of measurement for different types of risks



Source: Anderson, 2007

A number of factors have made credit risk measurement increasingly important during the last few years. Among them are: (i) increased competition in the financial services sector which squeezes the margins on loans (Altman et.al., 1998), (ii) the surge in the off-balance sheet instruments and credit derivates market (McKinsey, 1993), (iii) historically low nominal interest rates which has made investors seek new investment opportunities in high yield bonds with inherently higher credit risk, (iv) a dramatic worldwide increase in the number of bankruptcies among both financial and non-financial companies due to the credit crisis of 2007-09, and (v) implementation of Basel II which sets a new framework for calculating regulatory capital using the Internal Ratings-Based approach (BIS, 2004)

As a result, in the recent years academics as well as practitioners have developed a wide range of sophisticated models for credit risk measurement compared to the early models such as the 5 "Cs". In this system, which is almost as old as credit itself, 5 characters of the customer, namely character (reputation), capital (leverage), capacity (earnings volatility), collateral, and cycle (macroeconomic) conditions are assessed by human experts. Traditional expert systems specify no weighting scheme that would order the 5 C's in terms of their relative importance in forecasting Probability of Default.

Expert systems and subjective analysis has been the oldest and most common approach to credit risk measurement prior to the development of the more sophisticated statistical and objective methods. Despite the development of new methods, at all large international banks, "the human judgment exercised by experienced bank staff is central to the assignment of a rating" (Treacy et al., 2000). The same holds for the credit rating agencies where judgment of the "lead analyst" and the "rating committee" is the final word in determining the rating of an issue or issuer (Standard & Poor's, 2008).

Accounting based credit-scoring systems are also among the most common methods of credit risk measurement. In these models, the credit analysis is based on various key accounting ratios of the obligor, which are then weighted to produce a credit score, probability of default or credit limit. In particular, for privately held firms with no market data available, accounting-based scoring models are the most common approaches of assessment (Fernandes, 2005). There are at least four methodological approaches to developing credit-scoring systems: (i) linear probability model, (ii) logit model, (iii) probit model, and (iv) discriminant analysis model (Altman, 1998). One of the first and most important of these models is Altman's Z-score model (Altman, 1968) followed by the "Zeta model" (Altman et al., 1977).

During the recent years, a number of new models have become commercial. One of the most well-known models developed by JP Morgan is CreditMetrics which is based on analyzing the probability of moving from one credit rating to another within a given time horizon. The changes in value are related to the migration, either downward or upward, of the credit quality of the obligor, as well as to default. In other words, the model basically relies on rating transition probabilities based on average historical frequencies of defaults and credit migration. Details of this model can be found in CreditMetrics (1997).

Another equally popular model is developed by the KMV Corporation which, unlike CreditMetrics, relies upon the so-called "Expected Default Frequency" or EDF for each issuer. (Moody's, 2003). It is essentially based on the asset value model proposed by Merton (1974). According to this model, firm's liabilities are considered as contingent claims against its assets. The firm will then default whenever its asset value falls short of its debt value. Thus, the default likelihood and the loss at default depend on the firm's asset values and liabilities, default-free interest rate, and the asset volatility.

Also, Credit Suisse Financial Products has released CreditRisk+ in 1997 which assumes a Poisson process for the default of individual bonds or loans. Finally, McKinsey has proposed CreditPortfolio View which estimates the default probability as a function of macro-variables such as unemployment, interest rates level, economy's growth rate, etc. [1]

Another distinct method for credit assessment is the credit rating agencies' rating method; these methods essentially take into account both quantitative and qualitative conditions of the obligor simultaneously. A "lead analyst" is normally assigned to the applicant company. By gathering the information from different sources, using his expertise in that specific industry and also through meetings with the company's senior managers, the analyst comes to a conclusion about the business risk of the customer. The financial risk is then assessed by means of analyzing key financial ratios, sometimes specific to the industry, which is done both by the analysts and the models the agencies have developed. By combining the financial risk and business risk assessment, the overall rating of the company is elicited and announced. (S&P, 2008)

With the advent of information technology and the possibility of statistical analyses, financial institutions as well as other users of credit risk models in the non-financial sector tend to rely more on quantitative methods and steer away from subjective and qualitative analysis, in an

[1] For more comprehensive coverage of each of the models, see Saunders and Allen (2002).

attempt to streamline their methodology across different business lines and geographical areas, and among different customers.

