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How does credit default swap volatility influence the Z-Score Models?

Francisco Soeiro da Cunha Barreto [1]

José Nuno Teixeira de Abreu de Albuquerque Sacadura [2]

ABSTRACT

The literature on credit models has produced a large body of empirical research, but no consensus has emerged and scholars often disagree about the same empirical evidence. We contribute to the current literature by studying the relationship between Z-Score Models and Credit Default Swaps (CDS). The CDS provide a clean measure of risk as they are the compensation that market participants require for bearing credit default risk. We examine the CDS spreads, CDS market volatility and CDS annual performance and their relationship with Multi Discriminant Analysis Credit models (Altman's Z-Score (1968), Z-Score' (1983), Z-Model (1993) and Ohlson's O-Score (1980)).

Using a sample of 50 European companies and their annual CDS data available over the period 2006-2016, we find a strong negative relationship between all the credit models and the CDS market volatility and CDS market performance. We found little evidence between the models and the CDS spreads. These results suggest the notion that Credit Default Swaps have direct relevance to debtholders.

Key-words: CDS Volatility, CDS spread, Z-Score, Default Probability

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[1] Address: ISCAL, Av.Miguel Bombarda nº20, 1050-166 Lisbon, Portugal. Email: francisbarretpo95@gmail.com

[2] Corresponding Author: Address: ISCAL, Av.Miguel Bombarda nº20, 1050-166 Lisbon, Portugal. Email: jnsacadura@iscal.ipl.pt

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1.Introduction

A Credit Default Swap (CDS) is a contract that provides insurance against the default risk of a company or a sovereign. The use of this contract is common in financial markets, as it can be used as a tool to speculate in securities, but also to reduce financial leverage (Boehmer, Chava, & Tookes, 2015; Saretto & Tookes, 2013; Subrahmanyam, Tang, & Wang, 2014). Liu and Zhong (2017) associate the CDS contract to uncertainties such as political and financial risk. Moreover, the CDS can be used as a measure of default occurrence, either by the form of its CDS spread (L. Liu, Zhang, & Fang, 2016) or establishing the link between equity markets and the probability of default (Boehmer et al., 2015; Tolikas & Topaloglou, 2017).

Credit models have been studied by several authors, since the seminal work by Altman (1968a).Reisz and Perlich (2007) used the Log function of the Z-score (E. Altman, 1968a) to develop, in conjunction with the Black-Scholes model, a market based methodology to predict bankruptcy. Other authors used machine learning models, support vector machines, bagging boosting methods and MLP neural networks to assess and predict credit default (Barboza, Kimura, & Altman, 2017; Hernandez Tinoco & Wilson, 2013). Another method that was also used was the LASSO method by Tian & Yu (2017) in the Japanese market. All these studies concluded that the Z-Score Model is still the benchmark, despite its age.

The majority of works link default prediction to firm performance (Al-Kassar & Soileau, 2014; Goto, 2010; Rim & Roy, 2014), stock market behavior and valuation (Tolikas & Topaloglou, 2017). However, very few articles connect directly the CDS spread and credit models such as the Altman’s Z-Score (1968). The use of Multiple Discriminant Analysis credit models focuses in the Altman (1968) Z-Score, using this as a distance measure of the default of a company and correlating it as a sub proxy of either the firm value or the firm regulation driver for the equity market versus the CDS market (Boehmer et al., 2015).

How does credit default swap volatility influence the Z-Score Models?

In this paper, we aim to study the relationship between the Z-score Models and the CDS spread, CDS spread volatility and the CDS spread performance. Since the majority of the CDS studies focuses on the Chinese (Lin, Lo, & Wu, 2016), Japanese (Tian & Yu, 2017), but mostly American markets (E. Altman, 1968a; E. I. Altman, 1984; Barboza et al., 2017; Lin et al., 2016; Rim & Roy, 2014), we find relevant to focus on European Markets.

Our sample comprises 50 companies across 8 different European countries from 2006 to 2016.

We build our sample based on all the companies listed in Eurostoxx50 with a 10-year period to assure robustness and relevance of the study.

This paper is organized as follows: section 2 will explain the data methodology, that is how the sample was gathered and the problems associated with it. Section 3 will provide a CDS market overview. The regression analysis and findings between the models and the CDS explanatory variables will be described in section 4. Section 5 will summarize and present the conclusion of this paper.

