Are Financial Ratios Still Relevant for Capturing Credit Risk?

Evidence from the CDS Market

by

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Abstract

In this article we explore in depth the way changes in CDS spreads relate to financial ratios changes, and delve into the underlying properties of this relationship under the structural models theory. Our results suggest that financial ratios can help explain part of the CDS spread variability, while at the same time the CDS market is efficient in correctly anticipating the greatest part of changes in the financial ratios well before these are officially released. Using threshold regression's statistical theory we confirm the insights of both structural model theory and practical intuition behind the workings of that particular market. Our evidence implies that the relationship between CDS changes and the changes in the financial statements is indeed nonlinear, and the use of Leverage and Price to Book ratios as threshold variables can lead to piece-wise linear approximations in that association. We also observe that systemic factors become the dominant determinants of CDS changes in periods of financial turmoil. Finally, we verify the asymmetrical impact of financial ratios on the market's perception of a company's credit risk by employing quantile regression.

Keywords: CDS; Financial ratios; Structural models; Lasso estimator; Threshold regression; Asymmetrical impact; Quantile regression.

JEL: C21, G14, G15, G33

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1. Introduction - Motivation

Financial ratios are widely used both by the management and by the creditors of a firm. Management mainly employs financial ratios as a quantitative tool in its daily decision making process, while creditors utilize financial ratios to evaluate a firm's credit risk. In particular, creditors have to decide on a series of issues regarding the extension or not of credit to a customer, the amount of credit to be granted as well as the proper pricing of the credit risk undertaken. In that context, financial ratios have been used for 4 decades for evaluating a company's credit standing (Altman 1968, Ohlson 1982), though, some studies reveal that structural models (Merton 1974) perform better in evaluating a firm's credit risk compared to models based exclusively on financial statement variables. Hillegeist et al. (2004) infer that the probability of bankruptcy estimated using a Black-Scholes-Merton option pricing model incorporates much more information than Z-score and O-score, which are both calibrated on accounting data. The results of these studies indicate that the missing component that enables structural models to potentially outperform pure accounting-based measures of default is asset volatility[3] (Campbell et al 2003, Vassalou and Xing, 2004).

Nevertheless, some studies reveal that financial ratios have complementary informational content when used in parallel with structural models, especially in the presence of not fully efficient markets. Demirovic and Thomas (2007) conclude that accounting variables contain additional information not captured by a structural model that includes only the distance-to-default. Agarwal and Taffler (2008) find that structural models encapsulate different aspects of credit risk compared to accounting based models. Furthermore, Das et al (2009) and Ponce (2012) examine the explanatory power of market-based and accounting-based models on a company's CDS spread, just to confirm once again that the model with the higher explanatory power is the one that combines both market and accounting data. To that end, our study incorporates financial ratios coupled with the main variables prescribed under structural models theory, namely leverage and volatility, to examine how do financial ratios affect a firm's credit risk, as it is reflected in its CDS spread.

[3] Alternatively, equity volatility can be used as a proxy for asset volatility.

In particular, the principal aim of this study is to explore in depth the relationship between changes in a firm's financial ratios and changes in its CDS spread. In particular, in pursuing this objective, we seek to identify the properties of the aforementioned relationship, in the context of structural models theory and market efficiency. We can encapsulate the objectives of this study in the form of four questions: i) "Do changes in the financial ratios of a company explain part of the observed CDS spread changes?", ii) "Does the CDS market is efficient in anticipating changes in financial ratios, before these are officially made public?", iii) "Do company-specific characteristics, such as low vs. high leverage, or the temporal phase of the economic cycle affect the relationship between changes in financial ratios and CDS spread changes?", and iv) "Is the improvement or the deterioration of a company's credit-standing driven by the same financial ratios and in a symmetrical way?"

With regard to the first question, there is a number of relatively recent studies that employ financial ratios in an attempt to explain the variation of credit spread levels (Campbell and Taksler 2003, Das, Hanouna and Sarin 2009) or of credit spread changes (Collin-Duffresne, Goldstein and Martin (CGM - 2001), Ericsson, Jacobs and Oviedo 2009). We examine a larger dataset on a much more generic set of changes in financial ratios to verify that the CDS spreads are indeed affected by changes in financial ratios. Instead of using arbitrarily chosen models, the selection of the financial ratios that are included in our model specification is based on the Lasso estimator, which considers both parsimony and prediction accuracy. Our results suggest that financial ratios related to profitability, valuation and financial flexibility are statistical significant in determining a firm's CDS spread, improving the performance of structural models.

Concerning the absorption of the information contained in the financial ratios by the CDS market, we examine whether any news included in the financial ratios of a company is incorporated in the CDS market before these are officially made public. We search for potential "jumps" in the CDS spread around the announcement date of financial statements, arising from new "unprocessed" information contained in a firm's financial ratios. Our evidence suggest that the CDS market is largely efficient in anticipating changes in financial statement variables at least a week before these are announced, implying that the very announcement of financial statements doesn't offer any fresh news in the CDS market.

The motivation of our third question arises from the nonlinearities inherent in contingent claims theory (Merton 1974, Jones P., Mason S.and Rosenfeld E 1984, Eom Y., Helwege J. and Huang J.-Z 2004), according to which a firm's debt can be considered as a long position on a risk-free bond and a short position on a put on the assets of the firm. In most cases, while this firm is viable, this put remains deeply out-of-the-money resulting in a small Delta. Intuitively, this implies that the default premium of a healthy company exhibits a relatively small sensitivity to the changes of the firms' enterprise value that increases in magnitude as the firm approaches the default threshold. Since CDS spread changes are expected to have a non linear relation with the firm's fundamentals, and to be also affected by variables such as volatility, it is thus very likely that the relationship between changes in financial ratios and changes in CDS spreads does not remain invariant throughout the cross-section of debt issuers and the time dimension of the panel, but it depends on the capital structure, the growth prospects of the company, other firm-specific variables as well as the regime of the economy.

By employing threshold analysis we verify the non-linearity of the relationship between credit risk and its determinants even when we consider changes rather than levels. We find that Debt to Market Capitalization (Leverage ratio) and Price to Book Ratio (Valuation ratio) can be used as cross-sectional discriminatory variables to define statistically appropriate categorization within which regression coefficients are significantly different in the cross section. At the same time, our findings point to the existence of structural breaks in the relationship we explore, which occur along the time dimension. The relative impact of financial ratios in the CDS spread changes decreases in times of financial turbulence and the systemic factors become the dominant determinants of CDS spread changes.

Finally, we explore whether the effect of changes in certain financial ratios on the changes of CDS spread is symmetrical. We examine whether a particular type of returns, i.e. very positive or very negative, are driven by the same set of financial ratios and in the same manner by utilizing quantile regression[4]. Our analysis points changes in Leverage and Price to Book ratio as the most important ones, in driving the widening of CDS spreads. We also find evidence that the deterioration in the market's perception of a

[4] For more details on the economic applications of quantile regression see Fitzenberger B., Koenker R. and Machado J., 2002.

company’s credit risk is more likely to depend on “bad” news, rather than its improvement to depend on “good” news contained in a firm’s financial ratios.

The implications of our findings can be significant to a great number of interested parties. Our results suggest that the participants in the CDS market have to consider financial ratios as a complementary tool for determining a firm’s credit risk, since financial ratios are statistical significant and increase the explanatory power of a model that considers only leverage and volatility. The aspects of our study regarding the asymmetrical impact of financial ratios and the variability of the regression coefficients both along the cross-sectional and the time dimension, may help the participants in the CDS market gain a deeper understanding of the factors that drive CDS changes and thus better manage the risk of their positions as well as properly formulate their investments strategies. Our results indicate that different financial ratios matter for low vs. high leveraged firms and for growth vs. value firms, hence, it becomes evident that we have to zoom in on different focal points when examining firms with different characteristics.

The rest of the paper is organized as follows. Section 2 presents our data set and some summary statistics. In section 3 we introduce our main hypotheses. In section 4 we present all the empirical results of our analysis. Section 5 provides the necessary robustness checks that further assess our results in the context of relevant literature and section 6 concludes.

2. Data and Summary Statistics

2.1 Data Description

Our sample consists of 5yr CDS spreads on senior unsecured debt that is downloaded from Bloomberg. These data range from 31 Dec 2003 to 31 Dec 2008 and include companies all over the world for which data is available in Bloomberg. The selection of the 5yr CDS spread is primarily due to its higher liquidity among all tradable tenors, and since Bloomberg provides most quotes for it, compared to all other tradable tenors.

In performing our analysis we employ changes of our variables (CGM 2001, Avramov, Jostova and Philipov 2007, Ericsson, Jacobs and Oviedo 2009) instead of levels (Campbell and Taksler 2003, Carling, Jacobson, Lindi and Roszbach 2007, Das, Hanouna and Sarin 2009, Tang and Yan 2009, Bonfim 2009), as the mechanism that underlies the market's aggregate perception of an entity's credit risk as an absolute level tends to shift widely between different phases of the business cycle. Ericsson et al (2009) and Avramov et al (2007) note that this very fact could point to possible problems of non-stationarity of the variables used for the estimation of the level of CDS spreads. Furthermore, the use of percentage changes of financial ratios rather than their levels is more robust not only because financial ratios are non-stationary (Ioannidis, Peel and Peel 2003), but also because the level of ratios may be structurally different between different sectors, thus biasing regression estimates.

