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# Accounting indicators for credit risk analysis of firms: a historical perspective

**Simona Aquino**

## Abstract

Research on the prediction of the failure of firms by using accounting information started in the second half of the 19th century and was intensified in the second half of the 20th century. Towards the end of the nineteenth century the practice arose of comparing current assets with current liabilities. Some researches in the 1930's and 1940's showed that net working capital/total capital assets, net profit/net worth, net worth/debt, net worth/fixed assets, net working capital/total assets, and the current ratio could be good predictors of failure. In the 1960's Beaver found that the ability to predict failure is strongest for the cash-flow/total debt and net-income/total assets ratios. Starting from the late 1960's the multiple ratio analyses prevailed upon the univariate analyses of firms' failures. According to the Z-Score index obtained by a multiple discriminant analysis (MDA), the best predictors of failure are working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/book value of total debt, sales/total assets. In a second MDA generation model (ZETA® model), retained earnings/total assets, appeared to be by far the most reliable predictor of failure. In 1980 Ohlson, applying a methodology of conditional logit analysis, found that three accounting ratios are statistically significant for purposes of assessing the probability of bankruptcy: total liabilities/total assets, net income/total assets, working capital/ total assets. In recent years Altman, Sabato and Wilson have developed a methodology for evaluating credit risk of small and medium sized enterprises (SMEs). The best predictors of failures turned out to be retained profit/total assets, quick assets/current assets, net cash/net worth, change in net worth, change in retained profit.

**Keywords:** Failure of firms, credit risk analysis, predictors of failure, Z-Score, accounting ratio analysis.

## 1 – Introduction

The failure of a firm can be extremely costly to several stakeholders.

The Basel 2 capital accord and the financial crisis of 2007-2009 have provided renewed impetus to develop adequate failure prediction models for firms.

Some empirical researches have indicated that financial ratios can signal an increase in the probability of insolvency for as much as five years prior to the failure of a firm.

The potential application of the bankruptcy identification models include credit worthiness analysis of firms for financial and non financial institutions, identification of undesirable investment risk for portfolio managers and individual investors, more effective internal and external audits of firms with respect to going-concern considerations.

This paper presents a synthetic survey of the main lines of research regarding the use of accounting information for the prediction of firms' failures.

## 2 - Univariate analyses of accounting indicators as predictors of failure of firms

The standardization of accounting systems during the nineteenth century paved the ground for the advent of accounting ratios as the most important analytical instrument for financial statement analysis.

In the earlier years the development of ratio analysis was dominated by the credit analysis approach; according to Bhattacharya (2007, p.3), commercial banks began to subject financial statements to rigorous ratio analysis starting from 1870, and the practice became widespread in the 1890s, when the flow of financial information increased greatly[1].

[1] Standard & Poors (S&P), one of the three largest credit rating agencies in the world, traces its history back to 1860 with the publication by Henry Varnum Poor of a volume containing financial information about U. S. railroad companies.

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According to Foulke (1961) and Horrigan (1968), towards the end of the nineteenth century the practice arose of comparing current assets of a firm with its current liabilities, through a "current ratio" which was to have for a long time a more significant and long lasting impact upon financial statement analysis than any other accounting ratio[2].

In the first decade of the 20th century the idea emerged that for financial equilibrium the current ratio should be nearly 2, i.e. that the value of current assets should be about twice the value of current liabilities (Lough, 1917).

In 1919 the du Pont Company began to use a triangle of ratios: at the top was the return on investment ratio, and at the two sides of the base were the profit margin and the turnover of total assets (Bliss, 1923). Lincoln (1925) published 40 different ratios; the proliferation of ratios originated the problem of discerning the most relevant ones.

Smith and Winakor (1930) investigated the role of financial ratios as predictors of financial difficulty; their results showed that the ratio of net working capital to total capital assets was the best predictor of failure; their findings were however undermined by the absence of a control group.

Fizpatrick (1931, 1932), including a control group, found three accounting ratios as the best predictors of failure: net profit to net worth, net worth to debt, net worth to fixed assets.

One of the best studies on ratios as predictors of financial difficulties of firms was performed by Merwin (1942), who compared the mean ratios of continuing firms with those of discontinued firms for the period from 1926 to 1936.

