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

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Abstract. This paper uses a sample of 2,186 credit default swap spreads quoted in the European market during the period 2002–2009 to empirically analyze which model – accounting- or market-based – better explains corporate credit risk. We find little difference in the explanatory power of these two approaches. Our results indicate that a comprehensive model that combines accounting- and market-based variables is the best option to explain the credit risk, suggesting that both types of data are complementary. We also demonstrate that the explanatory power of credit risk models is particularly strong during periods of high uncertainty, such as those experienced in the recent financial crisis. Finally, the comprehensive model continues to produce the best results if the credit rating is used as the proxy for credit risk; however, accounting variables currently appear to have a more important role than market variables in determining corporate credit ratings.

Keywords: bankruptcy, credit default swaps, credit rating, credit risk, distance-to-default, European companies.

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Introduction

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

The use of credit risk models has been fully established in the literature since 1966, when Beaver published his pioneering work, 'Financial ratios as predictors of failure' in *Journal of Accounting Research*, which served as a reference for subsequent investigations[1]. This univariate model was followed by a multidimensional-type model that integrates all of the 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 both use information drawn from the financial statements of borrowers and are consequently known as 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. 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'[2]. 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 certain unrealistic assumptions; in particular, it represents the liability structure of the firm as consisting only of a non-callable zero coupon bond and assumes that bankruptcy cannot be triggered before maturity. In addition, this model presumes that the absolute priority rule always holds at maturity, implying that equity holders can only obtain a positive payoff after debt holders are completely reimbursed.

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. Anderson and Sundaresan (1996), Mella-Barral and Perraudin (1997) propose a structural model that accounts for the possibility of debt renegotiation. A number of other papers have also made more sophisticated assumptions, including Leland (1994), Longstaff and Schwartz (1995), Leland and Toft (1996), Fan and Sundaresan (2000), Collin-Dufresne and Golstein (2001). However, despite the theoretical advances of second-generation structural-form models with respect to the original Merton framework, Wei and Guo (1997) find no evidence that the Longstaff and Schwartz (1995) model produces a better empirical performance than the Merton (1974) model in the Eurodollar market.

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[1] Very early studies on bankruptcy prediction include the work of Fitzpatrick (1932a, b, c), and Smith and Winakor (1935).

[2] Another market-based approach for measuring credit risk refers to the approaches that are known as reduced-form models. 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. Significant studies on this topic include the works of Litterman and Iben (1991), Jarrow and Turnbull (1995), Duffie and Singleton (1999).

Our paper is closely related to recent studies that have investigated whether accounting-based or market-based approaches are more appropriate for measuring corporate credit risk. Accounting models have been criticized for the historic nature of the information that they use as inputs and for not accounting for the volatility of a firm's assets during estimations of its risk of default (e.g., Vassalou, Xing 2004)[3]. 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 either of the two most popular accounting-based measures (Z-Score and O-Score). By contrast, Agarwal and Taffler (2008) conclude that although there is little difference between the predictive abilities of the accounting- and market-based approaches, the accounting-based models lead to greater bank profitability in conditions involving differential decision 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 single variable for the measurement of corporate credit risk, market-based models exhibit better performance if accounting data are included. Tanthanongsakkun and Treepongkaruna (2008) and Das *et al.* (2009) reach similar conclusions.

The financial literature has used a range of metrics as proxies for credit risk. For instance, measures of credit risk that have been used by published studies include the company's financial condition (i.e., bankrupt *versus* non-bankrupt firms) (e.g., Altman 1968; Ohlson 1980; Hillegeist *et al.* 2004; Agarwal, Taffler 2008; Jakubík, Teplý 2011), the credit rating assigned to a company by a rating agency (e.g., Ang, Patel 1975; Blume *et al.* 1998; Demirovic, Thomas 2007), and the spreads of bonds that have been issued by the firm and listed on a secondary market (e.g., Collin-Dufresne *et al.* 2001; Longstaff, Rajan 2006; Wu, Zhang 2008). However, more recently, the empirical literature on credit risk has focused on credit default swap (CDS) spreads (e.g., Alexander, Kaeck 2008; Das *et al.* 2009; Ericsson *et al.* 2009; Forte, Peña 2009; Corò *et al.* 2013; Díaz *et al.* 2013).

