Using Market Values versus Accounting Data in Credit Risk Models: A Comparative Analysis[1]

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ABSTRACT

The use of credit scoring models has been fully documented in the financial literature. Most of these models incorporate information from the financial statements (balance sheet and profit and loss account) of the company, although it is increasingly common to find models that employ data extracted from the capital markets.

The aim of this paper is to analyze the differences in the credit rating derived from the employment of two types of model, a credit scoring model of accounting character and another of the structural type. The sample utilised comprises 105 companies quoted on the Spanish continuous market on 31 December 2004.

We have observed that both models provide similar results in the majority of sectors analysed. However, particularly relevant discrepancies are found in the technology and real state sectors.

Key words: Credit risk, Discriminant analysis, Structural models, Option pricing theory, Default probability.

JEL Classification: G13, G21, G28, G33.

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1. Introduction

In June 2004, the Basel Committee on Banking Supervision published the document "*International Convergence of Capital Measurement and Capital Standards: a Revised Framework*", commonly referred to as the Basel Agreement II. The theoretical inspiration behind this new Capital Agreement, which will replace the Agreement of 1988 currently in force, is the search for the convergence between economic and regulatory capital. In this respect, one of the more favourable aspects of the new Agreement is the decided utilisation of better and more sophisticated systems of measurement of credit risk, allowing and encouraging financial entities to develop their own models and employ them in the determination of bank capital.

Undoubtedly, a key factor in the determination of the economic capital is the estimation of the probability of default; this has meant that different alternatives for measuring the rate of insolvency of a possible borrower need to be sought.

In the financial literature authors have established, in principle, three ways of determining this rate of default (Trujillo, 2002): utilising the historical experience of defaults derived from internal systems of rating, based on the financial entity's own or shared database client portfolio; associating the system of rating of the bank with the probability of default derived from the historical experience of some of the credit rating agencies; or lastly, employing some statistical or financial model to derive, from knowledge of a data series easily accessible to the analyst, the probability of default individually for each asset, without the need to link it to discrete categories of risk.

The employment of models of "credit scoring" has been fully documented by the financial literature since 1966, when Beaver published the pioneering work "Financial ratios as Predictors of Failure", which served as a reference for subsequent investigations. The objective of Beaver was to analyze the utility of the financial ratios as predictors of business failure, and defined such failure as the incapacity of the company to meet its financial obligations when due.

The analysis of the data was divided into three parties: analysis of statistical profiles, test for dichotomous classification, and analysis of probability ratios. The use of financial ratios as predictors of business insolvency is, basically, a Bayesian approach, in that the principal problem becomes one of estimating the probability of failure (or not), conditional upon a pre-determined value of the ratio.

The principal problem of the model developed by Beaver was its univariate character; that is, we can only classify the companies "ratio by ratio", and the possibility exists that a particular company may be classified differently by two different ratios. In this context, Zavgren (1983) confirmed how the different variables can provide contradictory classifications and that the consideration of a large number of ratios, individually, is superior to the capacity of the analyst to assimilate all the relevant data.

In spite of the limitations of this first analysis, we should not forget that the Beaver's intention was not to find the best predictor of business failure, but rather to analyse the predictive ability of financial ratios.

Most of the variables deduced from the financial accounts of a company are highly correlated, so that the variables are correlated with each other in a complex way and it is not possible, without the danger of a redundancy and inconsistency, to speak of different groups, with respect to these variables, taken in isolation (Tatsuoka, 1970). The status of a company is multidimensional and no single ratio considered individually is capable of "capturing" that dimension; for this reason, there are many the authors who advocate a multivariate analysis, in which an attempt is made to integrate all the relevant variables that contribute to the success or failure of a company, and from this a unique diagnosis or global evaluation of the solvency of that company is offered systematically

The methods of multivariate analysis "of accounting character" construct a function that, from the weighting of various indicators, principally a series of ratios extracted from the financial statements of the customer, provides a score or a probability of failure of the company activity.

Since the publication of Altman (1968), with its well-known Zeta model, many researchers have applied some of the techniques of multivariate character in the attempt to determine the probability of failure of a possible borrower. The most utilised models include multiple regression analysis, discriminant analysis, qualitative regression (probit and logit) models, and most recently, models of neural networks, among others.

There are several concerns about the use of accounting models in estimating the default risk of a firm. Accounting models use information derived from financial statements. Such information is inherently backward looking, since financial statements aim to report a firm´s past perfomance, rather than its future prospects. In addition, and most importantly, accounting models do not take into account the volatility of a firm´s assets in estimating its risk of default, which would imply that two companies with similar financial ratios, but different asset volatilities, had similar probabilities of default. Clearly, the volatility of a firm´s assets provides crucial information about the firm´s probability to default (Vassalou and Xing, 2004).

However, despite the disadvantages cited, such models do achieve a considerable degree of success in their predictions.

More recently, models have employed data extracted from the capital markets, where the shares or the issued by the companies in question are traded, in the estimation of the probability of default of a borrower. In theory, market prices reflect investors´expectations about a firm´s future performance. As a result, they contain forward-looking information, which is better suited for calculating the likelihood that a firm may default in the future.

Among the models that utilise market data, we should emphasis those for which the theoretical inspiration is the model of Merton (1974), according to which default is an endogenous variable related to the capital structure of the company: a default occurs when the value of the firm's assets fall below a particular critical level that is related to the outstanding debt due for payment. Consequently these are known as structural models.

Merton proposes that the position of the shareholders can be considered as similar to purchasing a call option on the assets of the company, and the price at which they will exercise this option to purchase is equal to the book value of company's debt due for payment in the defined time horizon. In this way, Merton was the first to demonstrate that a firm's option of defaulting can be modelled in accordance with the assumptions of Black and Scholes (1973).

Thus, if the company is quoted on an organized market, we can utilize the option pricing theory to derive both the market value and the volatility of the asset, from knowledge of the value of the shares that comprise the equity of the company analyzed, and their volatility. This process can be considered similar to that utilized by investors in determining the implied volatility of an option from the observed option price.

Once the market value of the company and the debt due for payment in a defined time horizon are known, it should be easy to obtain the probability of a company going bankrupt at any given moment of time.

The most significant restriction of Merton's model is that it assumes that the liabilities of a company consist of a single issue of bonds and that its insolvency can occur only when such obligation becomes due. In principle, this would prevent the probability of default being determined for a time horizon shorter than the period within which the debt falls due. This hypothesis is relaxed in later studies, such as that of Black and Cox (1976) or the more recent study of Zhou (1997). In both these studies, the default can be considered to occur before the debt falls due, for example, in the event that the value of the assets falls to a certain lower limit. These approaches are known by the name of *first-passage models*.

Geske (1977) proposes a generalisation of Merton's model using the idea that if a share is an option on the assets of the company, then an option on a share is one option on another, that is, a compound derived asset. In this way, several types of debt with different terms of payment or due dates can be included.

Leland (1994, 1998), Anderson et al. (1996) and Mella-Barral and Perraudin (1997) extend the models of Merton and Geske to take into account the possibility of renegotiating the debt, and the existence of agency and bankruptcy costs. In a recent article, Forte and Peña (2002) introduce the concept of a refinancing contract that would permit the repayment of the existing debt by the issue of new obligations.

Lastly, a more modern approach to determining default probability encompasses the so-called models of reduced form. Under this approach, the probability of default is extracted from the credit risk premium, which is determined by the market prices of the bonds traded in the financial markets (e.g., Litterman and Iben, 1991; Jarrow and Turnbull, 1995; Duffie and Singleton, 1999).

This approach, however, does encounter a series of problems. In the first place, it is difficult to differentiate, without additional hypotheses, which part of the credit risk premium corresponds to the probability of default and which part to the rate of recovery. We should add to this the finding of authors such as Elton et al. (2001) or Delianedis and Geske (2001) that the components associated with the risk of default explain only a very small proportion of the premium, and that the greater part of this can be attributed to factors associated with fiscal effects and effects of systematic risk. In any case, the number of companies whose bonds are traded in organized markets is appreciably lower than the number of companies whose shares are quoted in such markets.

Although considerable research effort has been put toward modelling default risk from firm´s accounting data, little attention has been paid to analize the firm´s default risk derived from corporate credit risk models based on stock price.

This paper analyzes the differences between the credit rating derived from accounting-based credit scoring systems, and that from another model of the structural type, in which the probability of default takes the firm´s stock prices as the basis for analysis. The sample employed comprises 105 companies quoted on the Spanish continuous market on 31 December 2004. We have eliminated from the study companies of financial services sector because of their untypical accounting characteristics.