The credit crisis of 2007-09, however, showed that, (1) there is still a long way in developing and improving the credit risk methods in place, and (2) purely statistical and quantitative methods are not flawless and should not completely replace expert judgment (Brunnermeier, 2009). Credit Rating Agencies as well as other financial institutions will certainly conduct major investigations on their rating methodologies in an attempt to avoid similar crises in the future. This, however, is not limited to the financial services industry, and non-financial companies are also revising their credit risk models both to weather the current crisis and to avoid similar issues in the future.

This paper explores the revision process of a credit risk model in a major petrochemical company in Europe. The company (Company hereforth) is exposed to the default risk of its customers through its sales. Currently, the Company has a credit risk model which is based on the financial information of the customers, and in particular, is built upon Altman's z-score with minor adjustments. For a group of customers with the largest exposure, mainly in Chemicals & Intermediates industry, we attempt to amend the current financial model by identifying and incorporating a group of non-financial factors with the highest predicive power of customer's default probability.

The rest of this paper is structured as follows; in the next section we explain our research methodology and specify our sample. In section III, we present our findings and use expert judgment as our benchmark for back-testing and section IV concludes.

II. Data and Methodology:

The Company uses Altman's Z-Score model for assessing the credit risk of the applicants. Z-Score is a model involving multiple variables that measures the financial health of a company, as shown below (Altman, 1968):

$$Z = 1.2T_1 + 1.4T_2 + 3.3T_3 + .6T_4 + .999T_5$$

Where:

T_1 = Working Capital / Total Assets

T_2 = Retained Earnings / Total Assets

T_3 = Earnings Before Interest and Taxes / Total Assets

T_4 = Market Value of Equity / Book Value of Total Liabilities

T_5 = Sales/ Total Assets

In order to improve Z-Score's performance in predicting the applicant's credit risk, we develop an "A-Score" which scores the non-financial indicators of credit risk. By multiplying Z-Score and A-Score, we adjust Z-Score to improve its predictive power:

$$Z_{Adjusted} = Z_{Score} * A_{Score} \tag{1}$$

The actual credit granting process in the Company is different for two types of customers:

1) Customers with credit requests of less than 500,000 Euro: the credit assessment of these customers is outsourced to a credit agency and according to the recommendation made by the agency, the Company decides on the amount of credit to be granted.
2) Customers with credit requests of more than 500,000 Euro: the credit assessment is done internally and is explained below.

As soon as the credit application is submitted by either the customer or a sales & marketing staff member, one of the credit analysts of the Company is assigned and is responsible for the analysis. The analyst considers the credit limit recommended by the Company's internal rating model.

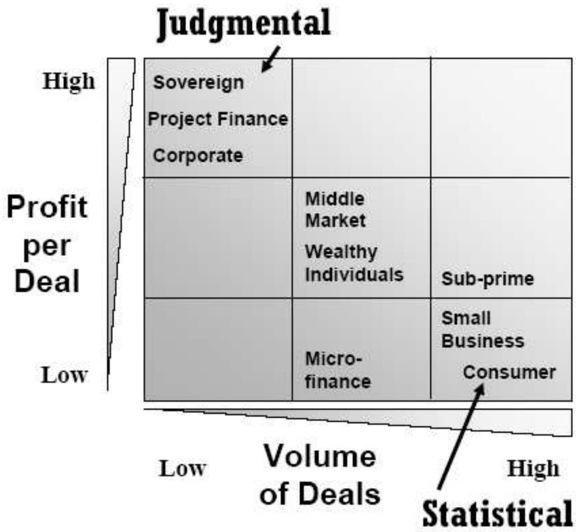
The model uses Altman's z-score as its core, which is then slightly adjusted by some other factors reflecting the applicant's financial health. Based on the model score and the applicant's amount of equity, a credit limit is recommended by the model. The analyst then, according to his expert analysis and based on the financial facts & figures and any other information he obtains via industry experts or personal visits to the customers, may adjust the recommended credit limit.