CDS spreads are downloaded for one week before and one week after each announcement date of the financial statements. We denote as:

- $CDS(+5d)_i$: the CDS level 5 days after the announcement date for quarter i,
- $CDS(-5d)_i$: the CDS level 5 days before the announcement date for quarter i,
- $CDS(+5d)_{i-1}$: the CDS level 5 days after the announcement date of the previous quarter i-1

We calculate two week changes (ΔCDS_{2W_i}) as well as quarterly CDS spread changes (ΔCDS_{Q_i}) as follows:

$$\Delta CDS_{2W_i} = \ln\left(\frac{CDS(+5d)_i}{CDS(-5d)_i}\right) \qquad \Delta CDS_{Q_i} = \ln\left(\frac{CDS(+5d)_i}{CDS(+5d)_{i-1}}\right) \tag{1}$$

For every announcement date and for each company we also estimate 90 days equity return volatility changes, following the same rational as described above, both for two weeks and for the quarterly changes. For each company and for each quarter we also download from Bloomberg a broad range of financial ratios that cover the broad categories of Leverage & Capital structure, Cash flow protection & Liquidity, Valuation, Profitability and Financial Flexibility, as Bloomberg describes them. For each of these ratios we then calculate quarterly percentage changes. Finally, we include in our sample data regarding general characteristics of a company that can be used as Dummy variables in the analysis (i.e. Country, Sector, Credit Rating, and Quarter).

2.2 Summary Statistics

After excluding all financial ratios with a few observations to maximize our sample, we end up with 6,244 observations from 533 companies. There are on average 12 quarterly observations, out of a total of 20 quarters that our dataset spans, for each company in our sample. Our final sample includes 22 financial ratios that cover the aforementioned broad accounting categories, and we present them in the table that follows.

Leverage & Capital structure	Profitability	Valuation	Financial Flexibility	Cash flow protection & Liquidity
Debt to market capitalization	Profit margin	Price to sales per share	Sales growth to Tangible Assets	Cash and cash equivalents per share
Common equity to assets	Operating income per share	Price to book ratio	Asset Turnover	Cash from operation to Total Debt
Debt to total assets	Earnings per share	Price to Earnings ratio	Book Value per share	Operating income to Long term debt
Long term debt to common equity	Revenue per share		Increase in Equity as a percent of Total Liabilities	Operating Income to Total Capital
	Return on common equity		Retained Earnings to Tangible Assets	
	Return on assets			

In table 1 we present the Country and Credit rating profile of our sample. About two thirds of our observations come from the US, and about two thirds have a credit rating of A or BBB, at the date of downloading the dataset. Furthermore, table 2 exhibits our sample by quarter dimension. There are on average 312 observations per quarter and the average CDS spread for all companies included in our sample is 123 bps.

[Insert Table 1 about here]

[Insert Table 2 about here]

3. Hypothesis Development

We develop our analysis in four successive stages, each of which follows naturally from the previous one. We frame each stage in the form of an individual hypothesis which we then put to test. The succession of hypotheses that we examine in this study can be stated as follows:

Hypothesis 1: *Changes in the financial ratios of a company explain part of the observed CDS spread changes.*

This hypothesis can be expressed in the form of a panel regression:

$$\Delta CDS_{\mathrm{Q_i}} = C + b_1 \Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(1)} + b_2 \Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(2)} + ... + b_N \Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(N)} + \varepsilon_{\mathrm{i}} \tag{2}$$

In equation (2), $\Delta CDS_{\mathrm{Q_i}}$ is defined as in (1), $\Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(m)}$ correspond to quarterly logarithmic changes in financial ratios calculated from quarter i-1 and i, and period fixed effects are also included. The alternative hypothesis $b_1 = b_2 = ... = b_N = 0$ implies that any variation in the financial ratios is not related to the observed CDS changes.

Hypothesis 2: *The CDS market is efficient in anticipating changes in the financial ratios of a company, before these are officially made public.*

This hypothesis can be structured with the help of a panel regression:

$$\Delta CDS_{\mathrm{2W_i}} = C + b_1 \Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(1)} + b_2 \Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(2)} + ... + b_N \Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(N)} + \varepsilon_{\mathrm{i}} \tag{3}$$

In (3), $\Delta CDS_{\mathrm{2W_i}}$ is defined as in (1), testing in effect whether the adjustment in the CDS spread takes place within the two-week period that encloses the announcement date, $\Delta \mathrm{X}_{\mathrm{Q_i}}{}^{(m)}$ correspond again to quarterly changes in published financial ratios, and period fixed effects are again considered. The stated hypothesis coincides with the restriction $b_1 = b_2 = ... = b_N = 0$ which can be tested against the unrestricted model in (3). Non-rejection of the restriction implies that the CDS spread adjustment precedes the announcement date.

Hypothesis 3: *The set of financial ratios that explain CDS spread changes remains invariant throughout the cross-section of debt issuers and the time dimension.*

We test this hypothesis using threshold analysis. To that end, we adopt equation (2) as the null hypothesis of no threshold and as the alternative a threshold linear model of the form:

$$\Delta CDS_{Q_i} = C + b_1'\Delta X_{Q_i}{}^{(1)} + b_2'\Delta X_{Q_i}{}^{(2)} + ... + b_N'\Delta X_{Q_i}{}^{(N)} + \varepsilon_i, \quad x \le \theta$$

$$\Delta CDS_{Q_i} = C + b_1''\Delta X_{Q_i}{}^{(1)} + b_2''\Delta X_{Q_i}{}^{(2)} + ... + b_N''\Delta X_{Q_i}{}^{(N)} + \varepsilon_i, \quad x > \theta \tag{4}$$

The regression above is estimated using the fixed effect estimator. The threshold variable x in equation (4), determining the shift from one regime to the alternative, can be either a cross-sectional or a time variable[5]. In the first case, the validity of equation (4) against the null implies the non-linearity of the response function that links the dependent with the regressor variables. In the second case, the existence of a time threshold implies a structural break in that relationship that occurred at some point in time.

Hypothesis 4: *The response of CDS changes is symmetrical both in sign and magnitude with respect to the changes in financial ratios.*

An OLS estimation of equation (2) reveals a relationship between the means of the dependent and the independent variables. We use quantile regression to estimate (2) for a number of quantiles to test, in effect, whether changes in financial ratios of different sign and magnitude have a distinct impact on the CDS spreads. In particular, we investigate whether there are alterations in the estimates as well as in the significance of the coefficients in (2) across different quantiles.

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[5] In this case the period fixed effects are omitted.

4. Empirical Analysis

Generally speaking, an increase in Profitability, Valuation and Liquidity are likely to indicate an improvement in the financial health of a firm, thus tightening its CDS spread. On the other hand, an increase in Leverage suggest the heightened financial risk of a given company, widening its CDS spread.

Initially, we define our basic model (eq. 2) to the end of testing hypothesis 1. We then use this model to examine the validity of the next 3 hypotheses. The set of regressors consists of financial ratios calculated from a firm's published quarterly financial statements, as well as period fixed effects as in Tang (2009). In section 5, we employ macroeconomic variables in the spirit of CGM (2001), Campbell J. et al (2003), Das S. et al (2009) and Bonfim D. et al (2009) among others, to evaluate the robustness of our results and to verify that our main findings still hold.

Among the 22 financial ratios that we examine, we make the final choice of the variables to include in our principal model on the basis of their significance when testing hypothesis 1. To this end, we implement the Least Angle Regression (LARS) algorithm proposed by Efron, Hastie, Johnstone and Tibshirani (2004) to derive the Least Absolute Shrinkage and Selection Operator (LASSO) estimates, which combine both model parsimony and prediction accuracy.

The Lasso estimator can be considered as an "adjusted" version of the Ordinary Least Square (OLS) estimator. The OLS estimator minimizes the sum of the squared residuals, while the LASSO estimator applies the constraint that the L_1 norm (rectilinear distance) of the parameters' vector is not higher than a given value. For smaller values of the constraint the Lasso contracts the OLS regressors towards zero, enhancing the prediction accuracy (Hastie et al 2001).

The implementation of the LARS[6] algorithm enable us to derive all Lasso estimates in a more computationally efficient way. The calculation burden is substantially decreased under the LARS algorithm, since it considers rather larger steps compared to the Forward Stagewise method, still not so large as the Forward Stepwise regression. The Least Angle Regression (LARS) starts by selecting the explanatory variable with the highest absolute correlation (X_{i1}) with the dependent variable and performs

[6] For a detailed overview of the LARS algorithm, please consult Efron, Hastie, Johnstone and Tibshirani (2004).

an OLS estimation. The residuals obtained from the previous regression are then considered as the dependent variable so as for the next variable (X_{i2}) with the highest absolute correlation to be identified. As opposed to the Forward Stagewise and Forward Stepwise approaches, in which the process carries on along (X_{i1}), under the LARS algorithm both predictors are equally considered until a third regressor is identified to be included in the set of variables that are the most correlated, and so on. The number of steps required by the LARS algorithm equals the number of regressors whose inclusion or not in the model is examined, hence the computations are substantially speeded up.