2.Data and Sample Construction

2.1.CDS Data

In order to build our sample, we retrieved information from Bloomberg regarding the firms quoted in Eurostoxx50, covering 50 companies from eight different European countries. The Gross National Product (GNP), which is a variable necessary to build the O-Score model (Ohlson, 1980), was gathered from Datastream for each different country. Our Data sample comprised annual observations from 2006 to 2016, covering a 10-year interval and with 549 observations for 50 companies. Table 1 presents the description of the companies analyzed, the period of the sample, the country of origin of each company and the industry sector of each company. Table 2 presents the model variables taking into consideration in this paper as well as their respective abbreviations. Table 3 summarizes the general statistics of the sample namely the control and explanatory variables of the ZSCORE1, ZSCORE2, ZMODEL and OSCORE models.

2.2. Empirical Analysis

For our empirical analysis we chose three MDA models developed by Altman (1968, 1983, 1993) and the model developed by Ohlson (1980) which was the first to employ conditional probabilities in the model. The MDA models developed by Altman and that we selected are present as follows (Fig1):

Fig1-Z-Score Models developed by Altman

ALTMAN MODELS	Z-SCORE (1968)	Z-SCORE (1983)	Z-MODEL (1993)
X1	Working capital / Total Assets	Working capital / Total Assets	Working capital / Total Assets
X2	Retain earnings / Total Assets	Retain earnings / Total Assets	Retain earnings / Total Assets
X3	EBIT/Total Assets	EBIT/Total Assets	EBIT/Total Assets
X4	Market equity value/ book value of total debt	Book Equity value/ total Liabilities	Book Equity value/ total Liabilities
X5	Sales/Total Assets	Sales/Total Assets	_
Safe zone	Z >2.99	Z >2.90	Z >2.90
Grey zone	1.80< Z <2.99	1.23< Z <2.90	1.23< Z <2.90
Distress Zone	Z < 1.80	Z < 1.23	Z < 1.23
	Z-Score (Altman 1968) *Z =1.2*X1+1.4*X2+3.3*X3+0.6*X4+0.999X5* *Z-Score' (Altman 1983)* *Z'= 0.717*X1+0.847*X2+3.107*X3+0.420X4+0.998*X5* *Z-Model (Altman 1993)* *Z-MODEL= 6.56*X1+3.26*X2+6.72*X3+1.05*X4*		

Source: Own elaboration (2018).

The Z-Score Models and Z-score methodology is based on Multi Discriminant Analysis (MDA).

Using this statistical approach, Altman developed these models classifying the observations into groups according to its qualitative data, namely into bankrupt or non-bankrupt.

Altman (1968a) used this technique in conjunction to the statistical significance of each ratio to select the financial ratios for the model in order to accurately predict default occurrence.

The table above shows the models that were developed and improved by Altman the Z-score (1968), the Z-Score'(1983) and Z-Model (1993). However these models were not the only revisions made in the original Z-score (1968) and the Z-Score Mythology, some revisions worth mentioning regarding the Z-score and its applications were , the application of the logarithm function on the Z-score (Lepetit & Strobel, 2015), the inclusion of the real earnings into the Z-Score (1968) as explained and developed by Lin, Lo, and Wu (2016).
Other Application and updated in the Z-Score(1968) was the creation of the emerging market score, EMS Score, developed by Altman (2005).

In this paper, we define alternatively our Dependent Variables as ZSCORE1 which is the Z-score model from 1968, ZSCORE2 being the Z-Score'(1983) and ZMODEL which is Z-Model (1993).

Rim and Roy (2014) and Boehmer, Chava, and Tookes (2015) who used the Z-score'(1983) and mostly Z-Score (1968) to classify the firms regarding its credit worthiness and default probability, correlated the model with the firm value and connected it indirectly with the CDS premium. They concluded that the Z score'(1983) is a good barometer for assessing a company credit worthiness and perceive its default risk. Tolikas and Topaloglou (2017) employ the Z-score (1983 and 1968) to measure the average financial distress of firms worldwide and correlate the results with the stock market and CDS Spread. They suggest that there is no difference between the models used. Other authors just correlate the Z-score and firm value and establish a indirect link in their correlation with the CDS Market, focusing only on the default effect of the firm value (Boehmer et al., 2015) or the effect of CDS trading on firm value (Lepetit & Strobel, 2015; Lin et al., 2016; Tolikas & Topaloglou, 2017), however they disregard the Z-model (1993).

Due to the widespread of the Z-Score methodology namely the Z-Score of 1968 and due to its simplicity and applicability this model has a more wide use than the other models and later improvements (Lepetit & Strobel, 2015; Lin et al., 2016).

Despite including not only the ZMODEL and ZSCORE2 we also include in our regression tests the OSCORE which is the Ohlson (1980) O-score Model, based on the model described in the table below. We computed all the data of the entire sample like we did for the other models previously mentioned and assess the relevance of the OSCORE and its relation with the CDS Z-Score models and the O-score which was implied to have a similar performance between them (Lin et al., 2016). Figure 2 shows the variables considered by Ohlson (1980).