Following on from this introduction, Section 2 presents the results of the empirical application to our sample of companies by an accounting-based credit scoring model. Section 3 shows the theoretical default probability calculated from

Merton´s (1974) structural credit risk model, derived from stock market. Section 4 analyzes the differences, by activity sector, of the credit ratings obtained from the application of the cited models. Section 5 considers a linear regression analysis and finally section 6 provides and discusses the main conclusions.

2. Accounting-based credit scoring system

In recent decades, a large number of accounting-based quantitative systems for scoring credits have been developed. Most of them using discriminant analysis. This can be described as a multivariate technique that assigns a *score* to each company, utilising a linear combination of the independent variables.

When the object is to discriminate between groups or sets of healthy and failed companies, a cut-off point (the *cut-off score*) is established such that the companies with a score below this point are expected to "fail", while those that obtain a score above the cut-off point are expected to be viable. Put another way, a satisfactory score indicates the capacity to fulfil the obligation to pay the amounts agreed that the company assumed on contracting credit with the financial entity.

In the discriminant analysis model, the weightings that are assigned to the independent variables are those that maximise the difference between the variances of the two groups and at the same time minimises the dispersion within each group. We are concerned to find the function that would maximise the quotient between the variability between groups and the variability within groups. This function should have the maximum possible power of discrimination between the groups.

The first to use this type of technique applied to the prediction of company bankruptcy was Altman (1968), with his famous Zeta model, although this approach has been utilised in a great number of disciplines since its first application in the 1930's.

The initial Zeta function of Altman was formulated as:

$$Z = 0.012 \cdot X_1 + 0.014 \cdot X_2 + 0.033 \cdot X_3 + 0.006 \cdot X_4 + 0.999 \cdot X_5 \qquad [1]$$

where,

X_1 = Working capital/Total assets

X_2 = Retained Earnings/Total assets

X_3 = Earnings before Interest and Taxes/Total assets

X_4 = Market value of Equity/Book value of Total Liabilities

X_5 = Sales/Total assets

The rates of error were small for the two years prior to the company "failure", but fairly high for the third, fourth and fifth years prior to the event. Currently, discriminant analysis is, by a considerable margin, the most popular technique in studies of the prediction of company failure.

This initial model was modified in later stages with the object of making it applicable to all types of company, whether or not quoted on organised markets, including non-manufacturing companies. In consequence, the market value of equity was replaced by its book value in X_4 and the ratio Sales/Total assets, the variable most sensitive to the sector of activity, was eliminated from the function. The coefficients were recalculated.

The revised Zeta function (Z´´) proposed by Altman, Hartzell and Peck (1995) took the following form:

$$Z'' = 3.25 + 6.56 \cdot X_1 + 3.26 \cdot X_2 + 6.72 \cdot X_3 + 1.05 \cdot X_4 \qquad [2]$$

where,

X_1 = Working capital/Total assets

X_2 = Retained Earnings/Total assets

X_3 = Earnings before Interest and Taxes/Total assets

X_4 = Book value of Equity/Book value of Total Liabilities

The constant term (3.25) in the model allows the analysis to be standardised, so that a rating equivalent to a bankruptcy (rating D) is consistent with a score equal to or less than zero. This model is the one recommended by the authors for credit analysis in emerging markets, although, in general, its use is also advised when the sample is constituted by non-US companies.

It is precisely these last two characteristics of the function [2] (using only variables extracted from accounting statements and applicability to all activity sectors), apart from its acknowledged fame in the financial literature, that led us to opt for this model when undertaking the credit analysis "of accounting character".

The greater degree of certainty or reliability of the linear discriminant models is a powerful argument for their use, despite the violation of a series of statistical premises (principally normality and equality of the matrices of variances-covariances). In fact, if making a classification between various groups is the only objective of the construction of a model, this argument has validity. Altman and Spivack (1983) found that the scores obtained with the discriminant model provided classifications closely correlated with the Standard & Poor's bond ratings. However, the discriminant technique also gives us the probability of bankruptcy of each company observed, assuming that the score obtained is distributed normally. In such a case, there are several authors (see, in this respect, Press and Wilson (1978) or Ohlson (1980)) who state that these probabilities may be erroneous in the event that the hypotheses of normality and of equality of the matrices of variances-covariances are infringed.

Since our aim is not so much to obtain an exact measure of the probability of insolvency as to perform a task of classification, it would be expected that such restrictions of a statistical nature would not impair the results obtained. In any case, it can be assumed that the higher the scores obtained by the companies of the sample, the lower will be the probabilities, theoretical or empirical, of default.

For the empirical application of the Z'' function of Altman et al., we have employed the audited financial statements corresponding to the accounting period 2004 of 105 companies quoted on the Spanish continuous market. The results obtained are presented as Appendix A.

The relationship between the score provided by the model and its equivalent rating according to Standard & Poor's appears in table 1. This equivalence has been derived from a sample of rather more than 750 US companies with debt rated by one or more of the rating agencies during 1994.

[Insert Table 1 about here]

3. Structural credit risk model

In this section we shall estimate the probabilities of default one year ahead, on 31 December 2004, for our sample of companies, by applying the option pricing theory. In contrast to accounting models, structural models use the market value of a firm´s equity in calculating its default risk. The procedure that we shall follow will be similar to that employed by the company KMV; the theoretical basis of this model is that of Merton (1974).

The empirical application of models of this type is relatively recent, since they have only begun to achieve certain popularity in the last few years. Of the models that are currently being developed in this area of analysis, a particularly notable one is that developed by the KMV Corporation, recently acquired by Moody's

Merton (1974) considers the equity of a firm as a European-type call option on its assets, and the price for exercising that option is the accounting value of the outstanding debt due for repayment in the defined time horizon.

In the following we shall give a brief exposition of the bases of the model. Let us suppose, for this, a leveraged company that has made only one issue of debt, consisting of zero coupon bonds that fall due at time *T*. This company does not pay dividends. We also assume that the markets are perfect and that there are no frictions, such as taxes or costs of bankruptcy.

In this case, the market value of the firm´s equity, *E*, at the time *T* when the debt falls due is:

$$E_T = \max (V_T - D, 0) \qquad [3]$$

where V_T is the market value of the company's assets and *D* (the price of exercising the option or strike price) is the book value of the debt due at *T*. It should be noted that [3] represents the payment of a call option of the European type whose underlying security is the value of the company. Therefore, we can use the formulation of Black and Scholes (1973) to obtain the probability that the company may become bankrupt at any given moment of time.

If we assume the customary hypotheses of the Black-Scholes-Merton model (lognormality of the underlying security, volatility and constant rates of interest, continuous contracting, and perfect markets), we can relate the market value of the firm´s equity today, E_0, with the market value of the assets, V_0, and the volatility of the return on these assets, σ_V, using the known expressions of the model:

$$E_0 = V_0 N(d_1) - De^{-rT} N(d_2)$$

$$d_1 = \frac{\ln(V_0 / D) + (r + \sigma_V{}^2 / 2)T}{\sigma_V \sqrt{T}}$$

$$d_2 = \frac{\ln(V_0 / D) + (r - \sigma_V{}^2 / 2)T}{\sigma_V \sqrt{T}} = d_1 - \sigma_V \sqrt{T} \qquad [4]$$

where N is the cumulative density function of the standard normal distribution, r is the risk-free rate of interest in continuous terms, and the rest of the variables are as already defined.

It can be observed that the model has two unknowns, V_0 and σ_V. To estimate these parameters, we need an additional equation that relates the volatility of the option to that of the underlying security:

$$\sigma_E = \frac{V_0}{E_0}\frac{\partial E}{\partial V}\sigma_V \qquad [5]$$

This last partial derivative, $\partial E/\partial V$ is, simply, the delta of a call option, $\Delta = N(d_1)$, that has the assets of the company as the underlying security.

This equation, together with the previous ones, shown in [4], makes it possible to determine V_0 and σ_V by means of a numerical algorithm using the values of E_0 and σ_E; these are variables that are easy to quantify in quoted companies.

In this model, the neutral-risk probability that the value of the company is greater than the value of the debt on the date T, that is $V_T \geq D$, is $N(d_2)$. Therefore, the risk-neutral probability that the company may default on the debt at time T determined at any time t is:

$$q_t(T) = 1 - N(d_2) = N(-d_2) \qquad [6]$$

This risk-neutral probability of default is that "foreseen" by the market and can be considered as the expected frequency of default conditional on the actual value of the company, on its leverage, volatility, structure of debt and risk-free interest rate.

The "natural" default probability can also be calculated, but the expected rate of growth of the company must be available to be able to do this, μ. In this case, the probability that we seek is:

$$p_t(T) = N\left[-\frac{\ln(V_t / D) + \left(\mu - \frac{\sigma_V^2}{2} \right)(T-t)}{\sigma_V \sqrt{T-t}} \right] \qquad [7]$$

the result of substituting the risk-free rate by the expected rate of growth of the assets, in equation [6].

