Race across mud: The best choice for measuring credit risk

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Abstract

This paper considers whether the existing measures of credit risk order and quantify corporate credit risk in the same way. Eight measures of credit risk of different natures are compared: Altman's Z, Ohlson's O, Hannan and Hanweck model, Zmijewski model, bond spreads, CDS spreads, Black-Scholes-Merton model and Moody's credit rating. With respect to the first aim mentioned, we find that the different measures of credit risk do not offer the same ordering, and we even find clusters of measures. The second aim is to study the accuracy of each method with regards to real credit risk. We use information on defaults from Moody's Default and Recovery Database instead of using other variables of credit risk, as some authors do in the literature. As in previous works, we find that the Black-Scholes-Merton model is superior to the other measures speaking of accuracy, but we additionally show that other measures are relatively poor predictors of corporate failure.

Key words: Credit risk models, ranking order, default prediction.

JEL Classification: G32, G33.

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1. Introduction

Credit risk is perceived as the oldest and most important risk in the financial system. Indeed, the significant problems experienced by banks during the Global Financial Crisis have highlighted the critical importance of measuring and providing for credit risk. Since Beaver's (1966) pioneering work, a wide variety of measures of credit risk, utilized both by practitioners and academics, have been proposed. The most classic models are based on accounting information, such as Altman's (1968) Z-score or Ohlson's (1980) O-score. Others consist of using the spreads of corporate instruments as a measure of the credit risk of the company. For example, traditionally bond spreads have been used as an indicator of credit risk, and more recently, the spreads of the Credit Default Swaps (CDS) are used in the same way. Another alternative is the group of measures based on the price of equity of a company, such as Moody's KMV model or the so-called Black-Scholes-Merton measure. Finally, rating agencies provide a qualification of the credit quality of a company's issues. Although we can consider all these measures interchangeable, ranking they provide may vary depending on the measure we choose to assess credit risk.

It must be highlighted that the results obtained are important both for the process carried out by investors in which they order companies based on their credit risk, and for quantifying credit risk in order to relate it to other variables, such as stock returns. For example, in the study of the relation between credit risk and the momentum effect, several authors use different measures for proxying credit risk, and obtain different results. Thus, Avramov et al. (2007) use credit rating, Abinzano et al. (2014) use Black-Scholes-Merton model, and Agarwal and Taffler (2008), the Altman's Z-score, categorized as a binary variable to distinguish between financially distressed and healthy firms. Possibly, the differences in results are due to the different methods for measuring credit risk.

With the aim to determine if all the measures of credit risk order and quantify corporate credit risk in the same way, this paper has two focuses. First, to compare the order obtained using different measures, and second, to study the accuracy of each method with regards to real credit risk.

Related to the first focus, Löffler (2004) assesses whether the rating or the market-based KMV model are more suitable for formulating portfolio governance rules, and finds that is not evident whether one is superior. However, the author does not compare the results to other type of measures, like accounting-based methods or bond-related prices.

For this reason, in this paper we seek to compare the results obtained by eight different measures of credit risk, namely Altman's Z, Ohlson's O, Hannan and Hanweck model, Zmijewski model, bond spreads, CDS spreads, Black-Scholes-Merton measure and Moody's credit rating.

Related to the second focus, the existing literature is more extensive. As we can see in Table 1, we find several works that evaluate the performance of alternate default-risk models, in order to find which measure performs best. Thus, Kealhofer (2003) compares the market-based KMV model with Standard and Poor's rating, while Hillegeist et al. (2004) compare Altman's Z-score and Ohlson's O to the Black-Scholes-Merton model. Gharghori et al. (2006) on the other hand compare the Black-Scholes-Merton model to an accounting-ratio model similar to Z-score, and Hilsher and Wilson (2016) investigate the information in corporate credit ratings compared to a simple model based on publicly available financial information. These authors conclude similarly: stock market-based methods perform better as a predictor of default. However, we must highlight that these papers compare simultaneously only measures of two types: market-based with accounting-based, or market-based with credit rating. It is true that there are other authors that compare more than two types of measures at the same time, such as those of Tanthanongsakkun and Treepongkaruna (2008), Das et al. (2009) and Cardone et al. (2014). They use CDS spreads or ratings as the reference to check accuracy instead of using actual data of corporate default, but we should note that CDS spreads or ratings are themselves credit-risk measures, so they should not be taken as reference without being proved first as a true indicator of credit risk.

Therefore, this paper seeks to evaluate the performance of different credit risk measures, specifically the ones aforementioned, and using as a reference actual information concerning the occurrence or non-occurrence of corporate credit events.

The rest of the work is organized as follows. Section 2 describes the models and measures of credit risk analyzed in the paper. Section 3 presents the database. Section 4 shows the results of the analysis. Finally, Section 5 presents the main conclusions.

2. Measures of credit risk

In this section we present the eight measures of credit risk studied in order to analyze the ranking they give and also the adjustment to real credit risk. As we have already mentioned, we are considering both accounting and market-based measures. Specifically, the accounting models are Altman's Z, Ohlson's O, Zmijewski's model and the probability of Hannan and Hanweck (1988), while the market-based measures are credit default swap (CDS) spreads, bond spreads, credit rating and the Black-Scholes-Merton model.

Starting from the accounting models, Altman's Z can be considered the classic measure of default risk. Using discriminant analysis, Altman (1968) attempted to predict defaults from five accounting ratios:

- X_1: Working capital/Total assets
- X_2: Retained earnings/Total assets
- X_3: Market value of equity/Book value of total liabilities
- X_4: Sales/Total assets
- X_5: Earnings before interest and taxes/Total assets

The Z-score was calculated with the following expression:

$$Z = 1.2X_1 + 1.4X_2 + 0.6X_3 + 0.999X_4 + 3.3X_5 \tag{1}$$

According to Altman (1968), if the Z-Score is greater than 3.0, the company is unlikely to default. If it is between 2.7 and 3, it is recommended to be on alert. If it is between 1.8 and 2.7, there is a good chance of default. And finally, if it is less than 1.8, the probability of default is very high.

The second accounting based model used in this study is the one proposed by Ohlson (1980). Instead of five variables, like Altman's Z, O-Score is obtained from nine variables, including both financial ratios and specific dummies, to attempt to enhance the predictability of this model:

$$O = -1.32 - 0.407SIZE + 6.03TLTA - 1.43WCTA + 0.0757CLCA - \\ 2.37NITA - 1.83FUTL + 0.285INTWO - 1.72OENEG - 0.521CHIN \tag{2}$$

where:

- SIZE is the log of the total assets/log of GNP price level index
- TLTA: Total liabilities /Total assets
- WCTA: Working capital/Total assets
- CLCA: Current liabilities /Current assets
- NITA: Net income /Total assets
- FUTL: Cash flows from operations /Total liabilities
- INTWO: One if net income was negative for the last two years, zero otherwise.
- CHIN: $(NI_t-NI_{t-1})/(|NI_t|-|NI_{t-1}|)$, where NI is Net Income

As we can notice, contrary to Altman's Z, the higher the O-Score, the higher default risk.