A difference in means was observed for as much as six years before failure, and the difference increased as the year of failure approached[3]; according to Merwin's results the three best predictors of financial difficulties were net working capital to total assets, net worth to debt and the current ratio.

Since the credit risk applications of accounting ratios showed that, in addition to the current ratio, the movement of a comprehensive set of ratios would give advance notice to the lenders about financial difficulties, some benchmarks for these ratios began gradually to be put in debt covenants; in particular: earnings/debt related outflows, total debt/earnings, total debt/total assets, the current ratio (current assets/current liabilities).

Starting from the 1950s, the British Institute of Management developed in Britain the practice of accounting ratios, in the perspective of managerial control; RoI was considered the primary ratio to be analyzed.

The Centre for Inter-firm comparison in the UK began to gather data from participating organizations and publish them as a duPont pyramidal ratio system. While in the USA ratio analysis was developed mainly with a credit scoring orientation, in he UK it was developed with a managerial focus. In the USA the Small Business Administration (SBA) generated much interest in the utility of ratios to monitor and manage small firms.

Horrigan (1965) investigated the statistical nature of accounting ratios, in order to verify the validity of using standard statistical techniques to test their predictive power in credit risk analysis.

He considered five groups of ratios: short time liquidity ratios, long term solvency ratios, capital turnover ratios, profit margin ratios, return on investment ratios.

Financial ratios seem to be in general nearly normally distributed, even though they are often positively skewed, when they have a lower limit of zero and an indefinite upper limit.

According to Horrigan's results, the usual parametric statistical techniques can then be applied to financial ratios.

Horrigan also found that many financial ratios are significantly correlated with each other; this entails the need of caution and parsimony in the selection of ratios; some financial ratios seem to be significantly correlated over time, since firms tend to maintain stable relative financial ratio positions.

One of the most relevant empirical analyses of the relevance of accounting indicators for predicting failures of firms were performed in the late sixties by Beaver (1966). The primary concern of Beaver (1966) was "to provide an empirical verification of the usefulness (i.e., the predictive ability) of accounting data (i.e. financial statements)" (p. 72).

On the basis of financial statement accounting data taken from Moody's Industrial Manual, Beaver (1966) obtained a sample of failed and non failed firms for the period 1954-1964, similar for size and industrial sector.

For every set of available financial statement beaver computed 30 accounting ratios.

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[2] "A simple guide to the ability of a company to meet its short term obligations is to link current assets and liabilities in what is commonly termed the current ratio. This appears to have been developed by bankers towards the end of the 19th century as one of their first and, as it proved, one of their last contribution to financial analysis." (Vause, 2002, p. 175).

[3] The difference between the means has however a low predictive power if the distributions of financial ratios are nonsymmetrical (skewed) and the dispersion around the means is great. In this case, the extreme observations may be responsible for most of the difference in the means, and there could be a complete overlap of the distributions for most of failed and non failed firms.

The firm is viewed by Beaver as a reservoir of liquid assets, which is supplied by inflows and drained by outflows.

The solvency of the firm can be defined in terms of the probability that the reservoir will be exhausted, at which point the firm will be unable to pay its obligation as they mature.

The larger the reservoir, the smaller the probability of failure; the larger the net liquid-asset flow from the operations (cash flow), the smaller the probability of failure; the larger the amount of debt held, the greater the probability of failure; the larger the fund expenditures for operations, the greater the probability of failure. On the basis of these theoretical propositions, Beaver (1966) tested some predictions regarding the mean values for failed and non failed firms of six financial ratios: cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratios, and the no-credit interval[4].

For each accounting ratio Beaver (1966) performed a classification test to make a prediction of failure or non failure; the values of each ratio were arranged in ascending order, a cut off point was found to minimize incorrect predictions, and a firm was classified according to its value of the relevant ratio being greater or smaller of the cut-off point.

Beaver found that the ability to predict failure is strongest for the cash-flow to total debt ratio; the error was only 13 per cent in the first year before failure, and 22 per cent in the fifth year before failure.