In our case t = 0 = 31/12/04 and T = 1 = 31/12/05. Although the model of Merton assumes that insolvency can only occur when the debt falls due, in practice this limitation is usually overcome by assuming that there can be a default on the liability at the end of any given time horizon. In our case, this is one year ahead.

It should be observed that the equation that we shall utilize incorporates the rate of growth of the company, μ, in place of the risk-free rate of interest, r. With this, we obtain a "natural" probability of default that is different from the risk-neutral probability indicated in [6].

The determination of the rate of growth of the assets is not a simple task. Du and Suo (2003) utilize the mean variation of the asset values during the twelve months prior to the time when the default probability is to be estimated. In our case, we have chosen to use as a *proxy* the rate of growth of the Spanish GDP; for the year 2005, this is estimated at around 3%. In any case, this variable appears to have little discriminant power in the default of a firm (Crosbie and Bohn, 2003).

Since our objective is to determine the probability of default one year ahead, we will assume that the amount of debt falling due within a year or default point is equal to the book value of the current liabilities plus half of the long term debt. Although we are determining the probability of default one year ahead, the inclusion of part of the long-term debt is customary in the studies on the subject. KMV argues that it is observed empirically that insolvency usually takes place before the value of the company falls below its current liabilities. Du and Sou (2003) and Vassalou and Xing (2004) make the same comment. All these authors add 50% of the long term to the short term debt. Again, these data have been extracted from the accounts that the various companies quoted on the Spanish continuous market periodically have to provide.

Finally, with respect to the calculation of the asset values, V_0, and their volatilities, σ_V, these have been estimated using expressions [4] and [5], by means of a numerical algorithm, taking the market value of equity, E_0, during the month of December 2004 and their daily volatilities annualized during this year, σ_E. Although we wish to determine the default probability for the company at 31/12/2004, it seemed to us more appropriate to take the mean value of its shares during the month of December, instead of taking the value on the last dealing day of the year, with the object of trying to avoid possible market anomalies.

Having estimated the probability of default of the firm by means of the equation [7], it is easy to quantify its distance-to-default (*DD*) by the expression (Vassalou and Xing, 2004):

$$DD_t = \frac{\ln(V_t / D) + \left(\mu - \frac{\sigma_V^2}{2} \right)(T - t)}{\sigma_V \sqrt{T - t}} \qquad [8]$$

Default occurs when the ratio of the value of assets to debt is less than 1, or its log is negative. The preceding equation tells us by how many standard deviations the log of this ratio needs to deviate from its mean in order for default to occur. The greater the distance-to-default of a company, the less its probability of insolvency and vice versa, both variables being related by equation [9]:

$$p_t(T) = N(-DD) = N\left[-\frac{\ln(V_t / D) + \left(\mu - \frac{\sigma_V^2}{2}\right)(T-t)}{\sigma_V \sqrt{T-t}} \right] \qquad [9]$$

We have assumed that the future values of the assets follow a Normal type distribution function. However, in practice, this probability function is difficult to test. A possible solution would be to analyse the relationship between the distance-to-insolvency and the default probability in a historical series of insolvencies, generating a table of frequencies to relate the two variables, as done by KMV. In this way an "empirical" probability would be obtained whose value may differ significantly from the theoretical value previously cited, although it would be expected that the two would be strongly correlated.

Appendix B presents the results of the calculation of the distance-to-default for the 105 companies selected.

4. Comparative analysis

In this section we shall analyse the different ranking according to credit scores provide by the Z´´ function and the model of Merton, for our sample of companies. With this objective, we have grouped together these companies using the industry sector classification employed by the Madrid Stock Exchange.

Awarning must be given that the numerical results provided by the two functions are not comparable although, in both cases, one would expect that the higher the score obtained (*Z´´- Score* or *Distance to Default*), the better the credit-worthiness or solvency of the company, and vice versa. This will allow us to draw the pertinent conclusions.

A) PETROLEUM AND ENERGY SECTOR

[Insert Table 2 about here]

Observing the above it can be deduced that the ranking provided by the two models is, in general terms, fairly similar. Endesa, Enagas, Red Eléctrica Española and Unión Fenosa obtain the worst results. According to the correspondence between scores and bond *ratings* established by Altman in Table 1, all the issues of debt of these companies would be graded as "speculative". At the other extreme, Repsol YPF and Gas Natural are situated among the better scores, both with debt of "investment" grade.

The biggest differences are seen in Iberdrola and Cepsa.

B) BASIC MATERIALS, INDUSTRIAL AND CONSTRUCTION SECTOR

[Insert Table 3 about here]

Again there are considerable similarities in the classifications obtained. Both the Z´´ function of Altman et al. and Merton's model situate Acerinox, Arcelor, Hullas Coto and Tubacex among the best of the sector, both rating these companies' debt as "investment" grade (see Table 1). Española de Zinc obtains a negative Z´´ score, which puts it in a situation of default. It also gets the worst distance-to-insolvency according to the structural model, 4.64 times its standard deviation.

[Insert Table 4 about here]

Gamesa and Zardoya Otis get good scores with both functions. However, there are divergences in the ranking between Mecalux, Nico. Correa and Azkoyen.

[Insert Table 5 about here]

In the construction sector, unlike the previous sector, the classifications given by the two models differ significantly. In addition, except for Acciona, Altman et al.´s function situates this sector as being the least solvent. It does not happen thus with the model of Merton.

[Insert Tables 6, 7, 8 and 9 about here]

In the construction materials and chemical industry subsectors, the rankings are identical. It should be noted that Tableros de Fibras would be graded with a CCC rating according to the equivalence provided by Altman.

C) CONSUMER GOODS SECTOR

[Insert Table 10 about here]

Except for Barón de Ley, which obtains the best results, it is difficult to find similarities for the rest of the companies.

[Insert Table 11 about here]

Both Inditex and Adolfo Domínguez are positioned among the two best companies of the sector. Sniace is the worst classified, with a grading equivalent to CCC. With the exception of Tavex Algodonera, the two classifications are analogous.

[Insert Table 12 about here]

Again the models coincide in situating both Iberpapel and Unipapel as the two best of the sector (with a rating equivalent to AAA) and Reno de Medici as the worst classified. Equally, the rankings are similar except for Miquel y Costas, whose grading differs significantly.

[Insert Table 13 about here]

Zeltia and Puleva Biotech obtain fairly high results from the two functions, with the maximum rating according to the previously-mentioned equivalence.

[Insert Table 14 about here]

This sector presents strong divergences with respect to the rankings provided by the two functions. Although Tudor is the company that gets the best Z´´ score, the model of Merton places it at only 5.16 times its standard deviation from insolvency.

D) CONSUMER SERVICES SECTOR

[Insert Tables 15, 16, 17, 18, 19 and 20 about here]

In the consumer services sector (tables 15 to 20), the classifications provided by the two models are very similar. However, it must be recognised that this similarity of results is facilitated by the relatively small number of companies that comprise each subsector.

E) REAL STATE SECTOR

[Insert Table 21 about here]

In the property sector, the rankings obtained are found to be fairly heterogeneous. Whereas the Z´´ function of Altman et al. shows Urbanizaciones y Transportes to be the best positioned, Merton's model situates this company as being the least solvent.

F) TECHNOLOGY AND TELECOMMUNICATIONS SECTOR

[Insert Table 22 about here]

Telecommunications is perhaps the sector where the differences between the two functions become most evident. Despite both Jazztel and Avanzit presenting Z´´ scores equivalent to AAA ratings, their distances to insolvency are only 4.86 and 3.28, respectively. Quite the opposite occurs with Telefónica and its subsidiary Telefónica Móviles; these are situated among the best of the sector by Merton's model but get credit ratings close to CCC according to the equivalence indicated in Table 1.

Once examined the different rankings provide by the two functions, we will complete the analysis with a study of the correlation between the Z´´ score of Altman and the distance to insolvency provided by the Merton´s model. In theory, this correlation should be greater than zero (what it would imply that both variables are related) and positive (to greater Z´´ greater distance to the insolvency, and vice versa).

[Insert Figure 1 about here]

Figure 1 shows the scatter diagrams by activity sector[1,2]. The observation of such makes estimate a relation of linear type in most of the cases, which takes to us to reject another class of functions (exponential, quadratic, etc.).

[Insert Table 23 about here]

Except for real estate and technology sectors, all the correlations are positive and with values around the 60-70%, which illustrates certain degree of positive and linear relationship between both variables, something that already we noted when observing the sectorial scatter diagrams. On the other hand, all of them are statistically significant (different from zero) at the 0.10 level. The correlation coefficient obtained by the telecommunications sector (-0.633) explains the disparity in the ranking provided by the Z´´ score of Altman´s model and the distance to default. In this case, how much greater it is a variable, minor is the other, and vice versa. Alternatively, the low value of the Pearson´s correlation coefficient provided by the real estate sector (-0,276)[3] seems to indicate absence of relationship between both variables.

