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Examining what best explains corporate credit risk: Accounting-based versus market-based models

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EXAMINING WHAT BEST EXPLAINS CORPORATE CREDIT RISK: ACCOUNTING-BASED VERSUS MARKET-BASED MODELS

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Abstract

Using a sample of 2,186 credit default swap (CDS) spreads quoted in the European market during the period 2002-2009, this paper empirically analyzes which model – accounting- or market-based – better explains corporate credit risk. We find that there is little difference in the explanatory power of the two approaches. Our results suggest that both accounting and market data complement one other and thus that a comprehensive model that includes both types of variables appears to be the best option for explaining credit risk. We also show that the explanatory power of accounting- and market-based variables for measuring credit risk is particularly strong during periods of high uncertainty, as experienced in the recent financial crisis, and that it decreases as the CDS contract matures. Finally, the comprehensive model continues to show the best results when using the credit rating as the proxy for credit risk, but accounting variables currently appear to have a more important role than the market variables.

JEL classification: C52; G13; G33; M41.

Keywords: bankruptcy; credit default swaps; credit risk; distance-to-default

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EXAMINING WHAT BEST EXPLAINS CORPORATE CREDIT RISK: ACCOUNTING-BASED VERSUS MARKET-BASED MODELS

1. Introduction

Investors' or potential lenders' ability to correctly measure the credit risk of companies is an issue that has historically attracted attention in the financial literature. This desire to understand the determinants of default risk has regained its strength following Lehman Brothers' bankruptcy in September 2008 and the 2011 European sovereign debt crisis.

The use of credit risk models has been fully documented in the literature since 1966, when Beaver published his pioneering work, 'Financial ratios as predictors of failure' [Journal of Accounting Research], which served as a reference for subsequent investigations. This univariate model was followed by a multidimensional-type model that integrates all relevant variables that contribute to the success or failure of a company and provides a single diagnosis or overall assessment of their creditworthiness. The two best-known multidimensional models of credit risk are Altman's Z-score model (1968) and Ohlson's O-score model (1980). These models have in common the use of information drawn from the financial statements of borrowers and consequently are called accounting-based models.

More recently, 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.

Among the models that use market data, we must highlight those based on Merton (1974), who introduced the original model that led to subsequent research on 'structural models'.[1] Relying on the contingent claims analysis of Black and Scholes (1973), Merton (1974) proposes considering the value of the equity as a call option on the value of the assets of the firm with a strike price equal to the face value of the firm's debt. From this perspective, the company will default if its asset value falls below a certain default boundary related to the company's outstanding debt. However, Merton's (1974) model presents some unrealistic assumptions. It considers that the liability structure of the firm consists only of a non-callable zero coupon bond and that bankruptcy cannot be triggered before maturity. In addition, this model supposes that the absolute priority rule always holds at maturity, meaning that equity holders can only obtain a positive payoff after debt holders are reimbursed completely.

Many papers have extended Merton's (1974) original model to incorporate more realistic assumptions. Black and Cox (1976) allow default to occur as soon as a firm's asset value falls below a certain threshold (i.e., at any time). Geske (1977) uses the compound option technique to value a corporation's risky coupon bonds. He considers that bankruptcy occurs when the value of assets is so low that equity holders no longer find it profitable to service debt. Anderson and Sundaresan (1996) and Mella-Barral and Perraudin (1997) propose a structural model that takes into account the possibility of debt renegotiation. A number of other papers have also made more sophisticated assumptions, including Leland (1994), Leland and Toft (1996), Longstaff and Schwartz (1995), Fan and Sundaresan (2000) and Collin-Dufresne and Golstein (2001).

[1] The company KMV, later integrated into Moody's, is one of the great defenders of this type of model for measuring credit risk.

Another market-based approach for measuring credit risk refers to the so-called reduced-form models. Unlike structural models, where all relevant credit risk elements, including default, are functions of the structural characteristics of the firm (asset volatility and leverage primarily), reduced-form models do not condition default on these values. The reduced-form approach relies on the assumption that the credit event occurs at a completely inaccessible time and consists of modeling the conditional law of this random time. These models use the market prices of the firms' defaultable securities to extract their default probabilities, relying on the market as the only source of information regarding the condition of the firms' balance sheets. Significant studies on this topic include those of Litterman and Iben (1991), Jarrow and Turnbull (1995) and Duffie and Singleton (1999).

Our paper is closely related to recent studies that have investigated which of these two approaches – accounting-based or market-based – is more appropriate for explaining corporate credit risk. Accounting models have been criticized for the historic 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 (e.g., Vassalou and Xing, 2004).[2] However, the inefficiencies of capital markets may lead to prediction errors in market-based models. Hillegeist et al. (2004) conclude that a measure based on the Black-Scholes-Merton option-pricing model provides significantly more information than the two most popular accounting-based measures (Z-Score and O-Score). However, Agarwal and Taffler (2008) conclude that although there is little difference in the predictive ability of both models, the accounting-based model leads to greater bank profitability in terms of differential decisions' error costs and competitive pricing regimes. Other studies report mixed results. Demirovic and Thomas (2007) find that although distance-to-default is the most significant

[2] This assumption does not hold for Merton's model, in which firms may have similar levels of equity and debt but very different likelihoods of default if the volatilities of their assets differ.

variable in the measuring of corporate credit risk, market-based models perform better when accounting data are included. Tanthanongsakkun and Treepongkaruna (2008) and Das et al. (2009) reach similar conclusions.

The financial literature has used a range of measures to proxy for credit risk. For example, studies have used as a measure of credit risk the company's financial condition (i.e., bankrupt versus non-bankrupt firms) (e.g., Altman, 1968; Ohlson, 1980; Hillegeist et al., 2004; Agarwal and Taffler, 2008), the credit rating assigned by an agency rating (e.g., Ang and Patel, 1975; Blume et al., 1998; Demirovic and Thomas, 2007), and the spreads of bonds issued by the firm and listed on a secondary market (e.g., Collin-Dufresne et al., 2001; Longstaff and Rajan, 2006; Wu and Zhang, 2008). However, more recently, the empirical literature on credit risk has focused on credit default swap (CDS) spreads (e.g., Alexander and Kaeck, 2008; Das et al., 2009; Ericcson et al. 2009; Forte and Peña, 2009).

Credit default swaps are credit protection contracts whereby one party agrees to make a contingent payment in the case of a defined credit event in exchange for a periodic premium.[3] For buyers of credit protection, the CDS market offers an opportunity to reduce credit concentration and regulatory capital while maintaining customer relationships. For sellers of protection, it offers the opportunity to take credit exposure over a customized term and earn income without having to fund the position (Packer and Suthiphongchai, 2003).

As Das et al. (2009) note, CDSs provide a viable alternative for measuring credit risk for several reasons. First, CDS spreads offer cross-sectional and time-series credit quality information. This continuous variable contrasts with studying binary data samples of

[3] The regular payment made by the CDS buyer to the CDS seller is expressed as a percentage (normally as basis points) of the contract's notional value and is known as the CDS premium (or the CDS spread) (Ismailescu and Kazemi, 2010).

bankruptcies, where a company is identified as healthy until default occurs. Second, CDS spreads reflect market perceptions of default rather than those of a rating agency. Third, spreads capture both the default and recovery risk aspects of firm distress. Finally, CDS spreads are less susceptible than corporate bond spreads to liquidity and tax effects (Elton et al., 2001). Additionally, the 'price' of a CDS is normally quoted as a constant maturity spread, whereas bond spreads are calculated by subtracting an unknown risk-free interest rate from the bond yield and are not directly comparable when maturities of the underlying bonds differ (Alexander and Kaeck, 2008).

This paper contributes to the literature in three ways. First, to the best of our knowledge, this study is the first to investigate whether significant differences between accounting- and market-based approaches for measuring credit risk can be observed in the European market.[4] Moreover, given the benefits identified in the literature, we have chosen to use CDS spreads as the best proxy for credit risk. Second, although most of the extant research stops at the onset of the recession, we consider an extended time span, from 2002 to 2009, that includes both high-growth and economic crisis periods. Extending the analysis to include the crisis period enables us to test whether findings reported in previous papers are robust to changes in the economic cycle. Finally, this paper compares the results obtained when credit ratings are used instead of CDS spreads as a measure for creditworthiness.

The paper is structured as follows. Section 2 describes the data and methodology employed in the empirical research and defines the explanatory variables. Section 3 presents and discusses the results obtained. Section 4 summarizes and concludes.

[4] A notable exception includes Demirovic and Thomas (2007), who use a sample of UK-listed companies over the 1990–2002 period.