The second best predictor was the net-income to total assets ratio, followed by the total-debt to total asses ratio, then working capital to total assets, the current ratio[5], and, last, the no-credit interval (23 % of errors the first year before failure and 37% of errors the fifth year before failure).[6]

Another important result of Beaver's analysis was that non failed firms can be correctly classified to a greater extent that the failed firms.

On the basis of the cash flow to total debt ratio (i.e. the best predictor), the type I error (classifying as nonfailed a failed firm) was 22 per cent in the first year and 42 per cent in the fifth year before failure); the type II error (classifying as failed a non failed firm) was 5 per cent in the first year and 4 per cent in the fifth year before failure).

This means that even with the use of the best predictor according to Beaver (1966) it is quite high the probability of investing in a firm that will fail, while is quite low the probability of not investing in a firm that will not fail. Beaver (1966) conducted a univariate analysis, since he examined the predictive ability of different ratios one at a time. According to Beaver (1966, p. 100), it is possible that a multiratio analysis would predict better than the single ratios. Some preliminary efforts were made by the same Beaver in the direction of multiratio analyses but his results were not encouraging, since the best single ratio appeared to predict about as well as the multiratio models.

## 3 - Multiple discriminant analyses for the prediction of failure of firms

The univariate type of empirical analysis adopted by Beaver cannot take into account neither statistical relationships between different accounting ratios nor compensating effects.

Altman (1968), pursuing some hints already present in Beaver (1966), tried to combine several financial indicators to obtain a better predictor of the failure of firms, using multiple discriminant analysis (MDA)[7].

Starting from a list of 22 variables[8] classified into five standard accounting categories (liquidity, profitability, leverage, solvency and activity), five

[4] The no-credit interval is the time for which the company can finance its continuing operations from its immediate assets, if all the other sources of short time finance are cut-off.

[5] Beaver (1966) pointed out that the mean current ratio of the failed firm was slightly above the magic "2:1" standard in all five years before failure, but significantly lower than for non failed firms . This was interpreted by Beaver as evidence of "window dressing".

[6] The ratio distributions of the failed firms exhibit a marked deterioration as failure approaches; the result is a widening gap between the failed and nonfailed firms. The gap produces persistent differences in the mean ratios of failed and nonfailed firms, and the difference increases as failure approaches.

[7] Multiple discriminant analysis (MDA) is a statistical methodology used to classify an observation into one of several groupings dependent upon its characteristics. It is used primarily to make predictions when the dependent variable is qualitative, as bankrupt or non-bankrupt. MDA attempts to derive a linear combination of the characteristics which discriminates best between the groups; if accounting ratios are available for all firms considered , the MDA determines a set of discriminant coefficients; this methodology has the advantage of considering at the same time several accounting indicators as well as their interactions, while a univariate analysis cam consider the indicators only one at a time.

[8] Although Beaver (1966) had concluded that the cash flow to debt ratio was the best predictor of failure, this ratio was non considered by Altman (1968), because of the lack of consistent and precise depreciation and cash flow data.

were selected as the best predictors of corporate bankruptcy.

His empirical work conducted to the estimation of the first version of the famous Z discriminant function: Z = 1.2 (working capital/total assets) + 1.4 (retained earnings/total assetts) + 3.3(earnings before interest and taxes/total assets) + 0.6(market value of equity/book value of total debt) + 1.0(sales/total assets).

In the Z discriminant function Altman (1968) added to accounting variables taken from financial statements a market value dimension (the market value of all shares of stocks, preferred and common).

The predictive accuracy of the Z discriminant function was according to Altman (1968, p. 604) as high as 95 per cent one year before failure, 72 per cent two years before failure, but only 48 per cent three years before failure, 29 per cent four years before failure, 36 per cent five years before failure.

By observing the firms misclassified by the discriminant analysis, Altman (1968) pointed out that all firms having a Z score greater than 2.99 clearly fall into the non-bankrupt group, all firms having a Z score smaller than 1.81 clearly fall into the bankrupt group[9], while the area between 1.81 and 2.99 was called by Altman the "zone of ignorance" or "grey area". In general, the Z value that discriminated best between the bankrupt and non-bankrupt firms was, according to Altman (1968) 2.675[10].