Due to multicollinearity problems that arise when testing our initial set of 22 variables, we remove 8 financial ratios[7] for which there exist such concerns and we perform the LARS algorithm again. Furthermore, from the variables that are finally selected by the LARS algorithm, we remove the ones that are not statistical significant from our final model specification. As a result of the abovementioned process, the quarterly changes of the following variables are included in our base model (eq. 2):

Debt to Market Capitalization (DM): This ratio is calculated as (Short Term Debt + Long Term Debt)/Market Capitalization. Market Capitalization is calculated as (Closing Price as of fiscal period end date) x (Shares outstanding at that period end date).

$$DM = \left(\frac{\text{Short Term Debt} + \text{Long Term Debt}}{\text{Closing Price} \times \text{Shares outstanding}} \right)$$

Price to Book Ratio (PB): Ratio of the stock price to the book value per share.

$$PB = \left(\frac{\text{Stock price}}{\text{Book value per share}} \right)$$

Earnings per Share (EPS): Computed as Net Income Available to Common Shareholders divided by the Basic Weighted Average Shares outstanding. Net income includes the effects of all one-time, non-recurring and extraordinary gains/losses. In calculating the Basic Weighted Average Shares, the effects of convertibles are excluded.

[7] The variables that are removed due to multicollinearity problems, the results of the statistical tests for multicollinearity as well as the intermediate regression results are available by the authors upon request.

$$EPS = \left(\frac{\text{Net Income}}{\text{Basic Weighted Average Shares outstanding}} \right)$$

Sales Growth to Tangible Assets (SGTA): Annual Sales change is calculated using for interim periods the comparative period of the preceding year. We use a full year in calculating Sales Growth so as to exclude potential seasonal effects from the analysis.

$$SGTA = \left(\frac{\text{Net Sales for the current period - Net Sales for the last period}}{\text{Tangible Assets}} \right)$$

Not surprisingly, the financial ratios that are included in our model as determinants of a firm's CDS spread cover the categories of leverage, valuation, profitability and financial flexibility common to many studies from 1968 (Altman E.) up to now. The significance of Debt to Market Capitalization (leverage) is in line with most articles trying to predict financial distress (Campbell J. et al, 2003, Molina C. A. et al 2005, Campbell J. et al, 2008) or explain corporate bond credit spread changes (CGM 2001).

The Price to Book ratio (valuation ratio) is found as an important determinant of credit risk in Vassalou M. et al (2004) and in Avramov D. et al (2007). In particular, Vassalou notes that firms with high probabilities of default have high Book to Market ratios. Expressing this finding in terms of changes in probabilities of default, one can say that firms facing increases in their probabilities of default, as it is denoted by an increase in their CDS spread, also experience a decrease in their Price to Book ratio.

It is worth mentioning that the financial ratios regarding Debt to Market Capitalization and Price to Book ratios incorporate, along with the potentially "unprocessed" information of financial statements, information coming from the stock market. Therefore, the channel of the information from the equity market is incorporated in our established models, in line with the approach followed by CGM (2001) who employ DM or interchangeably a firm's stock return to explain bond credit spreads.

Earning per Share is a profitability ratio similar to the ones used in Altman E. (1968) and Ohlson J. (1982). Finally, the significance of Sales Growth to Tangible Assets ratio is in line with metrics that incorporate sales expansion, common in Das S. et al (2009) and in Moody's Private Debt Manual[8].

For all of the financial ratios, except for Earnings per Share, we estimate logarithmic changes. For Earning per Share we use the difference from the previous quarter, as earnings per share can turn negative, and hence logarithmic changes cannot be defined. Table 3 presents descriptive statistics for the variables we use in the analysis, whether included as dependent or as independent variables in the models we set up.

[Insert Table 3 about here]

4.1. Testing Hypothesis 1: Changes in the financial ratios of a company explain part of the observed CDS spread changes.

We initiate our analysis by first examining the set of financial ratios that explain part of the CDS spread changes variability. In our basic model (eq. 5) we fit through a panel regression with period fixed effects the CDS quarterly changes (ΔCDS_{Q_i}) with respect to a set of independent variables that consists of a constant (C) and the changes in financial ratios (ΔDM, ΔPB, ΔEPS, ΔSGTA).

Model 1: $\Delta CDS_{Q_i} = C + b_1 \Delta DM_i + b_2 \Delta PB_i + b_3 \Delta EPS_i + b_4 \Delta SGTA_i + \varepsilon_i$

(5)

Using a simple F- Statistic, we test hypothesis 1 by testing the restriction of $b_1 = b_2 = b_3 = b_4 = 0$ against the unrestricted alternative. The validity of this restriction is rejected at the 0.01 level as the F-statistic equals 30.2.

In estimating Model 1 (base model) we use the White methodology to adjust the standard errors of the coefficients for heteroskedasticity and autocorrelation so as to produce robust estimates. Moreover, we

[8] It is published on Moody's KMV website.

examine the independent variables for multicollinearity using variance inflation factors, but no such evidence is found.

Our results, presented in table 4, indicate that Model 1 (eq. 5) explains about 44% of the changes in the CDS spread. We can also notice that the coefficients for the change of Debt to Market Capitalization (leverage ratio) and Sales Growth to Tangible Assets (financial flexibility ratio) are positive, indicating a widening in CDS spreads when leverage or Sales increase, while the coefficients of the change of Price to Book ratio (valuation ratio) and Earning per Share ratio (profitability ratio) are negative, implying a tightening in CDS spreads when Price to Book ratio and Earning per Share ratio increase. At the same time both the significance and the magnitude, in absolute terms, of the coefficients suggest that the effect of the change in Debt to Market Capitalization (0.12) and Price to Book ratio (0.16) dominate over the effect of Sales Growth to Tangible Assets (0.04) and Earning per Share ratio (0.0095).

We next augment our Model 1 (eq. 5) by including the equity return volatility quarterly change (ΔVOL), calculated from the most recent 90 trading days[9], both to examine whether the financial ratios used in our model encompass some of the information content of equity return volatility as well as to align our analysis with contingent claims theory that asserts the importance of asset volatility in determining a firms credit risk. Not surprisingly, the total explanatory power of our new model (Model 2 - eq. 6) increases by 2.3 percentage units, as depicted in the increased Adjusted R-squared in Table 4.

Model 2: $$\Delta CDS_{\mathrm{Q_i}} = C + b_1 \Delta \mathrm{DM_i} + b_2 \Delta \mathrm{PB_i} + b_3 \Delta \mathrm{EPS_i} + b_4 \Delta \mathrm{SGTA_i} + b_5 \Delta \mathrm{VOL_i} + \varepsilon_\mathrm{i} \tag{6}$$

[9] Of course, we should note here that the equity volatility the structural model theory alludes to, is the market-expected, forward-looking volatility of total assets. This is usually inferred from stock options, which however are not readily available for a significant part of our sample. For exactly this reason, we use historical volatility instead of the implied one as many authors have done before us (for example Ericsson et al (2009)). The argument goes that implied volatility is linked to past realized volatility (Christensen, Prahbala, 1999, Chalamandaris, Rompolis, 2010), thus we use this variable as one that is simply correlated to total asset volatility.

In setting up Model 2, we again utilize the LASSO algorithm after including volatility changes into our set of independent variables. The LASSO algorithm selects[10] the financial ratios employed under Model 1, as well as price to earnings, revenue per share and cash flow from operations to total debt. However, these latter financial ratios are not statistical significant and hence we do not include them in Model 2. Moreover, to further assess the robustness of our result we also include quarterly equity return changes into the set of our independent variables. Our findings[11] indicate that the financial ratios already identified remain statistical significant, apart from earnings per share that becomes insignificant and price to book ratio that remains significant at the 10% confidence level. Therefore, the identified financial ratios do explain a part of the CDS spreads that is not captured neither by equity returns nor by equity returns volatility.

The coefficient for the volatility change appears to have the strongest effect in determining CDS spread changes, as it has both the largest magnitude and significance. Financial variables remain significant, though, both their magnitude and their significance slightly decrease, apart from the significance of the coefficient for ΔDM which remains almost at the same level. By identifying leverage and volatility as the cornerstones in determining financial distress, our findings verify the importance of structural models theory. However, leverage and volatility do not incorporate the 100% of a firm's credit-related information since financial ratios remain highly statistical significant. Thus, any models attempting to capture credit risk have to be complemented with financial ratios. Furthermore, changes in equity volatility seem to convey part of the information regarding a firm's changes in profitability, as the coefficient for Earnings per Share becomes marginally insignificant at the 10% confidence level.

The change in the coefficients of time dummies[12] for Model 1 (eq. 5) and Model 2 (eq. 6) suggest that equity volatility in Model 2 captures some of the time series variation attributed to time dummies. The mean of the time dummies is closer to zero for Model 2 (Model 1: 0.0262, Model 2: 0.0122), as well as the standard deviation of the time dummies in Model 2 is smaller (Model 1: 0.2740, Model 2: 0.2471). These

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[10] All results are available on request.

[11] All results are available on request.

[12] The coefficients of time dummies are not presented here for the sake of saving space. All results are available on request.

findings are similar to those of Campbell (2003), implying that equity volatility contains systemic premia priced in the CDS market. Furthermore, our results are also in line with Tang (2009) who identifies implied volatility as the most important firm specific credit spread determinant, and Campbell (2003) who highlights the significance of idiosyncratic equity volatility in corporate bond yield spreads, even in the presence of other important factors that drive credit risk. Last but not least, our empirical evidence is supported by the intuition gained from structural models, in the sense that the price of an out-of-the-money put depends on the implied volatility of the underlying more than on anything else.