2. Data and methodological aspects

2.1. *Sample*

Our sample comprises firms listed on the FTSEuroFirst 100 Index with information about CDS spreads available in the Markit database during the period 2002-2009.[5] Markit's CDS data do not reflect any specific trading activity; they are post-trade valuation information drawn from numerous financial institutions, including inter-dealer brokers, electronic trading platforms, major market makers and many significant buy-side firms. The data set undergoes a rigorous cleaning process: stale, flat curves, outliers, and inconsistent data are discarded.[6]

As is customary, firms operating in the financial sector are excluded from the analysis due to the different structure of their financial statements.[7] Entities that present abnormal ratios or extreme values were also eliminated from the sample as outliers. After the completion of this filtering, the final sample consisted of 2,186 observations from 51 unique firms in six different European countries (France, Germany, Italy, Netherlands, Spain, and United Kingdom). Table 1 shows the number of observations that compose the sample by year and CDS maturity.

INSERT TABLE 1 HERE

As in similar studies, we used unconsolidated statements, thus preventing relevant differences in profit and loss statements and balance sheets of parent companies and

[5] The FTSEurofirst 100 Index includes the 60 largest companies ranked by market capitalization in the FTSE Developed Europe Index and 40 additional European companies selected for their size and sector representation. See http://www.ftse.com for more details.

[6] See http://www.markit.com for a detailed description of the database.

[7] For an analysis of the relationship between market- and accounting-based variables in the banking industry, see Kato and Hagendorff (2010).

subsidiaries from negating one other. We obtained the accounting data from the Amadeus database, and market information is taken from the Datastream database.[8]

2.2. *Definition of variables*

2.2.1. Dependent variable

As previously stated, we use CDS spreads from the Markit database as the dependent variable. Although there exists a high concentration of CDS quotes at the five-year maturity, which led most studies dealing with corporate credit data to focus on this one specific maturity (e.g., Longstaff et al., 2005), this approach only observes the credit risk effects for one single point on the term structure. Therefore, to provide more detailed insight, we include the whole maturity spectrum, from 1-year to 30-year maturities. We collect the CDS constant maturity spreads on a daily basis at the end of each year (average of the last 10 trading days) over the period 2002-2009. All contracts are on senior unsecured obligations with the modified-modified restructuring clause, which is common in Europe.

Moreover, we regress the natural logarithm of CDS spreads on explanatory variables. As Aunon-Nerin et al. (2002) note, regressions in the logarithm of spreads fit better than in the levels directly.

In Table 2, we present some descriptive statistics of CDS spread values by maturity and year. CDS premiums vary significantly by maturity, ranging on average from 71 bps for 1-year CDS contracts to 112 bps for 30-year contracts. We also see a downward trend in premiums from 2002 to 2006 for all maturities, reaching a minimum of 34 bps on average in 2006. In 2007, as a result of the onset of the financial crisis, there is a change in

[8] See http://bvdinfo.com and http://online.thomsonreuters.com/datastream for detailed information about Amadeus and Datastream, respectively.

the trend. The worsening of the global credit crisis in 2008 led, among others reasons, by the collapse of Lehman Brothers dramatically increased the CDS spreads by up to 298 bps on average. Although CDS premiums fell in 2009, they did not reach the levels prior to the start of the crisis.

INSERT TABLE 2 HERE

2.2.2. Independent variables

Our aim is to analyze which data, accounting- or market-based, better explain borrowers' CDS spreads.

2.2.2.1 Accounting-based variables

We use 10 accounting variables to proxy for (1) liquidity, (2) capital structure, (3) debt service, (4) cash flow generation, (5) performance (profitability), and (6) firm size. All of these variables have been widely used by previous studies as drivers of credit risk, and most are included in the two best-known accounting-based models of credit risk (i.e., the Z-score (Altman, 1968) and the O-score (Ohlson, 1980)).

To proxy for financial liquidity, we use the ratio of current liabilities to current assets (CL/CA) and the ratio of working capital to total assets (WC/TA). The former is constructed by dividing current liabilities by current assets. One would expect that a larger ratio indicates lower liquidity. A company whose ratio exceeds unity may even have problems meeting its payments in the short term. We thus expect a positive relationship between the CL/CA ratio and the CDS premium. The working capital to total assets ratio is a measure of the net liquid assets of the firm relative to total assets. Working capital is defined as the difference between current assets and current liabilities. In this case, we expect a negative relationship between the WC/TA ratio and the CDS premium.

We use the following two common ratios to analyze the effect of capital structure on the credit risk of companies: the ratio of retained earnings to total assets (RE/TA) and the debt-to-equity ratio (TL/Eq). Retained earnings refer to the account that reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The age of a firm is implicitly considered in this ratio; a relatively young firm will likely show a low RE/TA ratio because it has not had time to build accumulated profit. The RE/TA ratio also measures the leverage of a firm. Firms with high RE, relative to TA, have financed their assets through the retention of profits and have not utilized as much debt. The TL/Eq ratio, also referred to as the debt-to-equity ratio, is another leverage ratio that compares a company's total liabilities to its total shareholders' equity.[9] A higher percentage and a greater potential variability of earnings translate into a greater potential for default. Consequently, we predict opposite values for the coefficients of these ratios in the regression analysis, i.e., negative for the RE/TA ratio and positive for the TL/Eq ratio.

Debt service is measured by the interest coverage ratio, i.e., earnings before interest and taxes (EBIT) divided by total interest payments. This ratio is used to determine how easily a company can pay interest on outstanding debt. Similar to Blume et al. (1998), we transform the interest coverage ratio in two ways. First, we set any interest coverage ratio to zero if it is negative. Second, any interest coverage ratio that exceeds 100 is censored on the assumption that further increases in value convey no additional information. A lower ratio indicates a greater degree to which a company is burdened by debt expense. When a company’s interest coverage ratio is 1.5 or lower, its ability to meet interest expenses may be questionable. We thus expect a negative relationship between the interest coverage ratio and credit risk.

[9] We decide to use the debt-to-equity ratio instead of the debt ratio (total liabilities divided by total assets) to avoid potential problems of collinearity with the RE/TA ratio.

The earnings before interest, taxes, depreciation, and amortization to total liabilities (EBITDA/TL) ratio measures a company's ability to repay debt obligations from annualized operating cash flow. This ratio is a common metric used by credit rating agencies to assess the probability of defaulting on issued debt. A low EBITDA/TL ratio suggests that a firm may not be able to service its debt in an appropriate manner and may result in a lowered credit rating. Conversely, a high ratio may suggest that the firm may want take on more debt if needed, and it often warrants a relatively high credit rating. We hypothesize a negative relationship between the EBITDA/TL ratio and the CDS premium.

To measure operating performance, we use the asset turnover ratio, which is defined as the ratio between net sales and total assets. This ratio helps to measure the effectiveness with which the management uses its assets to generate sales or revenue (i.e., the productivity of a company's assets). A high asset turnover ratio is desirable compared to a low ratio because the former is indicative of better operating performance. A negative relationship between the asset turnover ratio and the firm's credit risk is expected. If we use EBIT instead of net sales in the numerator of the ratio, we obtain a measure of profitability that is well known in the literature, i.e., the return on total assets (ROA), which is considered an indicator of how effectively a company is using its assets to generate earnings before contractual obligations must be paid. Moreover, as is customary in the literature (e.g., Arslan and Karan, 2009), a third profitability ratio is constructed as net income divided by total assets (NI/TA). Again, a negative relationship between these ratios and CDS spreads is expected.

Finally, because the effect of size on firm's credit risk seems to be non-linear, we use the logarithm of firm assets to accommodate this non-linear relationship. We expect that a company with a larger asset size will have a lower CDS premium.

2.2.2.2 Market-based variables

In contrast to accounting models, a market-based approach uses either the market value of the firm's equity or the trading price of its bonds as the main variable to estimate the company's credit risk. The empirical application of models of this type is very recent, achieving popularity in recent years. Of the models that are currently being developed in this area of analysis, a particularly notable one is KMV Corporation's (acquired by Moody's) structural type model. As previously stated, its theoretical inspiration is Merton's (1974) model. Merton (1974) considers the equity of a firm as a European-type call option on its assets, with the strike price being the accounting value of the outstanding debt due for repayment in the defined time horizon.

We will now provide a brief exposition of the theoretical base of the model. Let us consider a leveraged firm that has only issued debt consisting of a zero-coupon bond with maturity *T*. Moreover, there are no issues of any type of security during the life of the debt contract. This company does not pay dividends. We also assume that markets are perfect and that there are no frictions, such as taxes or bankruptcy costs.[10] In this case, the market value of the firm's equity, *E*, at maturity *T* is given by:

$$E_T = \max(V_T - D, 0) \tag{1}$$

where V_T is the market value of the company's assets and *D* is the book value of the debt at maturity. According to this equation, if the debt payment is not made, the bondholders receive the value of the firm, and equity holders receive nothing. However, if the asset

[10] Other assumptions considered by the model are as follows: (1) every individual acts as if he can buy or sell as much of any security as he wishes without affecting the market price; (2) there is a riskless asset, whose rate of return is known and constant over time; (3) trading takes place continuously, and individuals may take short positions in any security, including the riskless asset; and (4) the dynamics for the value of the assets can be described by a diffusion-type process defined by a stochastic differential equation.

value is higher than the face value of the debt, the equity holders, as residual claimers, receive the difference between these two values. It should be noted that (1) represents the payment of a European call option on the value of the firm with strike price *D*. Therefore, we can use the formulation of Black and Scholes (1973) to determine the probability that the company will default.