In three subsequent tests Altman examined 86 financially distressed firms from 1969-1975, 110 bankrupts firms from 1976-1995 and 120 from 1997-1999, and found that the Z-Score model, using 2.675 as the cut-off score, was between 82% and 94% accurate one financial reporting period before bankruptcy (Altman, 2002, p. 18). Since the original Altman's Z-Score model requires stock price data, it is only applicable to publicly traded firms.

For private firms Altman substituted the book values of equity for their market values, obtaining the following model: Z' = 0.72 (working capital/total assets) + 0.85 (retained earnings/total assetts) + 3.10(earnings before interest and taxes/total assets) + 0.42(book value of equity/book value of total debt) + 1.0(sales/total assets). Private firms can be considered in "safe" area if Z' is greater than 2.9; if Z' is smaller than 1.23 the firm is in a "distress" area; firms with values of Z' ranging from 1.23 to 2.9 are in a "grey" area. Since the values of the sales/total assets ratio appear to change significantly in different productive sectors, a version of the Z-Score model most suitable for private non-manufacturing firms and emerging markets was proposed which excludes such a variable: Z'' = 6.56 (working capital/total assets) + 3.26 (retained earnings/total assetts) + 6.72(earnings before interest and taxes/total assets) + 1.05(book value of equity/book value of total debt).

Firms with a value of Z'' greater than 2.6 are considered to be in a "safe" area, if Z'' is smaller than 1.1 the firm is in a "distress" area, firms with values of Z'' ranging from 1.1 to 2.6 are in a "grey" area. Altman, Haldeman and Narayanan (1977) proposed a second generation model with several enhancements to the original Z-Score model (ZETA® model), which seems to be effective in classifying bankrupt companies up to five years prior to failure.

Since the ZETA® model is a proprietary effort, its characteristics have not been fully disclosed. According to Altman (2000) the ZETA® model appeared to be quite accurate for up to five years prior to failure with successful classification of well over 90% one year prior and 70% five years before failure; it should be particularly better for larger firms and for retailing companies.

Data and footnotes to financial statements have been analyzed in order to include the most recent changes in financial reporting. Twenty seven variables were considered, regarding profitability, coverage and other earnings relative to leverage measures, capitalization ratios, and earnings variability.

The basic data were adjusted in accordance with the most relevant accounting innovations (capitalization of noncancelable operating and finance leases, consolidation of subsidiaries, deduction of goodwill and intangibles from assets and equity, etc.).

Through an iterative process a seven-variable model was selected that proved the most reliable in various validation procedures: return on assets (earnings before interest and taxes/total assets), stability of earnings (standard error of estimate around the trend of return on assets), debt service (interest coverage ratio = earnings before interest and taxes/total interest payments), cumulative profitability (retained earnings/total assets), liquidity (the current ratio was found slightly more informative than the working capital/total assets ratio), capitalization (five year average of total market value of common equity/total capital), size (measured by total assets); the cumulative profitability variable, which reflects non only profitability but also the age of the firm and dividend policies, appeared to be by far the most important.

The accuracy of the ZETA model appeared to be significantly higher than the Z-Score model for the period from 2 to 5 years before failure. In particular, by the fifth year before failure the ZETA model resulted to be still 70% accurate while the Z-Score accuracy falls to 36%.

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[9] According to Altman (2002, p. 18), in 1999 more than 20% of U. S. industrial firms had a Z-Score smaller than 1.81.

[10] Altman (2002, p. 21) reported the following correspondence between Standard $ Poor bond ratings and average Z-Scores for the period 1995-1999: AAA – 5.02, AA – 4.30, A – 3.60, BBB – 2.78, BB – 2.45, B – 1,67, CCC – 0.95.