Another classical accounting-based method is the model proposed by Zmijewski (1984), determined by probit analysis, described by the following expression:

$$X = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \tag{3}$$

where:

- X_1: Net income/Total assets
- X_2: Total liabilities/Total assets
- X_3: Current assets/Current liabilities

Based on a theoretical framework, Hannan and Hanweck (1988) propose a measure of default probability using three financial variables: capital ratio, expected return on assets and the estimated variance of assets. This way, the default risk is given by the probability of the losses of the company being higher than its equity:

$$Probability\left(R < -\frac{E}{A}\right) \tag{4}$$

where *R* is the return on assets, and *E/A* is the equity/assets ratio. Based on Tchebysheff's inequality, they define the probability of default (*DP*) as:

$$DP = Min\left\{1, \left(\frac{\sigma_R}{E(R)+\frac{E}{A}}\right)^2\right\} \tag{5}$$

where σ_R is the standard deviation of the return on assets and *E(R)*, the expected return on assets.

As Hillegeist et al. (2004) and Cardone et al. (2014) point out, accounting models have been criticized for the historical nature of the information they take as input and for not taking into account the volatility of a firm's assets in estimating its risk of default. Thus, more recently in the financial literature credit risk models have used data from the capital markets, in which the shares or bonds issued by the companies in question are traded. In theory, market prices reflect investors' expectations about a firm's future performance. As a result, these prices contain forward-looking information, which is ideally suited for calculating the probability that a firm will default in the future.

This way, market prices can be taken directly as measures of credit risk, as it has occurred traditionally with bond spreads. Bond spreads are the difference between the interest paid by a company's debt and the risk-free rate. This way, the higher the bond spread, the higher the probability of default. More recently, the empirical literature on credit risk has focused on credit default swap (CDS) spreads (e.g. Das et al., 2009; Ericcson et al. 2009; Forte and Peña, 2009). According to Hull et al. (2004), the relationship $y - r = s$, should therefore hold approximately, where y-r is the corporate bond spread and s is the CDS spread on the company's debt.

Another market-given measure is the credit rating, offered by the credit rating agencies. This measure has the advantage of being simple and easy to understand, but, as occurs with CDS spreads, we must take into account that there is no available credit rating for some stocks, especially small firms, and that this could result in a size-biased sample. It has also other disadvantages. One of them is that a firm's credit worthiness can vary significantly before its credit rating is readjusted. Another is that it implies that two firms with the same credit rating would also have the same default risk. However, as shown by Crosbie and Bohn (2003), substantial differences in default rates may exist within the same bond rating class.

An alternative to using the above-mentioned measures of default risk is to construct a measure using firms' market share prices, as in Moody's KMV model, Vassalou and Xing (2004), Byström et al (2005) and Byström (2006), to name a few. These studies start from Merton's (1974) proposal, which is to consider the firm's own equity value as a European call option on its assets and use the Black and Scholes (1973) formula to calculate the equity value.

As explained in the Appendix, the measure proposed in this paper for the approximation of default risk is given by the following expression[2]:

$$P_{def,t} = N\left(-\frac{\ln\frac{V_{A,t}}{D_t} + \left(\mu_t - \frac{\sigma_{A,t}^2}{2}\right)(T-t)}{\sigma_{A,t}\sqrt{T-t}} \right) \tag{6}$$

where $V_{A,t}$ is the value of the firm's assets at time t, μ_t is the expected immediate rate of return on $V_{A,t}$, $\sigma_{A,t}$,, is asset return volatility, D_t is the debt's face value, T is the maturity period and $N(\cdot)$ is the cumulative probability of the Normal distribution.

To find the values of $V_{A,t}$ and $\sigma_{A,t}$ we use an iterative process starting from the market price of the firm's shares. Thus, the advantage of the BSM measure over accounting based models is that it not only considers past data, but, by using the market price of the shares, it also incorporates investors' expectations regarding their future performance. It also takes into account asset return volatility. Furthermore, compared with the credit rating, as a default proxy, the BSM measure has the advantage of no lag between variation in credit worthiness and its incorporation into the risk measure, given that in the BSM measure market prices are discounting expected future cash flows. In addition, it is a firm-specific measure in that it provides a value for each firm based on its financial situation and its capitalization, which may differ from that obtained for another firm with the same credit rating, thus enabling more finely tuned rankings. However, as Cardone et al. (2014) indicate, in the case of market-based credit risk measures, we must consider that the inefficiencies of capital markets might lead to prediction errors in market-based measures.

3. Data

We apply these measures to companies listed in the New York Stock Exchange (NYSE) for the period January 1986 to January 2016. Banks, finance companies and insurance companies have been excluded from the analysis, because the peculiarities of their capital structure might skew the desired default risk data. The information about prices and accounting variables has been obtained from Thomson Reuters Datastream,

[2] As we use the default proxy only for sorting purpose, we compute probability of default, instead of the distance to default measure as in Vassalou and Xing (2004).

while the data for rating and default events has been taken from Moody's Default and Recovery Database.

In keeping with the nature of the study, we use monthly data for the different variables. Following Vassalou and Xing (2004), to avoid problems related to reporting delays, we do not use the book value of accounting variables of the new fiscal year, until 4 months have elapsed.

In the case of the BSM measure, in line with other studies[3], we calculate the book value of debt as short-term debt plus 50% of long-term debt. Furthermore, as we can see in the Appendix, we need the risk-free rate in order to obtain the implied value of assets. Since we are considering the probability of default in one year, we take the market yield on U.S. Treasury securities at one year for the whole of the study period.

Regarding CDS spreads, we have obtained data available in Datastream for 5-year credit default swaps in the category of Modified Restructuring, according to the ISDA[4] Credit Derivatives Definitions of 2003 (revised in 2014).

In the case of bond spreads, in line with Hull et al. (2004), bonds considered must not be puttable, callable, convertible, or reverse convertible. Bonds must not be subordinated or structured and must be single currency. We also filtered the bonds in terms of time to maturity to eliminate long maturity, in order to be comparable with the spreads of 5-year CDSs.

