MODELING CREDIT RISK THROUGH CREDIT SCORING

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Abstract
Credit risk governs all financial transactions and it is defined as the risk of suffering a loss due to certain shifts in the credit quality of a counterpart. Credit risk literature gravitates around two main modeling approaches: the structural approach and the reduced form approach. In addition to these perspectives, credit risk assessment has been conducted through a series of techniques such as credit scoring models, which form the traditional approach. This paper examines the evolution of these initiatives.

Keywords: credit risk, credit scoring models, Z – score, O – score, failure models

JEL Classification: G30, G32, G33

Introduction:

Credit risk is a ubiquitous component of the risk faced by financial institutions involved in lending operations and it is defined as the risk of suffering a loss that derives from incapacity of a borrower to make the foreseen payments. Credit risk literature is vast and can be divided into two main classes: the structural class and the reduced form class.

The structural class originates from the work of Black-Scholes (1973) and Merton (1974) and focuses on the evolution of the value of the firm. The logic behind this approach is that a firm will default at the moment when its total value is lower than the value of its liabilities. Structural credit risk modeling has quickly become very popular. Key studies in this area are Vasicek (1984), Longstaff and Schwartz (1995), Hull and White (1995), Collin-Dufresne and Goldstein (2001) or Becker, Koivusalo and Schäfer (2012).

Calin and Popovici (2012 a) review the main developments brought to the structural modeling approach, focusing also on the literature concerned with the testing of the performance of this models.

The reduced form model class treats default as a random event described by a certain probability. Defaults can thus occur unexpectedly without a structural degradation of the value of the firm. The general assumption of reduced form models is the fact that default is related to an exogenous variable that forces the default probability to be different than zero at any moment. The reduced form approach was developed by Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), Duffie and Singleton (1999), or Dionne et al. (2011). For a detailed presentation of the evolution of reduced form models see Calin and Popovici (2012 b).

Besides these perspectives, academic literature and business practice have considered a series of alternative techniques. Among these, credit scoring proved to be a tractable instrument in credit risk assessment during the last decades and continues to be used and refined. The purpose of the paper is to analyze the evolution of credit scoring systems and to evaluate their efficiency in the modern economic environment.

Methodology

In order to clearly characterize the evolution of scoring models we consulted academic research ranging from 1968 to present.

The research papers were gathered from databases like JStor, EBSCO Publishing, ScienceDirect, Scopus, ProQuest and SpringerLink, REPEC, after searching key words like: credit risk; default risk; credit scoring, Z-score, O-score, failure models.

Credit Scoring Models

The basic principle of credit scoring models is to determine the factors that can influence the default probability and to combine them into a relevant score. These factors are in general accounting variables that are weighted and fused into a multivariate model. The output of the multivariate model can be a credit score or a measure of the default probability as explained in Altman and Saunders (1998). The obtained score is compared to a benchmark value in order to determine the creditworthiness of a counterpart. Often, the scoring models were used and translated into failure prediction models.

From a methodological point of view these models have been built on techniques like: Multivariate Discriminant Analysis, the linear probability model, the logit model or the probit model (Altman and Saunders (1998)). Other similar initiatives incorporate: *recursive partitioning* (Bruwer and Hamman, (2006)), *artificial neural networks* (Odom and Sharda, (1990), *case-based forecasting* (Jo, Han and Lee, 1997) or *rough sets* ((Dimitras, Slowinski, Susmaga and Zopounidis, 1999).

One of the first and most studied credit scoring models is the Z-score introduced by Altman (1968). In this seminal paper, Altman used a sample of 33 bankrupt and 33 non bankrupt firms in the 1946-1965 period, to devise a tool for classifying corporate firms and for predictions on the default probability. Having as core a multivariate discriminant analysis, the Z-score model has the following form:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \quad (1)$$

Where *Z* represents the cumulative score and the X_i variables are:

$$X_1 = Working\frac{Capital}{Total}Assets\left(\frac{WC}{TA}\right)$$

This ratio is a measure of the liquidity of the firm's assets. The first term consist in the difference between the current assets and the current liabilities. Altman considers that a firm with heavy operational losses will have diminishing current assets compared to the total assets.

X_2 = *Retained Earnings/Total Assets (RE/TA)*

Retained earnings represents the position that reports the total amount of reinvested earnings. Altman (2000) notes that the retained earnings account can be influenced by certain corporate strategies like reorganization or dividend declarations. The author considers this indicator as a measure of the cumulative profitability in time, and the age of a firm is considered in this ratio in the sense that a recent founded firm without a history of cumulative profits will have a low RE/TA. This makes young firms more vulnerable to be classified as bankrupt in comparison to more established firms. To counteract this idea, Altman (2000) shows that this situation is synonymous to reality and quotes a study by Dun and Bradstreet (1993) which reported that 50% of the firms that defaulted in 1993 had a history lower than five years.