The correlation analysis supports what we said previously. This is, except for real estate and technology sectors, we can discern a certain degree of linear positive relationship between the credit qualifications provided by the accounting-based credit scoring model and the based one on market data.

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1 Although there are sectors where the number of variables is small, the differences found between such advice to maintain the analysis by activity sector. On the other hand, using subsector activity reduces in excess the sample.

2 We have excluded from the study those extreme values that could alter the analysis. In particular, we have not considered the values obtained by Iberpapel and Ercros.

3 Due to the small number of companies that comprise the sample model, the correlation coefficient is not statistically significant for the value obtained in this case.

5. Linear regression analysis

Finally, once known the existence of certain linear dependency among both approaches of measurement of the risk, the equation [10] (see table 24) shows the result of fitting a linear model to describe the relationship between the two variables studied on the basis of 85 companies quoted in the Spanish Continuous Market. We have eliminated of the analysis the companies of the real estate and technology sector, as well as the extreme values before referred (Iberpapel and Ercros)[4].

$$Z'' = 2.661 + 0.421\ DD \qquad [10]$$

Being, as we know, Z´´ the score offered by the function of Altman et al. and DD the distance to the default, obtained by the application of Merton´s model.

Also, we could have considered the linear regression analysis using the distance to the insolvency as dependent variable. The equation of the fitted model in this case is

$$DD = 4.708 + 0.791\ Z'' \qquad [11]$$

[Insert Table 24 about here]

Anyway, the correlation coefficient equals 0.577, whereas the R-Squared statistic indicates that the model as fitted explains 33.32% of the variability in the dependent variable. The Pearson correlation coefficient indicates a positive and moderately strong relationship between the variables. This one is something less than the sectorial coefficients, which would confirm the thesis of a linear relation differentiated by sectors.

[4] The shortage of companies that compose the diverse sectorial samples made us consider, in this case, a regression analysis on an added basis. The absence of relationship between the two variables in the companies of the real estate sector, or the incorrect value of the same one, in the technology sector, advised to leave such companies outside the regression analysis.

Since the p-value in the analysis of variance (ANOVA) is less than 0.01, there is a statistically significant relationship between both variables at the 99% confidence level.

6. Conclusions

According to the foregoing data, it is concluded that there is a certain degree of positive linear relationship between the credit qualifications provided by the accounting-based credit scoring model and that one based on market data. As a result, such models provide similar results in the majority of the analysed sectors. However, particularly relevant discrepancies are found in the technology sector, perhaps because for companies in this sector, there is an especially evident difference between the accounting values and those of the market, which are influenced more by expectations of future growth than by historical results.

Equally the differences in the results obtained by these two functions in the property sector are also considerable. In this case, these differences are possibly influenced by the fact that, in the assessment of the solvency of a property developer, the decisive factor is the viability of the projects in question; this viability is not usually reflected in the accounts of these companies.

In the rest of sectors, apart from some exceptions, the classifications provided by the two models usually coincide.

The usefulness of the credit scoring models that utilise accounting ratios in the assessment of credit risk in companies is fully documented. However, the option pricing theory provides us with a very interesting alternative framework for estimating the risk of default of a firm. This type of estimation is an objective assessment, based on market data, which also allows it to be frequently updated.

But, despite its evident theoretical solidity, the market approach comes up against a powerful obstacle in countries like Spain, where there are still relatively few companies whose shares are quoted, since share prices form the principal input of the model.

The models analysed are now being discussed among the financial entities with the object of establishing internal systems of rating that would enable them ultimately to adopt an advanced approach to risks, in accordance with the new Capital Agreement. As this Agreement is configured, it would represent a substantial improvement in the capital requirement figures and, therefore, in the returns obtained, compared with systems based on ratings awarded by credit rating agencies.

Appendix A

Z´´-Score of the companies of the Spanish Continuous Market (at 31/12/04)

	X_1 = WC/TA	X_2 = RE/TA	X_3 = EBIT/TA	X_4 = BVE/TL	Z" -Score
Abengoa	0.4201	0.2256	0.0379	0.3554	7.37
Abertis	-0.0341	0.2160	0.0721	1.1473	5.42
Acciona	0.1346	0.4839	0.0434	1.2248	7.29
Acerinox	0.1464	0.6249	0.0957	2.4612	9.47
ACS	-0.2700	0.2744	0.0699	0.6125	3.49
Adolfo Dguez.	0.4331	0.6099	0.2135	4.2986	14.03
	-0.0700	0.4035	0.1164	1.6137	6.58
Aldeasa	0.2457	0.4580	0.1417	1.8355	9.23
Altadis	-0.0896	0.0260	0.1984	0.3451	4.44
Amadeus	-0.0487	0.4783	0.1522	1.9278	7.54
Amper	-0.4102	0.5869	-0.0496	1.2046	3.40
Antena 3 TV.	0.2391	0.2687	0.1466	0.7577	7.48
Arcelor	-0.0350	0.0033	0.0682	5.4423	9.20
Aux. Ferrocar	0.1854	0.2059	0.0331	0.3445	5.72
Avanzit	0.1091	1.1337	0.4223	0.9752	11.52
Azkoyen	-0.1859	0.2011	-0.0616	1.0398	3.36
Barón de Ley	0.3906	0.6205	0.0503	3.3073	11.65
Befesa	-0.0726	0.1157	0.0460	1.1436	4.66
Bo. Riojanas	0.2642	0.3276	0.0506	0.7784	7.21
C.V.N.E.	0.3874	0.5350	0.0742	1.8973	10.03
Campofrío	0.2489	0.2795	0.0660	0.6195	6.89
Cem. Port. Val	0.0556	0.7735	0.1553	9.0391	16.67
Cepsa	0.0891	0.3416	0.1730	1.0365	7.20
Cie. Automot.	0.0351	0.2228	0.0662	0.4466	5.12
Cintra	0.0906	0.6212	0.1396	4.5070	11.54
Cortefiel	0.3092	0.3022	0.0662	0.6704	7.41
D. Felguera	0.0276	0.0455	0.0451	0.4431	4.35
Dogi	0.2154	0.3470	0.0134	0.3891	6.29
EADS	0.0473	0.6021	0.0192	1.8829	7.63
Ebro Puleva	-0.0252	0.4804	0.0824	1.7489	7.04
Elecnor	0.0791	0.1796	0.0601	0.3037	5.08
Enagas	-0.0468	0.1489	0.0788	0.5089	4.49
Endesa	-0.0908	0.2799	0.0608	0.5951	4.60
Ercros	0.0818	0.3334	0.2644	21.0850	28.79
Esp. del Zinc	-0.6686	0.2743	-0.5655	-0.2806	-4.34
Europa & C	0.0423	0.0942	0.0280	0.7411	4.80
Europistas	-0.0334	0.0935	0.1532	0.5306	4.92
Fadesa	0.3079	0.0916	0.0823	0.1698	6.30
Faes Farma	-0.0348	0.4538	0.1775	1.9049	7.69
FCC	-0.2417	0.3157	0.1121	0.8775	4.37
Ferrovial	-0.0904	0.2648	0.0778	0.5615	4.63
Funespaña	0.0295	0.6722	0.0702	7.8959	14.40
Gamesa	0.1598	0.5048	0.2986	4.4165	12.59
Gas Natural	-0.0293	0.4477	0.1288	1.7137	7.18
Gr. Emp. Ence	-0.0610	0.2968	0.0846	1.4544	5.91