The first column of Table 2 shows the number of companies we have data for, for each measure. The differences in the number of observations are due to the amount of variables required to obtain each measure and/or to the type of information used. For example, only certain companies are evaluated by credit rating agencies, and few companies have a credit default swap issued on their debt. The rest of Table 2 shows the information about default of companies obtained from Moody's Default and Recovery Database. The number of companies with information about default or non-default is shown, and also the number of defaulted companies. Moreover, in this table we indicate the main statistics for each measure, for both defaulted and non-defaulted companies. We

[3] See, for example, Crouhy et al. (2000), Crosbie and Bohn (2003) and Vassalou and Xing (2004).
[4] International Swaps and Derivatives Association.

should remark that, except in the case of the probability of Hannan and Hanweck, these measures indicate lower credit risk for the companies of the non-defaulted sample.

4. Results

4.1. Comparison of the order of measures

With the aim of determining whether the different measures of credit risk offer the same order, we analyze the percentage of coincidence in quartiles. As we can see in Table 3, the early impression is that this coincidence is not the same for all the pairs of measures. Hence, the BSM measure has approximately 50% of coincidence in quartiles with the rest of market-based measures (CDS spreads, bond spreads and rating), while is lower with respect to the accounting-based models. We also can appreciate the similarities of ordering between accounting-based measures, such as Zmijewski, Altman's Z and Ohlson's O.

Furthermore, using non-parametric techniques, if we look at the Spearman rank-correlation coefficients in Table 4, we identify a low correlation between the BSM measure and accounting methods and credit rating, and a higher correlation between the BSM measure and bond-related measures. We also observe an almost non-existent or even negative correlation between the probability of Hannan and Hanweck and the rest of the measures. A high correlation is evident between the rest of the accounting-based methods and CDS spreads, bond spreads and credit rating.

These results indicate that the ordering given by the different measures of credit risk is not the same, so we should be cautious when we apply some of these measures to build portfolios or study any relationship with other variables, such as returns, and we should take into account the results related to accuracy of measures put forward in the next section.

4.2. Analysis of the adjustment of credit risk

As Kraft et al. (2014) say, an important criterion to assess the quality of the score function is its discriminatory power, i.e. its ability to separate good from bad applicants. Sobehart et al. (2001) develop the use of several metrics for evaluating model performance, namely cumulative accuracy profile (CAP) plots and accuracy ratios (AR).

They address the fundamental issues that arise in validating and determining the accuracy of a credit risk model under what is measured (or the metrics by which the "goodness" of a model should be defined), and how it is measured (the framework that should be used to ensure that the observed performance can reasonably be expected to represent the behavior of the model in practice.

Although accuracy is only one dimension of model quality (Dhar and Stein, 1997), it is often the most prominent one in discussions of credit risk models. It is important to understand each model's strengths and weaknesses because credit risk models are often used to generate opinions of credit quality on which investment decisions are taken.

As Sobehart et al. (2001) indicate, when used as classification models, default risk models can err in one of two ways. First, the model can indicate low risk when in fact, the risk is high (Type I error). The cost to the investor can be the loss of principal and interest that was promised, or a loss in the market value of the obligation. Second, the model can assign a high credit risk when in fact, the risk is low (Type II error). In the case of tradable loans or securities, this error may result in the selling of obligations that could be held to maturity, at disadvantageous market prices. Unfortunately, minimizing one type of error usually comes at the expense of increasing the other type of error.

Comparing the performance across different default prediction models is challenging, since the models themselves usually measure slightly different aspects of the default events and time horizons, and may be expressing a quantification of credit risk using different types of outputs.

As we can see in previous works as Cantor and Mann (2003), Kealhofer (2003) or Gharghori et al. (2006), the key metrics used are the "cumulative accuracy profile" (CAP) or power curve, and the accuracy ratio, which is a way of compressing the information in the CAP curve into a single number.

CAP curves are useful for making visual assessments of the information content embedded in the relative ranking of credit risk provided by a set of ratings. The CAP is constructed by plotting, for each rating category, the proportion of defaults accounted for by firms with the same or a lower rating against the proportion of all firms with the same or a lower rating. The CAP curve is also known as a "power curve," because it shows how effective a rating system is at detecting defaults from the population. The further the curve bows toward the northwest corner, the greater the fraction of all defaults that can be accounted for by the lowest rating categories. The closer the curve is to the 45º line, which is the power curve associated with randomly assigned ratings, the weaker is the information content of the rating system.

In Figure 1 we can see CAP curves for the eight credit risk measures applied to our sample. To plot these curves we need to label firm-months observations as default or non-default. Following Gharghori et al. (2006), the firm-months for defaulted firms within twelve months of the default date are labelled as default, and all other firm-months as non-default. We must also remember that we are following other works where BSM measure is computed by taking book value of debt as short-term debt plus 50% of long-term debt. In Figure 2 we analyze the accuracy of BSM measure using debt as mentioned, and considering the whole debt. A visual inspection of Figure 1 indicates that the CDS spreads seem to be superior to the rest of the models studied. However, for some measures this is less clear, as with the BSM model and Altman's Z. Looking at Figure 2 we can appreciate that the adjustment of BSM measure remains practically unaltered when debt is computed taking only half the long-term debt.

As Sobehart et al. (2001) emphasize, while CAP plots are a convenient way to visualize model performance, it is often more convenient to summarize the predictive accuracy of each risk measure for both Type I and Type II errors in a single statistic. A way to compress the information depicted in the CAP curve is to use the Accuracy Ratio (AR). The accuracy ratio is the ratio of the area between a model's CAP and the random CAP to the area between the ideal CAP and the random CAP. It is a fraction between minus one and one. Risk measures with ARs close to zero display little advantage over a random assignment of risk scores while those with ARs near one offer almost perfect predictive power.

For this reason, we complement CAP curves with ARs as shown in Table 5[5]. In this table, we represent the ARs for each measure using the information from all the companies with data for occurrence or non-occurrence of credit events. In the first row we can see that the predictive power of CDS spreads is the highest, followed by bond spreads and the BSM measure. However, we must take into account that the sample of

[5] We have also computed AR for BSM with half or full debt, obtaining 58.30% and 58.29%, respectively. These ratios corroborate the intuition in Figure 2.

companies for each measure is not the same, as we can infer from Table 2. Therefore, we could misunderstand the results since we have companies with different characteristics in terms of size, book-to-market, and other relevant characteristics. Indeed, in Table 6 we can see the characteristics for all the companies with information for each credit risk measure. We observe, for example, the differences in market value of equity between the companies with data on BSM measure or with data of CDS spreads, bond spreads and credit rating. As we have already mentioned, only certain companies have available measures as CDS spreads, bond spreads or rating, usually big companies. Indeed, Hilsher and Wilson (2016) point out that rated firms may be different in important ways from non-rated firms, in size, leverage and volatility, which are essential variables in the explanation of credit risk.