Comparing our findings with those of CGM (2001) on credit spread changes of corporate bonds, we can note that their proposed model has an explanatory power of about 19%-25% across all maturities and different leverage group, which is much lower than the explanatory power of Model 2 (46%). A part of this difference could be attributed to the macro variables used by CGM (2001) that take into account only the observable systemic components, while our model employs period fixed effects to capture both the observed and the potential latent systemic components. However, our results[13] suggest that even if we use macroeconomic variables instead of time dummies, the explanatory power of our model is 33.7%, about 10% higher than in CGM (2001). Therefore, the higher explanatory power of our model verifies Ericsson's et al (2009) conclusions that the CDS market offers a better measure of an issuer's credit risk compared to the corporate bonds market.

[Insert Table 4 about here]

4.2. Testing Hypothesis 2: The CDS market has predictive power in anticipating changes in the financial ratios of a company, before these are officially made public.

Having decided on the set of financial ratios whose changes influence CDS spread changes, we continue to the next stage of our analysis in which we investigate whether the CDS market has predictive power and it is able to anticipate financial statement alterations well before their announcement date. To

[13] These results are available on request.

frame this research question into a testable hypothesis, we use as dependent variable the CDS 2-week change (ΔCDS_{2W_i})[14] and examine whether or not this CDS spread change is explained by the recorded quarterly changes in the financial ratios of the firm. These financial statement variable changes[15] become officially known to the public only on their announcement date. If the CDS market is unable to predict these changes at all, then the adjustment of the CDS spreads that is caused by the release of the new financial report, will take place in its entirety within these 2 weeks. The volatility change that we include in these regressions is calculated for the same time period of two weeks (ΔVOL_{2W_i}) as the CDS 2 weeks change (ΔCDS_{2W_i}).

Model 3a: $\Delta CDS_{2W_i} = C + b_1 \Delta DM_i + b_2 \Delta PB_i + b_3 \Delta EPS_i + b_4 \Delta SGTA_i + \varepsilon_i$

(7a)

Model 4a: $\Delta CDS_{2W_i} = C + b_1 \Delta DM_i + b_2 \Delta PB_i + b_3 \Delta EPS_i + b_4 \Delta SGTA_i + b_5 \Delta VOL_{2W_i} + \varepsilon_i$

(8a)

Our evidence from these regressions in conjunction with our results in the previous section, point to the conclusion that changes in financial ratios have already been incorporated in the CDS spread a whole week before their official announcement. Indeed, in table 5, panel A, we find that all the coefficients of the financial statement variables for Models 3a and 4a are not statistically significant. In other words, the CDS changes variability of this particular 2-week period is driven by factors that are not related to the financial report in question. If the financial ratios hadn't already been incorporated in the CDS spread by the beginning of our testing period, we would have expected a "jump" at the announcement date of financial statements, leading to increased explanatory power for some of the financial ratios. The only variable that remains significant is the 2-week volatility change (ΔVOL_{2W_i}) in Model 4, further highlighting the

[14] This is defined as the (log-) change for the period that starts 1 week before the announcement date and ends 1 week after the announcement date t_i. See also equation (1).

[15] The financial ratio changes are defined as the (log-) differences between the figures recorded on the financial statement of t_i minus the figures recorded on the previous quarterly release on t_{i-1}.

importance of volatility as the dominant short-term determinant of credit risk, and one that we would expect anyway given the systemic factors that are constituents of this variable.

Intuition suggests that there might not be the same financial ratios that explain quarterly CDS changes and two week CDS changes, hence, we next proceed by exploring whether there are any financial ratios from the ones under our initial set that are significant for determining two week CDS changes. The selection of the financial ratios is again performed by the LASSO algorithm, and we present our results in Panel B of Table 5. Out findings imply that changes in Price to Earnings, Sales Growth to Tangible Assets and Cash Flow from Operations to Total Debt are statistical significant in determining 2 week CDS spread changes, while Operating Income to Total Capital becomes significant at the 10% confidence level when we also consider 2 week volatility in our model. It seems that the announcement of the financial ratios that are related somehow with firm profitability slightly affect its CDS spread, by in a sense performing some sort of mild fine-tuning between expected and published results.

Model 3b: $\Delta CD\mathrm{S}_{2\mathrm{Wi}} = C + b_1 \Delta \mathrm{PE_i} + b_2 \Delta \mathrm{SGTA_i} + b_3 \Delta \mathrm{CFTD_i} + \varepsilon_\mathrm{i}$

(7b)

Model 4b: $\Delta CD\mathrm{S}_{2\mathrm{Wi}} = C + b_1 \Delta \mathrm{PE_i} + b_2 \Delta \mathrm{SGTA_i} + b_3 \Delta \mathrm{CFTD_i} + b_4 \Delta \mathrm{OITC_i} + b_5 \Delta \mathrm{VOL}_{2\mathrm{Wi}} + \varepsilon_\mathrm{i}$

(8b)

However, given the very small sensitivities of the financial ratios as well as the explanatory power of Models 3b and 4b that is almost identical to the explanatory power of Models 3a and 4a respectively, there is no evidence of a “jump” in the CDS spread after the announcement date of financial statements. Furthermore, the explanatory power of the abovementioned models is mainly attributed to the systemic factors, which are captured by the fixed effects in the time dimension, and it approaches zero in case the fixed effects are removed. Taking all the above into account, we can conclude that the CDS market has incorporated almost any changes in financial ratios, before these have been officially announced. To put it differently, the CDS spreads imply the use of unbiased estimates for the imminent financial ratios in the pricing of a firm’s credit risk, thus incorporating any necessary adjustment well before the announcement date of the financial statements. This finding is in agreement with studies that examine the impact of rating announcements (Hull et al 2004, Norden and Weber 2004), rather than the announcement of financial reports, on CDS spreads.

[Insert Table 5 about here]

4.3. Testing Hypothesis 3: The set of financial ratios that explain CDS spread changes remains invariant throughout the cross-section of debt issuers and the time.

In this subsection, we explore in greater depth the incorporation of financial ratios in CDS changes by examining if the causal pattern that Model 2 dictates remains invariant throughout the cross-section of debt issuers and the time dimension.

This research question is again motivated by option pricing theory. Indeed, by construction, structural models stipulate non-linear relationships between financial ratios and changes in credit risk. However, in empirical studies of the relevant literature, a number of researchers approach the problem with linear approximations similar to our Model 2 (e.g. Schaefer S.M. and L.A. Strebulaev 2008, Tang 2009, Ericsson et al 2009). A question that arises naturally in those articles refers to whether the regression coefficients are stable when the model is calculated for different sub-samples. CGM, 2001 proceed in an ad-hoc segmentation of the original panel in terms of leverage and finds that the coefficients are indeed not stable[16]. In particular, while GCM (2001) use arbitrarily chosen leverage ratio subgroups to examine the same thing, we differentiate our work by pursuing a statistically consistent way to identify any clusters as well as we search for more than one cross-section variable that could potentially discriminate between subgroups.

[16] Our attempts to include in the original regressions (Model 1, 2) non-linear terms of leverage or other cross-sectional variables does not improve the fit of the model which is a finding in line with CGM 2001 et al and Avramov et al, 2007. All the coefficients for the nonlinear terms are invariable statistically non-significant. The results of these regressions are available from the authors upon request.

Splitting a panel dataset in subsamples, requires a choice to be made on the appropriate variable that determines the split, i.e. the threshold variable. At the same time, the value of that variable at which the panel is divided into subsamples, i.e. the threshold value, must also be determined. While for categorical variables such as credit rating, country, etc., we can identify the threshold values relatively easily, we need to select a statistically plausible method to do the same for continuous variables. To avoid doing so in an arbitrary fashion, one needs the appropriate asymptotic theory that provides tests about its existence and grants the required statistical confidence concerning its position[17].

For the purposes of our analysis we follow Hansen, E. B. (2000) approach, who has developed the required statistical theory for the existence of a single threshold. According to Hansen (2000) the threshold regression model can be written as

$$\begin{aligned} y_i &= \theta_1 \cdot x_i + e_i, q_i \leq \gamma \\ y_i &= \theta_2 \cdot x_i + e_i, q_i > \gamma \end{aligned} \tag{9}$$

In the model of equation (9) q_i is the threshold variable used to split the sample, γ the value of the threshold variable, e_i the regression error, θ_1 the coefficient of the first sub-sample and θ_2 is the coefficient of the second subsample.

We test for the existence of the threshold based on a particular threshold variable q_i with the help of the heteroskedasticity-consistent Lagrange multiplier (LM) test for a threshold of Hansen (1996). Since the threshold γ is not identified under the null of no-threshold effect, the p-values are computed with the help of a bootstrap procedure. If we find evidence that a threshold value γ does exist by rejecting the null of the LM test, then equation (9) can be used as a valid representation of the relationship between the dependent and the independent variables. In this case, the above two equations are merged into one using a dummy variable that is indexed on the threshold variable, introducing the effect of the different sub-samples into our model. Least squares estimators are then derived by minimizing the sum of squared errors function[18].

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[17] Regression trees have been one alternative (for example Durlauf N. and Johnson P, 1995), which however requires a number of rather arbitrary decisions on the parameterization of the tree.