## 4 - Probabilistic methodologies for predicting the failure of firms

A logit[11] analysis of the use of accounting ratios for predicting corporate failure was performed by Ohlson (1980), using American observations from 105 bankrupt firms and 2,058 nonbankrupt firms for the period 1970-76. The econometric methodology of conditional logit analysis was chosen by Ohlson in order to avoid some statistical requirements associated with multivariate discriminant analysis (in particular, normally distributed predictors and similarity of variance-covariance matrices for failed and non failed firms). The following nine accounting indicators were used by Ohlson as predictors of the probability of corporate failure: total assets/GNP price level index (as an indicator of the size of the firm), total liabilities/total assets, working capital/total assets, current liabilities/current assets, a dummy variable for firms whose total liabilities exceeded total assets, net income/total assets, funds provided by operations/total liabilities, a dummy variable for firms whose net income had been negative for the last two years, the relative change in net income for the last year[12]. First of all Ohlson (1980, p. 119) pointed out that these indicators deteriorate as one moves from nonbankrupt firms to two years prior to bankruptcy to one year prior to bankruptcy.

Three sets of estimates were computed for the logit model using these predictors: 1) the probability of bankruptcy within one year, 2) the probability of bankruptcy within two years given that the firm did not fail after one year, 3) the probability of bankruptcy within one or two years. As expected, the estimates of the probability of bankruptcy within one year originated somewhat stronger goodness-of-fit statistics than the other two sets of estimates. In all the estimates the probability of failure appears to be significantly lower for larger firms; the other predictors derived from financial statements which appeared to be statistically significant for assessing the probability of bankruptcy were total liabilities/total assets (a measure of leverage), net income/total assets and funds provided by operations/total liabilities (measures of performance), working capital /total assets (as a measure of current liquidity). The expected prediction error rate estimated by Ohlson (1980, p. 126) is somewhat greater (about 15 per cent) than those reported in previous studies (often about 5 per cent). According to Ohlson (1980, pp. 127-129) it appears unlikely that the difference could be explained by different estimation procedures or by differences in the selection of predictors, with a possible important exception represented by the fact that he did not used as predictors non accounting data such as market-price data[13].

Beaver, McNichols and Rhie (2004), using a hazard model for the period 1962-2002 [14], found a significant failure explanatory power of three accounting ratios: return on assets (ROA), Ebitda to total liabilities (ETL), total liabilities to total assets (LTA).

## 5 - Market prices of firms and the prediction of failures

Beaver (1968a) was one of the first to investigate the extent to which changes in market prices of stocks can predict the failure of a firm. Beaver (1968a) used the same sample of firms as Beaver (1966), consisting of 79 failed and 79 non failed firms during the period 1954 to 1964, in which for every failed firm in the sample there was a non failed firm from the same industrial sector and from approximately the same asset size class.

Annual rates of return, based on dividends paid and changes in market prices of stocks, were com-

[11] Logit analysis is typically used when the dependent variable is dichotomous (for example, a firms can be either failed or not failed), and one is interested in estimating the probability of one of the two possibilities (for example the possibility of failure) as a function of some firm's quantitative characteristics (accounting and/or market indicators). With logistic regression (logit) analysis the probability of failure is represented by the logistic cumulative distribution function, whose value ranges from 0 to 1, as the independent variable range from - ∞ to + ∞. A possible alternative is probit regression analysis, where the normal cumulative distribution function is used rather than the logistic cumulative distribution function. The chief difference between logit and probit analyses is that the normal or probit curve approaches the axes ( i. e. the values of 0 or 1) more quickly than the logistic curve.

[12] Ohlson did not include any market price data of the firms, although he was then undertaking some work in this direction ; this was perceived as a disadvantage, since one may expect that the predictive power of the model could be enhanced by incorporating such data. The use of price data implicitly is another way of using more information, and this could also be viewed as another way of indirect use of accounting data (Ohlson , 1980, p. 111).

[13] " … a significant improvement in goodness-of-fit is more likely to occur by augmenting the accounting based data with market-price data. ……. I would hypothesize that many 'reasonable' procedures will lead to results which will not differ much" (Ohlson, 1980, p. 129).

[14] According to Bhattacharya (2007), hazard models are inspired by living organism, which have finite life along a time path; the cumulative probability of death is an increasing function of time, starting from zero approaching one over time.

puted for the failed firms and their non failed mates for five years before failure. Since failed firms would have a higher probability of failure than non failed mates, investors would require an ex ante rate of return on investment higher for failed firms. If, however, at any time a firm is in a solvency state worse than expected, there will be a downward adjustment of market prices of its stocks, and the ex post rate of return will be less than the expected rate of return. An examination of the ex post returns will permit an indirect assessment of the magnitude of the unexpected deterioration in the solvency state of a firm. Beaver (1968a, p. 182) showed that ex post returns were smaller for failed firms than for non failed firms in the years before failure, and the difference increased as failure approached; this indicates that the unexpected deterioration in the solvency position is sufficiently large to induce lower ex post returns for failed firms. Investors appear to adjust to the new solvency position continuously over time, with the largest unexpected deterioration occurring in the year before failure; this means that investors seem to be still surprised at the occurrence of failure even in the final year before failure.