Credit default swaps are credit protection contracts in which one party receives periodic premiums in exchange for agreeing to make a contingent payment if a defined credit event occurs[4]. 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, CDSs offer the opportunity to earn income for taking on credit exposure over a customized term without having to fund the position in question (Packer, 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; as a result, studies of this continuous variable contrast with studies

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[3] 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.

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

examining binary data samples of bankruptcies, which consider a company to be healthy until a default occurs. Second, CDS spreads reflect market perceptions of default rather than the perspective of a particular rating agency. Third, spreads capture both the default and the 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). In addition, 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 therefore not directly comparable if the maturities of the underlying bonds differ (Alexander, 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[5]. Given the benefits that have been 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. The extension of the analysis to include the crisis period enables us to assess whether the findings reported in previous papers are robust to changes in the economic cycle. Finally, this paper evaluates the results that are obtained when credit ratings are used instead of CDS spreads as a measure for creditworthiness.

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

1. Data and methodological aspects

1.1. 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[6]. Markit's CDS data do not reflect any specific trading activity; instead, these data 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 in which stale, flat curves, outliers, and inconsistent data are discarded[7].

As is customary, firms operating in the financial sector are excluded from the analysis of this study due to the different structure of their financial statements. Entities that present abnormal ratios or extreme values were also eliminated from the sample as outliers.

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[5] One notable exception is Demirovic and Thomas (2007), who examine a sample of UK-listed companies over the 1990–2002 time period.

[6] The FTSEurofirst 100 Index includes the 60 companies with the greatest market capitalization in the FTSE Developed Europe Index and 40 additional European companies that are selected for their size and sector representation. Please see http://www.ftse.com for more details.

[7] Please see http://www.markit.com for a detailed description of this database.

After the completion of this filtering process, the final sample consisted of 2,186 observations from 51 unique firms in six different European countries (France, Germany, Italy, the Netherlands, Spain, and the United Kingdom). Table 1 illustrates the number of observations that compose the sample, organized by year and by CDS maturity.

Table 1. Number of observations

	CDS maturities							
	1-Year	2-Year	3-Year	5-Year	10-Year	15-Year	30-Year	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

In accordance with the procedures used by similar studies, we used unconsolidated statements, thus preventing relevant differences in the profit and loss statements and the balance sheets of parent companies and subsidiaries from negating each other. We obtained the accounting data from the Amadeus database, and market information was acquired from the Datastream database[8].

1.2. Definition of variables

1.2.1. Dependent variable

As stated above, we use CDS spreads from the Markit database as the dependent variable. Although there exists a high concentration of CDS quotes with 5-year maturities, which has led most studies dealing with corporate credit data to focus on this one specific maturity timeframe (e.g., Longstaff *et al.* 2005), this approach only examines the credit risk effects for one single point on the CDS term structure. Therefore, to provide more detailed insight, we include the whole maturity spectrum, which ranges from 1 year to 30 years. We collect the CDS constant maturity spreads on a daily basis at the end of each year (averaged for the last 10 trading days) over the period 2002–2009. All of the examined contracts are senior unsecured obligations containing the modified-modified restructuring clause, which is commonly used in Europe.

We regress the natural logarithm of CDS spreads on the explanatory variables. As Aunon-Nerin *et al.* (2002) note, better fits are provided by regressions involving the logarithms of spreads than by direct regressions of the spreads.

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

In Table 2, we present 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 CDS contracts. We also observe a downward trend in premiums from 2002 to 2006 for all maturities, and the average premium reaches a minimum of 34 bps in 2006. In 2007, as a result of the onset of the financial crisis, there is a change in this trend. The worsening of the global credit crisis in 2008, which was led by, among other factors, the collapse of Lehman Brothers, dramatically increased the CDS spreads by an average of up to 298 bps. Although CDS premiums fell in 2009, they did not reach the levels that were observed prior to the start of the crisis.