To take this into account, from the second row of Table 5, we repeat the analysis for the subset of companies with data for two specific measures at the same time to consider the same companies. We also indicate the number of companies studied in each analysis, and the number of defaulted companies included. We observe that when compared individually to the rest of measures, the BSM measure outperforms the rest of the models. In the case of Altman's Z, the fit is the best except for the BSM. Contrarily, other accounting models as Ohlson's O or Hannan and Hanweck's probability have a worse adjustment of credit risk than the rest of measures. However, in the case of the model of Zmijewski, we observe that it has a high predictive power, but lower than the one of CDS spreads and credit rating. When we compare the accuracy ratios of CDS spreads and bond spreads, the latter is higher, while if we compare to the accuracy ratios of rating, the CDS spreads have a better adjustment. Finally, we can notice that the predictive power of bond spreads and credit rating is similar.

Up until this point, we have considered as default all the default events included in the Moody's Default and Recovery Database. However, we must remark that the accounting-based models were constructed to reflect the possibility of bankruptcy of the companies. Thus, in Table 7 we show the accuracy ratios for the eight measures without considering as default non-banktrupcty events such as a delay of interests or a dividend not paid. We can appreciate that for the non-matched sample all the measures increase their adjustment with the exception of Zmijewski's model. We also observe that BSM is now slightly worse than bond spreads and rating at reflecting real credit risk. We can notice the high increase of accuracy ratios when we compare Altman's Z and rating if only severe default is included. The same occurs when we analyze bond spreads and rating. These results help to see that in general the credit risk measures improve their accuracy when only bankruptcy-type events are considered. But when we compare the accuracy with respect to other measures, we see that BSM is better than the rest of the measures if all-type default events are taken into account. Thus, to select the appropriate measure we must determine first the type of credit risk that we want to detect.

As explained before, in line with previous works as Sobehart et al. (2001), Cantor and Mann (2003) and Gharghori et al. (2006), we have considered default in one year in our study of the accuracy of credit risk models. However, as Du Jardin and Severin (2011) and Du Jardin (2015) point out, reviews on financial distress prediction models indicate that these techniques give reliable estimates of probabilities of default only for relatively short horizons, rarely beyond two years. Beyond three years, such models rarely give reliable estimates, perhaps not much better than flipping a coin. Notwithstanding, many studies show that failure process can take a number of years so that symptoms can be traced back to more than one year before failure (Hambrick and D'Aveni 1988, Laitinen 1991, Laitinen 1999, Ooghe and de Prijcker 2008). Thus, Altman et al. (2016) study the predictive ability of both financial and non-financial variables over a long horizon of up to 10 years for private small and medium-sized enterprises (SMEs), finding that several variables can help analysts to identify weak signals of bankruptcy even more than 5 years prior to failure.

For this reason, we go on to study how the measures perform when we consider a longer horizon for default. Specifically, in Tables 8[6] and 9 we show the accuracy ratios when default can occur in five years, taking into account both all the default events and only bankruptcy-related events. In the first row of Table 8 we observe that when the horizon of the prediction is five years, the accuracy of the models decreases, with the exception of CDS spreads, that increases. We must remember that 5-year CDSs were taken from Datastream. In the rest of Table 8 we see that BSM loses the power with respect to Altman's Z and CDS spreads. We also can notice that rating is less accurate than Zmijewski's model, and that CDS spreads have higher ARs than bond spreads and rating. If we compare the results in Table 9 with results in Table 7, all the measures reduce

[6] We have also checked the accuracy of BSM measure with both half and full long-term debt. We obtain a higher accuracy ratio for the debt with only half long-term debt (43.37% vs. 40.86%).

the accuracy for the non-matched sample, with no exception. For the matched samples, we observe that CDS spreads are slightly less accurate than credit rating only when severe default events are taken into account. From the results of both Tables 8 and 9, we can perceive that when the prediction horizon is longer, the accuracy of accounting-based models is lower. We also observe that in the case of samples with information of market-based measures as CDS spreads, bond spreads or rating, the accuracy ratios remain high, meaning that these models give reliable estimates of default probability even in 5 years.

Finally, in line with Gharghori et al. (2006), we have implemented some univariate and multivariate logistic regressions to identify whether one or more of the credit-risk measures considered are successful in explaining default. Table 10 shows results of the univariate logistic regression. From the table we see that the eight measures are significant in explaining default risk. Further, the coefficients in these regressions are all in the direction predicted. For example, the negative coefficient in Altman's Z indicates that as this score increases, default-risk decreases. On the other hand, in Table 11 we show the results for the multivariate models. We show the regressions for each measure of credit risk considering other variables, as the logarithm of market value of the company, book-to-market ratio, leverage and volatility of return on equity. Only the BSM measure and credit rating maintain the significance for all the independent variables. Indeed, Hilsher and Wilson (2016) find that credit risk is multidimensional, so it would not be possible for one measure to capture all the relevant information. Conversely, the coefficients of Ohlson's O and CDS spreads are not statistically significant when additional variables are considered, showing that these two models do not offer complementary information.

In Tables 12 and 13 we repeat the logistic regressions for default in five years. In the case of univariate models, we observe that Hannan and Hanweck's coefficient is not significant. This is consistent with the poor results detected previously for the accuracy of this measure. In Table 13 we appreciate that when we consider other variables, the coefficient of Hannan and Hanweck is significant, but the sign is the contrary to that expected. Here we also see that Ohlson's O measure is not significant explaining default in five years, as was the case for default in one year. Whereas, we must emphasize that when default is allowed in five years, CDS spreads' coefficient is significant. This makes sense, since the horizon of this credit derivative is five years. Finally, we must remark that size is not significant for the regressions of CDS spreads, bond spreads and rating.

The explanation could be that these measures are only available for big companies, so size is not relevant in the prediction of default because is already implied in the measure.

5. Conclusions

This paper considers whether a wide range of measures of credit risk order and quantify corporate credit risk in the same way. Thus, eight measures of credit risk of different nature are analyzed: four accounting-based models, three market-data measures and a market-based constructed model.

The first aim of the paper is to compare the order obtained using the different measures. We show that the different measures of credit risk do not offer the same ordering, and we even find clusters of measures, such as the BSM measure and the spreads of CDSs and bonds. Thus, we should be cautious when we use some of these measures to build portfolios or study any relationship with other variables, such as returns, and we should take into account the results related to the accuracy of measures.