According to the general assumptions of the Black-Scholes-Merton model, we can relate the market value of the firm's equity at time 0, 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:

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

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

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

where *N* is the cumulative density function of the standard normal distribution, *r* is the risk-free interest rate in continuous time, and the remaining variables are as defined above.

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 option's volatility to that of the underlying security:

$$\sigma_E = \frac{V_0}{E_0} \frac{\partial E}{\partial V} \sigma_V \qquad (3)$$

This equation, together with the previous ones shown in (2), 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 variables are easy to calculate for listed companies.

The neutral-risk probability that the value of the company is greater than the value of the debt on the date T, i.e., $V_T \geq D$, is $N(d_2)$. We can also calculate the natural default probability, but the expected rate of growth of the company, μ, is required. In this case, the probability that we seek is:

$$p_t(T) = N\left[-\frac{\ln(V_t / D) + \left(\mu - \frac{\sigma_V^2}{2}\right)(T-t)}{\sigma_V \sqrt{T-t}} \right] \tag{4}$$

Having estimated the probability of default of the firm using equation (4), it is easy to quantify its distance-to-default (DtD) by the expression (Vassalou and Xing, 2004):

$$DtD_t = \frac{\ln(V_t / D) + \left(\mu - \frac{\sigma_V^2}{2}\right)(T-t)}{\sigma_V \sqrt{T-t}} \tag{5}$$

Default occurs when the ratio of the value of assets to debt is less than 1 or when its log is negative. The preceding equation tells us by how many standard deviations the log of this ratio must deviate from its mean for default to occur. Because a company with a higher DtD has a lower probability of insolvency (and vice versa), we expect a negative relationship between this variable and the CDS spread. DtD has been widely used in the literature as a market-based variable for estimating credit risk (e.g., Das et al., 2009; Demirovic and Thomas, 2007)

We make the following assumptions to obtain the DtD. E_0 (the market value of equity) is computed as the market capitalization during the month of December, whereas the input σ_E (the annualized standard deviation of equity returns) is estimated from the prior year of stock price returns.[11] We consider $t = 0$ and $T = 1$. Similar to previous studies

[11] We also consider the annualized standard deviation of equity returns σ_E as a specific independent variable, which allows for testing the effect of the volatility of the equity market in isolation. Higher equity volatility

(e.g., Du and Suo, 2007; Vassalou and Xing, 2004), we assume that the amount of debt or default point D is equal to the book value of the current liabilities plus half of the long-term debt. We use the 1-year constant maturity Treasury rate as the risk-free rate r. Finally, μ is a proxy for the real GDP growth rate for n + 1 years.

In addition to the DtD, we consider other common market-based variables, such as the price-to-earnings (P/E) ratio, which is a measure of the price paid for a share relative to the annual net income per share. Therefore, the P/E ratio can alternatively be calculated by dividing the company's market capitalization by its total annual earnings. This ratio is normally used for valuation: a higher P/E ratio means that investors are paying more for each unit of net income, so the stock is more expensive compared to one with a lower P/E ratio. We can thus expect a negative relationship between the P/E ratio and the firm's credit risk. Similar considerations could be made for the price-to-cash flow (P/C) ratio. Finally, the price-to-book (P/B) ratio is the inverse of the known BM (book-to-market) ratio. Vassalou and Xing (2004) find that the BM ratio has a significant relationship with default risk; small firms with a high BM ratio tend to have a high default risk, whereas large firms with a low BM ratio are likely to have a low credit risk. Therefore, we predict a negative sign for the P/B ratio in our equation.

2.2.2.3 Control variables

To account for country-specific and industry-specific effects, we include country and industry dummies, respectively. The country dummy variables must capture differences in, for example, the institutional framework, the degree of competition, and the accounting standards among the European countries. However, the industry dummies must control for

often implies higher asset volatility, leading firm value to be more likely to fall below the default threshold (Zhang et al., 2009).

differences among the industries considered (basic materials, consumer goods, consumer services, health care, industrials, oil and gas, utilities, and telecommunications). In addition, we include a set of year dummies to account for macroeconomic conditions and time-specific effects.[12]

Finally, we control for maturity in years of the CDS contract. We hypothesize a positive relationship between the CDS maturity and the credit risk; i.e., the longer the maturity of the contract, the higher the CDS premium.

Table 3 summarizes the explanatory variables and their expected signs as considered in the present study.

INSERT TABLE 3 HERE

Table 4 shows descriptive statistics on the accounting and market-based determinants of CDS spreads. In this table, every given company is represented as many times as CDS premiums are available for that firm.

INSERT TABLE 4 HERE

2.3. *Methodology*

Following the same procedure used by Das et al. (2009) for the U.S. market, we estimate the following three multivariate empirical models for the European market: (1) an accounting-based multivariate model of the determinants of credit spreads, compared in in terms of explanatory power with (2) a model that uses market information and (3) a comprehensive model that includes both accounting- and market-based information.

[12] Because we are only interested in knowing which firm-specific variables (accounting- or market-based) are better determinants of credit risk, we chose to include year dummies to control for all macroeconomic variables. A detailed analysis of the macroeconomic determinants of credit risk is provided by Bonfim (2009) and Tang and Yan (2010).

2.3.1. *Accounting-based model (Model 1)*

We estimate the following linear regression:

$$Y_{i,t} = \beta_1 \cdot \text{CL/CA}_{i,t} + \beta_2 \cdot \text{WC/TA}_{i,t} + \beta_3 \cdot \text{RE/TA}_{i,t} + \beta_4 \cdot \text{TL/Eq}_{i,t} + \beta_5 \cdot \text{Coverage}_{i,t} + \beta_6 \cdot \text{EBITDA/TL}_{i,t} + \beta_7 \cdot \text{Turnover}_{i,t} + \beta_8 \cdot \text{ROA}_{i,t} + \beta_9 \cdot \text{NI/TA}_{i,t} + \beta_{10} \cdot \text{Size}_{i,t} + \beta_{11} \cdot \text{Maturity}_{i,t} + \beta_{12} \cdot \text{Industry (dummy)}_{i,t} + \beta_{13} \cdot \text{Country (dummy)}_{i,t} + \beta_{14} \cdot \text{Year (dummy)}_{i,t} + \varepsilon_{i,t}. \quad (6)$$

Here, subscripts *i* and *t* index firms and time in years, respectively; *Y* denotes the dependent variable, which is the natural log of the CDS spread at the end of the year. As stated above, we consider 10 firm-specific accounting variables and several additional dummy variables to account for the industry, the country, and the macroeconomic environment. Finally, we control for the maturity of the CDS contract. The notations of these explanatory variables are described in Table 3. $\varepsilon_{i,t}$ is the disturbance, which contains the unobserved firm-specific effect (η_i) and the idiosyncratic error ($\nu_{i,t}$).

2.3.2. *Market-based model (Model 2)*

We now estimate the following linear regression:

$$Y_{i,t} = \beta_1 \cdot \text{DtD}_{i,t} + \beta_2 \cdot \sigma_{Ei,t} + \beta_3 \cdot \text{P/E}_{i,t} + \beta_4 \cdot \text{P/C}_{i,t} + \beta_5 \cdot \text{P/B}_{i,t} + \beta_6 \cdot \text{Maturity}_{i,t} + \beta_7 \cdot \text{Industry (dummy)}_{i,t} + \beta_8 \cdot \text{Country (dummy)}_{i,t} + \beta_9 \cdot \text{Year (dummy)}_{i,t} + \varepsilon_{i,t}. \quad (7)$$

Again, subscripts *i* and *t* index firms and time in years, respectively; *Y* denotes the dependent variable, which is the natural log of the CDS spread at the end of the year. We consider 5 firm-specific market-based variables and several dummy variables to account for the industry, the country, and the macroeconomic environment. Finally, we control for the maturity of the CDS contract. The notations of these explanatory variables are described in Table 3. $\varepsilon_{i,t}$ is the disturbance, which contains the unobserved firm-specific effect (η_i) and the idiosyncratic error ($\nu_{i,t}$).