Table 2. CDS spread descriptive statistics

		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
	St. Dev.	57	56	57	56	57	58	69	59
2003	Mean	43	55	62	66	76	81	52	62
	St. Dev.	132	172	184	162	154	156	21	149
2004	Mean	15	22	30	45	66	70	74	46
	St. Dev.	21	29	37	50	57	59	61	52
2005	Mean	12	19	27	43	68	73	76	45
	St. Dev.	8	14	20	31	41	42	43	40
2006	Mean	7	12	17	29	51	59	63	34
	St. Dev.	4	7	10	16	26	28	27	29
2007	Mean	26	33	40	51	67	74	92	54
	St. Dev.	13	14	16	18	22	23	44	32
2008	Mean	323	328	319	299	274	271	274	298
	St. Dev.	302	291	281	271	254	233	229	266
2009	Mean	42	56	68	87	103	104	113	81
	St. Dev.	16	25	30	38	42	43	46	43
All years	Mean	71	79	84	91	103	108	112	92
	St. Dev.	163	163	159	148	135	129	123	147

Note: CDS spreads are in basis points.

1.2.2. Accounting-based independent 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 of these metrics are included in the two best-known accounting-based models of credit risk, namely, 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 would indicate lower liquidity; in fact, a company with a CL/CA ratio that exceeds unity may even experience problems in meeting its short-term obligations. 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 the firm's 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 lifetime. The age of a firm is implicitly incorporated into this ratio; a relatively young firm will likely possess 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 largely financed their assets through the retention of profits and have not greatly utilized 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 with its total shareholders' equity[9]. A higher percentage of liabilities and a greater potential earnings variability produce a greater potential for default. Consequently, we predict opposite values for the coefficients of these ratios in the regression analysis, i.e., we predict a negative coefficient for the RE/TA ratio and a positive coefficient 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 the interest on its outstanding debt. In accordance with the work of Blume *et al.* (1998), we transform the interest coverage ratio in two ways. First, we set any negative interest coverage ratios to zero. 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 that a company is burdened by debt expense to a greater degree. If 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 the credit risk of firms.

The earnings before interest, taxes, depreciation, and amortization to total liabilities (EBITDA/TL) ratio measures a company's ability to repay debt obligations from its 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

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

and may result in a lowered credit rating. Conversely, a high ratio may suggest that a company may wish to consider taking on more debt and often implies that the firm in question warrants a relatively high credit rating. We hypothesize that a negative relationship exists 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 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 because it 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, namely, the return on total assets (ROA), which is considered to be an indicator of how effectively a company is using its assets to generate earnings before its contractual obligations must be paid. Moreover, in accordance with the customary practices of the literature (e.g., Arslan, Karan 2009), a third profitability ratio of net income divided by total assets (NI/TA) is also constructed. A negative relationship between all of these ratios and the CDS spreads is expected.

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

1.2.3. Market-based independent variables

As stated above, the theoretical inspiration for structural approach 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. 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 following known expressions of the model:

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

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

$$d_2 = \frac{\ln(V_0/D) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}} = d_1 - \sigma_V \sqrt{T}, \tag{1}$$

where N is the cumulative density function of the standard normal distribution, r is the continuous-time risk-free interest rate, D is the book value of the debt with maturity T, 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 the volatility of the underlying security:

$$\sigma_E = \frac{V_0}{E_0} \frac{\partial E}{\partial V} \sigma_V.$$

(2)

This equation, together with the previously provided equations that are denoted by (1), makes it possible to determine V_0 and σ_V through the application of a numerical algorithm that uses the values of E_0 and σ_E; these variables are easy to calculate for listed companies.

The risk-neutral probability that the value of the firm's assets will be less than the value of the debt on the date T, i.e., the probability that $V_T < D$, is $N(-d_2)$. We can also calculate the theoretical default probability by using μ, the expected rate of growth in the asset value. If this expected growth rate is known, the probability that we seek, at any time t, is provided by the following equation:

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

(3)

After the probability of default by a firm is estimated using equation (3), it is easy to quantify the distance-to-default (DtD) for the firm in question by applying the following expression (Vassalou, Xing 2004):

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

(4)

Default occurs when the ratio of the value of assets to debt is less than 1, which implies that the logarithm of this ratio is negative. The preceding equation tells us the number of standard deviations that the logarithm 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 to observe 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., Demirovic, Thomas 2007; Das *et al.* 2009).