The second aim is to study the accuracy of each method with regards to real credit risk. We use the information on defaults of Moody's Database instead of using other variables of credit risk, as some authors do in the literature. We study the predictive power of the different credit risk measures in explaining credit events, complementing the existing literature by applying measures of different natures at the same time. Firstly, considering the possibility of default in one year, as previous works, we find that the Black-Scholes-Merton is superior to the rest of measures with respect to accuracy. Furthermore, we show that other measures are relatively poor predictors of corporate failure, such as Ohlson's O and the probability of Hannan and Hanweck. Secondly, when default is allowed to occur in five years, we show that in general the accuracy of measures decreases, with the exception of CDS spreads, which seem to be more accurate than all the measures excepting Altman's Z. For both, default in one year and in five years, we observe that the adjustment of the models depends on the sample considered, since only big companies have information concerning certain type of credit risk measures, for example CDS spreads, bond spreads or credit rating. This should be carefully studied, since the performance of the models could be related to the characteristics of the companies.

We have also tested the accuracy of the credit risk measures when only severe default events are considered, since many of the default models were constructed to reflect only the risk of bankruptcy. We find that the accuracy of all the models increases in general terms. Furthermore, we show that the BSM measure in this case predicts somewhat worse than bond spreads or credit rating. This reflects that this model would be more useful to reflect corporate credit risk in general, not only bankruptcy risk.

Finally, using logistic regressions a more in-depth analysis is done, in order to find the variables and measures that best explain credit risk. We find that when other variables are added to the credit risk measure, some models lose their predictive power, such as Hannan and Hanweck and Ohlson's O, as was also the case in the accuracy analysis.

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Appendix

Based on Merton (1974), the value of a firm's assets is supposed to follow a geometric Brownian motion, given by this expression:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{1}$$

where V_A is the value of the firm's assets, μ is the expected immediate rate of return on V_A, σ_A is assets-return volatility and W is a standard Brownian motion.

Supposing that the firm is financed entirely by equity and a zero-coupon bond with face value D_t at time t and maturity T, default risk can be defined as the probability of the value of the firm's assets at T being less than the book value of its debt, that is:

$$P_{def,t} = \text{Prob}(V_{A,T} \leq D_t \mid V_{A,t}) = \text{Prob}(\ln V_{A,T} \leq \ln D_t \mid V_{A,t}) \tag{2}$$

Given that firm value follows (1), it can be deduced that:

$$\ln V_{A,T} = \ln V_{A,t} + \left(\mu_t - \frac{\sigma_{A,t}^2}{2} \right)(T-t) + \sigma_{A,t}\sqrt{T-t}\,\varepsilon_T \tag{3}$$

with:

$$\varepsilon_T = \frac{W(T)-W(t)}{\sqrt{T-t}} \tag{4}$$

where ε_T are iid variables over the interval N(0,1). Thus, expression (2) can be written as:

$$P_{def,t} = \text{Prob}\left(\ln V_{A,t} - \ln D_t + \left(\mu_t - \frac{\sigma_{A,t}^2}{2} \right)(T-t) + \sigma_{A,t}\sqrt{T-t}\,\varepsilon_T \leq 0 \right)$$

$$= \text{Prob}\left(-\frac{\ln \frac{V_{A,t}}{D_t} + \left(\mu_t - \frac{\sigma_{A,t}^2}{2} \right)(T-t)}{\sigma_{A,t}\sqrt{T-t}} \geq \varepsilon_T \right) \tag{5}$$

Using the Merton (1974) implied probability distribution, as in other studies in the literature[7], default risk is given by:

$$P_{def,t} = N\left(-\frac{\ln\frac{V_{A,t}}{D_t} + \left(\mu_t - \frac{\sigma_{A,t}^2}{2}\right)(T-t)}{\sigma_{A,t}\sqrt{T-t}} \right) \tag{6}$$

where *N(·)* is the cumulative probability of the Normal distribution.

It is worth noting that in order to implement expression (6), we must know the value of the firm's assets, $V_{A,t}$, the volatility of its return, $\sigma_{A,t}$, and the value of μ_t. However, the value of the firm's assets is not directly observable and therefore neither are the volatility nor the average rate of return. The one observable variable is the market value of equity, $V_{E,t}$ which can be used to estimate the volatility of its return, $\sigma_{E,t}$. Note that Merton (1974), applying Black and Scholes (1973) to the pricing of the firm's equity, find that the value of $V_{E,t}$ is given by the following expression:

$$V_{E,t} = V_{A,t} N(d_1) - D_t e^{-r(T-t)} N(d_2) \tag{7}$$

with:

$$d_1 = \frac{\ln\frac{V_{A,t}}{D_t} + \left(r + \frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A\sqrt{T-t}} \tag{8}$$

$$d_2 = d_1 - \sigma_A\sqrt{T-t} \tag{9}$$

where *r* is the risk-free interest rate. Furthermore, it is known that $\sigma_{A,t}$ and $\sigma_{E,t}$ can be related as follows:

[7] See Vassalou and Xing (2004), Hillegeist et al. (2004), Byström et al. (2005) and Byström (2006) among others. Instead of using the normal distribution, Moody's KMV uses an empirical distribution of actual defaults based on KMV's large, proprietary database.

$$\sigma_{E,t} = \frac{V_{A,t}}{V_{E,t}} N(d_1)\sigma_{A,t} \tag{10}$$

Therefore, by starting from the market price of the firm's equity and solving the system of equations (7) – (10) it is possible to estimate $V_{A,t}$, σ_A and μ and substitute their values in (6) to obtain $P_{def,t}$.

To implement this measure, this study follows a procedure similar to that used by Vassalou and Xing (2004), which begins by estimating the volatility of equity, $\sigma_{E,t}$, by calculating the standard deviation of the last 12 months' return on equity. This estimate of $\sigma_{E,t}$ is taken as the initial value for the estimation of $\sigma_{A,t}$. Substitution of $\sigma_{A,t}$, $\sigma_{E,t}$ and $V_{E,t}$ into the system of equations (7) - (10) gives the initial value of $V_{A,t}$. The described process is then repeated for every month of the study period to obtain a series of $V_{A,t}$ estimates. To estimate $\sigma_{A,t}$, instead of applying expression (10) directly, a more complex iterative procedure is used. Thus, starting from the values estimated for $V_{A,t}$, it is obtained the first estimation identified as the standard deviation of its return over the previous 12 months. The process is then repeated until the values of $\sigma_{A,t}$ converge for two consecutive iterations, for a tolerance level of 0.001. Having found the convergence value of $\sigma_{A,t}$, the final value of $V_{A,t}$ can be obtained using expression (7). By calculating the average annual variation in $\ln V_{A,t}$ over the previous 12 months, we can obtain an estimate of the value of μ_t. In the event that the estimated value of μ_t is lower than the annual risk-free interest rate for that month, r_t, as in Hillegeist *et al* (2004), it is understood that $\mu_t = r_t$. Finally, expression (6) is used to derive the value of $P_{def,t}$.