Fig 2 – O-Score Model developed by Ohlson

OHLSON (1980)	O-SCORE MODEL VARIABLES AND MODEL EQUATION
X1	X1=ln (Total Assets/GNP Price Level)
X2	X2= Total Liabilities /Total Assets
X3	X3= Working Capital / Total Assets
X4	X4= Current Liabilities / Current Assets
X5	X5= Net Income/ Total Assets
X6	X6= Operational Cash flow / Total Liabilities
X7	X7= 1 if net income negative for last 2 years, 0 otherwise
X8	X8= 1 if Total Liabilities > Total Assets, 0 otherwise
X9	NI – Net Income $X9 = (NI_t - NI_{t-1})/(\lvert NI_t \rvert + \lvert NI_{t-1} \rvert)$
$\boldsymbol{OS = -1.33 - 0.407X1 + 6.03X2 - 1.43X3 + 0.076X4 - 2.37X5 - 1.83X6 + 0.285X7 - 1.72X8 - 0.521X9}$	

Source: Own elaboration (2018).

2.3.CDS Variables

The data gathered to build the explanatory variables retrieved from Bloomberg regards the period 2006 - 2016, being all annual data. We created three independent CDS variables.

The variable CDSPX represents the end-of-year quote for the CDS spread for each company in the sample, covering all the 10-year period. To measure the annual volatility, we created a variable named VOLACDS, which is the annualized daily volatility of the CDS market spread gathered from Bloomberg terminal. In order to assess the variation of the CDS premium and its behavior we gather daily CDS premium observations of each Year and calculated its natural logarithm for each company attaining in the end the annual logarithm of the CDS premium, here named as LOGCDS, which is the CDS Performance.

2.4. Control Variables

Regarding the control variables and using the methodology of Rim and Roy (2014) that used the financial ratios as control variables we apply the same logic in our paper and regarding both the Z-Score models from Altman(1968,1983,1993) and the O-score from Ohlson (1980).

With that for the Z-score models we constructed the following individual regression equations with the control variables:

(1) $ZSCORE1_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 BVL_{i,t} + \beta_6 EAR_{i,t} + \beta_7 VOLACDS_{i,t} + \varepsilon_{i,t}$

(2) $ZSCORE1_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 BVL_{i,t} + \beta_6 EAR_{i,t} + \beta_7 CDSPX_{i,t} + \varepsilon_{i,t}$

(3) $ZSCORE1_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 BVL_{i,t} + \beta_6 EAR_{i,t} + \beta_7 LOGCDS_{i,t} + \varepsilon_{i,t}$

(4) $ZSCORE2_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 TE_{i,t} + \beta_6 TL_{i,t} + \beta_7 EAR_{i,t} + \beta_8 VOLACDS_{i,t} + \varepsilon_{i,t}$

(5) $ZSCORE2_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 TE_{i,t} + \beta_6 TL_{i,t} + \beta_7 EAR_{i,t} + \beta_8 CDSPX_{i,t} + \varepsilon_{i,t}$

(6) $ZSCORE2_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 TE_{i,t} + \beta_6 TL_{i,t} + \beta_7 EAR_{i,t} + \beta_8 LOGCDS_{i,t} + \varepsilon_{i,t}$

(7) $ZMODEL_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 TE_{i,t} + \beta_6 TL_{i,t} + \beta_7 VOLACDS_{i,t} + \varepsilon_{i,t}$

(8) $ZMODEL_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 TE_{i,t} + \beta_6 TL_{i,t} + \beta_7 CDSPX_{i,t} + \varepsilon_{i,t}$

(9) $ZMODEL_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 RET_{i,t} + \beta_4 EBIT_{i,t} + \beta_5 TE_{i,t} + \beta_6 TL_{i,t} + \beta_7 LOGCDS_{i,t} + \varepsilon_{i,t}$

Regarding the Olson O-score the regression equations the equations are the following:

(10) $OSCORE_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 GNP_{i,t} + \beta_4 TL_{i,t} + \beta_5 CL_{i,t} + \beta_6 CA_{i,t} + \beta_7 NI_{i,t} + \beta_8 OCF_{i,t} + \beta_9 VOLACDS_{i,t} + \varepsilon_{i,t}$

(11) $OSCORE_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 GNP_{i,t} + \beta_4 TL_{i,t} + \beta_5 CL_{i,t} + \beta_6 CA_{i,t} + \beta_7 NI_{i,t} + \beta_8 OCF_{i,t} + \beta_9 CDSPX_{i,t} + \varepsilon_{i,t}$