We make the following assumptions to obtain the *DtD* for a firm. E_0 (the market value of equity) is considered to be the firm's 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[10]. We consider $t = 0$ and $T = 1$. In

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[10] We also consider the annualized standard deviation of equity returns σ_E to be a specific independent variable. This approach allows for the effect of the equity market volatility in isolation to be assessed. Higher equity volatility often implies higher asset volatility, which would cause firm values to be more likely to fall below the default threshold (Zhang *et al.* 2009).

accordance with previous studies (e.g., Vassalou, Xing 2004; Du, Suo 2007), we assume that D, the amount of debt or the default point, 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 to represent r, the risk-free rate. Finally, μ has little discriminating power in the Merton model and it is proxied by the GDP growth rate for next year.

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. This ratio is normally used for valuation: a higher P/E ratio indicates that investors are paying more for each unit of net income and therefore that the stock in question is more expensive than a stock with a lower P/E ratio. We expect a negative relationship between the P/E ratio and the firm's credit risk. Similar reasoning applies to 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.

1.2.4. Control variables

To account for country- and industry-specific effects, we include country and industry dummy variables, respectively. The country dummy variables must capture differences in factors such as the institutional framework, the degree of competition, and the accounting standards among the European countries. The industry dummies must control for differences among the industries that are considered (basic materials, consumer goods, consumer services, health care, industrials, oil and gas, utilities, and telecommunications). In addition, we include a set of year dummy variables to account for macroeconomic conditions and time-specific effects[11].

Finally, we control for the maturity (in years) of the CDS contract. We hypothesize a positive relationship between the CDS maturity and the credit risk, i.e., contracts with longer maturities will tend to have higher CDS premiums.

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

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[11] 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), Tang and Yan (2010).

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	–
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	

1.3. Methodology

Following the same procedure that was used by Das *et al.* (2009) to examine the US market, we estimate and compare the explanatory power of the following three multivariate empirical models for the European market: (1) an accounting-based multivariate model of the determinants of credit spreads, (2) a model that uses market information, and (3) a comprehensive model that includes both accounting- and market-based data.

1.3.1. Accounting-based model (Model 1)

We estimate the following linear regression:

$$Y_{i,t} = \alpha + \beta_1 \cdot \text{CL/CA}_{i,t} + \beta_2 \cdot \text{WC/TA}_{i,t} + \beta_3 \cdot \text{RE/TA}_{i,t} + \beta_4 \cdot \text{TL/Eq}_{i,t} +$$
$$\beta_5 \cdot \text{Coverage}_{i,t} + \beta_6 \cdot \text{EBITDA/TL}_{i,t} + \beta_7 \cdot \text{Turnover}_{i,t} + \beta_8 \cdot \text{ROA}_{i,t} + \beta_9 \cdot \text{NI/TA}_{i,t} +$$
$$\beta_{10} \cdot \text{Size}_{i,t} + \beta_{11} \cdot \text{Maturity}_{i,t} + \delta \cdot \text{Industry dummies}_i + \gamma \cdot \text{Country dummies}_i +$$
$$\theta \cdot \text{Year dummies}_t + \varepsilon_{i,t}. \tag{5}$$

For this regression, the subscripts i and t index firms and years, respectively, whereas Y denotes the dependent variable, which is the natural logarithm 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. In the regression above, $\varepsilon_{i,t}$ is the disturbance term.

1.3.2. Market-based model (Model 2)

We now estimate the following linear regression:

$$Y_{i,t} = \alpha + \beta_1 \cdot DtD_{i,t} + \beta_2 \cdot \sigma_{Ei,t} + \beta_3 \cdot P/E_{i,t} + \beta_4 \cdot P/C_{i,t} + \beta_5 \cdot P/B_{i,t} +$$
$$\beta_6 \cdot \text{Maturity}_{i,t} + \delta \cdot \text{Industry dummies}_i + \gamma \cdot \text{Country dummies}_i +$$
$$\theta \cdot \text{Year dummies}_t + \varepsilon_{i,t}. \tag{6}$$

Again, for this regression, the subscripts i and t index firms and time periods, respectively, whereas Y denotes the dependent variable, which is the natural logarithm 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. We also 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 term.