2.3.3. Comprehensive model (Model 3)

Finally, our third model attempts to determine whether market-based measures add any value if used in combination with accounting measures. Therefore, the linear regression is as follows:

$$Y_{i,t} = \beta_1 \cdot \text{CL/CA}_{i,t} + \beta_2 \cdot \text{WC/TA}_{i,t} + \beta_3 \cdot \text{RE/TA}_{i,t} + \beta_4 \cdot \text{TL/Eq}_{i,t} + \beta_5 \cdot \text{Coverage}_{i,t} + \beta_6 \cdot \text{EBITDA/TL}_{i,t} + \beta_7 \cdot \text{Turnover}_{i,t} + \beta_8 \cdot \text{ROA}_{i,t} + \beta_9 \cdot \text{NI/TA}_{i,t} + \beta_{10} \cdot \text{Size}_{i,t} + \beta_{11} \cdot DtD_{,t} + \beta_{12} \cdot \sigma_{Ei,t} + \beta_{13} \cdot \text{P/E}_{i,t} + \beta_{14} \cdot \text{P/C}_{i,t} + \beta_{15} \cdot \text{P/B}_{i,t} + \beta_{16} \cdot \text{Maturity}_{i,t} + \beta_{17} \cdot \text{Industry (dummy)}_{i,t} + \beta_{18} \cdot \text{Country (dummy)}_{i,t} + \beta_{19} \cdot \text{Year (dummy)}_{i,t} + \varepsilon_{i,t}. \quad (8)$$

As stated above, *Y* denotes the dependent variable, which is the natural log of the CDS spread for firm *i* at the end of year *t*. Model 3 considers firm-specific accounting- and market-based variables as well as additional variables to account for the industry, the country, the macroeconomic environment, and the maturity of the CDS contract.

3. Results

3.1. *Univariate analysis*

As a first approximation, we perform a univariate analysis of the sample. We calculate the Pearson's correlation coefficient between the natural log of the CDS spread and all of the explanatory variables. The results are presented in Table 5.

INSERT TABLE 5 HERE

As seen, the highest correlations with the CDS premium correspond to two of the market-based variables, the DtD (-0.54 on average) and the annualized standard deviation of equity returns (0.62 on average), both of which have the predicted signs. This result suggests that market-based variables play an important role in explaining credit risk. In addition, we can see that the correlation of the CDS spread with these two variables decreases as CDS maturity increases, from -0.68 to -0.54 for the DtD and from 0.74 to 0.62 for the equity volatility, for a maturity of 1- and 30-year, respectively.

Table 5 also shows that the accounting-based variables used for measuring debt service and firm profitability have the highest correlations with CDS spreads (-0.21 for Coverage; -0.19 and -0.18 for NI/TA and ROA, respectively). However, the CL/CA ratio and the variable that captures the firm's size show lower correlation coefficients, both of which are close to zero.

3.2. *Multivariate analysis*

After univariate analysis, we conduct a regression analysis.[13] Table 6 reports our results for the three credit risk models considered.

INSERT TABLE 6 HERE

In the accounting-based equation (Model 1), we find that all the variables considered have the expected sign. The WC/TA ratio shows a negative and statistically significant relationship with CDS spreads, meaning that lower liquidity implies higher credit risk. In

[13] First, however, we perform an analysis of multicollinearity for the previously selected independent variables. A study of the matrix of correlations indicates that most of the coefficients of bivariate correlation are lower than 0.65. We subsequently confirm that collinearity would not be a problem by calculating the variance inflation factor (VIF); it reaches a value close to 1 for most of the variables.

past studies (e.g., Altman, 1968), this ratio has also been found to be a significant indicator of corporate problems.

The two variables that measure the effect of capital structure on credit risk (RE/TA and TL/Eq ratios) show a strong relationship with CDS spreads. Firms with higher retained earnings relative to total assets are expected to have lower credit risk levels due to older age and less leverage. Similarly, a higher value of TL/Eq implies greater leverage and thus a higher probability of default.

Corroborating our univariate results, we find a strong negative relationship between the interest coverage ratio and CDS spreads. Therefore, the CDS premium declines as the firm's EBIT relative to total interest payments increases. Nevertheless, we do not find the EBITDA/TL ratio to be a statistically significant driver of credit risk.

As expected, the regression coefficients show a negative relationship between profitability measures and corporate credit risk. However, only the coefficient of the NI/TA ratio is statistically significant (at the 5% level). Finally, as with our univariate results, we do not find size to be a determinant of CDS spreads.

Similar to Das et al.'s (2009) findings, the explanatory power of our accounting-based model is high, explaining 67.42% of the variation in our sample of CDS spreads.

Model 2 (market-based) supports the results found by the univariate analysis. Both distance-to-default and the annualized standard deviation of equity returns are statistically significant (at the 1% level), and the signs are as predicted. A higher value of DtD and a lower equity volatility imply lower credit risk. The P/E, P/C, and P/B ratios produce no significant association with the CDS spreads. However, the coefficient sign of P/E ratio is not as we predicted. As Wang et al. (2011) note, the P/E ratio may have two opposite effects on CDS spreads: a high P/E ratio implies high future asset growth, reducing the likelihood of financial distress, but high-growth firms tend to have high return volatilities, which increase credit risk. The explanatory power of this second model is slightly higher than the accounting-based model, with an R^2 of 68.41% versus 67.42% in the latter equation.

Model 3 includes both accounting- and market-based variables for explaining credit risk. Most of the explanatory variables retain the same signs and the same statistical significances. Nevertheless, the WC/TA and the NI/TA ratio lose some statistical significance, while the P/E ratio and the P/B ratio are now statistically significant (at the 10% and 1% level, respectively).

The coefficient of determination R^2 improves from 67.42% (Model 1) and 68.41% (Model 2) to 72.76%, suggesting that both accounting and market data complement one other. Therefore, a comprehensive model including both types of variables appears to be the best option for explaining credit risk. This finding is in accordance with results found by Agarwall and Taffler (2008) and Das et al. (2009) for the U.K. and the U.S. markets, respectively.

3.3. *Robustness checks*

To further confirm the aforementioned findings, we conduct a number of robustness checks. First, we split the sample into two periods: a pre-crisis period (from 2002 to 2006) and a crisis period (from 2007 to 2009). By doing this, we investigate the possible impact of the recent financial crisis on our credit risk models. Although our results do not change (see Table 7) in that a comprehensive model including both types of variables remains the best option for measuring credit risk, we do observe certain differences between both periods (before and during the crisis) with respect to the explanatory power of models and the statistical significance of some explanatory variables.

INSERT TABLE 7 HERE

In relation to the explanatory power of models, we find that it is considerably higher during the crisis period. This finding is consistent with that reported by other authors such as Chiaramonte and Casu (2012) and Annaert et al. (2010) for the banking industry. The former study suggests that the explanatory power during the pre-crisis period is lower because CDS spreads were flat at that time. With respect to the explanatory variables, although most of them remain unchanged in terms of signs and levels of significance, we do observe that liquidity ratios appear to play an important role as determinants of default risk during periods of crisis. Something similar happens with the P/C ratio. Investors seem to value positively greater liquidity in times of crisis, reducing the premium paid for eventual default among companies with better liquidity ratios. Finally, we find a little difference in the variable that measures the effect of size on credit risk. This variable is positive and statistically significant (at the 1% level) in the accounting-based model for the crisis period, which may suggest that a larger size could have implied higher levels of credit risk during this period.

Second, we perform a robustness check to analyze how the maturity of the CDS contract affects our results (see Table 8). We consider only 1-, 5-, and 30-year CDS spread data. Our main finding remains unalterable; that is, the comprehensive model still provides the greatest explanatory power for all maturities considered. However, we find that the coefficient of determination R^2 decreases as the maturity increases (from 87.80% to 70.11% for the comprehensive model and for 1-year and 30-year CDS contracts, respectively). This result may be due to several factors. First, the CDS contracts at different maturities may have different levels of liquidity, which may be reflected in their quoted spreads.[14] Second, it has been long recognized in the literature that a critical component of systematic economic risk may be missing in credit risk modeling (e.g., Collin-Dufresne et al. 2001). Wang et al. (2011) report that this component increases with the maturity of the CDS contract.

INSERT TABLE 8 HERE

Third, we evaluate the method of estimation used in the analysis. Because panel data are used, we can re-estimate the models with fixed or random effects. Because the Hausman test suggests that the fixed effects estimator is more appropriate in our case, we report these results in Table 9.[15] By doing this, we assume that omitted variables may potentially correlate with the existing regressors (e.g., CDS liquidity, corporate governance, etc.). As expected, the comprehensive model has the greatest explanatory power. Moreover, we re-estimate our base equations with only the variables that are statically significant. Again, most of the explanatory variables retain both their signs and their statistical significance. However, we do observe some loss of explanatory power, as shown by the coefficients of determination (64.30%, 68.04% and 70.51% for Models 1, 2, and 3, respectively).[16]

INSERT TABLE 9 HERE

[14] CDS contracts may not be significantly affected by liquidity due to their contractual nature, which allows negotiating large notional amounts compared to the corporate bond market; hence, CDS spreads may better illustrate a default risk premium (e.g., Longstaff et al., 2005). However, Pan and Singleton (2007) suggest a liquidity factor as a possible cause of higher CDS spreads.

[15] We use only the most liquid 5-year CDS contract.

[16] We do not report these values because of space limitations. However, they are available under request.

Finally, we replace the DtD with the probability of default, as defined in (4). Both the sign (positive) and the statistical significance are as expected. This new model specification is able to explain 68.14% (Model 2) and 71.01% (Model 3) of the variance in the logarithm of CDS spreads.