Once the final recommendation is made it needs to be approved. Below a certain threshold, the analyst can approve it on his/her own. Above that threshold, another credit analyst should also approve the advised credit limit. From certain higher limits above, the endorsement of the senior risk managers or board members are also required for the approval.

One of the drawbacks of the current model is its reliance merely on the financial facts and figures. In other words, the only part of the analysis which is formalized is the financial attributes of the customer. Non-financial factors are mainly taken into account in the subjective analysis as well as "feeling" the analyst gets about the customer and makes him sometimes arbitrarily propose significant adjustments to the credit limit recommended by the model. This, in turn, leads to inconsistency of the assessments across different analysts and for different customers. In order to minimize the amount of arbitrary adjustments involved in the credit granting process and bringing more consistency to it, a model needs to be developed which accounts for the most crucial "non-financial" attributes of the customers and ranks them in a more coherent fashion.

Additionally, the higher the amount of the credit requested and thus, potential profit and risk involved, the more resources should be dedicated to the credit assessment process and the more human judgment is involved. As a result, retail portfolios are normally automatically assessed and monitored by the credit risk models. However, for corporate credits (i.e. large exposures) more judgmental factors are involved given that there is little amount of historical data available and also that dedicating analysts to the assessment is worthwhile as a result of the high amount potential loss and profit per credit. Figure 2 shows the wide range of credit categories and their differences.

Figure 2. Volumes and Profits



Source: Anderson, 2007

Based on the above argument, the largest group of customers were selected. These companies are all categorized as the Chemicals & Intermediates and are mainly active in the chemical or oil & gas industry. In total, 42 corporates were identified meeting this criteria with their exposure ranging from half a million to more than 150 million Euro and each being supplied through several of their affiliates. Out of 42 companies, 14 are rated by one or more of the major credit rating agencies[2]. Also, 25 companies are publicly listed and thus, the data for share prices are accessible.

Another important factor for determining the credit assessment method is the amount of data available from various sources. Anderson (2007) identifies six sources of data for risk assessment which are defined in Table 1. Depending on the amount of data sources available for a group of customers, the factors to be anlyzed and included in the model differ. One of the most important factors in determining the availability of these six sources is the company size. Table 2 summarizes the sources of data normally available depending on the size of the company.

[2] Standard & Poor's, Moody's, and Fitch

Table 1. Available data sources for risk assessment

No.	Source	Explanation
1	Payment history	Information on borrowers' payment patterns, which is a loose surrogate for character/management.
2	Principal assessments	A look at the entrepreneur(s) behind the business, including their credit histories.
3	Financial Assessments	A review of obligors' financial positions, as presented in recent balance sheets and income statements.
4	Environmental inputs	Review of industry and regional factors, whether using economic data and forecasts, or historical aggregates based on internal/bureau data.
5	Market value of traded securities	The level, volatility, and buy/sell spreads of market prices provide forward-looking information, which is a summary of market participants' views on obligors' credit risk (the gold standard for corporate credit). Both bond and equity prices may be used.
6	Human input	Relationship managers' and underwriters' eyes and ears are still a primary source of information. The goal is to ensure that their observations are as objective as possible, but in many instances, subjective inputs are required.

Source: Anderson 2007

Table 2. Company Size versus Data

Company Size	Market prices	Judgmental inputs	Environment Inputs	Financial statements	Payment history	Principal assessment
Very Large	✓	✓	✓	✓		
Large		✓	✓	✓		
Middle		✓	✓	✓	✓	
Small				✓	✓	✓
Very Small					✓	✓

Source: Anderson 2007

As most of the selected companies are large or medium in size, with a few being very large, the main sources of data available about them are as follows:

1) Judgmental input
2) Environmental inputs
3) Financial statements
4) Payment history

Hence, both from the nature of analysis and the available data, implementation of quantitative analysis on the companies was only possible to a limited extend and thus, expert judgment was selected as the main source of assessment for the model. For developing the A-Score, the following steps were taken:

1) Developing a list of potential factors
2) Assessing the importance and measurability of each factor by means of single-factor analysis using expert judgment
3) Selecting the most important factors for the model
4) Weighting the selected factors using the Analytic Hierarchy Process (AHP)
5) Calculating the A-Score and the adjusted Z-score for the sample of applicants

These steps are explained in turn in the remainder of this section.