[18] For a detailed illustration of the methodology employed here, see Hansen E. B. 2000.

The estimator we use assumes heteroskedastic errors since preliminary tests in our sample reveal that this is necessary.

In our analysis at this stage, we use Model 2 as the Null Hypothesis of no threshold effect. We then split our panel in 3 different ways, each time by adopting one of the 3 candidate threshold variables as the one that determines the statistically appropriate categorization. We successively test as threshold variables (i) Debt to Market Capitalization ratio, (ii) Price to Book ratio and (iii) Time, that is an integer denoting the quarter of the particular observation. The aim of this exercise is dual. Firstly to examine the degree at which a specification of the variables in Model 2 is inherently non-linear, and secondly to investigate the intricacies and implications of this specification in the individual sub-samples. We utilize the fixed effects estimator in the calculations that follow.

Starting with our first candidate, we use Hansen's (1996) threshold (LM) test to examine if there is some value of the Debt to Market Capitalization ratio for which a statistically appropriate categorization exists. The bootstrap p-value (<0.0001) indicates that if we split once the regression in two subsamples, based on this variable, we will end up with a nonlinear model in the form of equation (10), in which the respective regression coefficients $b_i^{(a)}$ and $b_i^{(b)}$ are significantly different.

$$\begin{aligned}
\Delta CDS_{\mathrm{Q_i}} &= C^{(a)} + b_1^{(a)}\Delta \mathrm{DM_i} + b_2^{(a)}\Delta \mathrm{PB_i} + b_3^{(a)}\Delta \mathrm{EPS_i} + \\
&+ b_4^{(a)}\Delta \mathrm{SG_i} + b_5^{(a)}\Delta \mathrm{VOL_i} + \varepsilon_\mathrm{i}, \quad \mathrm{DM_i} < \gamma \\
\\
\Delta CDS_{\mathrm{Q_i}} &= C^{(b)} + b_1^{(b)}\Delta \mathrm{DM_i} + b_2^{(b)}\Delta \mathrm{PB_i} + b_3^{(b)}\Delta \mathrm{EPS_i} + \\
&+ b_4^{(b)}\Delta \mathrm{SG_i} + b_5^{(b)}\Delta \mathrm{VOL_i} + \varepsilon_\mathrm{i}, \quad \mathrm{DM_i} \geq \gamma
\end{aligned} \tag{10}$$

The first threshold value is 0.4221 and is presented in table 6, implying that firms having a Debt to Market Capitalization ratio higher than 0.4221 behave differently from firms having a smaller one. After the first sample split, the explanatory power of our model increases to 0.479 as indicated by the Total joint R-squared, an increase of about 1.5 percentage units compared with our base Model 2.

We replicate the procedure by testing whether the next larger subsample, i.e. firms with Debt to Market Capitalization from 0 to 0.4221, can be further split in two. Again, we reject the hypothesis of no-threshold effect in this subsample based on the bootstrap p-value (0.0006). The estimated threshold level for Debt to Market Capitalization in this case is 0.111. Having split our sample into 3 sub-samples the total joint R-squared grows further to 0.484, that is, 2 percentage units higher compared to our base model (eq. 6 - Table 4, Model 2).

Finally, we examine if the upper part of our sample, i.e. firms with Debt to Market Capitalization ratio higher than 0.4221, can be further split into two sub-samples. The Bootstrap p-value (zero) provides evidence of an additional split. The threshold level for Debt to Market Capitalization ratio for this case is equal to 2.5811. The estimated model of 4 regimes has a total joint R-squared of 0.492, about 3 percentage units higher compared to the linear model (eq. 6 - Table 4, Model 2).

We must stress here, that we use the aforementioned testing procedure only to acquire an informative comparison with the insights of structural models. We neither seek the "true" number of breaks nor the "true" break sequence[19].

[Insert Table 6 about here]

In Table 7, we display the coefficients of the four regime model (eq. 10) when using as threshold variable the Debt to Market Capitalization ratio. The volatility changes regressor variable remains significant in all 4 regimes, exhibiting however lower significance (lower t-statistic) for firms with very high leverage. This is consistent with theory, since highly leveraged firms have a higher "delta" with respect to their fundamentals, thus diminishing the effect of volatility in this segment of the panel. Furthermore, the higher magnitude and significance of the coefficient for the Debt to Market Capitalization change indicates that the more leveraged a firm is, the stronger the impact of leverage on its CDS spread. Indeed, the Debt to Market coefficient becomes insignificant for low leveraged firms. These results are in line with CGM 2001, who examined the significance of changes in a firm's leverage, for a series of some ad hoc leverage groups. Finally, for highly leveraged firms the effects of price to book ratio

[19] It is important to note this, because the test itself assumes a unique threshold break and thus it is not clear how the theoretical results regarding the confidence intervals of the threshold levels extend in our application. This is why we avoid the presentation of the standard errors of the inferred thresholds as this could be misleading.

changes decreases in magnitude and in significance when examining CDS spread changes, suggesting that the impact of price to book ratio on CDS spreads is surpassed by other factors.

The coefficients for Debt to Market Capitalization change, for Price to Book change and for Volatility changes in the linear model are 0.115, -0.131 and 0.328 respectively (Table 4, Model 2, eq. 6), while for the statistically different sub-samples, they range from 0.07 to 0.19 for $\Delta \mathrm{DM}$, from -0.12 to -0.17 for $\Delta \mathrm{PB}$ and from 0.29 to 0.39 for $\Delta \mathrm{Vol}$, when taking into account only the sub-samples for which these coefficients remain significant. These findings confirm the non-linearities inherent in the structural model theory, since the sensitivities of the financial ratios do not remain invariant throughout the cross-section of debt issuers, across different levels of leverage.

[Insert Table 7 about here]

In order to validate the robustness of our observations in terms of alternative cross-sectional variables, we repeat the above procedure using this time as threshold variable not a leverage ratio, but the next most significant financial ratio examined, i.e. the Price to Book ratio. Successive application of the Hansen's heteroskedasticity consistent (LM) test provides evidence for (at least) 4 splits based on different Price to Book ratio categorizations: (0 – 0.89), (0.89 - 1.53), (1.53 - 2.28), and (>2.28), indicating again that the regression coefficients of Model 2 are significantly different in each subsample (Table 6). The total joint R-squared of the triple-threshold model increases to 0.485, about 2.2 percentage units higher than the linear Model 2 of the no-threshold hypothesis.

The coefficients of Model 2 in each of the four sub-samples, presented in Table 8, indicate that volatility remains again significant in all subsamples, validating once again its "exceptional" position in the context of structural models. The magnitude and the significance of changes in Debt to Market Capitalization are larger for low Price to Book firms, indicating that leverage does matter more for "value" than for "growth" firms. What is more, earnings per share changes are not significant in any regime for this panel categorization, while the coefficient for Sales to Tangible Assets changes increases in significance for high Price to Book firms. This latter observation may indicate the additional risks that sales expansion entails for “growth” firms and that these risks are priced in the CDS market by the market participants.

The coefficients for Debt to Market capitalization change, for Price to Book change and for Volatility changes for our base model are 0.115, -0.131 and 0.328 and respectively (Table 4, Model 2), while for the statistically different sub-samples, they range from 0.11 to 0.22 for Debt to Market Capitalization change, from -0.37 to -0.10 for Price to Book change and from 0.24 to 0.44 for volatility changes, when considering only the sub-samples for which these coefficients remain significant.

All in all, our findings provide clear evidence that the impact of financial statement variables on CDS spread changes depends on the particular segment of the population that the firm in question belongs. This is demonstrated using either the Leverage or the Price to Book ratio as the discriminating variable.

[Insert Table 8 about here]

At a final application of the threshold analysis for CDS changes, we use it to test for structural breaks along the time dimension in the relationship of Model 2 (Table 4, eq. 6). To this end, we exclude the Time Dummies from Model 2, and employ Quarters as the threshold variable. We then replicate the analysis we described previously. At each application of the threshold test, and the subsequent estimation of the larger model, we find that its explanatory power increases, from 18% to 25% after the first split, then to 28.5% after the second and finally to 33.8% after the third split, suggesting high variation across the time dimension.

In table 9 we present the coefficients of the resulting threshold model. We can observe that volatility changes become the dominant driver of CDS changes after the 17th quarter (31/03/2008) due to the outbreak of the financial crisis. After that time, changes in volatility and in leverage have a dominant role in determining CDS spread changes. This evidence is in line with the common perception that since that time, correlation in CDS spreads has increased dramatically.

The coefficients in the different subsamples, when taking into account only the sub-samples for which these coefficients remain significant, range from 0.06 to 0.15 for Debt to Market Capitalization change, from -0.22 to -0.13 for Price to Book change and from 0.27 to 0.74 for volatility changes. These findings verify that financial ratios do not remain invariant throughout the time dimension of our sample.

[Insert Table 9 about here]

4.4. Testing Hypothesis 4: The response of CDS changes is symmetrical both in sign and magnitude with respect to the changes in financial ratios.

On the release of a new financial report concerning the quarterly results of a company, both intuition and theory stipulate the perception that a firm's credit risk will change in an asymmetrical fashion. Notwithstanding whether a company is healthy or not, we expect negative results to have a larger impact in the CDS market, given that the latter prices a pure downside risk which is asymmetric by nature. The aim of this subsection is to verify this lack of symmetry by examining whether the set of factors that drive firms to default, i.e. widening of CDS spreads (positive changes), is identical to the one that drives firms to prosperity, i.e. tightening of CDS spreads (negative changes), and whether their respective coefficients remain relatively constant.