Comparing returns with financial ratios, Beaver (1968a) found that percentage errors of classifying failed and non failed firms is smaller with the cash flow to total debt ratio than with the rate of return variables; this both for total errors and for type I errors (classifying as non failed a failed firm) and type II errors (classifying as failed a non failed firm ).

According to Beaver (1968a) the best performer financial ratio (cash flow to total debt ratio) had superior discriminatory power than return rates based upon the changes in market prices of stocks.

In conclusion, the findings of the cross-section and time series analyses performed by Beaver (1968a) pointed out that investors seem to recognize and adjust to the changing solvency position of firms, and the price changes in the common stocks act as if investors rely upon ratios for their assessment and impound the ratio information into the market prices.

The dramatic price decline in the final year before failure and the non perfect association between the price changes and the ratios seem to suggest however that investors rely upon other information as well and/or use the ratio information in a multivariate context.

Beaver (1968a) performed some cross section and time series analyses; the conclusion (p. 192) was that " investors recognize and adjust to the new solvency positions of failing firms ... and that the price changes of the common stocks act as if investors rely upon ratios as a basis for their assessments, and impound the ratio information into the market prices."

A market value dimension (the market value of all shares of stocks, preferred and common), was included by Altman (1968) in the Z discriminant function together with accounting variables taken from financial statements.

A drastic use of market prices for predicting failures is typical of the expected default frequency (EDF) model developed by KMV Corporation, purchased by Moody's in 2002, and presently adopted by Moody's KMV, a leading provider of estimates of default probabilities for essentially all publicly traded firms[15]. The EDF model is based conceptually on the option-theoretic, zero coupon, corporate bond valua-

[15] Standard & Poors, Moody's, and Fitch are the oldest and by far the largest credit rating agencies in the world (the "big three"). Standard & Poors (S$P) traces its history back to 1860 with the publication by Henry Varnum Poor of a volume containing financial information about U.S. railroad companies. S$P and Fitch rating rate borrowers on a scale from AAA to D; AAA, AA, A, and BBB are "investment grade" ratings; ratings from BB to D are "non-investment grade" or "junk bunds".

The rating methodology used by each rating agency is proprietary, and it is not usually revealed. In general, a rating agency can use primarily analysts opinions (analyst drive ratings) or mathematical model based upon accounting or market indicators (model driven ratings) or a combination of the two methodologies. Standard & Poor's ratings are based on analyses of experienced professionals who evaluate and interpret information received from issuers and other available sources. Moody's was founded in 1909 by John Moody.

Fitch rating, founded in 1913 by John Knowles Fitch, developped in 1924 the rating grade system that was later adopted also by S$P. Fitch used to be much smaller, but over the last decade has become nearly as large ase S$P and Moody's.

Credit rating agencies have been subject to strong criticism in the wake of large losses beginning in 2007 in the collateralized debt obligation (CDO) market; credit ratings of AAA were given to a large portion of even the riskiest loans.

For Italian firms an index of credit ratings is produced by CeBi (centrale dei bilanci).

As for the credit ratings of Moody's and S&P, the actual methodology employed by CeBi has non been revealed, since it is proprietary of CeBi. The firms present in database of CeBi are ranked with a score ranging from to 1 to 9, in increasing order of risk of default. As for the ratings of S&P, the CeBi's ratings have only an ordinal significance; this means that a rating of 6 does not implies a risk default twice as high as a ratings of three.

While Moody's and S$P ratings apply usually only to firms listed on the stock exchange, the CeBi ratings are assigned to all firms present in the CeBi's database.

tion approach introduced by Merton (1974). The market value and volatility of the firm are estimated first on the basis of the market value of its stock, the volatility of its stock, and the book value of the firm's liabilities; then the firm's default point is calculated relative to the firm's liabilities coming due over time and an expected value of the firm is estimated on the basis of its current value.