Figure 1: CAP curves for the different measures of credit risk. Non-matched sample. Default in one year.

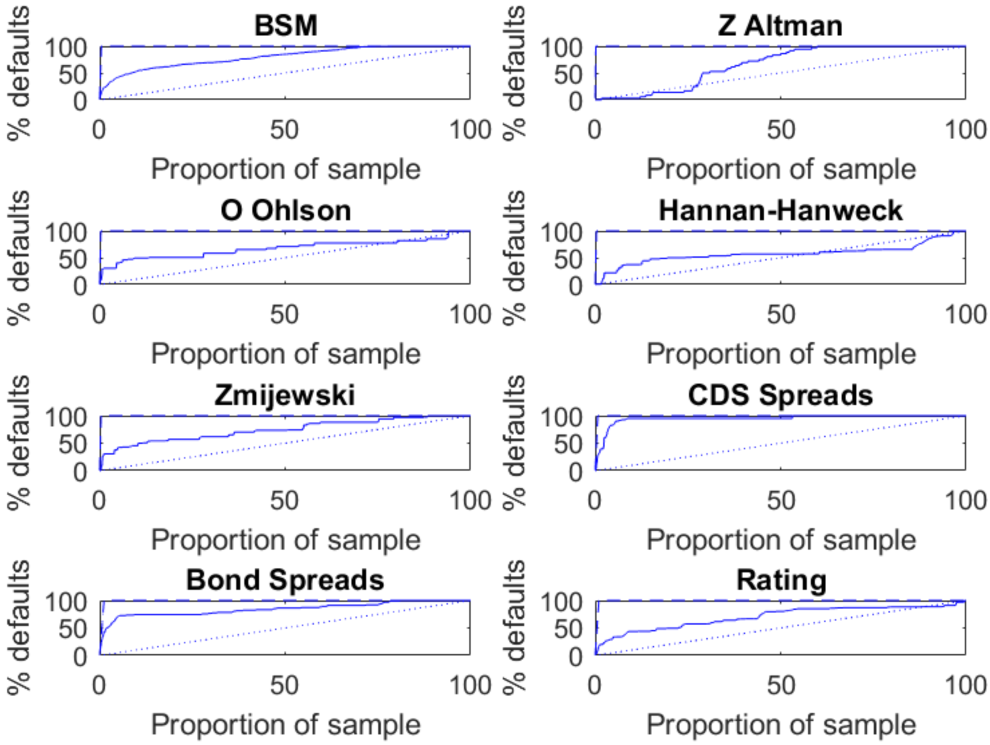
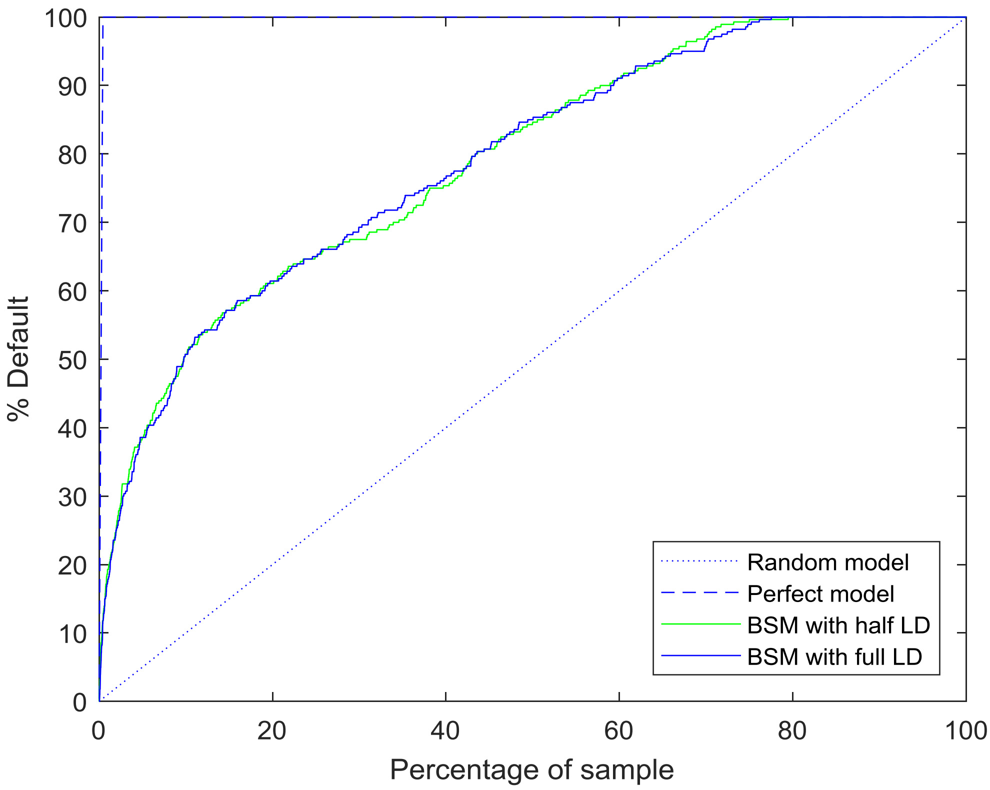


Figure 2: CAP curves for BSM measure using half long-term debt and using full long-term debt. Default in one year.