(12) $OSCORE_{i,t} = \beta_0 + \beta_1 WC_{i,t} + \beta_2 TA_{i,t} + \beta_3 GNP_{i,t} + \beta_4 TL_{i,t} + \beta_5 CL_{i,t} + \beta_6 CA_{i,t} + \beta_7 NI_{i,t} + \beta_8 OCF_{i,t} + \beta_9 LOGCDS_{i,t} + \varepsilon_{i,t}$

Fig 3 – Model Variables

VARIABLES		DESCRIPTION OF VARIABLES
TA	**(5)**	Total Assets
TE	**(2), (3)**	Total Equity
BVL	**(1)**	Book Value of Liabilities
WC	**(5)**	Working Capital
EAR	**(1), (2)**	Earnings
EBIT	**(1), (2), (3)**	Earnings Before Interest and Taxes
RET	**(1), (2), (3)**	Retained Earnings
GNP	**(4)**	Gross National Product
TL	**(2), (3), (4)**	Total Liabilities
CA	**(4)**	Current Assets
CL	**(4)**	Current Liabilities
NI	**(4)**	Net Income
OCF	**(4)**	Operational Cash Flow
CDSPX	**(5)**	CDS spread
LOGCDS	**(5)**	CDS performance
VOLACDS	**(5)**	Annualized Daily volatility of the CDS
(1) ZSCORE1; (2) ZSCORE2; (3) ZMODEL; (4) OSCORE; (5) ALL MODELS		

Source: Own elaboration (2018).

Regarding the assembly of the control variables of the models, all data was gathered from Bloomberg terminal, missing data was gathered from the companies' financial statements and reports, with the exception of the GNP variable that was gathered from the Reuters Datastream.

3.CDS Market Overview

According to (van der Merwe, Andria, 2016) there is a false pretentions that the CDS market as contracted due to the use of the portfolios that might reduce some contract numbers due to portfolio compression eliminating redundant positions. This reduction is referring specially to the notional of the contract of CDS, however it is not being considered significant regarding the CDS index products (van der Merwe ,Andria, 2016).

The most popular types of contracts according to (van der Merwe ,Andria, 2016) are Single name CDS which are linked only to a reference entity , asset backed securities CDS which is a type of contract backed by an asset like commercial mortgages for instance and structured financed CDS which have a loan as a reference entity, this types of contracts are vastly and most commonly used and its popularity and use has not shown any decrease through time.(van der Merwe ,Andria, 2016)

For instance, in terms of numbers and according with BIS the regarding the notional amounts of the CDS contracts it has been a decrease from $61.2 trillion at end-2007 to $9.4 trillion 10 years later, however the shares investments regarding the great financial crisis have been risen in 2017 to 64% specially regarding CDS of credit events contracts.

Regarding the CDS market news worldwide, there have been a recent turmoil regarding the use of CDS contracts and derivatives. In the US, there were news that a trade conflict between a company (Hovnanian) that defaulted part of its debt allowing other company (GSO) that had a contract to profit from a separate credit derivative, offering a relative cheap financing to the other party. This is a form of loop hole that are becoming more and more frequent and that its use turns the CDS contract useless due to the fact that this loophole prevents the CDS pay-outs ("Blackstone, Solus Settle Fight Over Hovnanian CDS Trade," 2018).

Deutsche Bank has been in a turmoil regarding its short sellers and increase of credit derivatives pilling on it, which signal doubt regarding the company future, even if they have capital reserves to ensure the doubt of investors, this movement on the behalf of the investors is because DB bank mentioned on the US. Regulatory report as being one of the banks present in the regulatory watch list which indicates that the bank might have problems, this led to a decrease of the one level regarding its rating notation and an increase on the Bearish movements by the investors , meaning an increase in CDS contracts.(“Deutsche Bank’s Slow Bleed Continues as a Pivotal Month Begins,” 2018)

In other news political conflicts in Italy is driving chaos regarding the increase in credit risk , increase on CDS spread which has passed even countries considered as being junk rated by the investors such as Brazil, Turkey and South Africa, despite this Italy is still considered an investment country by the rating agencies even if its experiencing political and fiscal Risk. (“Italy Now Troubles Bond Investors More Than Crisis-Ridden Turkey,” 2018) this situation led to the pope mentioning that the CDS traders are a form of sinful contract that bet on the demise of others and profit on their default being considered by the Pope as being predatory specially regarding the investors who speculate on the derivatives market. However this view of the Pope is considered short sided due to the fact that the benefits of the CDS contracts and derivatives were not considered such us achieving lesser borrowing costs , and allowing countries to get credit that would be out of reach otherwise.(“Pope’s Beef With CDS Market Is a Beef With All Markets,” 2018)