Using these two values plus the firm's volatility, a measure is obtained that represents the number of standard deviations from the expected firm value to the default point (the distance to default).

Finally, a mapping is obtained between the distance to default and the default rate based upon the historical default experience of companies with different distance-to-default values.

For private companies, in absence of stock prices and default data, KMV estimates the value and volatility on the basis of their observed characteristics and values based on market comparables.

The starting point of the KMV model is the proposition that when the market value of a firm drops below a certain level, the firm will default on its obligations.

In particular, a firm would default when its total market value falls below the book value of its liabilities.

Based upon empirical analysis of default, KMV has found that the most frequent default point is at a firm value approximately equal to its current liabilities plus 50% of its long-term liabilities.

Given the firm's expected value at the horizon, and its default point at the horizon, KMV determines the percentage drop on the firm value that would bring it to the default point. By dividing the percentage drop by the volatility, KMV controls for the effect of different volatilities.

The number of standard deviations that the asset value must drop in order to reach the default point is called the distance to default. The distance to default metrics is a normalized measure; hence it can be used for comparing different firms.

A key assumption of the KMV approach is that all relevant information for determining relative default risk is contained in the expected market value of assets, the default point, and the asset volatility.

Distance to default is also an ordinal measure akin to a bond rating, but it does not indicates the default probability.

In order to extend this risk measure to a probability measure KMV uses historical default experience to determine an expected default frequency as a function of distance to default.

It does this by comparing the calculated distances to default and the observed actual default rate for a large number of firms from their database; a smooth curve fitted to those data yields the EDF as a function of the distance to default.

## 6 - Credit risk rating of small and medium sized enterprises

Small and medium sized enterprises (SMEs)[16] are the predominant type of firms in several countries, and particularly in Italy.

Until the early 2000's, however, credit risk analyses usually considered mainly the larger firms[17].

In recent years Altman and Sabato (2005, 2007) and Altman, Sabato and Wilson (2008) have specifically tried to develop a methodology for evaluating credit risk of SMEs. Altman and Sabato (2007) applied a failure prediction model estimated specifically for U. S. SMEs based on a set of accounting data, showing that banks should use rating systems specifically addressed to SMEs. The account ratio used in the analysis were cash/total assets, Ebitda/total assets, Ebitda/interest paid, retained earnings/total assets, short term debt/equity.

Credit risk modelling for SMEs are usually constrained by data availability; not only market data are not available for unlisted firms, but many SMEs are granted concessions limiting the accounting data which they are required to file. Altman, Sabato and Wilson (2008) have explored the predictive power of qualitative information for credit rating of SMEs, and developed a default prediction model for the large part of SMEs for which accounting information is quite limited.

They considered over 5.8 millions records of accounting and other publicly available information concerning U. K. firms active over the period from 2000 to 2007, with an incidence of insolvency of about 1.2%. Particularly innovative is the model constructed to predict insolvency for the SME that opt to submit abridged accounts as fulfilment of their reporting requirements (about 60% of accounts submitted by U. K. firms).

The accounting variables that turned out to be significant predictors of failures were the following: retained profit/total assets, quick assets/current assets, net cash to net worth, change in net worth, change in retained profit. It also turned out that failed firms tend

16 In the European Union are considered SME firms with less than 250 employees or less than 50 million euro of yearly sales. For the Basel II accord are considered SME firms with less than 50 million euro of yearly sales; for SME the banks' capital requirement is lighter, presumably because of the lower default correlation with each other.

17 This is particularly true for the analyses including among the predictors of failure the market value of equities which is only available for listed firms. Some exceptions to this trend have been Merwin (1942) and the researches of the small business administration (SBA) in the U.S.

to have higher values of both trade creditors to total liabilities, and total debtor to total assets.

The authors' interpretation is that the higher trade debtors could be explained by attempts to boost sales by offering credit, or by the tendency of customers to avoid paying suppliers in financial difficulty, or by the fact that many SME could fail just because of late payments by customers.