Hull et al, (2004) and Norden and Weber (2004), among others, have shown that the impact of negative news regarding the rating of a company on CDS returns is more pronounced and statistically significant when compared to the statistically insignificant impact of positive news. Using the same framework from another point of view, we examine this asymmetry with the help of quantile regression analysis. Indeed, while the method of ordinary least squares provides us with estimates of the conditional mean of the dependent variable given certain values of the independent variables, quantile regression provides us with estimates of either the median or other quantiles of the response variable. Therefore, it seems to be the natural tool to help us distinguish between potentially different sets of regressor variables and their respective coefficient patterns, that are responsible for causing different response in the CDS market.

We perform our analysis starting from Models 1 & 2 assuming that the model that links CDS changes to changes in financial ratios is inherently linear[20]. Quantile regression is then examined in the following 5 quantiles: 10%, 25%, 50%, 75% and 90%. At the lower quantiles, i.e. 10% - large negative changes and 25% - medium negative changes, we examine what drives CDS spread decreases. Whereas at the upper quantiles, i.e. 75% - medium positive changes and 90% - large positive changes, we examine what drives CDS spread increases[21]. It is the upper quantiles that are of major interest to us, since these quantiles will reveal the real "culprits" of CDS spread increases, and so, the variables that are really perceived as significant in leading firms to default.

The quantile regression results for Model 1 (eq. 5) are displayed in table 10, in which we use only financial ratios and fixed effects in the time dimension. Comparing our findings with those in Table 4, in which all variables are significant, we can observe that changes in Debt to Market Capitalization (leverage) and Price to Book (valuation) ratios are significant in all quantiles, while changes in Earnings per Share (profitability) are significant only for CDS increases, i.e. the 75% and the 90% quantile. In other words, an increase in CDS spreads can be attributed, among other things, to a decrease in profitability.

Regarding the coefficients of our regression, we can notice that the coefficient of the Price to Book ratio change is substantially higher, almost doubled, for the upper quantiles, i.e. -0.2411 and -0.2249 for the 75% and the 90% quantiles respectively, compared to its estimate at the lower quantiles, i.e. -0.1167 and -0.1149 for the 10% and 25% quantiles respectively. These results suggest the higher impact of Price to Book ratio when CDS spreads widen.

On the other hand, Sales Growth to Tangible Assets appears not to affect large CDS spread increases as it becomes insignificant at the 90% quantile. It seems that most of the times, it is only a decrease or a small to medium increase in Sales Growth to Tangible Assets that affects CDS spreads. Although the sign

[20] Although the threshold analysis in the previous subsection provided us with strong evidence that this assumption is not quite valid, we do this for 2 reasons: First, because the linear model alone has enough explanatory power compared with its non-linear alternatives and, secondly, because this assumption will allow us to use the entire sample. We have also conducted quantile regression analysis on the 4 subsamples defined by the previously estimated thresholds on Debt to Market ratio, the results of which are not qualitatively different from the ones we present here. They are also available from the authors upon request.

[21] See also Table 3 for more information regarding the descriptive statistics of the variables examined.

of this coefficient appears to be counterintuitive, we should stress that the contribution of this variable is felt only during periods that we observe credit tightening. Therefore, we could interpret it as a sign of an imminent turning in the business cycle.

A final observation concerns the explanatory power of our model that raises significantly when we move to higher quantiles, as the pseudo R-squared increases from 18% for the 10% quantile to 35% for the 90% quantile. Therefore, our model indicates the existence of a strong link between negative news disseminated by the financial reports and the deterioration in a firm's credit risk. When it comes to interpreting the improvement of CDS spreads as being caused by "positive" news from the financial report, this link appears much weaker.

[Insert Table 10 about here]

We proceed our analysis by performing quantile regression analysis for Model 2 (eq. 6). Comparing our results in Table 11 with those in Table 4, we can observe that changes in Debt to Market Capitalization and Volatility remain significant across all quantiles. However, the coefficient for $\Delta \mathrm{Vol}$ substantially increases both in magnitude and in significance at higher quantiles, that is, from 0.19 at the 10% quantile to 0.34 at the 90% quantile. This is in line with the findings of GCM (2001) who note that increases in volatility have a strong impact on credit spreads while decreases do not.

Changes in the Price to Book ratio are also significant for all quantiles at the 5% confidence level, apart from the 10% quantile in which they are significant at the 10% confidence level (p-value 5.21%). The coefficient for Price to Book ratio is more than doubled at the upper quantiles, i.e. -0.2161 and -0.2258 for the 75% and 90% quantiles respectively, compared to the lower ones, i.e. -0.0864 and -0.1085 at the 10% and 25% quantiles respectively. To sum up, our empirical evidence suggests that while the Price to Book ratio contributes more in CDS spread increases, its significance remains at high levels at all quantiles.

In our main specification (Model 2, Table 4) we find that changes in Earnings per Share are not significant in determining CDS spread changes. However, our results under the quantile regression analysis suggest that profitability matters for medium CDS spread increases (75% quantile). Finally, Sales Growth to Tangible Assets is significant in the first four quantiles while it appears not to contribute in the large positive CDS spread changes as it becomes insignificant at the 90% quantile. This can be attribute to the fact that Sales expansion is not that type of variable that would cause immense fears about an issuer, and hence lead to huge CDS spread widening.

The explanatory power of Model 2 is higher than of Model 1 by about one percentage unit at all quantiles. What is more, the explanatory power of Model 2 (eq.6) increases significantly when we move from lower to higher quantiles, as in Model 1. The pseudo R-squared increases from 18.8% at the 10% quantile to 36.8% at the 90% quantile.

All in all, the above analysis indicates that the CDS market responses are asymmetrical with respect to changes in the financial statement variables, verifying once again the inherent asymmetric nature of credit risk.

[Insert Table 11 about here]

5. Robustness Checks

In setting up our models in section 4, we use fixed effects in the time dimension to capture both the observable and unobservable components of systemic factors in our analysis. There is a number of studies that restricts the systemic factors to those whose variation can be captured with the help of observable macroeconomic variables (CGM. 2001, Avramov 2007, Das S. 2009, Tang D. 2009). In an attempt to assess the robustness of our results, we re-examine models 1-2 using instead of fixed effects in the time dimension the following macroeconomic variables: GDP growth rates, at-the-money implied volatility changes for stock indices, stock index returns, changes in sentiment indices, changes in volatility smirk (the difference between the volatility of at-the-money options minus the volatility of out-of-money options), changes in 3m rates (Euribor or Libor), changes in 2yr swap rates, changes in 10yr swap rates, changes in the slope of the yield curve (10yr minus 2yr swap rates), changes in the difference between the credit spread of BBB firms minus AAA firms, changes in inflation, squared changes for 3m rates, 2yr swap rates and 10yr swap rates, as well as cubed changes for the 10 yr swap rates. We map the macroeconomic variables to each firm based on the country of its operations and its respective currency.

We perform Principal Component Analysis on these macroeconomic variables and examine the effects of their principal components in Models 1 and 2. We do so to avoid, in our model, the well-known interactions among these macroeconomic variables (e.g. positive relationship between interest rates and inflation, etc.) that may cause multi-colinearity problems. Untabulated[22] results suggest that even after the inclusion in our base models of the first four principal components of the macroeconomic variables, neither the significance nor the level of the coefficients for the financial ratios we use are materially affected. In particular, all the coefficients remain highly significant, except for the coefficient of Price to Book ratio in Model 2 (eq. 6) that remains significant only at the 10% confidence level.

What we consider next as important in assessing the robustness of our results is whether our model performs equally well, whether we use implied or historical volatility. There are studies (Christensen and Prabhala 1998, Chalamandaris G. and Rompolis L., 2009) that demonstrate that past realized volatility is linked to current implied volatility. Untabulated results[23] confirm that we reach to the same qualitative conclusions as those in Model 2 (Table 4) in case we use a subsample of 4650 observations for which changes in implied volatility are available in our sample. The only worth-mentioned difference is that the coefficients for Earnings per Share and the Sales Growth to Tangible Assets lose a bit in significance, however, they remain significant at the 10% confidence level. Therefore, for the purposes of our analysis the use of 90 days historical volatility change can be considered as an adequate "proxy" for implied volatility change since our findings remain almost unaffected.

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[22] These results are available on request.

[23] These results are available on request.

6. Conclusions

In this study we utilize a large dataset consisting of 6,244 announcements of quarterly financial reports for companies around the world for which data is available in Bloomberg, to analyze how changes in financial ratios affect CDS spreads changes, and explore further the underlying properties of this relationship under the frame of structural models theory.

Our findings in many ways confirm both the insights of structural model theory and the intuition behind the workings of the CDS market. First of all, we find that only a relatively small set of 4 financial ratios, selected via the LASSO approach, is enough to capture most of the information in the entire financial statements that is relevant to changes in the CDS spreads. Among the 22 financial ratios that are examined, we include in our main model just Debt to Market Capitalization (leverage), Price to Book Ratio (valuation), Earnings per Share (profitability) and Sales Growth to Tangible Assets.