3.4. Are there differences in using credit ratings instead of CDS spreads?

Credit ratings have also been used as a typical proxy for credit risk in the literature (e.g., Demirovic and Thomas, 2007). However, rating agencies have been questioned as effective evaluators of credit risk by regulators and investors, particularly after the 2007 subprime crisis. A key criticism is that issuers must pay the credit ratings agencies to rate their securities, which may lead to conflicts of interests. Another important concern with the ratings agencies refers to their slowness to adapt their measurements to changes in the firm´s financial and economic conditions (e.g., Enron's debt was rated investment grade four days before the company went bankrupt) or to their recent errors of judgment in rating structured products such as mortgage-backed securities. All of the above would involve considering the credit rating as a noisy measure of credit risk.

Because these credit ratings are inherently ordered, we now use an ordered logistic regression for modeling the relationship between the credit risk and both the accounting and the market-based data. We use discrete values of credit ratings as a dependent variable; i.e., we convert the ratings provided by the agencies into numerical groupings: from 1 for the best ratings to 7 for ratings of BBB- or lower. Table 10 reports the credit rating provided by the three major international rating agencies (Standard & Poor´s, Moody´s and Fitch) for the sample firms over the 2002-2009 period as well as the assigned numerical values. Each company is assigned the rating it has at the end of the year. If the company is rated by more than one of the agencies in a single year, each rating is considered a separate observation. In total, we have 706 observations for 51 unique firms listed in the FTSEurofirst 100 index.

INSERT TABLE 10 HERE

Our results (see Table 11) are very similar to those found when using the CDS spread as the proxy for credit risk. Again, a comprehensive model including both accounting and market data has the greatest explanatory power (22.82%). However, our results indicate that when the credit rating is used as the credit risk measure, accounting data play a more important role than market data in explaining a firm´s creditworthiness (the accounting-based model explains 20.58% of the variability, whereas the market-based model explains only 14.45%). The same conclusion is reached by Demirovic and Thomas (2007) for the UK market. Finally, with regard to the explanatory variables, although most of them remain unaffected in terms of their sign and level of significance, we do observe that liquidity ratios now appear to be more important drivers of default risk and that equity volatility loses much of its explanatory power. We also find that the variable that measures the effect of size on credit risk is positive and strongly statistically significant, suggesting that a greater the size is associated with a higher rating.

INSERT TABLE 11 HERE

4. Conclusions

Using a sample of 2,186 credit default swap (CDS) spreads taken from the European market during the period 2002-2009, this paper empirically analyzes which model – accounting- or market-based –better explains corporate credit risk.

We find little difference in the explanatory power of each approach. Our results suggest that both accounting and market data are complementary to one other. Therefore, a comprehensive model including both types of variables appears to be the best option for explaining credit risk. This finding is in accordance with results reported by Agarwall and Taffler (2008) and Das et al. (2009) for the U.K. and the U.S. markets, respectively.

We also show that the explanatory power of accounting- and market-based variables for measuring credit risk is particularly strong during periods of high uncertainty, as experienced in the recent financial crisis, and that it decreases as the CDS contract matures. Although the former may be because CDS spreads become more sensitive during periods of crisis and thus act as better credit risk indicators, the latter may be due to either differences in liquidity, which are not captured by our model, or a component of systematic economic risk that is greater for longer CDS maturities.

Finally, when the credit rating is used as a proxy for credit risk, our main conclusion is unchanged; i.e., the best results are reached when accounting and market data are taken together. Nevertheless, our results suggest that accounting variables play a more important role than market variables in explaining credit ratings.

References

Agarwal, V. and Taffler, R., 2008. Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance* 32, 8, 1541–1551.

Alexander, C. and Kaeck, A., 2008. Regime dependent determinants of credit default swap spreads. *Journal of Banking and Finance* 32, 1008–1021.

Altman, E., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23, 589-609.

Altman, E.I., Marco, G., and Varetto, F., 1994. Corporate distress diagnosis: Comparisons using discriminant analysis and neural networks (the Italian experience)”. *Journal of Banking and Finance* 18, 505-529.

Altman, E. and Sabato, G., 2007. Modelling credit risk for SMEs: Evidence from the U.S. market. *Abacus* 43, 332-355.

Annaert, J., M. De Ceuster, M. Van Roy, and C. Vespro. 2010. What determines euro area bank CDS spreads? National Bank of Belgium Working Paper no. 190, National Bank of Belgium, Brussels, May.

Anderson, R. and Sundaresan, S., 1996. Design and valuation of debt contracts. *Review of Financial Studies* 9, 37-68.

Ang, J. and Patel, K., 1975. Bond rating methods: Comparison and validation. *Journal of Finance* 30, 631–640.

Arora, N., Bohn, J., Fanlin, Z., 2005. Reduced form vs. structural models of credit risk: A case study of three models. *Journal of Investment Management* 3, 43–67.

Arslan, Ö. and Karan, M. B. Credit risks and internationalization of SMEs. *Journal of Business Economics and Management* 10, 361-368.

Aunon-Nerin, D., Cossin, D., Hricko, T. and Huang, Z., 2002. Exploring for the determinants of credit risk in credit default swap transaction data: Is fixed income markets’ information sufficient to evaluate credit risk? Working Paper, HEC-University of Lausanne and FAME.

Beaver, W. H., 1966. Financial ratios as predictors of failure. *Journal of Accounting Research* 4, 71-127.

Bharath, S.T. and Shumway T., 2008. Forecasting default with the Merton distance-to-default model. *The Review of Financial Studies* 12, 1340-1369.

Black, F. and Cox J. C., 1976. Valuing corporate securities: Some effects of bond indenture provisions. *Journal of Finance* 31, 351-367.

Black, F. and Scholes, M., 1973. The Pricing of options and corporate liabilities. *Journal of Political Economy* 81, 399-418.

Blume, M., Lim, F. and MacKinlay, A.C., 1998. The declining credit quality of U.S. corporate debt: Myth or reality? *Journal of Finance* 53, 1389–1413.

Bonfim, D., 2009. Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking and Finance* 33, 281-299.

Chiaramonte L. and Barbara, C., 2012. The determinants of bank CDS spreads: evidence from the financial crisis. *The European Journal of Finance*, DOI:10.1080/1351847X.2011.636832

Collin-Dufresne, P. and Goldstein, R., 2001. Do credit spreads reflect stationary leverage ratios? *Journal of Finance* 56, 1929-1957.

Collin-Dufresne, P., Goldstein, R., Spencer Martin, J., 2001. The determinants of credit spread changes. *Journal of Finance* 56, 2177–2207.

Das S., Hanouna P. and Sarin A., 2009. Accounting-based versus market-based cross-sectional models of CDS spreads. *Journal of Banking and Finance* 33, 719-730.

Demirovic A. and Thomas, D. C., 2007. The relevance of accounting data in the measurement of credit risk. *The European Journal of Finance* 13, 253–268.

Du, Y. and Suo, W., 2007. Assessing credit quality from the equity market: Can a structural approach forecast credit ratings? *Canadian Journal of Administrative Sciences* 24, 212–228.

Duffie, D. and Singleton, K.J., 1999. Modelling term structures of defaultable bonds. *Review of Financial Studies* 12, 687-720.

Elton, E.J., Gruber, M.J., Agrawal, D. and Mann, C., 2001. Explaining the rate spread on corporate bonds. *Journal of Finance* 56, 247–277.

Ericsson, J., Jacobs, K., and Oviedo-Helfenberger, R, 2009. The determinants of credit default swap premia. *Journal of Financial and Quantitative Analysis* 44, 109-132.

Fabozzi, F.J., Cheng, X. and Chen, RR., 2007. Exploring the components of credit risk in credit default swaps. *Finance Research Letter* 4, 10-18.

Fan, H. and Sundaresan, S., 2000. Debt valuation, renegotiation and optimal dividend policy. *Review of Financial Studies* 13, 1057-1099.

Forte, S. and Peña, J.I, 2009. Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. *Journal of Banking and Finance* 33, 2013-2025.

Geske, R., 1977. The valuation of corporate liabilities as compound options. *Journal of Financial and Quantitative Analysis* 3, 541-552.

Hillegeist, S., Keating, E., Cram, D., and Lundstedt, K., 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies* 9, 5-34.

Hull, J., Predescu, M. and White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of Banking and Finance* 28, 2789-2811.

Ismailescu, I. and Kazemi, H., 2010. The reaction of emerging market credit default spreads to sovereign credit rating changes. *Journal of Banking and Finance* 34, 12, 2861-2873.

Jarrow, R. A. and Turnbull, S. M., 1995. Pricing derivatives on financial securities subject to credit risk. *Journal of Finance* 50, 53-85.

Jarrow, R.A., Lando, D. and Turnbull, S.M., 1997. A Markov model for the term structure of credit risk spreads. *Review of Financial Studies* 10, 481-523.

Kato, P. and Hagendorff, J., 2010. Distance to default, subordinated debt, and distress indicators in the banking industry. *Accounting and Finance* 50, 853–870.