As a start, a comprehensive list of potential factors which can potentially predict default were gathered from different sources. For identifying such factors, besides the literature, around ten interviews were conducted with experts from the risk management department as well as senior sales and marketing managers of the Company. Additionally, the rating methodology of the major credit rating agencies and one of the commercial banks were carefully studied. In total, a list of 34 potential factors were identified. The list of factors along with their definition are provided in Appendix 1.

The next step is selecting the most important factors for the model using expert judgment. six persons were selected for the interview, three of whom were credit analyst or senior risk managers and three were sales & marketing managers. Selection of sales & marketing managers was justified by their close contact and affinity with the customers. For each of the potential factors two dimensions were measured by the respondents during the meeting:

1- Importance: How important is the factor in terms of predicting delinquency/default;
2- Availability: How easily can the factor be judged or measured given the limitations of access to data and objective judgment about them.

Each factor was then measured using a scale of 0 to 5, with 0 implying no importance/availability and 5 exhibiting the highest level of importance/availability. The factors were subsequently ranked based on their average scores of importance and availability. The top 10 variables are shown in Table 3 along with their average importance and availability score. For the final selection of the variables, a group meeting was set with three credit analysts and two senior risk managers. After discussions, quality of the financial information was omitted from the model with the justification that the majority of Chemicals & Intermediate customers have reliable financial information audited by major auditing companies.

Table 3: Top 10 factors

Factor	Importance Score	Availability Score
Payment behaviour	5.0	4.8
Quality of the financial information	4.5	3.7
Type of transaction with Company	4.5	4.8
Exposure to event risks	4.0	2.7
Operational diversity	3.8	4.0
Stability of purchase from Company	3.8	4.5
Legal form	3.8	4.7
Company's share in customer's supply	3.8	3.7
Level of integration of the business	3.7	4.0
Industry risk	3.7	4.3

Also, stability of purchase from Company was considered to be captured by the type of transaction with Company and thus, was ruled out. With regards to the Company's share in the customer's supply, during the discussions it was revealed that despite its ease of measurement, it cannot be interpreted in a clear-cut way; in other words, for each amount of the Company's share in the customer's supply, it could be interpreted two different ways depending on the market and industry of the customer. As a result, it was decided that Country Risk would be included in the model, instead, which had the importance score of 3.3 and availability of 4.2.

In total, 8 factors were selected for the model. Also, during the meeting, factors which among the experts had a difference of three or more in their highest and lowest importance score, were closely discussed by the corresponding analysts in order to resolve the difference and investigate the reasons of such deviations.

These factors were subsequently weighted in order to determine their relative importance. For weighting, the Analytic Hierarchy Process (AHP) was used. AHP is a methodology for systematic evaluation of the relative importance of qualitative criteria. Like other Multi-Attribute Decision Models (MADM), the AHP attempts to resolve conflicts and to analyze judgments through a process of determining the relative importance of a set of criteria. The AHP can be applied to a wide range of situations from marketing decisions (Wind and Saaty, 1980) to corporate credit-granting problem (Srinivasan and Kim, 1986). Zahedi (1986) provides a review of non-financial applications of AHP.

In a meeting with three credit analysts and one senior manager, the AHP method was used to determine the relative importance of the variables. Table 4 shows the weights assigned by AHP. In order to verify the consistency of the factor weights, the Consistency Ratio was calculated. As the Consistency Ratio is 7.6% and thus, less than 10%, the method is considered to be acceptable (Saaty, 1994).