X_3 = *(Earnings Before Interest and Taxes/Total Assets (EBIT/TA))*

X_3 represents a real measure of the productivity of the firm's assets. Given the fact that a firm's success depends on the capacity of its assets to generate income, this rate is very useful in this type of analysis.

X_4 = *(Market Value of Equity/Book Value of Total Liabilities (MVE/TL)*)

This rate shows the amount by which the value of the assets of the firm can fall before the liabilities surmount the assets, and thus the firm is insolvent.

X_5 = *(Sales/Total Assets (S/TA))*

This ratio shows the ability of the firm's assets to generate sales. Besides this fact, this ratio is a measure of the management's capacity to operate in competitive conditions. Altman (2000) states that given the relationship with the other variables considered in the analysis this ratio has a significant impact on the model.

The calculated Z score is then compared to two benchmark values, 1.81 and 2.99. If Z<1.81, there is a high chance of a default, while a Z score above 2.99 suggests that the company will avoid financial distress.

The original Altman model has undergone an important number of alterations during the years. For example, Altamn and LaFleur (1981) consider a more tractable form of equation 1.

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (2)$$

Other well-known variants of the original Z score model are the Z' and Z''. As their predecessor, these models use a discriminant analysis on data sets that describe defaulting firms, and firms which survived this state.

In order to build the Z' model, Altman modifies the X_4 component by substituting the book value of equity for the market value. This alteration changes all the coefficients, and the classification criteria Altman (2000).

The Z' and Z'' models have the following forms:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \quad (3)$$

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (4)$$

In a subsequent application Altman, Hatzell and Peck (1995) explain that the constant +3.25 has been added to the Z'' specification in order to obtain a standardization between the zero score and a bond classified in the D (default) class.

Altman, Haldeman and Narayanan (1977) introduced a new model which intended to be an enhancement of the original Z score. The new ZETA model relied on seven variables, and according to its authors clearly outperformed the prior modeling initiatives. From this point, the literature considering the use of Z scoring models for credit risk assessment flourished at an impressive scale. For example, Altman, Baidya and Riberio-Dias (1979) adapted the original Z score for the Brazilian economy, obtaining a model that was 88% accurate in predicting defaults. Ko (1982) introduced an alternative to Z score that incorporated three of the five parameters used by Altman. The benchmark value was zero, which meant that any firm with a score above this value was in a state of less than 50% probability of default.

A strong alternative to Altman's research was introduced by Springate (1978). The author also used a multiple discriminate analysis that relied on four financial rations in order to derive a score that could distinguish between efficient and distressed firms. The study was conducted on 40 firms and had a 92.5% accuracy rate.

The Springate Model has the following form:

$$S = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4 \quad (5)$$

Where:

$$X_1 = \frac{Working\ Capital}{Total\ Assets}$$

$$X_2 = \frac{Net\ Profit\ before\ Interest\ and\ Taxes}{Total\ Assets}$$

$$X_3 = \frac{Net\ profit\ before\ Taes}{Current\ Liabilities}$$

$$X_4 = \frac{Sales}{Total\ Assets}$$

In terms of interpretation of the score, any value under 0.862 indicated the firm was predicted to default.

Fulmer et al (1984) brought forward an extensive model composed of nine variables which came to be known in the scientific literature as the H score. Fulmer's model had 98% accuracy in classifying firms one year prior to default, and an 81% accuracy rate for a longer time horizon. The general form of the Fulmer model is the following

$$H = 5.528X_1 + 0.212X_2 + 0.073X_3 + 1.270X_4 -$$

$$-0.120X_5 + 2.335X_6 + 0.575X_7 + 1.083X_8 + 0.894X_9 - 6.075 \quad (6)$$

Where

$$X_1 = \frac{Retained\ Earnings}{Total\ Assets}$$

$$X_2 = \frac{Sales}{Total\ Assets}$$

$$X_3 = \frac{EBT}{Equity}$$

$$X_4 = \frac{Cash\ Flow}{Total\ Debt}$$

$$X_5 = \frac{Debt}{Total\ Assets}$$

$$X_6 = \frac{Current\ Liabilities}{Total\ Assets}$$

$X_7 = Long\ Tangible\ Assets$

$X_8 = \frac{Working\ Capital}{Total\ Debt}$

$X_9 = \frac{Log\ EBIT}{Interest}$

The emulation brought by the works of Altman, Springate and Fullmer made the multiple discriminant analysis the dominant statistical tool for failure models. Reference papers in this area were conducted by: Deakin (1972, 1977), Edmister (1972), Taffler and Tisshaw (1977), Bilderbeek (1979), Ooghe and Verbaere (1982), Micha (1984), Gloubos and Grammatikos (1988), Declerc et al. (1991), or Lussier and Corman (1994). Similar modern initiatives have been carried out by: Leksrisakul and Evans (2005), Lugovskaja (2009), Chijoriga (2011), or Pervan et al (2011).