	X_1 = WC/TA	X_2 = RE/TA	X_3 = EBIT/TA	X_4 = BVE/TL	Z" -Score
Gr. Inmocaral	0.4942	0.3981	0.0354	0.8998	8.97
Hullas Coto	0.0433	0.4724	0.0796	2.0983	7.81
Iberdrola	0.0806	0.2366	0.0560	0.7107	5.67
Iberia	0.1615	0.1087	0.0796	0.7423	5.98
Iberpapel	0.2554	0.7803	0.0975	227.1993	246.68
Inbesos	-0.0631	0.3850	0.0236	1.2591	5.57
Inditex	0.1452	0.4004	0.1733	1.5742	8.33
Indo Interna	-0.0401	0.3605	0.0493	1.3351	5.89
Indra	0.2127	0.2155	0.0948	0.4661	6.47
Inm. Colonial	-0.2527	0.1692	0.0665	0.3364	2.94
Inm. Urbis	0.3566	0.1929	0.0836	0.4456	7.25
Jazztel	0.2285	3.5341	-0.3072	7.4346	22.01
La Seda B.	-0.2390	0.0478	0.0203	0.4802	2.48
Lingotes Esp.	0.0763	0.2559	0.0393	0.9035	5.80
Logista	-0.2444	0.1321	0.0549	0.2071	2.66
Mecalux	0.1313	0.3687	0.0247	0.8872	6.41
Metrovacesa	0.2363	0.1094	0.1040	0.2472	6.12
Miquel Cost.	0.1174	0.3852	0.1792	2.0506	8.63
Natra	-0.0440	0.2877	0.0091	3.9031	8.06
Natraceutical	0.2120	0.3680	0.0513	2.7297	9.05
NH Hoteles	0.0824	0.2168	0.0137	0.7152	5.34
Nico.Correa	0.3146	0.4629	-0.0907	1.5741	7.87
OHL	-0.0374	0.1625	0.0380	0.2458	4.05
Paternina	0.4817	0.0000	-0.0767	0.4599	6.38
Pescanova	0.0825	0.0851	0.0972	0.8740	5.64
Prim	0.3525	0.3720	0.1293	1.0047	8.70
Prisa	0.0534	0.3595	0.0303	0.7158	5.73
Prosegur	-0.0525	0.1713	0.0085	0.3947	3.94
Puleva Bio.	0.4832	0.4911	0.0406	9.7613	18.54
R.E.E.	-0.0933	0.1562	0.0835	0.4079	4.14
Reno M.	0.0629	0.0778	-0.0063	0.5045	4.40
Repsol YPF	0.0457	0.4971	0.0517	1.7667	7.37
Sacyr Val.	-0.1380	0.2550	0.0775	0.8342	4.57
Service P.S.	-0.0703	1.1529	-0.0428	0.8900	7.19
Sniace	-0.1772	0.0000	0.0606	-0.1358	2.35
Sogecable	-0.0365	0.2471	-0.0299	0.1303	3.75
Sol Meliá	-0.0700	0.4908	0.0093	0.4591	4.94
Sos Cuetara	-0.0167	0.1907	0.0423	0.7779	4.86
Sotogrande	0.1074	0.4226	0.3139	2.7838	10.36
Ta. Fibras	-0.0654	0.0140	0.0223	1.1316	4.20
Tavex Algod.	0.0045	0.2191	0.0526	1.0013	5.40
Tecnocom	0.1621	0.9743	0.0205	2.9835	10.76
Tele Pizza	-0.1910	0.1615	0.1137	0.3460	3.65
Telecinco	0.1913	0.1647	0.3215	1.5308	8.81
Telefónica	-0.1684	0.1581	0.0596	0.3896	3.47
Telf. Móviles	-0.0638	0.0666	0.0764	0.3753	3.96
Testa Inm.	-0.0147	0.0829	0.0944	0.6759	4.77
TPI	0.2211	0.1442	0.3100	0.6607	7.95
Transp. Azkar	-0.0245	0.0661	0.0408	1.1337	4.77
Tubacex	-0.0387	0.3149	0.0912	3.9159	8.75
Tubos Reuni.	0.0639	0.1886	0.0494	0.4654	5.10

	X_1 = WC/TA	X_2 = RE/TA	X_3 = EBIT/TA	X_4 = BVE/TL	Z" -Score
Tudor	0.2794	0.4343	0.0284	3.5720	10.44
Unión Fenosa	0.0717	0.1650	0.0598	0.4020	5.08
Unipapel	-0.0308	0.6628	0.0579	7.0713	13.02
Uralita	-0.0386	0.0917	0.0755	0.4581	4.28
Urban.y Tran.	0.7598	0.0096	0.3465	1.2893	11.95
Vidrala	-0.0031	0.4779	0.1584	3.2062	9.22
Viscofan	0.0531	0.7038	0.0219	3.7994	10.03
Zardoya Otis	0.1177	0.0827	0.4094	0.2660	7.32
Zeltia	0.6533	0.8592	0.0086	8.3659	19.18

Appendix B

Distance-to-Default of the companies of the Spanish Continuous Market (at 31/12/04), determined by applying a structural model.

	Market value of equity (E_0)*	Volatility of equity (σ_E)	Default point (book liabilities) (D)*	Market asset value (V_0)*	Volatility of asset value (σ_V)	Default Probability (p_t)	Distance-to-default (DD)
Abengoa	667,335	22.04%	486,777	1,143,853	12.86%	4.7675E-12	6.81
Abertis	8,134,963	13.63%	1,698,587	9,797,087	11.32%	8.6669E-56	15.69
Acciona	3,960,670	16.30%	1,891,998	5,812,054	11.11%	2.9673E-25	10.32
Acerinox	2,946,732	18.92%	538,278	3,473,455	16.05%	4.8588E-32	11.72
ACS	5,831,505	15.99%	1,812,602	7,605,197	12.26%	7.5406E-33	11.88
Adolfo Dguez	147,610	21.91%	18,266	165,483	19.54%	4.5337E-30	11.33
Ag. Barna.	2,118,932	17.87%	476,622	2,585,323	14.65%	8.4138E-32	11.68
Aldeasa	609,752	28.01%	80,059	688,092	24.82%	2.2885E-18	8.66
Altadis	9,107,195	20.20%	1,870,453	10,937,496	16.82%	1.5893E-26	10.59
Amadeus	4,151,737	27.58%	508,370	4,649,194	24.63%	1.2938E-19	8.98
Amper	115,220	30.62%	39,645	154,014	22.91%	1.4196E-09	5.94
Antena 3 TV.	732,871	28.68%	428,967	1,152,629	18.23%	1.9425E-08	5.50
Arcelor	10,714,868	28.11%	1,399,840	12,084,659	24.92%	2.7034E-18	8.64
Aux. Ferrocar	209,694	17.50%	387,194	588,576	6.24%	4.1524E-13	7.16
Avanzit	50,315	42.28%	46,769	96,080	22.14%	0.00052553	3.28
Azkoyen	138,875	26.37%	18,583	157,059	23.32%	2.4562E-20	9.17
Barón de Ley	270,810	16.25%	10,565	281,148	15.65%	6.457E-99	21.08
Befesa	418,325	29.36%	73,433	490,182	25.06%	1.8508E-14	7.57
Bo. Riojanas	51,992	23.17%	25,292	76,741	15.70%	3.3997E-13	7.18
C.V.N.E.	149,122	27.43%	34,598	182,977	22.35%	3.9175E-14	7.47
Campofrío	615,574	14.11%	400,809	1,007,779	8.62%	1.8502E-28	11.00
Cem. Port. Val	1,249,559	15.79%	85,317	1,333,046	14.80%	2.4481E-78	18.70
Cepsa	8,036,967	16.52%	2,176,152	10,166,405	13.06%	2.6108E-33	11.97
Cie. Automot.	260,376	18.91%	153,005	410,097	12.01%	2.2022E-17	8.40
Cintra	3,883,176	8.78%	357,132	4,232,643	8.06%	1.174E-211	31.03
Cortefiel	869,695	25.64%	186,557	1,052,247	21.19%	1.213E-16	8.20
D. Felguera	108,406	21.03%	121,407	227,190	10.03%	4.062E-11	6.50
Dogi	97,101	30.64%	82,815	178,137	16.70%	1.4153E-06	4.68
EADS	17,989,627	30.06%	8,665,500	26,469,111	20.43%	1.7913E-08	5.51
Ebro Puleva	1,580,032	16.40%	271,909	1,846,104	14.04%	1.4776E-43	13.79
Elecnor	374,294	20.35%	422,348	787,514	9.66%	9.7692E-12	6.71
Enagas	2,680,355	17.59%	1,318,288	3,970,344	11.87%	1.2996E-21	9.48
Endesa	17,768,088	16.51%	8,458,599	26,045,112	11.26%	1.0417E-24	10.20
Ercros	117,199	43.33%	3,817	120,934	41.99%	2.9556E-16	8.09
Esp. del Zinc	20,623	27.56%	32,076	52,010	10.93%	1.7182E-06	4.64
Europa & C	135,712	18.75%	92,877	226,595	11.23%	1.7714E-16	8.15
Europistas	602,357	14.27%	132,242	731,760	11.75%	1.3043E-49	14.76
Fadesa	1,514,578	15.41%	1,806,731	3,282,525	7.09%	6.4089E-19	8.81
Faes Farma	667,765	18.73%	47,034	713,789	17.52%	3.3603E-55	15.61
FCC	4,334,962	16.92%	1,034,797	5,347,545	13.72%	6.528E-35	12.27
Ferrovial	5,044,668	19.42%	1,699,902	6,708,079	14.60%	2.0446E-22	9.67
Funespaña	86,901	25.75%	3,443	90,270	24.79%	6.1829E-40	13.17