Secondly, are results imply that the CDS market is efficient in correctly anticipating the greatest part of changes in the financial ratios a whole week before these are officially made known, indicating that there are not any "surprises" in the CDS market arising from the announcement of a firm's financial statements.

Thirdly, being motivated by contingent claims theory we find evidence that the relationship between CDS changes and the changes in the financial ratios is nonlinear. The coefficients of the model that links the two sets of changes vary, depending on the leverage of a particular entity or on its valuation ratios. At the same time, using again threshold analysis we verify the intuition that in periods of financial turmoil the CDS market is driven mostly by systemic factors.

Fourth, our findings confirm the empirical evidence of other studies pertaining to the asymmetrical impact of financial ratios on the pricing of credit risk of individual issuers. We observe that while negative news transmitted by the financial statements largely affect the widening of CDS spreads, positive news do not have a similar contribution.

Finally, we perform a series of robustness checks to assess the validity of our results. Using observable systemic factors rather than fixed effects in the time dimension we find that our inferred models remain qualitatively the same. At the same time, using a sub-sample of our dataset for which options data are available, we test whether our model performs equally well when using implied instead of historical volatility, only to verify once again that our findings still hold.

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Table 1: Country & Credit Rating profile of our sample

Panel A

Country	Observations
US	4,119
Germany	461
Italy	202
Switzerland	196
Netherlands	177
Spain	165
Canada	161
Sweden	149
Finland	117
Great Britain	111
France	87
Other	299
Total	6,244

Panel B

Credit Rating	Observations
AAA	8
AA	411
A	2,032
BBB	2,426
BB	728
B	290
CCC	126
CC	15
C	5
Default	20
Not Rated	183
Total	6,244

Panel A and Panel B of Table 1 present the Country and the Credit rating profile of our sample respectively. There are 6,244 observations in our sample that are downloaded from Bloomberg. Our dataset ranges from 31/12/2003 to 31/12/2008 and include companies all over the world for which data is available on Bloomberg. About two thirds of our observations come from the US, and about two thirds have a credit rating of A or BBB, as of the date of downloading the dataset.

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Table 2: Analysis of sample by quarter dimension

Quarter	End Date	Observations	Average CDS spread (in b.p.)
1	31-Mar-2004	234	66
2	30-Jun-2004	247	73
3	30-Sep-2004	289	61
4	31-Dec-2004	292	49
5	31-Mar-2005	312	71
6	30-Jun-2005	312	64
7	30-Sep-2005	308	72
8	31-Dec-2005	303	68
9	31-Mar-2006	304	56
10	30-Jun-2006	302	63
11	30-Sep-2006	312	55
12	31-Dec-2006	289	41
13	31-Mar-2007	284	47
14	30-Jun-2007	296	87
15	30-Sep-2007	291	77
16	31-Dec-2007	332	148
17	31-Mar-2008	325	149
18	30-Jun-2008	328	195
19	30-Sep-2008	453	326
20	31-Dec-2008	431	419
Total		6,244	123

The number of observations per quarter as well as the average CDS spread of each quarter are presented in Table 2. There are 6,244 observations of 5yr CDS spreads changes on senior debt, ranging from 31/12/2003 to 31/12/2008, that are downloaded from Bloomberg. There are on average 312 observations per quarter, and the average CDS spread for all companies included in our sample is 123 b.p..

Table 3: Descriptive statistics of variables

	CDS 3-months change	CDS 2-weeks change	Volatility 3-months change	Volatility 2-weeks change	Debt to Market Capitalization change
Mean	0.1033	0.0064	0.0739	0.0351	0.0356
Median	0.0193	-0.0037	0.0498	0.0213	0.0053
Maximum	2.3834	1.3794	2.0588	0.9185	2.0032
Minimum	-2.1924	-0.8252	-1.2092	-0.8303	-2.0010
Std. Dev.	0.4271	0.1465	0.2565	0.0760	0.2932
Skewness	0.8481	1.1622	0.7825	1.7498	0.9050
Kurtosis	4.3301	10.8873	6.1389	18.1269	15.0400
Observations	6,244	6,244	6,244	6,244	6,244
	Price to Book Ratio change	**Earnings per Share change**	**Sales Growth to Tangible Assets**	**Price to Book Ratio**	**Debt to Market Capitalization**
Mean	-0.0268	-0.0612	0.0152	2.9114	1.1711
Median	-0.0107	0.0051	0.0095	2.0505	0.3750
Maximum	0.9677	8.5112	0.6077	53.8083	27.2931
Minimum	-1.2470	-11.8234	-0.4250	0.0475	0.0026
Std. Dev.	0.2079	1.2757	0.0502	4.2586	2.8323
Skewness	-0.7228	-2.2046	1.3217	8.4067	5.6509
Kurtosis	10.7010	37.2198	20.6772	89.5152	42.1347
Observations	6,244	6,244	6,244	6,244	6,244

In table 3 we display descriptive statistics for the variables that are used in the analysis, whether included as dependent or as independent variables. Our sample contains 6,244 observations and covers the period from 31/12/2003 to 31/12/2008.

Table 4: Explaining the CDS spread 3-months changes

	Model 1		Model 2	
	Coefficient	t-statistics	Coefficient	t-statistics
Constant	0.0483	3.7347*	0.0442	3.3440*
Debt to Market Capitalization change	0.1213	5.3153*	0.1147	5.3548*
Price to Book Ratio change	-0.1600	-5.5212*	-0.1310	-4.6819*
Earnings per Share change	-0.0095	-2.3863*	-0.0061	-1.6318
Sales Growth to Tangible Assets	0.0436	2.5960*	0.0383	2.3934*
Volatility change – 3 months			0.3282	10.9439*
Time Dummies	Yes		Yes	
R-squared	0.4408		0.4636	
Adjusted R-squared	0.4387		0.4615	
Observations	6,244		6,244	

Table 4 reports regression coefficients and t-statistics (adjusted for heteroskedasticity and autocorrelation) for Models 1 & 2. The dependent variable is the 3 month CDS spread change. The independent variables that are included in our models are selected by employing the LASSO approach. These are the following financial ratios: Debt to Market Capitalization change, Price to Book Ratio change, Earnings per Share change and Sales Growth to Tangible Assets. Model 1 includes as independent variables only financial ratios and period fixed effects, while Model 2 incorporates also the equity return Volatility change. T-statistics above 2.577 (in absolute terms) mean significance at 1% confidence level, t-statistics above 1.96 (in absolute terms) mean significance at 5% confidence level and t-statistics above 1.645 (in absolute terms) mean significance at 10% confidence level. * Denotes significance at 5%.

Table 5: Explaining the CDS spread 2-weeks changes

Panel A					Panel B				
	Model 3a		Model 4a			Model 3b		Model 4b	
	Coefficient	t-statistics	Coefficient	t-statistics		Coefficient	t-statistics	Coefficient	t-statistics
Constant	0.0093	1.7992	0.0053	1.0051	Constant	0.007087	0.74	0.002543	0.26
Debt to Market Capitalization change	0.0054	0.7097	0.0062	0.8102	Price to Earnings Change	0.018797	3.06*	0.018804	3.03*
Price to Book Ratio change	-0.0032	-0.296	-0.0008	-0.0747	Sales Growth to Tangible Assets	-0.01653	-3.7*	-0.01598	-3.59*
Earnings per Share change	-0.0013	-0.8601	-0.0011	-0.7362	Cash Flow from Operations to Total Debt change	0.002568	1.77	0.003201	2.15*
Sales Growth to Tangible Assets	-0.0064	-0.742	-0.0045	-0.5193	Operating Income to Total Capital Change	-	-	-0.00592	-1.9
Volatility change - 2 weeks			0.1531	3.7543*	Volatility change - 2 weeks	-	-	0.168863	6.92*
Time Dummies	Yes		Yes		Time Dummies	Yes		Yes	
R-squared	0.1664		0.1721		R-squared	0.1694		0.1771	
Adjusted R-squared	0.1633		0.1689		Adjusted R-squared	0.1660		0.1735	
F-statistic	53.973		53.872		F-statistic	51.13		48.98	
Observations	6,244		6,244		Observations	5,485		5,485	

Table 5 displays regression coefficients and t-statistics (adjusted for heteroskedasticity and autocorrelation) for Models 3a-b & 4a-b. The dependent variable is the 2 weeks CDS spread change. The independent variables included in models 3a and 4a are the ones selected under our main model specifications, while the independent variables included in models 3b and 4b are selected by examining again the initial set of financial ratios with the use of the LASSO algorithm. Furthermore, 2-weeks equity returns' Volatility change are included in Models 4a and 4b. * Denotes significance at 5%.

Table 6: Threshold analysis for CDS spread 3-months changes

Threshold Variables	Number of Splits	Threshold Value	Bootstrap p-value	Total Joint R-squared
Debt To Market Capitalization	No split	-	-	0.4636
	1st Split	0.4221	0.0000	0.4790
	2nd Split	0.1100	0.0006	0.4840
	3rd Split	2.5811	0.0000	0.4923
Price to Book Ratio	No split	-	-	0.4636
	1st Split	2.2849	0.0000	0.4750
	2nd Split	0.8923	0.0587	0.4805
	3rd Split	1.5280	0.0233	0.4853
Quarter	No split	-	-	0.1820
	1st Split	14	0.0000	0.2500
	2nd Split	8	0.0000	0.2854
	3rd Split	17	0.0000	0.3378

In table 6 we summarize the splits that our sample can be divided in using a statistically appropriate categorization within which regression coefficients are significantly different, following Hansen's (2000) methodology. In the table we also include the threshold variable, the respective threshold values, the significance of each threshold value indicated by the Bootstrap p-value, as well as the total explanatory power of our model after each sample split given by the Total joint R-squared.