	Altman's Z	Ohlson's O	Accounting ratios	Credit rating	Bond spreads	CDS spreads	BSM Model	KMV Model	Period	Countries	Benchmark of default to compare
Kealhofer (2003)				X (S&P 's)				X	1973 - 2003	United States	KMV default database
Hillegeist *et al.* (2004)	X	X					X (Dividend modified)		1980 - 2000	Worldwide	Moody´s default database
Löffler (2004)				X (Moody´s)				X	1980 - 2002	Worldwide	Portfolio performance
Hull *et al.* (2004)				X (Moody´s)	X	X			1998 - 2002	Worldwide (31 companies)	Moody's rating
Byström (2006)				X (Moody´s)			X		2001	United States	Moody's rating
Gharghori *et al.* (2006)	X						X		1994 – 2003	Australia	List of defaulted firms
Tanthanongsakkun and Treepongkaruna (2008)			X	X (S&P 's)			X		1992 – 2003	Australia	S&P´s rating
Das *et al.* (2009)			X			X	X		2001 - 2005	Worldwide	CDS spreads
Cardone *et al.* (2014)			X			X	X		2002 - 2009	France, Germany, Italy, Netherlands, Spain and UK	CDS spreads

Table 1. Main features of representative studies on adjustment of credit risk modelling

Table 2: Main statistics of credit risk measures for defaulted and non-defaulted companies

	Companies with measure	Companies with data of default	Defaulted companies	Defaulted companies			Non-defaulted companies		
				Mean	Max.	Mín.	Mean	Max.	Mín.
BSM	1081	629	84	0,0517	0,9977	0	0,02016	0,9999	0
Z-Altman	520	318	49	4,6093	405,5125	-2,4114	241,3564	434018,468	-3,4392
O-Ohlson	582	353	53	-6,7986	2,5281	-20,4556	-6,9899	3,1637	-47,1413
Hannan-Hanweck	999	581	80	0,0157	1	0	0,0107	1	0
Zmijewski	852	509	75	-0,5557	186,7766	-19,8308	-1,9002	353,5629	-6,9158
CDS Spreads	148	138	30	527,04861	13366,96	22,2599	282,5889	9673,973	12,58
Bond Spreads	141	129	32	444,1808	7681,5	10,5	358,8457	4149,7	10,8
Rating	459	459	87	8	23	1	8,3333	22	1
TOTAL	4684	184							

Table 3: Percentage of coincidence in quartiles (in %)

	Z-Altman	O-Ohlson	H-H	Zmijewski	CDS	Bond spreads	Rating
PANEL A: Non-matched sample							
BSM	45.80	41.68	31.93	46.64	50.14	46.32	41.32
Z-Altman		44.30	26.83	59.00	46.67	37.45	41.87
O-Ohlson			29.25	50.95	38.44	36.98	45.27
H-H				29.14	34.15	31.49	31.40
Zmijewski					39.61	36.90	37.80
CDS						60.61	47.50
Bond spreads							60.13
PANEL B: Matched sample							
BSM	37.22	45.74	37.96	38.70	51.30	49.81	49.44
Z-Altman		52.59	23.70	63.89	53.70	41.85	47.59
O-Ohlson			17.78	74.44	60.37	60.74	56.11
H-H				20.00	26.48	17.59	21.30
Zmijewski					47.22	45.56	43.70
CDS						62.22	57.59
Bond spreads							72.96

Table 4: Spearman rank-correlation coefficients.

	Z-Altman	O-Ohlson	H-H	Zmijewski	CDS	Bond spreads	Rating
PANEL A: Non-matched sample							
BSM	0.59703***	0.47***	0.16098***	0.57663***	0.6566***	0.60747***	0.46801***
Z-Altman		0.57068***	0.057494***	0.78042***	0.52629***	0.40871***	0.50566***
O-Ohlson			0.139***	0.65048***	0.35452***	0.35144***	0.55877***
H-H				0.10953***	0.24817***	0.1989***	0.20043***
Zmijewski					0.41112***	0.34042***	0.42643***
CDS						0.80278***	0.64962***
Bond spreads							0.76052***
PANEL B: Matched sample							
BSM	0.38291***	0.28028***	0.30101***	0.24847***	0.61571***	0.57577***	0.3442***
Z-Altman		0.55498***	-0.22883***	0.68212***	0.67564***	0.45903***	0.58633***
O-Ohlson			0.032515	0.86115***	0.67574***	0.68934***	0.84042***
H-H				-0.096013**	0.10051**	0.12343***	0.089141**
Zmijewski					0.62079***	0.52105***	0.68514***
CDS						0.80909***	0.70715***
Bond spreads							0.7652***

*** and ** denote coefficients that are significant at the 1 and 5 per cent levels, respectively.

Table 5: Accuracy Ratios for the different measures of credit risk. Default in one year.

Size of sample	Defaulted companies	BSM	Z-Altman	O-Ohlson	H-H	Zmijewski	CDS Spreads	Bond Spreads	Rating
Non-matched sample		60.31%	32.24%	34.53%	15.18%	48.70%	90.88%	70.09%	41.11%
227	4	53.74%	45.18%						
273	7	86.42%		31.17%					
421	12	74.81%			26.62%				
365	11	78.75%				60.60%			
109	3	88.62%					86.67%		
89	3	89.92%						83.50%	
275	14	67.33%							55.79%
274	3		37.01%	-25.28%					
316	6		32.23%		-52.60%				
314	6		32.15%			-20.21%			
45	1		64.88%				9.41%		
50	1		62.66%					26.07%	
144	3		18.22%						-1.44%
352	13			34.50%	35.21%				
352	13			34.50%		58.76%			
59	3			57.26%			87.91%		
57	3			32.59%				80.53%	
161	6			44.25%					76.61%
509	24				17.65%	48.70%			
86	3				59.75%		87.13%		
86	3				69.44%			83.05%	
256	12				14.69%				60.30%
75	3					82.77%	87.27%		
82	3					87.47%		83.00%	
218	11					52.86%			60.84%
41	3						89.65%	92.26%	
79	4						96.39%		91.13%
80	4							60.31%	59.35%

Table 6: Average values of main characteristics of companies with each measure

	Market value of equity	Total assets	Book to Market	Leverage
BSM	2780100866.11	2888628148.62	0.54	0.27
Z-Altman	6130327385.04	6330974983.69	0.49	0.31
O-Ohlson	4937961094.46	5230671273.12	0.49	0.30
H-H	2882646018.14	3457174934.95	0.62	0.36
Zmijewski	3340971081.83	3799902028.92	0.53	0.38
CDS	8953360503.15	8816113077.89	0.46	0.39
Bond spreads	11754535724.21	16790643560.03	0.47	0.36
Rating	4299316187.93	5787150434.58	0.59	0.41

Table 7: Accuracy Ratios for the different measures of credit risk. Only severe default events considered. Default in one year.