1.3.3. Comprehensive model (Model 3)

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

$$Y_{i,t} = \alpha + \beta_1 \cdot \text{CL/CA}_{i,t} + \beta_2 \cdot \text{WC/TA}_{i,t} + \beta_3 \cdot \text{RE/TA}_{i,t} + \beta_4 \cdot \text{TL/Eq}_{i,t} +$$
$$\beta_5 \cdot \text{Coverage}_{i,t} + \beta_6 \cdot \text{EBITDA/TL}_{i,t} + \beta_7 \cdot \text{Turnover}_{i,t} + \beta_8 \cdot \text{ROA}_{i,t} +$$
$$\beta_9 \cdot \text{NI/TA}_{i,t} + \beta_{10} \cdot \text{Size}_{i,t} + \beta_{11} \cdot DtD_{i,t} + \beta_{12} \cdot \sigma_{Ei,t} + \beta_{13} \cdot P/E_{i,t} +$$
$$\beta_{14} \cdot P/C_{i,t} + \beta_{15} \cdot P/B_{i,t} + \beta_{16} \cdot \text{Maturity}_{i,t} + \delta \cdot \text{Industry dummies}_i +$$
$$\gamma \cdot \text{Country dummies}_i + \theta \cdot \text{Year dummies}_t + \varepsilon_{i,t}. \tag{7}$$

In this regression, Y once again denotes the dependent variable, which is the natural logarithm 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.

2. Results

2.1. Comparative analysis of credit risk models

Table 4 reports our results for the three credit risk models that are considered[12].

Table 4. Comparative analysis of credit risk models

	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)

[12] 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); this factor reaches a value that is close to 1 for most of the variables.

	Model 1 (Accounting-based)	Model 2 (Market-based)	Model 3 (Comprehensive)
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%
Adjusted R^2	66.97%	68.04%	72.32%

Notes: This table reports linear regressions of the logarithm 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.

In the accounting-based equation (Model 1), we find that all of the variables that were considered have the expected sign. The WC/TA ratio demonstrates a negative and statistically significant relationship with CDS spreads, meaning that lower liquidity implies higher credit risk. In 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) evince strong relationships with CDS spreads. Firms with higher retained earnings relative to total assets are expected to have lower credit risk levels due to their older age and lower leverage. However, a higher value of TL/Eq implies greater leverage and thus a higher probability of default. Recently, Jakubík and Teplý (2011) assess a sample of Czech firms for the period 1993–2005 and conclude that the TL/Eq ratio, along with the WC/TA ratio and the interest coverage ratio, are the most important indicators of business failure.

We demonstrate a strong negative relationship between the interest coverage ratio and CDS spreads. Therefore, the CDS premium declines as the firm's EBIT relative to its 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 indicate a negative relationship between profitability measures and corporate credit risk, although only the coefficient of the NI/TA ratio is statistically significant (at the 5% level). Finally, we do not find size to be a determinant of CDS spreads. However, because the sample is composed of large Euro-

pean companies that are similar in size (the coefficient of variation for the size variable is only 25%), a degree of caution should be exercised in interpreting this outcome.

Similarly to the results obtained by Das *et al.* (2009), the explanatory power of our accounting-based model is high, as this model accounts for 67% of the variation of CDS spreads.

In Model 2 (the market-based model), we find that both distance-to-default and the annualized standard deviation of equity returns are statistically significant (at the 1% level), and the signs of the coefficients for these variables are as predicted. In particular, 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 the P/E ratio disagrees with our predictions. 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 adjusted R^2 value of 68% for Model 2 versus 67% for Model 1.

Model 3 includes both accounting- and market-based variables for explaining credit risk. Most of the explanatory variables retain the same signs and statistical significances as were observed in Models 1 and 2. However, the WC/TA and the NI/TA ratio lose statistical significance relative to the results of the previous models, whereas the P/E ratio and the P/B ratio become statistically significant in Model 3 (at the 10% and 1% level, respectively).

The adjusted R^2 improves from 67% (Model 1) and 68% (Model 2) to 72%, suggesting that accounting- and market-based data are complementary. This finding is in accordance with the results of Agarwall and Taffler (2008) and Das *et al.* (2009) for the UK and the US markets, respectively.