Leland, H. 1994. Corporate debt value, bond covenants and optimal capital structure. *Journal of Finance* 49, 1213-1252.

Leland, H. and Toft, K., 1996. Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *Journal of Finance* 51, 987-1019.

Litterman, R. B. and Iben, T. (1991). Corporate bond valuation and the term structure of credit spreads. *The Journal of Portfolio Management* 17, 52-64.

Longstaff, F. A., Mithal, S. and Neis, E., 2005. Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance* 60, 2213–2253

Longstaff, F. and Rajan, A., 2006. An empirical analysis of the pricing of collateralized debt obligations. *Journal of Finance* 63, 529–563.

Longstaff, F. and Schwartz, E., 1995. Valuing risky debt: A new approach. *Journal of Finance* 50, 789-820.

Mella-Barral, P. and Perraudin, W., 1997. Strategic debt service. *Journal of Finance* 51, 531-556.

Merton, R. C., 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance* 29, 449-470.

Ohlson, J., 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 19, 109-131.

Packer, F. and Suthiphongchai, C., 2003. Sovereign credit default swaps. *BIS Quarterly Review*, 79-88.

Pan, J. and Singleton, K. J., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. *The Journal of Finance* 63, 2345–2384.

Tang, D. Y and Yan, H., 2010. Market conditions, default risk and credit spreads. *Journal of Banking and Finance* 34, 743-753.

Tanthanongsakkun, S. and Treepongkaruna, S., 2008. Explaining credit ratings of Australian companies: An application of the Merton model. *Australian Journal of Management* 33, 261-275.

Vassalou, M. and Xing, Y., 2004. Default risk in equity returns. *Journal of Finance* 2, 831-868.

Wang, H., Zhou, H. and Zhou, Y. (2011). Credit default swap spreads and variance risk premia. Working paper Federal Reserve Board, Washington, D.C.

Wu, L. and Zhang, F. X., 2008. A no-arbitrage analysis of macroeconomic determinants of the credit spread term structure. *Management Science* 6, 1160-1175.

Zhang, B. Y., Zhou, H. and Zhu, C., 2009. Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. *Review of Financial Studies* 22, 5099-5131.

Table 1. Number of observations

Our sample consists of 2,186 CDS spreads for the 2002-2009 period from 51 unique firms listed in the FTSEurofirst 100 Index. Firms operating in the financial sector are excluded from the analysis. Entities that present abnormal ratios or extreme values are also eliminated from the sample as outliers. We obtained CDS spread information from the Markit database. Accounting data were obtained from the Amadeus database, whereas market data were taken from the Datastream database.

	CDS maturities							
Year	**1**	**2**	**3**	**5**	**10**	**15**	**30**	**All maturities**
2002	28	28	28	28	28	25	12	**177**
2003	34	35	35	35	35	34	30	**238**
2004	38	39	39	39	39	38	38	**270**
2005	41	41	41	41	41	41	41	**287**
2006	42	42	43	43	43	43	43	**299**
2007	47	47	47	47	47	46	45	**326**
2008	46	46	46	46	46	46	46	**322**
2009	39	39	39	39	39	39	33	**267**
All years	**315**	**317**	**318**	**318**	**318**	**312**	**288**	**2,186**

Table 2. CDS spread descriptive statistics

Our sample consists of 2,186 CDS spreads for the 2002-2009 period from 51 unique firms listed in the Eurofirst 100 Index. CDS spreads were obtained from the Markit database as the average of the last 10 trading days at the end of each year. Statistics are shown by year, by CDS maturity, and for the full sample. CDS spreads are in basis points.

		CDS maturities							
		1-Year	**2-Year**	**3-Year**	**5-Year**	**10-Year**	**15-Year**	**30-Year**	**All maturities**
2002	**Mean**	71	75	81	88	99	110	126	89
	Median	49	56	60	69	81	93	100	70
	Max.	261	242	247	231	233	236	265	265
	Min.	12	14	16	20	27	33	58	12
	St. Dev.	57	56	57	56	57	58	69	59
2003	**Mean**	43	55	62	66	76	81	52	62
	Median	15	20	27	34	42	49	50	34
	Max.	781	1034	1112	986	950	950	102	1112
	Min.	4	8	8	11	13	14	10	4
	St. Dev.	132	172	184	162	154	156	21	149
2004	**Mean**	15	22	30	45	66	70	74	46
	Median	9	15	20	31	49	52	53	31
	Max.	118	180	226	299	341	342	353	353
	Min.	3	5	7	10	19	15	18	3
	St. Dev.	21	29	37	50	57	59	61	52
2005	**Mean**	12	19	27	43	68	73	76	45
	Median	8	14	20	35	58	65	66	36
	Max.	48	78	109	166	222	227	214	227
	Min.	3	5	6	9	18	18	24	3
	St. Dev.	8	14	20	31	41	42	43	40
2006	**Mean**	7	12	17	29	51	59	63	34
	Median	7	11	15	27	50	58	59	26
	Max.	19	32	50	82	130	138	139	139
	Min.	1	2	2	4	7	9	20	1
	St. Dev.	4	7	10	16	26	28	27	29
2007	**Mean**	26	33	40	51	67	74	92	54
	Median	23	31	37	47	64	71	84	48
	Max.	83	88	89	95	119	127	312	312
	Min.	3	5	6	9	15	19	25	3
	St. Dev.	13	14	16	18	22	23	44	32
2008	**Mean**	323	328	319	299	274	271	274	298
	Median	201	217	216	203	193	197	198	206
	Max.	1691	1673	1625	1530	1387	1163	1155	1691
	Min.	34	81	82	80	68	74	63	34
	St. Dev.	302	291	281	271	254	233	229	266
2009	**Mean**	42	56	68	87	103	104	113	81
	Median	38	49	60	76	91	94	102	72
	Max.	104	134	160	195	215	219	222	222
	Min.	22	27	32	41	49	46	52	22
	St. Dev.	16	25	30	38	42	43	46	43
All years	**Mean**	71	79	84	91	103	108	112	92
	Median	21	28	36	49	68	74	79	52
	Max.	1691	1673	1625	1530	1387	1163	1155	1691
	Min.	1	2	2	4	7	9	10	1
	St. Dev.	163	163	159	148	135	129	123	147

Table 3. Explanatory variables and expected signs

Explanatory Variables	Notation	Classification	Expected signs
Accounting variables			
Current Liabilities/Current Assets	CL/CA	Liquidity	+
Working Capital/Total Assets	WC/TA	Liquidity	-
Retained Earnings/Total Assets	RE/TA	Capital structure	-
Total Liabilities/Equity	TL/Eq	Capital structure	+
Interest Coverage ratio	Coverage	Debt service	-
EBITDA/Total Liabilities	EBITDA/TL	Cash flow generation	-
Net Assets Turnover ratio	Turnover	Performance (Profitability)	-
Return on Assets	ROA	Performance (Profitability)	-
Net Income/Total Assets	NI/TA	Performance (Profitability)	-
Total Assets, logarithm	Size	Size	-
Market-based variables			
Distance to Default	DtD	Default risk	-
Annualized equity volatility	σ_E	Market risk	+
Price-to-earnings ratio	P/E	Market multiple	-
Price-to-cash flow ratio	P/C	Market multiple	-
Price-to-book ratio	P/B	Market multiple	-
Control Variables			
Maturity of CDS contract (1, 2, 3, 5, 10, 15, 30 years)	Maturity	Contract-specific variable	+
Industry, Country, and Year dummies		Control variables	

Table 4. Summary statistics on firm-specific variables

This table shows the summary statistics for the accounting and market-based variables considered in our study. The notations of these explanatory variables are described in Table 3.

	Number of Observations	Mean	Standard Deviation	25^{th} percentile	Median	75^{th} percentile
Accounting Variables						
CL/CA	2186	1.4817	1.7501	0.7293	1.0338	1.5082
WC/TA	2186	0.0419	0.0715	-0.0011	0.0100	0.0764
RE/TA	2186	0.3496	0.1668	0.2331	0.3342	0.4781
TL/Eq	2186	1.9704	7.5218	0.8267	1.4869	2.5090
Coverage	2186	3.7065	7.1857	0	1.0039	4.9151
EBITDA/TL	2186	0.1355	0.1502	0.0036	0.1117	0.2310
Turnover	2186	0.7295	0.7840	0.0746	0.5484	1.0099
ROA	2186	0.0632	0.0739	0.0238	0.0571	0.0924
NI/TA	2186	0.0584	0.0715	0.0258	0.0521	0.0805
Size	2186	5.9010	1.4507	4.5456	5.2073	7.3399
Market-based Variables						
DtD	2186	6.7307	3.2357	3.9615	6.4877	8.8012
σ_E	2186	0.3160	0.1618	0.2030	0.2681	0.4020
P/E	2186	15.5391	15.9912	9.8900	13.4000	17.6200
P/C	2186	8.1097	11.4707	4.9200	7.3450	9.9700
P/B	2186	2.8212	4.4111	1.4600	2.1100	3.1300

Table 5. Univariate analysis

This table reports the Pearson correlation coefficients between the log of CDS spreads and the firm-specific variables (accounting- and market-based) sorted by CDS maturity. *Signifies a correlation significantly different from 0 (5% level).