Size of sample	Defaulted companies	BSM	Z-Altman	O-Ohlson	H-H	Zmijewski	CDS Spreads	Bond Spreads	Rating
Non-matched sample		82.23%	34.70%	56.37%	20.10%	45.15%	90.56%	93.70%	51.46%
227	3	69.64%	40.53%						
273	6	89.79%		57.81%					
421	8	87.95%			47.11%				
365	8	87.67%				52.02%			
109	2	85.90%					84.23%		
89	3	90.99%						92.00%	
275	8	88.00%							90.96%
274	3		37.01%	-25.28%					
316	3		35.22%		-4.73%				
314	3		35.14%			-36.13%			
45	1		64.88%				9.41%		
50	1		62.66%					26.07%	
144	1		98.73%						96.56%
352	11			56.33%	28.85%				
352	11			56.33%		51.82%			
59	3			57.26%			87.91%		
57	3			56.07%				90.85%	
161	5			79.78%					95.31%
509	17				19.61%	45.15%			
86	3				59.75%		87.13%		
86	3				68.87%			92.16%	
256	8				38.54%				93.77%
75	3					82.77%	87.27%		
82	3					85.43%		92.13%	
218	8					68.79%			92.60%
41	3						89.65%	92.26%	
79	3						96.88%		97.43%
80	3							98.06%	93.01%

Table 8: Accuracy Ratios for the different measures of credit risk. Default in five years.

Size of sample	Defaulted companies	BSM	Z-Altman	O-Ohlson	H-H	Zmijewski	CDS Spreads	Bond Spreads	Rating
Non-matched		43.92%	-2.86%	7.62%	8.91%	38.10%	92.5%	28.49%	14.90%
227	4	27.17%	31.30%						
273	6	38.21%		-4.73%					
421	11	39.68%			14.41%				
365	10	39.69%				36.18%			
109	3	57.85%					65.87%		
89	4	70.55%						56.48%	
275	11	52.45%							48.64%
274	4		29.06%	-21.88%					
316	7		25.98%		-23.33%				
314	7		25.92%			-18.60%			
45	1		67.73%				50.31%		
50	1		68.33%					19.66%	
144	3		13.11%						-2.80%
352	10			-0.90%	6.56%				
				-0.90%		24.11%			
59	3			13.89%			68.69%		
57	3			1.21%				53.39%	
161	4			19.59%					57.91%
509	17				10.37%	32.28%			
86	3				26.44%		66.36%		
86	3				43.52%			58.26%	
218	7				17.09%				53.66%
75	3					29.50%	66.36%		
82	3					40.99%		58.25%	
218	7					69.26%			52.28%
41	3						68.74%	59.80%	
79	4						93.62%		92.65%
80	4							33.84%	32.95%

Table 9: Accuracy Ratios for the different measures of credit risk. Only severe default events considered. Default in five years.

Size of sample	Defaulted companies	BSM	Z-Altman	O-Ohlson	H-H	Zmijewski	CDS Spreads	Bond Spreads	Rating
Non-matched sample		39.09%	24.67%	10.99%	0.85%	13.25%	73.37%	60.00%	38.03%
227	3	26.77%	29.67%						
273	5	34.70%		7.62%					
421	7	29.03%			3.88%				
365	7	28.69%				17.59%			
109	2	54.40%					63.30%		
89	4	69.73%						57.41%	
275	5	61.48%							88.06%
274	4		29.06%	-21.88%					
316	4		25.11%		-12.76%				
314	4		25.05%			-19.99%			
45	1		67.73%				50.31%		
50	1		68.33%					19.66%	
144	1		-3.13%						69.43%
352	9			10.79%	-5.35%				
352	9			10.79%		11.29%			
59	3			13.89%			68.69%		
57	3			8.16%				55.32%	
161	4			68.60%					85.03%
509	12				-0.01%	13.25%			
86	3				26.44%		66.36%		
86	3				41.35%			59.90%	
256	5				31.66%				86.47%
75	3					29.50%	66.36%		
82	3					36.78%		59.91%	
218	5					71.93%			84.27%
41	3						68.74%	59.80%	
79	3						93.43%		97.56%
80	3							87.15%	85.25%

Table 10. Univariate default-risk logistic regressions. Default in one year.

	Constant	Coefficient
BSM	-5.8026***	4.2706***
Z-Altman	-5.4706***	-0.28392***
O-Ohlson	-3.2296***	0.41881***
H-H	-5.6423***	1.0518**
Zmijewski	-5.5412 ***	0.01261***
CDS	-5.2378***	0.000413***
Bond spreads	-5.8308***	0.0021765***
Rating	-7.1724***	0.20242***

*** and ** denote coefficients that are significant at the 1 and 5 per cent levels, respectively.

Table 11. Multivariate default-risk logistic regressions. Default in one year.

	Constant	CR Measure	Size (lnMV)	Leverage	Equity volatility
BSM	-2.272**	3.7207***	-0.1795***	1.2099***	-0.56907***
Z-Altman	-1.4504	-0.40597***	-0.11437	-4.3938***	0.85396***
O-Ohlson	1.3617***	0.038968	-0.99019***	1.6725***	0.91068***
H-H	13.576***	-1.099*	-0.98103***	1.4684***	0.59345***
Zmijewski	15.402***	0.023502***	-1.064***	1.2027***	0.43606**
CDS	25.437***	0.00025653	-1.5886***	4.3467***	-0.67764
Bond spreads	-4.3847	0.0014912***	-0.12256	2.1852***	1.2282***
Rating	-4.3873***	0.12348***	-0.16656***	1.9258***	1.1552***

*****,** ** and * denote coefficients that are significant at the 1, 5 and 10 per cent levels, respectively.

Table 12. Univariate default-risk logistic regressions. Default in five years.

	Constant	Coefficient
BSM	-4.4102***	3.0295***
Z-Altman	-4.8257***	-0.056745**
O-Ohlson	-3.3779***	0.17947***
H-H	-4.6202***	-032318
Zmijewski	-4.5142***	0.011765***
CDS	-4.5363***	0.000386***
Bond spreads	-3.964***	0.0017197***
Rating	-4.5192***	0.069347***

*** and ** denote coefficients that are significant at the 1 and 5 per cent levels, respectively.

Table 13. Multivariate default-risk logistic regressions. Default in five years.

	Constant	CRMeasure	Size (lnMV)	Leverage (TD/TA)	Equity volatility
BSM	-3.9616***	2.2367***	-0.047222*	1.3147***	0.10845
Z-Altman	-6.7963***	-0.22854***	0.18557**	-5.1097***	0.5465**
O-Ohlson	1.1107	-0.02662	-0.31105***	0.89353***	0.8969***
H-H	4.9948***	-1.5667**	-0.48367***	0.86229***	0.37658***
Zmijewski	5.3005***	0.015824***	-0.49002***	0.76523***	0.23866
CDS	-4.4169*	0.00089661***	-0.07053	1.9281***	0.53846*
Bond spreads	-5.588***	0.0012322***	0.038317	1.6217***	0.70169***
Rating	-4.8187***	0.045147***	-0.03561	1.6726***	1.0872***

*****,** ** and * denote coefficients that are significant at the 1, 5 and 10 per cent levels, respectively.