2.2. 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). Through this process, we investigate the possible impact of the recent financial crisis on our credit risk models. Although our broad results do not change (see Table 5) in that a comprehensive model using both types of variables remains the best option for measuring credit risk, we do observe certain differences between the two periods (before the crisis and during the crisis) with respect to the explanatory power of the models and the statistical significance of certain explanatory variables. In particular, we find that the explanatory power of the examined models is considerably higher during the crisis period than it was before the crisis period. We also observe that liquidity ratios appear to play an important role as determinants of default risk during periods of crisis. A similar phenomenon is observed for the P/C ratio. In times of crisis, investors appear to positively value greater liquidity and reduce the premiums paid for eventual default among companies with better liquidity ratios.

Table 5. Comparative analysis for the pre-crisis period (2002–2006) and the crisis period (2007–2009)

	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)

End of Table 5

	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)
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%
Adjusted R^2	56.90%	57.76%	62.12%	71.05%	71.88%	76.51%

Notes: This table reports linear regressions of the logarithm 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.

Second, we perform a robustness check to analyze the effect of the maturity of the CDS contract on our results[13]. We consider only 1-, 5-, and 30-year CDS spread data. Our main finding remains unchanged; that is, the comprehensive model provides the greatest explanatory power for all of the maturities that are considered.

Finally, we evaluate the method of estimation that is used in the analysis. Because panel data are used, we can re-estimate the models with either fixed or random effects. Hausman tests suggest that the fixed effects estimator is more appropriate in our case[14]. We now assume that the omitted variables (e.g., CDS liquidity and corporate governance, among others) may potentially correlate with the existing regressors. As expected, the comprehensive model has the greatest explanatory power.

2.3. Are there differences if credit ratings are used instead of CDS spreads?

Credit ratings have also been used as a typical proxy for credit risk in the literature (e.g., Demirovic, Thomas 2007). Because these credit ratings are inherently ordered, we 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 that range from 1 for the best ratings to 7 for ratings of BBB- or lower. Table 6 reports the credit rating provided by the three major international rating agencies (Standard & Poor's, Moody's and Fitch) for the firms of the sample 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 to be a separate observation. In total, we have 706 observations for 51 unique firms that are listed in the FTSEurofirst 100 index.

Our results from this analysis (see Table 7) are very similar to the results that were obtained by considering the CDS spread to be a proxy for credit risk. Again, a comprehensive model that includes both accounting and market data has the greatest explanatory power (23%). However, our outcomes 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 21% of the variability, whereas the market-based model explains only 14% of the variability). The same conclusion is reached by Demirovic and Thomas (2007) for the UK market. Finally, although most of the explanatory variables remain unaffected with respect to their signs and their levels of significance, we 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 greater firm size is associated with a higher credit rating.

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[13] We do not report these values due to space limitations. However, they are available upon request.

[14] We use only the most liquid 5-year CDS contracts to generate these results (not reported).

Table 6. Credit rating conversion

Standard & Poor´s	Moody´s	Fitch	Assigned value	No. of observations	Percentage
AAA	Aaa	AAA	1		
AA+	Aa1	AA+	1		
AA	Aa2	AA	1		
AA−	Aa3	AA−	1	66	9.35%
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%

(The "Rating" header spans Standard & Poor´s, Moody´s, and Fitch columns.)

Note: Rating data were obtained from Bloomberg.

Table 7. Comparative analysis using credit ratings

	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)

	Model 1 (Accounting-based)	Model 2 (Market-based)	Model 3 (Comprehensive)
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%

Note: 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 6 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.

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 these two approaches. Our results indicate that a comprehensive model that combines accounting- and market-based variables is the best option to explain the credit risk, suggesting that both types of data are complementary. This finding is in accordance with the results reported by Agarwall and Taffler (2008) and Das *et al.* (2009) for the UK and the US markets, respectively.

We also demonstrate that the explanatory power of accounting- and market-based variables for measuring credit risk is particularly strong during periods of high uncertainty. It may occur because CDS spreads become more sensitive during periods of crisis and therefore act as better credit risk indicators.

Finally, when the credit rating is used as a proxy for credit risk, our main conclusion is unchanged, i.e., the best results are obtained through the use of a combination of accounting- and market-based data. However, our results suggest that accounting variables play a more important role than market variables in determining credit ratings.

Acknowledgments

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