	Market value of equity (E_0)*	Volatility of equity (σ_E)	Default point (book liabilities) (D)*	Market asset value (V_0)*	Volatility of asset value (σ_V)	Default Probability (p_t)	Distance-to-default (DD)
Gamesa	2,410,975	27.45%	47,636	2,457,588	27.01%	2.0596E-48	14.57
Gas Natural	9,979,513	13.21%	1,826,888	11,767,184	11.20%	3.0777E-65	17.02
Gr. Emp. Ence	576,493	16.90%	187,094	759,571	12.83%	1.1662E-29	11.25
Gr. Inmocaral	301,681	31.35%	80,466	380,419	24.86%	1.264E-10	6.33
Hullas Coto	35,436	18.84%	13,641	48,784	13.69%	3.6663E-22	9.61
Iberdrola	16,471,775	11.52%	7,254,962	23,571,000	8.05%	1.346E-52	15.22
Iberia	2,380,673	29.85%	1,707,448	4,051,467	17.54%	1.4981E-07	5.12
Iberpapel	183,740	14.14%	271	184,005	14.12%	0	46.46
Inbesos	26,714	38.38%	20,663	46,933	21.85%	5.3288E-05	3.88
Inditex	13,566,613	21.74%	685,852	14,237,742	20.72%	9.9849E-50	14.78
Indo Interna	66,353	35.14%	17,041	83,028	28.08%	6.8704E-09	5.68
Indra	1,840,745	20.21%	753,130	2,577,708	14.43%	6.8454E-19	8.80
Inm. Colonial	1,618,922	20.57%	1,823,574	3,403,351	9.78%	3.8495E-12	6.84
Inm. Urbis	1,354,638	18.92%	1,375,507	2,700,618	9.49%	1.5915E-14	7.59
Jazztel	700,528	70.61%	20,854	720,934	68.61%	5.7353E-07	4.86
La Seda B.	88,466	23.54%	255,124	338,113	6.16%	2.4644E-07	5.03
Lingotes Esp.	46,682	25.26%	27,929	74,011	15.93%	2.4007E-10	6.23
Logista	1,722,096	27.39%	1,853,271	3,535,583	13.34%	2.8688E-07	5.00
Mecalux	165,212	29.85%	98,107	261,213	18.88%	7.543E-08	5.25
Metrovacesa	2,488,910	16.28%	1,577,395	4,032,444	10.05%	4.4419E-22	9.59
Miquel Cost.	246,123	42.04%	36,542	281,881	36.71%	2.3283E-08	5.46
Natra	94,370	25.66%	8,593	102,779	23.56%	2.7538E-26	10.54
Natraceutical	139,455	25.89%	11,843	151,043	23.90%	8.1278E-27	10.66
NH Hoteles	1,149,845	19.21%	516,587	1,655,343	13.34%	3.1911E-19	8.89
Nico. Correa	31,528	26.58%	16,226	47,406	17.68%	3.9691E-10	6.15
OHL	569,453	19.20%	1,508,722	2,041,783	5.36%	3.1618E-10	6.18
Paternina	37,676	31.23%	43,090	79,841	14.74%	7.9839E-06	4.31
Pescanova	205,544	19.44%	81,589	285,382	14.00%	5.0856E-20	9.09
Prim	78,729	29.78%	22,396	100,644	23.30%	5.1311E-11	6.46
Prisa	3,391,832	25.69%	701,357	4,078,134	21.37%	6.5609E-17	8.27
Prosegur	857,407	19.45%	227,384	1,079,910	15.44%	9.3183E-25	10.21
Puleva Bio.	152,581	17.63%	2,683	155,206	17.33%	2.088E-122	23.50
R.E.E.	2,133,777	13.31%	1,383,953	3,487,911	8.14%	8.0749E-32	11.68
Reno M.	184,849	34.69%	252,163	430,525	14.90%	0.00010049	3.72
Repsol YPF	22,797,368	14.85%	5,031,301	27,720,666	12.21%	8.3482E-46	14.16
Sacyr Val.	3,077,429	16.83%	694,870	3,757,382	13.78%	1.4314E-35	12.39
Service P.S.	1,122,631	36.78%	42,404	1,164,125	35.47%	1.1618E-20	9.25
Sniace	30,313	35.14%	48,965	77,859	13.69%	0.00020136	3.54
Sogecable	4,077,821	28.77%	1,301,838	5,351,713	21.92%	4.7151E-11	6.48
Sol Meliá	1,319,697	19.79%	780,209	2,083,127	12.54%	5.7096E-16	8.01
Sos Cuetara	234,723	9.67%	331,104	557,129	4.05%	3.4266E-42	13.56
Sotogrande	418,652	26.31%	68,029	485,220	22.70%	2.0963E-18	8.67
Ta. Fibras	659,120	50.43%	91,120	748,284	44.42%	2.2638E-06	4.59
Tavex Algod.	94,124	18.45%	50,563	143,601	12.09%	5.7643E-19	8.82
Tecnocom	86,645	36.34%	13,585	99,938	31.51%	1.786E-10	6.27
Tele Pizza	342,810	28.33%	128,974	469,015	20.71%	1.7353E-10	6.28
Telecinco	3,630,440	18.12%	284,532	3,908,864	16.83%	1.3518E-55	15.66

	Market value of equity (E_0)*	Volatility of equity (σ_E)	Default point (book liabilities) (D)*	Market asset value (V_0)*	Volatility of asset value (σ_V)	Default Probability (p_t)	Distance-to-default (DD)
Telefónica	68,208,710	18.23%	26,573,295	94,211,576	13.20%	9.1688E-23	9.75
Telf. Móviles	39,665,568	20.11%	6,326,482	45,856,244	17.40%	9.0773E-31	11.47
Testa Inm.	1,816,591	19.95%	817,008	2,616,061	13.85%	6.2609E-18	8.55
TPI	2,458,059	29.36%	260,996	2,713,452	26.60%	7.9254E-19	8.78
Transp. Azkar	298,378	15.14%	116,331	412,212	10.96%	3.0338E-32	11.76
Tubacex	245,871	22.62%	22,126	267,522	20.79%	1.2432E-33	12.03
Tubos Reuni.	118,000	23.05%	133,193	248,386	10.95%	1.7079E-09	5.91
Tudor	191,490	37.04%	53,988	244,311	29.03%	1.2452E-07	5.16
Unión Fenosa	4,793,588	16.80%	4,619,094	9,313,515	8.65%	1.9828E-17	8.41
Unipapel	185,527	15.57%	11,862	197,134	14.65%	2.1339E-83	19.31
Uralita	709,129	25.68%	334,530	1,036,478	17.61%	3.8966E-11	6.50
Urban.y Tran.	10,978	46.69%	3,603	14,503	35.34%	5.9412E-05	3.85
Vidrala	312,424	18.68%	33,540	345,244	16.90%	3.8802E-44	13.89
Viscofan	358,783	16.00%	43,993	401,832	14.29%	2.5628E-55	15.62
Zardoya Otis	4,122,573	17.78%	328,600	4,444,247	16.49%	3.6544E-57	15.89
Zeltia	1,073,784	21.69%	27,355	1,100,552	21.16%	7.8826E-69	17.49

* Data in thousands of euros.

References

Altman, E. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. The Journal of Finance, 1968; Vol. 23: 589-609.

Altman, E. Rating Migration of Corporate Bonds: Comparative Results and Investor/Lender Implications. NY University Salomon Center. December, 1996.

Altman, E.; Hartzell, J.; Peck, M. Emerging Markets Corporate Bonds: A Scoring System Salomon Brothers Inc, New York, 1995.

Altman, E.; Spivack, J. Predicting Bankruptcy: The value line relative financial strength system versus the zeta bankruptcy classification approach. Financial Analyst Journal, 1983; November-December: 60-67.

Anderson, R.; Sunderesan, S.; Tychon, P. Strategic Analysis of Contingent Claims. European Economic Review, 1996; 12: 871-881.

Basel Committee On Banking Supervision. Range of Practice in Banks´ Internal Ratings Systems. N. 66. January, 2000.

Basel Committee On Banking Supervision. Basel II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework. June, 2004.

Beaver, W. H. Financial Ratios as Predictors of Failure. Journal of Accounting Research, 1966; Supplement to number 4: 71-127.

Bohn, J. R. A Survey of Contingent-Claims Approaches to Risky Debt Valuation. The Journal of Risk Finance, 2000a; Spring: 53-70.

Bohn, J. R. An Empirical Assessment of a Simple Contingent-Claims Model for the Valuation of Risky Debt. The Journal of Risk Finance,2000b; Summer: 55-77.

Black, F.; Cox J. C. Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. Journal of Finance, 1976; 31: 351-367.