Table 4: Selected factors and their weight

Factor	Weight
Payment behaviour	36.4%
Industry risk	19.0%
Country risk	16.0%
Type of transaction with Company	12.0%
Operational Diversity	7.2%
Level of integration of the business	4.8%
Exposure to event risks	2.5%
Legal form	2.2%

At the next step, each factor was categorized according to the possible alternatives for it and each category was scored. For combining this model with z-score, two methods were considered; first, scoring each factor on a scale almost similar to Z-score (e.g. from 1 to 5) and then weighting the total non-financial score and combining it with the Z-score. Second, impacting the non-financial score in the form of multiple on the Z-score, so that each factor's category would be scored above or below one, and then the total non-financial score would be multiplied by the Z-score to adjust it. For example, if the company would have a z-score of 3 and a non-financial score of 1.05, the total score would be 3*1.05=3.15

For two reasons the second method was used; first, some of these factors were already in the company's model with scales around 1 (i.e. above one for rewarding a certain type of customers and below one for punishing some other category of customers) and thus, the data was readily available. Second, Z-score could take a wide spectrum of numbers and thus, confining the non-financial scale to 1 to 5, for example, might cause systemic deviation between the Z-score and the non-financial score which will make the total score upward or downward biased.

Thus, the non-financial score, or A-score, would be equal to:

$$A = 0.364*P + 0.190*I + 0.160*C + 0.120*T + 0.072*O + 0.048*L + 0.025*E + 0.022*F \qquad (1)$$

Where P is Payment behavior, I is Industry risk, C is country risk, T is type of transaction with the company, O is Operational Diversity, L is Level of Integration of the business, E is Exposure to event risk, and F is Legal Form.

III. Results:

The performance of the model is measured in terms of how well the model replicates expert judgment. In this respect, it is similar to studies by Srinivasan et al. (1987), Johnson et al. (1990), and Marais et al. (1985). This method could be argued to have some ambiguity in that the errors could be due to the model built or due to the expert judgment. However, we justify this by the fact that the Company is mostly relying on the judgment of its experts and is satisfied with this given the limited loss it has incurred. The motivation for the Company, however, is to identify and organize the underlying decision method the analysts use so that the whole process can be replicated by means of a model which would bring more consistency to the credit risk assessment process. Another reason for using the expert judgment instead of historical payment record of customers as benchmark is the lack of enough historical data about the customer's payment behaviour, especially for long periods.

For expert judgment, the assessment of the major credit analyst who is responsible for the specific group of customers considered in this study was used. The expert rated customers' riskiness with a scale of 1 to 3, with 1 representing the highest and 3 representing the lowest risk for that customer. The expert rated the customers based on his overall assessment of the customer's riskiness and his affinity with the customer's situation.

In the next step, customers were categorized in two categories; those with expert rating of 1 were labeled as High-Risk and those with ratings of 2 or 3 were categorized as Low-Risk customers. Then, for the model, customers with the combined score of less than 1.8 were categorized as Hig-Risk, as is the prescribed threshold by Z-score model. In 37 cases out of the 42, the model accurately categorized the customers. It is worth mentioning that due to lack of enough historical data, there was no possibility to use categorization similar to the Discriminant Analysis containing a number of bankrupt and non-bankrupt cases. Additionally, as mentioned before, the

Company has experienced negligible loss which implies the existence of very few customers with default.

As a second test, the Total Score for each customer, obtained by multiplying A-Score and Z-score were compared to the expert's rating of the customer. In 36 cases out of 42, the deviation of the Z-score and expert rating was reduced when A-score was included. Out of the six cases where the A-Score did not make an improvement, in a discussion with the credit analyst who had rated the companies, it was indicated that one case was rated the same as its guarantor, whereas in our model, the input was based on the information of the company itself. In one case, the financials were related to 2005 which is longer than the scope of Z-score, two years, and also due to the economic recession, the company's situation had been affected markedly compared to 2005. There were four cases where the A-score had made the deviation between Z-score and expert judgment larger.