Table 7: Explaining the CDS spread 3-months changes using Debt to Market Capitalization ratio as threshold variable

	Regime 1 (< 0.11)		**Regime 2 (0.11 <= Reg. 2 < 0.42)**		**Regime 3 (0.42 <= Reg. 3 < 2.58)**		**Regime 4 (>= 2.58)**	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.0489	0.7246	0.0468	2.3776*	0.0508	2.5842*	-0.0021	-0.0518
Volatility change – 3m	0.3935	5.5000*	0.3025	7.8092*	0.2902	7.3644*	0.3802	3.0931*
Debt to Market Capitalization change	0.0483	0.8729	0.0711	2.6680*	0.1567	4.9493*	0.1915	3.4480*
Price to Book Ratio change	-0.1687	-1.8543	-0.1402	-3.3276*	-0.1168	-2.9158*	-0.0325	-0.4101
Earnings per Share change	0.0098	0.7193	-0.0057	-0.8275	-0.0055	-1.2326	-0.0152	-1.3518
Sales Growth to Tangible Assets	0.1178	1.4681	0.0228	0.6763	0.0445	1.8529	-0.0181	-0.5153
Time Dummies	Yes		Yes		Yes		Yes	
Observations:	668		2,718		2,252		606	
Total Joint R-squared	0.4923							

In table 7 we describe regression coefficients and t-statistics (adjusted for heteroskedasticity) for the four sub-samples that our initial sample can be divided in. The dependent variable is the 3-months CDS spread change. As threshold variable the Debt to Market Capitalization ratio is used. The independent variables include the following 4 financial ratios: Debt to Market Capitalization change, Price to Book Ratio change, Earnings per Share change and Sales Growth to Tangible Assets. Furthermore, 90-days equity-returns volatility change is used as independent variable. Our sample contains 6,244 observations that were downloaded from Bloomberg.

* Denotes significance at 5%.

Table 8: Explaining the CDS spread 3-months changes using Price To Book Ratio as threshold variable

	Regime 1 (<0.89)		**Regime 2 (0.89 <= Reg. 2 < 1.53)**		**Regime 3 (1.53 <= Reg. 3 < 2.28)**		**Regime 4 (>= 2.28)**	
	Coefficient	t - statistic	Coefficient	t - statistic	Coefficient	t - statistic	Coefficient	t - statistic
Constant	-0.0404	-1.4859	0.0399	1.6565	0.0312	1.1549	0.0623	2.8304*
Volatility change – 3m	0.4401	4.6543*	0.2416	4.3735*	0.3904	6.6318*	0.2859	7.7839*
Debt to Market Capitalization change	0.2157	3.4433*	0.1105	2.7787*	0.1071	2.4653*	0.1084	3.8205*
Price to Book Ratio change	0.0795	0.8075	-0.3661	-5.9168*	-0.0566	-0.9012	-0.1021	-2.7696*
Earnings per Share change	-0.0007	-0.1027	-0.0122	-1.7889	-0.0088	-1.5409	0.0030	0.3271
Sales Growth to Tangible Assets	0.0596	1.2914	-0.0211	-0.6023	0.0331	1.2264	0.0723	2.1286*
Time Dummies	Yes		Yes		Yes		Yes	
Observations:	384		1,464		1,708		2,688	
Total Joint R-squared	0.4853							

Table 8 presents regression coefficients and t-statistics (adjusted for heteroskedasticity) for the four sub-samples that our initial sample can be divided in. The dependent variable is the 3- months CDS spread change. As threshold variable the Price to Book Ratio is used. The independent variables include the following 4 financial ratios: Debt to Market Capitalization change, Price to Book Ratio change, Earnings per Share change and Sales Growth to Tangible Assets. Furthermore, 90-days equity-returns volatility change is used as independent variable. * Denotes significance at 5%.

Table 9: Explaining the CDS spread 3-months returns with structural changes along the time dimension

	Regime 1 (< 8)		Regime 2 (8 <= Reg. 2 < 14)		Regime 3 (14 <= Reg. 3 < 17)		Regime 4 (>=17)	
	Coefficient	t - statistic	Coefficient	t - statistic	Coefficient	t - statistic	Coefficient	t - statistic
Constant	-0.0009	-0.1186	-0.0839	-10.5238*	0.4131	20.0689*	0.0332	2.2463*
Volatility change – 3m	0.3554	7.8580*	0.2670	6.7977*	0.0886	1.1556	0.7385	19.5347*
Debt to Market Capitalization change	0.1404	2.9493*	0.0569	1.7191	0.1497	2.3873*	0.1370	3.9335*
Price to Book Ratio change	-0.1277	-2.0349*	-0.2198	-4.3438*	-0.0517	-0.5464	-0.0090	-0.1962
Earnings per Share change	0.0060	0.6814	-0.0033	-0.4503	-0.0229	-1.5164	-0.0056	-0.9848
Sales Growth to Tangible Assets	0.0045	0.1816	0.0033	0.0959	0.2650	3.7692*	0.0732	1.9265
Time Dummies	No		No		No		No	
Observations:	1,994		1,794		919		1,537	
Total Joint R-squared	0.3378							

In table 9 we presents regression coefficients and t-statistics (adjusted for heteroskedasticity) for the four sub-samples that our initial sample can be divided in. The dependent variable is the 3- months CDS spread change. As threshold variable the Quarter is used. The independent variables include the following 4 financial ratios: Debt to Market Capitalization change, Price to Book Ratio change, Earnings per Share change and Sales Growth to Tangible Assets. Furthermore, 90-days equity-returns volatility change is used as independent variable. * Denotes significance at 5%.

Table 10: Explaining CDS spread 3-months changes for different quantiles – Model 1

Quantile:	**10%**		**25%**		**50%**		**75%**		**90%**	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	-0.1733	0.0000	-0.0812	0.0000	0.0339	0.0233	0.1731	0.0000	0.2774	0.0000
Debt to Market Capitalization change	0.0798	0.0000	0.1119	0.0000	0.1023	0.0000	0.1187	0.0000	0.0864	0.0402
Price to Book Ratio change	-0.1167	0.0000	-0.1149	0.0004	-0.1598	0.0000	-0.2411	0.0000	-0.2249	0.0001
Earnings per Share change	0.0011	0.7419	-0.0013	0.7826	-0.0052	0.2563	-0.0145	0.0010	-0.0172	0.0497
Sales Growth to Tangible Assets	0.0579	0.0001	0.0369	0.0820	0.0519	0.0022	0.0501	0.0143	-0.0117	0.6580
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Pseudo R-squared	0.1819		0.2201		0.2754		0.3442		0.3506	
Observations	6,244		6,244		6,244		6,244		6,244	

In table 10 we report quantile regression coefficients and p-values for Model 1 (eq. 5). The dependent variable is the 3 months CDS spread change. The independent variables include: Debt to Market Capitalization change, Price to Book Ratio change, Earnings per Share change, Sales Growth to Tangible Assets changes, changes in 90-days equity-returns volatility as well as fixed effects in the time dimension. The coefficients and the p-values for the factors that affect the CDS spread changes are examined in 5 quantiles, that is, 10% - large negative changes, 25% - negative changes, 50% - median, 75% - positive changes and 90% - large positive changes.

Table 11: Explaining CDS spread 3-months changes for different quantiles – Model 2

Quantile:	10%		25%		50%		75%		90%	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	-0.1609	0.0000	-0.0751	0.0000	0.0280	0.0747	0.1641	0.0000	0.3033	0.0000
Debt to Market Capitalization change	0.0888	0.0002	0.1109	0.0000	0.1096	0.0000	0.0946	0.0002	0.0945	0.0374
Price to Book Ratio change	-0.0864	0.0521	-0.1085	0.0000	-0.1441	0.0000	-0.2161	0.0000	-0.2258	0.0004
Earnings per Share change	-0.0008	0.8652	0.0005	0.8943	-0.0014	0.7463	-0.0103	0.0027	-0.0122	0.1299
Sales Growth to Tangible Assets	0.0491	0.0433	0.0340	0.0435	0.0587	0.0033	0.0408	0.0205	-0.0295	0.0954
Volatility change – 3m	0.1934	0.0000	0.1994	0.0000	0.2272	0.0000	0.2628	0.0000	0.3441	0.0000
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Pseudo R-squared	0.1881		0.2282		0.2840		0.3546		0.3676	
Observations	6,244		6,244		6,244		6,244		6,244	

In table 11 we present quantile regression coefficients and p-values for Model 2 (eq. 6). The dependent variable is the 3 months CDS spread change. The independent variables include: Debt to Market Capitalization change, Price to Book Ratio change, Earnings per Share change, Sales Growth to Tangible Assets changes, changes in 90-days equity-returns volatility as well as fixed effects in the time dimension. The coefficients and the p-values for the variables that affect the CDS spread changes are examined in 5 quantiles, that is, 10% - large negative changes, 25% - negative changes, 50% - median, 75% - positive changes and 90% - large positive changes.