The higher trade creditors could be explained by the fact that the SME that are restricted in bank credit may substitute trade credit for bank credit since suppliers can be less aware than banks of the firms' financial difficulties.

An unexpected result is that failed SME seem to have a smaller current assets/current liabilities ratio.

Another significant innovative feature of the analysis performed by Altman, Sabato and Wilson (2008) is the inclusion as predictors of failure for SME of some non accounting variables; in particular their results show that the probability of failure is higher for firms that file accounts later, do not submit a detailed cash flow statement, have received country court judgements for non payment of trade debts, have had "audited qualifications" (i. e. the auditor has indicated that the long term viability of the firm is in some doubt)[18].

Altman, Sabato and Wilson (2008) found a non linear relationship between the probability of failure and the size of SME: the probability of failure increases as size increases up to total assets of about 350.000 £, and then decreases when size increases.

This because firms with a low asset base are less likely to be forced into failure by creditors for the limited benefit of the procedure; after a certain threshold point the probability of failure declines as the firm's size increases.

## 7 - Conclusion

Researches on the use of accounting information for the prediction of failures of firms go back to the second half of the nineteenth century; their methodological rigour has improved substantially since the late sixties of last century and the practical interest in them has significantly increased since the early 2000's, also in the perspective of the application of the Basel 2 accord on the capital requirements of banks.

The most important works of the last 45 years in this field seem to have been performed by Beaver (1966), Altman (1968), Ohlson (1980), and Altman, Sabato and Wilson (2008). Merton (1974) introduced a methodology of research on the prediction of failures centered upon the dynamics of market prices of firms suitable for firms listed in the stock exchange.

Beaver (1966), building upon the seminal work by Merwin (1942), used a classification test to estimate the error rates a potential creditor would experience if he classified firms as failed or not failed on the basis of different accounting ratios considered one at a time (univariate analysis); the cash flow to total debt and net income to total assets ratios turned out to be the best predictors of failure.

Altman (1968) introduced the use of multiple discriminant analysis (MDA) in the prediction of failures, obtaining the Z-score predictor, based, in the first version, upon 4 accounting ratios (working capital/total assets, retained earnings/total assets, EBIT/total assets, sales/total assets) and one market indicator (market value of equity/book value of total debt).

For several years MDA was the most used technique in failure prediction researches, despite some significant methodological weakness (the predictors should be normally distributed, the variance-covariance matrices should be equal for failed and non failed firms, the standardized coefficients of the Z-score function do not indicate the relative importance of the different predictors of failure).

Ohlson (1980) proposed the use of logit analysis for the prediction of failures; the logit methodology is not limited by the restrictive requirements of MDA, yields a score between 0 and 1 as the probability of default (PD), the estimated coefficients give a measure of the importance of each predictor for the explanation of the probability of default.

Total liabilities/total assets and funds provided by operations/total liabilities resulted to be the most significant predictors of failure. Since the 1980's most of the academic literature used logit model for predicting default, although some studies seem to have shown that empirical results are similar in terms of prediction accuracy (Altman, Sabato and Wilson, 2008, p. 10). Altman and Sabato (2005, 2007) and Altman, Sabato and Wilson (2008) have specifically tried to develop a methodology for evaluating credit risk of SME.

In particular, Altman, Sabato and Wilson (2008) have explored the predictive power of qualitative information for credit rating of SME, and developed a default prediction model for the large part of SME for which accounting information is quite limited.

The accounting variables that turned out to be significant predictors of failures were retained profit/total assets, quick assets/current assets, net cash to net worth, change in net worth, change in retained profit.

It also turned out that failed firms tend to have higher values of both trade creditors to total liabilities, and total debtor to total assets.

Another significant innovative feature of the analysis performed by Altman, Sabato and Wilson

[18] In effect all audited firms seem to have a higher probability of failure than non audited firms, perhaps because firms that are subjected to the scrutiny of an auditor are less likely to continue to trade if are technically insolvent.

(2008) is the inclusion as predictors of failure for SME of some non accounting variables; in particular their results show that the probability of failure is higher for firms that file accounts later, do not submit a detailed cash flow statement, have received country court judgements for non payment of trade debts, have had "audited qualifications".

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