Black, F.; Scholes, M. The Pricing of Options and Corporate Liabilities. Journal of Political Economy, 1973; 81, pp. 399-418.

Carey, M.; Hrycay, M. Parameterizing Credit Risk Models with Rating Data. Journal of Banking and Finance, 2001; 25: 197-270.

Crosbie, P.; Bohn, J.R. Modeling Default Risk. KMV Corporation, 2003.

Crouhy, M.; Galay, D; Mark, R. A Comparative Analysis of Current Credit Risk Models. Journal of Banking & Finance, 2000; 24: 59-117.

Delianedis, G.; Geske, R. Credit Risk and Risk Neutral Default Probabilities: Information about Rating Migrations and Defaults. UCLA, Anderson School, Finance Working Paper, 1998.

Delianedis, G.; Geske, R. The Components of Corporate Credit Spreads: Default, Recovery, Tax, Jumps, Liquidity, and Market Factors. UCLA, Anderson School, Finance Working Paper, 2001.

Du, Y.; Suo, W. Assessing Credit Quality from Equity Markets: Is Structural Approach a Better Approach?. Available at www.defaultrisk.com, 2003.

Duffie, D.; Singleton, K. J. Modelling Term Structures of Defaultable Bonds, Review of Financial Studies, 1999; 12: 687-720.

Elton, E.; Gruber, M. J.; Agrawal, D; Mann, C. Explaining the Rate Spread on Corporate Bonds. The Journal of Finance, 2001; 56; 1: 247-277.

Fons, J. Using Default Rates to Model the Term Structure of Credit Risk. Financial Analysts Journal, 1994, September – October: 25-32.

Forte, S.; Peña, J.I. The Design of Refinancing Contracts. Mimeo. Universidad Carlos III, 2002.

Geske. The Valuation of Corporate Liabilities as Compound Options. Journal of Financial and Quantitative Analysis, 1977; 3: 541-552.

Jarrow, R.; Turnbull, S. Pricing Derivatives on Financial Securities Subject to Credit Risk. Journal of Finance, 1995; 50: 53-85.

Kealhofer, S. Managing Default Risk in Portfolios of Derivatives. In: Derivative Credit Risk: Advances in Measurement and Management. Risk Publications, 1995.

Kealhofer, S Comment on "A New Capital Adequacy Framework". KMV Corporation, San Francisco, 2000.

Kealhofer, S Portfolio Management of Default Risk. KMV Corporation, San Francisco, 2001.

Kealhofer, S.; Kwok, S.; Weng, W. Uses and Abuses of Bond Default Rates. KMV Corporation, 1998.

Leland, H. Corporate Debt Value, Bond Covenants and Optimal Capital Structure. Journal of Finance, 1994; 49: 1213-1252.

Leland, H. Agency Costs, Risk Management and Capital Structure. Journal of Finance, 1998; 52: 1214-1242.

Litterman, R.; Iben, T. Corporate Bond Valuation and Term Structure of Credit Spreads, Financial Analysts Journal, 1991; Spring: 52–64.

Longstaff, F. A.; Schwartz, E. S. A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. Journal of Finance, 1995; 50: 789-819.

Lucas, D. J. Default Correlation and Credit Analysis. The Journal of Fixed Income, 1995; March: 76-87.

Martín, J. L. Y Trujillo, A. La Gestión de Riesgos y la Nueva Regulación Bancaria. Grupo Editorial Universitario. Granada. 2005.

Mella-Barral, P.; Perraudin, W. Strategic Debt Service. The Journal of Finance, 1997; 51: 531-556.

Merton, R. C. Theory of Rational Option Pricing. Bell Journal of Economics and Management Science, 1973; 4: 141-183.

Merton, R. C. On the Pricing of Corporate Debt. Journal of Finance, 1974: 449-470.

Moody´S Investors Service. RiskCalc® for Private Companies: Moody´s Default Model. Global Credit Research. May, 2002.

Olhson, J. A. Financial Ratios and the Probabilistic Prediction of Bankrupcty. Journal of Accounting Research, 1980; Spring: 109-131.

Peña, J. I. La Gestión de Riesgos Financieros de Mercado y de Crédito. Ed. Prentice Hall. Madrid. 2002.

Pres, J.; Wilson, S. Choosing between logistic regression and discriminant analysis. Journal of the American Statistical Associaton, 1978; December: 699-705.

Saunders, A. Credit Risk Measurement: New Approaches to Value at Risk and Other Paradigms. John Wiley & Sons, 1999.

Shimko, D; Tejima, N. Y Van Deventer, D. The Pricing of Risky Debt when Interest Rates are Stochastic. Journal of Fixed Income, 1993; September: 58-65.

Tatsuoka, M. Discriminant Analysis: The study of Group Differences. Selected Topics in Advanced Statistics: An Elementary Approach, 1970; N 6.

Trujillo, A. Gestión del Riesgo de Crédito en Préstamos Comerciales. Ed. Instituto Superior de Técnicas y Prácticas Bancarias. Madrid, 2002.

Vasicek, O. An Equilibrium Characterization of the Term Structure. Journal of Financial Economics, 1977; 5: 177-188.

Vasicek, O. EDF Credit Measure and Corporate Bond Pricing. KMV Corporation, San Francisco. November, 2001.

Vassalou, M.; Xing, Y. Default Risk in Equity Returns. The Journal of Finance, 2004; Vol. LIX, 2. April: 831-868.

Westgaard, S.; Wijst, Van Der. Default Probabilities in a Corporate Bank Portfolio: A Logistic Model Approach. European Journal of Operational Research, 2001; 135: 338-349.

Zavgren, C. V. Corporate Failure Predictors: The State of the Art. Journal of Accounting Literature, 1983; 2.

Zhou, C. A Jump Diffusion Approach to Modelling Credit Risk and Valuing Defaultable Securities. Federal Reserve Board of Governors, 1997.

Internet addresses:

Bolsa de Madrid: www.bolsamadrid.es

Default Risk: www.defaultrisk.com

KMV Corporation: www.moodyskmv.com

TABLES

Table 1: Correspondence between the score from the Z" model and the rating of Standard & Poor's.

Z"-score	Equivalent Rating
8.15	AAA
7.60	AA+
7.30	AA
7.00	AA–
6.85	A+
6.65	A
6.40	A–
6.25	BBB+
5.85	BBB
5.65	BBB–
5.25	BB+
4.95	BB
4.75	BB–
4.50	B+
4.15	B
3.75	B–
3.20	CCC+
2.50	CCC
1.75	CCC–
0.00	D

Source: In-Depth Data Corporation –in Altman (1996)-

Table 2: Comparison between the credit scores for the petroleum and energy sector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Repsol YPF	7.37	Gas Natural	17.02
Cepsa	7.20	Iberdrola	15.22
Gas Natural	7.18	Repsol YPF	14.16
Ag. Barna	6.58	Cepsa	11.97
Iberdrola	5.67	Ag. Barna	11.68
Unión Fenosa	5.08	R.E.E.	11.68
Endesa	4.60	Endesa	10.20
Enagas	4.49	Enagas	9.48
R.E.E.	4.14	Unión Fenosa	8.41

Table 3: Comparison between the credit scores for the minerals. metals and transformation subsector

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Acerinox	9.47	Tubacex	12.03
Arcelor	9.20	Acerinox	11.72
Tubacex	8.75	Hullas Coto	9.61
Hullas Coto	7.81	Arcelor	8.64
Lingotes Esp.	5.80	Cie Automot.	8.40
Cie Automot.	5.12	Lingotes Esp.	6.23
Tubos Reuni.	5.10	Tubos Reuni.	5.91
Esp. del Zinc	- 4.34	Esp. del Zinc	4.64

Table 4: Comparison between the credit scores for the capital goods subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Gamesa	12.59	Zardoya Otis	15.89
Nico. Correa	7.87	Gamesa	14.57
Zardoya Otis	7.32	Azkoyen	9.17
Mecalux	6.41	Aux. Ferrocar.	7.16
Aux. Ferrocar.	5.72	Elecnor	6.71
Elecnor	5.08	D. Felguera	6.50
D. Felguera	4.35	Nico. Correa	6.15
Azkoyen	3.36	Mecalux	5.25

Table 5: Comparison between the credit scores for the construction subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Acciona	7.29	Sacyr Valle.	12.39
Ferrovial	4.63	FCC	12.27
Sacyr Valle.	4.57	ACS	11.88
OHL	4.05	Acciona	10.32
FCC	4.37	Ferrovial	9.67
ACS	3.49	OHL	6.18

Table 6: Comparison between the credit scores for the construction materials subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Cem. Port. Val.	16.67	Cem. Port. Val.	18.70
Uralita	4.28	Uralita	6.50
Ta. Fibras	4.20	Ta. Fibras	4.59