Despite this extensive and growing literature, some authors criticized the Altman approach or argued against the shortcomings of the multiple discriminant analysis (MDA).

Fulmer et al (1984) observed that the Zeta model introduced by Altman (1977) focused only on large firms with an average value of total assets around 100$ dollars. Other authors argue that the sales/total assets ratio may not be relevant for such an analysis as it can vary significantly from industry to another.

Besides these aspects, the scientific literature has pointed out a series of deficiencies of the multiple discriminant analysis.

Balcaen and Ooghe (2006) explain the fact that the classification rule is linear which contradicts with the fact that certain variables don't have a liner relationship with financial stability. Ohlson (1980) criticizes the existence of certain statistical requirements of the properties of the predictors. The author also states that the output of Z-scores is limited since it follows an ordinal ranking.

One of the assumptions of MDA model is the fact that the variables that compose it are multivariate normally distributed. Balcaen and Ooghe (2006) signal that in practice this assumption is often neglected which results in a bias in the estimated error rates. Furthermore, in general, variables built on financial ratios have non-normal distributions.

Ohlson (1980) criticizes the restrictive assumptions of the MDA model and corrects these shortcomings by using a logistic regression to forecast firm default. Thus, Ohlson uses a logit model and a series of data basis of American firms in order to estimate the default probability. The author isolates nine independent variables considered to be adequate in default estimation. Ohlson finds 105 defaulting firms and 2000 with a sound financial state and tests three forecasting models for time horizons that vary from 0 to 2 years.

The logit function suggested by Ohlson (1980) has the following form

$O = -1.3 - 0.4X_1 + 6.0X_2 - 1.4X_3 + 0.8X_4 -$

$$-2.4X_5 - 1.8X_6 + 0.3X_7 - 1.7X_8 - 0.5X_9 \quad (7)$$

Where

$$X_1 = \log\left(\text{total}\frac{\text{assets}}{\text{GNP}}\text{price} - \text{level index}\right)$$

$$X_2 = \text{total}\frac{\text{liabilities}}{\text{total}}\text{assets}$$

$$X_3 = \text{working}\frac{\text{capital}}{\text{total}}\text{assets}$$

$$X_4 = \text{current}\frac{\text{liabilities}}{\text{current}}\text{assets}$$

$$X_5 = 1 \text{ if total liabilities exceeds total assets, } 0 \text{ otherwise}$$

$$X_6 = \text{net}\frac{\text{income}}{\text{total}}\text{assets}$$

$$X_7 = \text{funds provided by}\frac{\text{operations}}{\text{total}}\text{liabilities}$$

$$X_8 = 1 \text{ if net income was negative for last two years, } 0 \text{ otherwise}$$

$$X_9 = \frac{(NI_t - NI_{t-1})}{(|NI_t| + |NI_{t-1}|)}, \textit{where } NI_t \textit{ represents the net income}$$

This model, is known in the literature as the O-score, and has become the most important alternative to Altman's Z-scores. This fact resulted in an important number of studies aimed at observing which of the two models is more suitable for default prediction.

Pongsatat, Ramage and Lawrence (2004) test both the Altman (1968) and the Ohlson (1980) models on a set of 120 companies from the Thailand Stock Exchange. The authors conclude that Altman's model is more efficient in detecting bankrupt firms. In a similar study, Bandyopadhyay (2006) tests logistic models and z-scores in order to forecast defaults for Indian companies, while Ugurlu and Aksoy (2006) use the O-scores and Z-scores for the Turkish market.

Moghadam, Zadeh, and Fard (2009) use the two models for a list of companies from the Tehran stock exchange. The authors conclude that the Ohlson (1980) model is more powerful in predicting bankruptcy for Iranian listed companies. Also, the authors reject the hypothesis that the MDA has more predictive power than the Logistic regression for the analyzed companies. In another study conducted on the Iranian Market, Karamzadeh (2013) obtains contrasting results that point to a superiority of the Altman model.

Hillegeist et al (2003) study Z-score and O-score models and compare them to the Black-Scholes-Merton model, reporting the clear superiority of the latter.

Conclusions:

Scoring models have become very popular during the last 40 years in credit risk applications, forming a vast and fast growing literature. In spite of this fact, their capacity of clear and sound default detection has been frequently questioned.

Z-score models have a series of shortcomings that cripples their prediction efficiency. They have a linear construction, while detecting default may require a nonlinear initiative. In addition to this, it is not clear if the variables used in Z-scores have a linear relation.

Scoring models are built on a series of accounting rates that are generally formed on the basis of historical values. Thus, it has been argued that this generation of models can't accurately capture the essential default data for a firm which has a rapidly deteriorating condition.

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