IV. Conclusion:

This paper seeks to develop a model for assessing the creditworthiness of a group of customers in the petrochemical industry. The model takes both financial and non-financial factors into account and tries to complement a known financial model, Z-Score, with other non-financial factors which are important in practice for doing business with other companies. Using the Analytic Hierarchy Process (AHP), we weight the most important factors that a group of credit managers and analysts have selected from a comprehensive list of potential factors. The method ensures proper aggregation of their judgment and consistency in the prioritization of the factors. The model is comprised of eight factors which reflect the creditworthiness of the customers and include: payment behavior, type of transaction with the Company, exposure to the event risks, operational diversity, legal form of the customer, country risk, level of integration, and industry risk.

Using expert judgment as the measure of the accuracy of the model, the model is tested as to how well it can replicate the judgment made by an expert who is directly responsible for credit granting to the group of companies present in the sample. Given that the model was able to improve the Z-Score in 86% of the cases and was able to discriminate between High-Risk and Low-Risk customers in 88% of the cases, the model is recommended for the Company for assessing the creditworthiness of the Chemicals & Intermediate customers.

There were a number of limitations, given the nature of our study. The most important limitation was lack of historical data on long-term payment behavior of the customers which made testing of our model limited to Expert Judgment. Also, given the good performance of the Company's credit analysts, there were few companies with financial distress in our sample. Larger sample size with larger number of high-risk companies could help our results to become more reliable. And finally, the subjective judgment involved both in factor selection and factor weighting by AHP can cause imprecision in the model.

There are a number of recommendations made for the Company, in order to improve their credit assessment procedures; first, the same approach could be applied to other groups of customers in other industries in order to ensure consistency in the procedures. Given the flexibility of the AHP method, the number of factors, the factors themselves, and their weight can be customized for a specific industry or group of customers.

Another important step for the company is to develop a suitable model for assessing the credit risk at the portfolio level. This is especially important because the company has a very concentrated portfolio due to the nature of its business. Thus, such an assessment seems to be necessary for the company from a risk management perspective.

In terms of future research, most models focus on the financial attributes of the companies and do not take into account the non-financial aspects of a business. Combining the two perspectives to come up with a more comprehensive model needs to be investigated more. Also, testing our approach on larger sample size and its performance in predicting the payment behaviour would could better assess the validity of using the AHP in conjuction with current financial models such as Z-Score.

References:

Altman E., “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy”, Journal of Finance, no. 23, pp. 569-609, 1968.

Altman, E., R. Haldeman and P. Narayanan, 1977, “ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations,” Journal of Banking & Finance, Vol. 1, No. 1, July, 29-54.

Altman, Edward I., Anthony Saunders, 1998, “Credit risk measurement: Developments over the last 20 years”, Journal of Banking & Finance 21, 1721-1742.

Anderson, R., 2007 “The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation”, Oxford University Press.

Bank for International Settlement (BIS), Basel Committee on Banking Supervision, “The new Basel Capital Accord”, Basel, Switzerland: Bank for International Settlement, January 2001.

Bank for International Settlement (BIS), Basel Committee on Banking Supervision, “Settlement Risk in Foreign Exchange Transactions: Report Prepared by the Committee on Payment and Settlement Systems of the Central Banks of the Group of Ten Countries”, Basel, Switzerland: Bank for International Settlement, March 1996

Bank for International Settlement (BIS), Basel Committee on Banking Supervision, “International Convergence of Capital Measurement and Capital Standards: A Revised Framework ”, June 2004

Brunnermeier, M. K., “Deciphering the Liquidity and Credit Crunch 2007–2008”, Journal of Economic Perspectives, Vol 23, Number 1, Winter 2009, Pages 77–100.

CreditMetrics, 1997. Technical Document. JP Morgan.

Crosbie, Peter, Jeff Bohn, 2003, “Modeling Default Risk”, Moody’s KMV, New York.

Fernandes, João, 2005, “Corporate Credit Risk Modeling: Quantitative Rating System and Probability of Default Estimation”, working paper, Banco BPI, Available at SSRN: http://ssrn.com/abstract=722941

Johnson, Ronald A.; Srinivasan, Venkat; Bolster, Paul J. “Sovereign debt ratings: a judgmental model based on the Analytic Hierarchy process”. Journal of International Business Studies, 1990, Vol. 21 Issue 1, p95-117

Marais, M. L., J. M. Patell and M. A. Wolfson, “The Experimental Desgn of Classfication Tests: The Case of Commercial Bank Loan Classification,” journal of Accounting Research, 1985, Vol. 22, Supplement.