Table 7: Comparison between the credit scores for the chemical industry subsector**.**

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Ercros	28.79	Ercros	8.09
La Seda Bar.	2.48	La Seda Bar.	5.03

Table 8: Comparison between the credit scores for the engineering and other industries subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Abengoa	7.37	Befesa	7.57
Befesa	4.66	Abengoa	6.81

Table 9: Comparison between the credit scores for the aerospace subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
EADS	7.63	EADS	5.51

Table 10: Comparison between the credit scores for the food and drinks subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Barón de Ley	11.65	Barón de Ley	21.08
C.V.N.E.	10.03	Viscofan	15.62
Viscofan	10.03	Ebro Puleva	13.79
Aldeasa	9.23	Sos Cuetara	13.56
Natra	8.06	Campofrío	11
Bo. Riojanas	7.21	Natra	10.54
Ebro Puleva	7.04	Pescanova	9.09
Campofrío	6.89	Aldeasa	8.66
Paternina	6.38	C.V.N.E.	7.47
Pescanova	5.64	Bo. Riojanas	7.18
Sos Cuetara	4.86	Paternina	4.31

Table 11: Comparison between the credit scores for the textiles. clothing and footwear subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Adolfo Dguez.	14.03	Inditex	14.78
Inditex	8.33	Adolfo Dguez.	11.33
Cortefiel	7.41	Tavex Algod.	8.82
Dogi	6.29	Cortefiel	8.20
Tavex Algod.	5.40	Dogi	4.68
Sniace	2.35	Sniace	3.54

Table 12: Comparison between the credit scores for the paper and printing subsector.

	Z´´- Score (Altman et al.)		**Distance-to-Default (Merton)**
Iberpapel	246.68	Iberpapel	46.46
Unipapel	13.02	Unipapel	19.31
Miquel Cost.	8.63	Gr. Emp. Ence	11.25
Gr. Emp. Ence	5.91	Europa & C	8.15
Europa & C	4.80	Miquel Cost.	5.46
Reno M.	4.40	Reno M.	3.72

Table 13: Comparison between the credit scores for the pharmaceutical products subsector.

	Z´´- Score (Altman et al.)		**Distance-to-Default (Merton)**
Zeltia	19.18	Puleva Bio.	23.50
Puleva Bio.	18.54	Zeltia	17.49
Natraceutical	9.05	Faes Farma	15.61
Prim	8.70	Natraceutical	10.66
Faes Farma	7.69	Prim	6.46

Table 14: Comparison between the credit scores for the other consumer goods subsector.

	Z´´- Score (Altman et al.)		**Distance-to-Default (Merton)**
Tudor	10.44	Vidrala	13.89
Vidrala	9.22	Altadis	10.59
Indo Interna	5.89	Indo Interna	5.68
Altadis	4.44	Tudor	5.16

Tabla 15: Comparison between the credit scores for the leisure. tourism and hotel subsector.

	Z´´- Score (Altman et al.)		**Distance-to-Default (Merton)**
NH Hoteles	5.34	NH Hoteles	8.89
Sol Meliá	4.94	Sol Meliá	8.01
Tele Pizza	3.65	Tele Pizza	6.28

Table 16: Comparison between the credit scores for the retail trade subsector.

	Z´´- Score (Altman et al.)		**Distance-to-Default (Merton)**
Service P.S.	7.19	Service P.S.	9.25

Table 17: Comparison between the credit scores for the communications media and publicity subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Telecinco	8.81	Telecinco	15.66
TPI	7.95	TPI	8.78
Antena 3 TV.	7.48	Prisa	8.27
Prisa	5.73	Sogecable	6.48
Sogecable	3.75	Antena 3 TV.	5.50

Table 18: Comparison between the credit scores for the transport and distribution subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Iberia	5.98	Iberia	5.12
Logista	2.66	Logista	5

Table 19: Comparison between the credit scores for the toll motorways and carparks subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Cintra	11.54	Cintra	31.03
Abertis	5.42	Abertis	15.69
Europistas	4.92	Europistas	14.76

Table 20: Comparison between the credit scores for the other services subsector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Funespaña	14.40	Funespaña	13.17
Prosegur	3.94	Prosegur	10.21

Table 21: Comparison between the credit scores for the real state sector.

	Z´´- Score (Altman et al.)		Distance-to-Default (Merton)
Urban. y Tran.	11.95	Metrovacesa	9.59
Sotogrande	10.36	Fadesa	8.81
Gr. Inmocaral	8.97	Sotogrande	8.67
Inm. Urbis	7.25	Testa Inm.	8.55
Fadesa	6.30	Inm. Urbis	7.59
Metrovacesa	6.12	Inm. Colonial	6.84
Inbesos	5.57	Gr. Inmocaral	6.33
Testa Inm.	4.77	Inbesos	3.88
Inm. Colonial	2.94	Urban. y Tran.	3.85

Table 22: Comparison between the credit scores for the technology and telecommunications sector.

	Z´´- Score (Altman et al.)		**Distance-to-Default (Merton)**
Jazztel	22.01	Telf. Móviles	11.47
Avanzit	11.52	Telefónica	9.75
Tecnocom	10.76	Amadeus	8.98
Amadeus	7.54	Indra	8.80
Indra	6.47	Tecnocom	6.27
Telf. Móviles	3.96	Amper	5.94
Telefónica	3.47	Jazztel	4.86
Amper	3.40	Avanzit	3.28

Table 23: Pearson's correlation coefficients

PETROLEUM AND ENERGY SECTOR

		Z´´	DD
Z´´	Pearson Correlation	1	0.628
	Sig. (2-tailed)	.	0.070
	N	9	9
DD	Pearson Correlation	0.628	1
	Sig. (2-tailed)	0.070	.
	N	9	9

BASIC MAT., INDUSTRIAL AND CON.

		Z´´	DD
Z´´	Pearson Correlation	1	0.621**
	Sig. (2-tailed)	.	0.000
	N	29	29
DD	Pearson Correlation	0.621**	1
	Sig. (2-tailed)	0.000	.
	N	29	29

**Correlation is significant at the 0.01 level (2-tailed)

CONSUMER GOODS SECTOR

		Z´´	DD
Z´´	Pearson Correlation	1	0.652**
	Sig. (2-tailed)	.	0.000
	N	31	31
DD	Pearson Correlation	0.652**	1
	Sig. (2-tailed)	0.000	.
	N	31	31

**Correlation is significant at the 0.01 level (2-tailed)

CONSUMER SERVICES SECTOR

		Z´´	DD
Z´´	Pearson Correlation	1	0.570**
	Sig. (2-tailed)	.	0.021
	N	16	16
DD	Pearson Correlation	0.570**	1
	Sig. (2-tailed)	0.021	.
	N	16	16

**Correlation is significant at the 0.05 level (2-tailed)

REAL STATE SECTOR

		Z´´	DD
Z´´	Pearson Correlation	1	-0.276
	Sig. (2-tailed)	.	0.472
	N	9	9
DD	Pearson Correlation	-0.276	1
	Sig. (2-tailed)	0.472	.
	N	9	9

TECH. AND TELECOMMUNICATIONS

		Z´´	DD
Z´´	Pearson Correlation	1	-0,633
	Sig. (2-tailed)	.	0.092
	N	8	8
DD	Pearson Correlation	-0,633	1
	Sig. (2-tailed)	0.092	.
	N	8	8

Table 24: Linear Regression Analysis

Dependent variable: Z´´	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.661	0.739		3.602	0.001
DD	0.421	0.065	0.577	6.440	0.000
Dependent variable: DD	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
(Constant)	4.708	0.958		4.913	0.000
Z´´	0.791	0.123	0.577	6.440	0.000

Correlation Coefficient	R Square	Adjusted R Square	Std. Error of the Estimate
0.577	0.333	0.325	2.90605

ANOVA

Dependent variable: Z´´		Sum of Squares	df	Mean Square	F	Sig.
	Regression	350.254	1	350.254	41.474	0.000
	Residual	700.947	83	8.445		
	Total	1051.201	84			
Dependent variable: DD		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
	Regression	657.714	1	657.714	41.474	0.000
	Residual	1316.252	83	15.858		
	Total	1973.966	84			

Collinearity Diagnostics

Dependent variable: Z´´		Eigenvalue	Condition Index	Variance Proportions	
	Dimension			(Constant)	DD
	1	1.904	1.000	0.05	0.05
	2	9.555E-02	4.465	0.95	0.95
Dependent variable: DD		**Eigenvalue**	**Condition Index**	**Variance Proportions**	
	Dimension			(Constant)	Z´´
	1	1.893	1.000	0.05	0.05
	2	0.107	4.199	0.95	0.95

Figure 1: Scatter Diagrams