	CDS maturities							**All Years**
	1-Year	**2-Year**	**3-Year**	**5-Year**	**10-Year**	**15-Year**	**30-Year**	
Accounting Variables								
CL/CA	0.0150	0.0348	0.0002	0.0101	0.0042	0.0028	0.0348	0.0136
WC/TA	-0.1133*	-0.1246*	-0.1265*	-0.1352*	-0.1400*	-0.1329*	-0.1529*	-0.1155*
RE/TA	-0.0645	-0.0759	-0.0792	-0.0826	-0.0920	-0.0985	-0.0733	-0.0723*
TL/Eq	0.0460	0.0543	0.0537	0.0537	0.0556	0.0613	0.0502	0.0492*
Coverage	-0.1884*	-0.2223*	-0.2363*	-0.2569*	-0.2619*	-0.2622*	-0.2575*	-0.2111*
EBITDA/TL	-0.1276*	-0.1348*	-0.1356*	-0.1340*	-0.1162*	-0.1080	-0.1097	-0.1091*
Turnover	-0.0802	-0.0919	-0.0912	-0.0914	-0.0933	-0.0877	-0.0553	-0.0745*
ROA	-0.2123*	-0.2219*	-0.2220*	-0.2165*	-0.2069*	-0.1994*	-0.1529*	-0.1809*
NI/TA	-0.2357*	-0.2371*	-0.2375*	-0.2276*	-0.2153*	-0.2035*	-0.1629*	-0.1939*
Size	0.0216	0.0265	0.0406	0.0428	0.0573	0.0515	0.0576	0.0359
Market-based Variables								
DtD	-0.6816*	-0.6638*	-0.6499*	-0.6164*	-0.5426*	-0.5454*	-0.5303*	-0.5461*
σ_E	0.7362*	0.7363*	0.7302*	0.7091*	0.6598*	0.6568*	0.6223*	0.6211*
P/E	-0.0904	-0.0862	-0.0794	-0.0689	-0.0618	-0.0658	-0.0475	-0.0679*
P/C	-0.0621	-0.0651	-0.0632	-0.0644	-0.0607	-0.0488	-0.0490	-0.0528*
P/B	-0.0882	-0.0975	-0.1053	-0.1066	-0.1202*	-0.1290*	-0.0641	-0.0816*

Table 6. Comparative analysis of credit risk models

This table reports linear regressions of the log of CDS spreads to accounting measures (Model 1), market-based measures (Model 2) and both (Model 3). See Table 3 for a description of the variables. Robust standard errors, which are clustered by firms, are reported in parentheses. Significance levels are indicated as follows: ***= significant at the 1% level, **= significant at the 5% level, and *= significant at the 10% level.

	Model 1 (Accounting-based)	Model 2 (Market-based)	Model 3 (Comprehensive)
Intercept	-2.5637*** (0.2165)	-2.7241*** (0.1724)	-2.8219*** (0.2274)
CL/CA	0.0246 (0.0195)	-	0.0134 (0.0105)
WC/TA	-0.3172** (0.1401)	-	-0.3165* (0.1707)
RE/TA	-0.1955*** (0.0424)	-	-0.2640*** (0.0394)
TL/Eq	0.0049*** (0.0014)	-	0.0056*** (0.0012)
Coverage	-0.0107*** (0.0030)	-	-0.0094*** (0.0023)
EBITDA/TL	-0.0496 (0.2184)	-	-0.1316 (0.1738)
Turnover	-0.0075 (0.0537)	-	-0.0320 (0.0417)
ROA	-0.1013 (0.4628)	-	-0.2738 (0.2937)
NI/TA	-0.2923** (0.1285)	-	-0.2333* (0.1291)
Size	-0.0330 (0.0411)	-	-0.0209 (0.0357)
DtD	-	-0.0154*** (0.0024)	-0.0142*** (0.0028)
σ_E	-	0.9732*** (0.3116)	0.7010*** (0.2534)
P/E	-	0.0011 (0.0008)	0.0012* (0.0007)
P/C	-	-0.0013 (0.0009)	-0.0008 (0.0007)
P/B	-	-0.0049 (0.0047)	-0.0436*** (0.0080)
Maturity	0.0166*** (0.0003)	0.0163*** (0.0003)	0.0165*** (0.0003)
Industry dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Clustering level	Firm	Firm	Firm
N	2,186	2,186	2,186
R^2	67.42%	68.41%	72.76%

Table 7. Comparative analysis for the pre-crisis period (2002-2006) and the crisis period (2007-2009)

This table reports linear regressions of the log of CDS spreads to accounting measures (Model 1), market-based measures (Model 2) and both (Model 3) for the pre-crisis period (2002-2006) and the crisis period (2007-2009). See Table 3 for a description of the variables. Robust standard errors, which are clustered by firms, are reported in parentheses. Significance levels are indicated as follows: ***= significant at the 1% level, **= significant at the 5% level, and *= significant at the 10% level.

	Pre-crisis period (2002-2006)			Crisis period (2007-2009)		
	Model 1 (Accounting-based)	**Model 2** (Market-based)	**Model 3** (Comprehensive)	**Model 1** (Accounting-based)	**Model 2** (Market-based)	**Model 3** (Comprehensive)
Intercept	-2.3560*** (0.3517)	-2.8845*** (0.1332)	-2.7616*** (0.3121)	-3.1429*** (0.1481)	-2.5277*** (0.1810)	-2.9636*** (0.2143)
CL/CA	0.0117 (0.0140)	-	0.0038 (0.0117)	0.0402** (0.0153)	-	0.0287*** (0.0100)
WC/TA	-0.1881 (0.4554)	-	-0.1656 (0.4330)	-0.8465** (0.4470)	-	-0.9378*** (0.3443)
RE/TA	-0.2325*** (0.0621)	-	-0.2445*** (0.0520)	-0.2152*** (0.0494)	-	-0.2983*** (0.0622)
TL/Eq	0.0093*** (0.0023)	-	0.0085*** (0.0019)	0.0041*** (0.0008)	-	0.0046*** (0.0009)
Coverage	-0.0089*** (0.0027)	-	-0.0097*** (0.0025)	-0.0098** (0.0047)	-	-0.0064* (0.0034)
EBITDA/TL	-0.1545 (0.2163)	-	-0.2046 (0.1997)	-0.2502 (0.3369)	-	-0.0376 (0.2578)
Turnover	-0.0221 (0.0669)	-	-0.0112 (0.0517)	-0.0111 (0.0397)	-	-0.0640** (0.0269)
ROA	-0.0218 (0.4597)	-	-0.1533 (0.3791)	-0.5956 (0.6918)	-	-0.3397 (0.5555)
NI/TA	-0.1558 (0.2876)	-	-0.4870* (0.2518)	-0.1405 (0.5850)	-	-0.4770 (0.5004)
Size	-0.1392** (0.0652)	-	-0.0609 (0.0515)	0.0741*** (0.0235)	-	0.0342 (0.0229)
DtD	-	-0.0088* (0.0047)	-0.0121* (0.0065)	-	-0.0076** (0.0033)	-0.0217** (0.0098)
σ_E	-	1.1591*** (0.2408)	0.7209*** (0.1856)	-	0.8599*** (0.2796)	0.5413** (0.2592)
P/E	-	0.0017* (0.0010)	0.0016** (0.0008)	-	0.0004 (0.0020)	0.0013* (0.0008)
P/C	-	-0.0002 (0.0005)	0.0000 (0.0005)	-	-0.0076*** (0.0026)	-0.0064*** (0.0016)
P/B	-	-0.0067 (0.0042)	-0.0370*** (0.0085)	-	-0.0086* (0.0047)	-0.0486** (0.0187)
Maturity	0.0222*** (0.0004)	0.0219*** (0.0004)	0.0220*** (0.0004)	0.0090*** (0.0004)	0.0088*** (0.0004)	0.0088*** (0.0004)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Firm	Firm	Firm	Firm	Firm	Firm
N	1,271	1,271	1,271	915	915	915
R^2	57.92%	58.59%	63.16%	72.00%	72.65%	77.41%

Table 8. Credit risk models grouped by CDS maturity

This table reports linear regressions of the log of CDS spreads to accounting measures (Model 1), market-based measures (Model 2) and both (Model 3), grouped by maturity of the CDS contract (1-, 5- and 30-years). See Table 3 for a description of the variables. Robust standard errors, which are clustered by firms, are reported in parentheses. Significance levels are indicated as follows: ***= significant at the 1% level, **= significant at the 5% level, and *= significant at the 10% level.