McKinsey, 1993. Special report on “The new world of financial services” The McKinsey Quarterly, Number 2.

Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 28, 449-470.

Treacy, William F., Mark Carey, 2000, “Credit rating systems at large US banks”, Journal of Banking & Finance 24, 167-201.

Saaty, Thomas L., 1994, “Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process”, RWS.

Standard & Poor’s, 2008, “Corporate Ratings Criteria”. New York.

Saunders, A. and L. Allen, 2002, Credit Risk Measurement: New Approaches to Value at Risk and Other Paradigms, New York: John Wiley and Sons, 2nd edition.

Wind, Y. & T.L. Saaty. 1980. Marketing applications of the analytic hierarchy process. Management Science, July: 641-58.

Zahedi, E 1986. The analytic hierarchy process-A survey of the method and its applications”. Interfaces, 16(4), 96-108.

Appendix 1: List of the potential factors and their definition

No.	Factor	Definition
1	Payment behaviour	How good the track record of the customer is with respect to its payments to the Company
2	Type of transaction with the Company	Whether the customer is a spot buyer or distributor or preferred buyer, etc
3	Years established	For how long the customer has been operating
4	Number of clients the customer has	To how many clients the customer is selling its products
5	Volatility of business of the customer’s clients	How volatile the sale of the clients of the customer is
6	Company's share in customer's supply	How many percentage of the customer's material is supplied by the Company
7	Duration of the relationship with Company	For how long there has been relationship and transaction with the customer in place
8	Market share	What is the company’s market share with respect to its peers in the market
9	Age of the youngest board member	How old is the youngest board member
10	Essential (as opposed to non-essential) equipment	Whether the Company's materials are an essential part of the customer's production and business or a non-essential part

11	Exposure to event risks	How likely is for the customer to face litigation, environmental liability, or changes in law or national policy
12	Volatility of asset value	How volatile is the value of the customer’s assets
13	Number of employees	Number of employees of the customer
14	Increase in the number of staff	The trend in the number of staff
15	Who approached whom (if customer approached the Company)	Whether the customer approached the Company for doing business or vice versa
16	Level of integration of the customer’s business	To what extent the customer's business is vertically integrated along its value chain
17	Visited by the Company staff or not	Whether the Company staff have visited the customer or not
18	Number of alternative customers the Company has	How many other customers the Company already has that could buy the material supplied to a specific customer
19	Stability of purchase from the Company	How much volatility is observed in customer's past purchases from the Company
20	Volatility of sales volume	How volatile the sales volume of the customer is
21	Volatility of revenue	How volatile the revenue of the customer is
22	Operational diversity	How diversified is the customer (in terms of number of businesses, product lines, manufacturing plants, distribution outlets)
23	Size	How big the customer is (in terms of assets)

24	Geographical diversity	How diverse is the market in which the customer is selling
25	Asset Flexibility	Whether the customer has some (peripheral) assets to sell in case of financial distress
26	Quality of the financial information	How reliable the financial information supplied by the customer, as determined by factors such as the size and capabilities of the accounting firm compared to the size and complexities of the customer and its financial statements
27	Willingness of the customer for revealing financial/accounting information	How willing the customer is in terms of providing financial and accounting information and how rich are the financial statements in terms of information they provide
28	Country risk	How much political and macroeconomics risk is perceived for the country in which the customer is based
29	Legal form	What legal structure the customer has (e.g. plc, etc)
30	Number of affiliates supplied	Number of different affiliates of a parent company that the Company is supplying
31	Publicly-listed (as opposed to private)	Whether the customer is publicly listed or not
32	Industry risk	How risky is the industry in which the customer is active
33	Management quality	Management skills and experience compared to the size and scope of the business
34	Being rated by rating agencies	Whether the custoemr has issued bonds and thus, is rated by one of the rating agencies