	1-year CDS			5-year CDS			30-year CDS		
	Model 1 (Accounting-based)	**Model 2** (Market-based)	**Model 3** (Comprehensive)	**Model 1** (Accounting-based)	**Model 2** (Market-based)	**Model 3** (Comprehensive)	**Model 1** (Accounting-based)	**Model 2** (Market-based)	**Model 3** (Comprehensive)
Intercept	-2.4130***	-2.7169***	-2.6336***	-2.4231***	-2.6089***	-2.6913***	-2.4326***	-2.3326***	-2.6739***
	(0.2681)	(0.1778)	(0.2474)	(0.2348)	(0.1803)	(0.2543)	(0.1886)	(0.1928)	(0.2145)
CL/CA	0.0301**	-	0.0186*	0.0255*	-	0.0141	0.0188	-	0.0087
	(0.0131)		(0.0110)	(0.0136)		(0.0115)	(0.0114)		(0.0095)
WC/TA	-0.3526	-	-0.3697*	-0.3219*	-	-0.3228*	-0.2248	-	-0.1873
	(0.3927)		(0.2179)	(0.1722)		(0.1726)	(0.2259)		(0.2489)
RE/TA	-0.2244***	-	-0.3054***	-0.1947***	-	-0.2640***	-0.1977***	-	-0.2479***
	(0.0588)		(0.0642)	(0.0450)		(0.0430)	(0.0436)		(0.0365)
TL/Eq	0.0059***	-	0.0082***	0.0047***	-	0.0052***	0.0049***	-	0.0035**
	(0.0020)		(0.0024)	(0.0015)		(0.0013)	(0.0012)		(0.0015)
Coverage	-0.0078**	-	-0.0065***	-0.0120***	-	-0.0105***	-0.0099***	-	-0.0090***
	(0.0030)		(0.0024)	(0.0033)		(0.0026)	(0.0035)		(0.0028)
EBITDA/TL	-0.1985	-	-0.3096*	-0.0172	-	-0.1099	-0.1126	-	-0.1360
	(0.2336)		(0.1825)	(0.2445)		(0.1991)	(0.2338)		(0.2101)
Turnover	-0.0146	-	-0.0388	-0.0050	-	-0.0350	0.0275	-	-0.0141
	(0.0644)		(0.0580)	(0.0588)		(0.0456)	(0.0474)		(0.0372)
ROA	-0.1374	-	-0.0273	-0.1320	-	-0.3118	0.0105	-	-0.1070
	(0.5317)		(0.0509)	(0.5037)		(0.3126)	(0.4417)		(0.3026)
NI/TA	-0.3273*	-	-0.2612	-0.3079*	-	-0.2162	-0.0475	-	-0.3038
	(0.1964)		(0.2509)	(0.1765)		(0.2033)	(0.3306)		(0.2617)
Size	-0.0761*	-	-0.0646*	-0.0366	-	-0.0239	-0.0070	-	-0.0066
	(0.0435)		(0.0353)	(0.0445)		(0.0404)	(0.0397)		(0.0326)
DtD	-	-0.0194***	-0.0203***	-	-0.0172**	-0.0161**	-	-0.0162*	-0.0115*
		(0.0028)	(0.0060)		(0.0070)	(0.0062)		(0.0087)	(0.0068)
σ_E	-	0.9942***	0.6683***	-	0.9994***	0.7299**	-	0.8110**	0.6580**
		(0.3218)	(0.2458)		(0.3280)	(0.2763)		(0.3289)	(0.2962)
P/E	-	0.0012	0.0012*	-	0.0012	0.0013*	-	0.0004	0.0008
		(0.0008)	(0.0007)		(0.0008)	(0.0007)		(0.0007)	(0.0006)
P/C	-	-0.0018	-0.0009	-	-0.0013	-0.0005	-	-0.0010	-0.0007
		(0.0011)	(0.0008)		(0.0010)	(0.0009)		(0.0008)	(0.0007)
P/B	-	-0.0065	-0.0478***	-	-0.0044	-0.0430***	-	-0.0073	-0.0402***
		(0.0051)	(0.0088)		(0.0044)	(0.0083)		(0.0054)	(0.0176)
Industry/ Country/Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

N	315	315	315	318	318	318	288	288	288
R^2	83.64%	84.14%	87.80%	72.61%	74.35%	80.79%	65.07%	66.24%	70.11%

Table 9. Fixed effects model

This table reports fixed effects model of the log of 5-year CDS spreads to accounting measures (Model 1), market-based measures (Model 2) and both (Model 3). See Table 3 for a description of the variables. Robust standard errors are reported in parentheses. Significance levels are indicated as follows: ***= significant at the 1% level, **= significant at the 5% level, and *= significant at the 10% level.

	Model 1 (Accounting-based)	**Model 2 (Market-based)**	**Model 3 (Comprehensive)**
Intercept	-2.7019*** (0.9400)	-2.3908*** (0.1514)	-1.9469** (0.8501)
CL/CA	0.0123 (0.0079)	-	0.0031 (0.0079)
WC/TA	-0.1235* (0.0655)	-	-0.2405 (0.3056)
RE/TA	-0.7770*** (0.1615)	-	-0.4323*** (0.1447)
TL/Eq	0.0036*** (0.0010)	-	0.0034*** (0.0011)
Coverage	-0.0072*** (0.0027)	-	-0.0058** (0.0028)
EBITDA/TL	-0.1384 (0.2360)	-	-0.0191 (0.2231)
Turnover	-0.0108 (0.0787)	-	-0.0036 (0.0696)
ROA	-0.0005 (0.0032)	-	-0.0024 (0.0028)
NI/TA	-0.2627* (0.1394)	-	-0.1764 (0.1989)
Size	-0.1520 (0.1584)	-	-0.0390 (0.1445)
DtD	-	-0.0205** (0.0090)	-0.0149** (0.0066)
σ_E	-	0.7337*** (0.2735)	0.6234** (0.2612)
P/E	-	0.0017** (0.0007)	0.0012* (0.0007)
P/C	-	-0.0008 (0.0008)	-0.0008 (0.0007)
P/B	-	-0.0061* (0.0032)	-0.0034* (0.0019)
Industry dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Clustering level	Firm	Firm	Firm
N	318	318	318
Adjusted-R^2	82.56%	83.86%	85.06%

Table 10. Credit rating conversion

This table presents the credit rating of the 51 firms that compose our sample provided by the three major international rating agencies (Standard & Poor´s, Moody´s and Fitch) for the 2002-2009 period as well as the numerical value assigned to each rating. When a company is rated by more than one of the agencies in any year, each rating is considered as a separate observation. Rating data were obtained from Bloomberg.

Rating					
Standard & Poor´s	**Moody´s**	**Fitch**	**Assigned value**	**No. of observations**	**Percentage**
AAA	Aaa	AAA	1		
AA+	Aa1	AA+	1	66	9,35%
AA	Aa2	AA	1		
AA-	Aa3	AA-	1		
A+	A1	A+	2	109	15,44%
A	A2	A	3	62	8,78%
A-	A3	A-	4	152	21,53%
BBB+	Baa1	BBB+	5	224	31,73%
BBB	Baa2	BBB	6	72	10,20%
BBB- or lower	Baa3 or lower	BBB- or lower	7	21	2,97%
				706	100,00%

Table 11. Comparative analysis using credit ratings

This table reports ordered logistic regressions of the long-term credit ratings provided by the three major international rating agencies (Standard & Poor´s, Moody´s and Fitch) to accounting measures (Model 1), market-based measures (Model 2) and both (Model 3). See Table 10 for the numerical values assigned to the credit ratings. See Table 3 for a description of the independent variables. Standard errors are reported in parentheses. Significance levels are indicated as follows: ***= significant at the 1% level, **= significant at the 5% level, and *= significant at the 10% level.

	Model 1 (Accounting-based)	**Model 2 (Market-based)**	**Model 3 (Comprehensive)**
CL/CA	0.4932*** (0.0934)	-	0.4406*** (0.0963)
WC/TA	-4.8666*** (1.4670)	-	-4.8688*** (1.5037)
RE/TA	-1.3507** (0.6775)	-	-1.8127** (0.7924)
TL/Eq	0.0181** (0.0091)	-	0.0126 (0.0138)
Coverage	-0.1710*** (0.0294)	-	-0.1748*** (0.0307)
EBITDA/TL	-1.0279 (1.4171)	-	-0.4149 (1.4367)
Turnover	-0.4284** (0.1789)	-	-0.7650*** (0.1858)
ROA	-0.0079 (0.0266)	-	-0.0161 (0.0277)
NI/TA	-2.8892 (2.1684)	-	-1.1739 (2.2590)
Size	-1.3907*** (0.2928)	-	-1.4703*** (0.3021)
DtD	-	-0.1631*** (0.0429)	-0.2244*** (0.0471)
σ_E	-	1.6225* (0.8855)	1.2209 (0.8798)
P/E	-	-0.0066 (0.0058)	-0.0062 (0.0059)
P/C	-	-0.0024 (0.0056)	-0.0001 (0.0061)
P/B	-	-0.1100*** (0.0361)	-0.1498*** (0.0431)
Industry dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Agency dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
N	706	706	706
Pseudo R^2	20.58%	14.45%	22.82%