4.Empirical Results and Hypothesis

As described in the previous sections, both the CDS contracts and Altman Z-score models are related to Default Probability. We hypothesize that the Z-score models are negative correlated with the CDS price (CDSPX), as a higher Z-score represents a lower likelihood of default (E. Altman, 1968a; Rim & Roy, 2014) and, therefore, an increase in default probability will increase the risk associated and implying a negative correlation between them. Table 4 presents the OLS results and relationship between the selected credit models and the explanatory variable CDSPX.

VOLACDS represents the annual volatility of the CDS spread. We hypothesize a negative correlation with the models due to the relationship between risk and Z-score (E. Altman, 1968a; E. Altman & Rijken, 2010). Thus, a higher volatility represents a higher uncertainty and therefore a negative correlation between the models and the explanatory variable. Table 5 presents the OLS results between volatility and the selected credit model.

The CDS premium performance is represented by the LOGCDS which is the natural log function of the annualized daily CDS premium observations. It is hypothesized a negative correlation between the Z-score models (E. Altman, 1968a; E. Altman & Rijken, 2010) and the LOGCDS variable due to its connection between the risk and the variation of the default probability and how the Z-score is linked with the default probability (Hull 2015). Table 6 presents the OLS regression of the LOGCDS and the respective results.

To insure the robustness of the OLS regressions, we performed several tests regarding the heteroscedasticity and autocorrelation. The majority of the regressions presented significant results after controlling for all the major errors.

5.Conclusion

Credit Default Swaps have been in the center of the public eye since the 2007-2008 financial crisis. This crisis exposed the need for CDS regulation and more academic studies in order to help regulators, bondholders and all stakeholders. In this paper, we have provided new empirical evidence on CDS market in a European context. In contrast to other studies focused on other markets, we collected a sample of 50 European companies from eight different countries. Our findings suggest that CDS market volatility and CDS performance can improve the existent Z-Score Models. These models are still the most relevant for credit analysis and are often used as benchmarks for developing other models (E. I. Altman, Haldeman, & Narayanan, 1977a; Lepetit & Strobel, 2015; Lin et al., 2016; Rim & Roy, 2014).

Concerning the CDS price variable we find mixed result, using the Z-Score Models or the O-Score. Although further research is needed to fully explain this result, it is consistent with the view from Lepetit and Strobel (2015).

The Z-score is a tool to determinate and assess the default probability as a form of locating the likelihood of default in different zones (E. Altman, 1968a; E. I. Altman, Haldeman, & Narayanan, 1977b) and that might mean that it is not directly correlated with the probability of default . In the other hand, the O-score is a tool that provides the direct probability of default straight from its output (Ohlson, 1980). This might explain why the correlation between the CDS Premium and the O-SCORE has a negative signal, while has a positive sign with the Z-SCORE model and its variants. This interpretation is corroborated by the results found by Lepetit and Strobel (2015) which suggest a reinterpretation of the default probability attained from the Z-score methodology as an odd of insolvency instead.

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TABLE 1 - Sample Description

Description of the sample including period of analysis, country of origin and industry sector of activities. All data from this table was collected from the Bloomberg terminal and all companies here refenced were quoted in the Eurostoxx50 during the period of analysis:

Name	Industry sector	Country	Period
ADIDAS	Personal & Household Goods	DE	2006-2016
AHOLD DELHAIZE	Retail	NL	2006-2016
AIR LIQUIDE	Chemicals	FR	2006-2016
AIRBUS	Industrial Goods & Services	FR	2006-2016
ALLIANZ	Insurance	DE	2006-2016
ANHEUSER-BUSCH INBEV	Food & Beverage	BE	2006-2016
ASML HLDG	Technology	NL	2006-2016
AXA	Insurance	FR	2006-2016
BASF	Chemicals	DE	2006-2016
BAYER	Health Care	DE	2006-2016
BBVA	Banks	ES	2006-2016
BCO SANTANDER	Banks	ES	2006-2016
BMW	Automobiles & Parts	DE	2006-2016
BNP PARIBAS	Banks	FR	2006-2016
CRH	Construction & Materials	IE	2006-2016
DAIMLER	Automobiles & Parts	DE	2006-2016
DANONE	Food & Beverage	FR	2006-2016
DEUTSCHE BANK	Banks	DE	2006-2016
DEUTSCHE POST	Industrial Goods & Services	DE	2006-2016
DEUTSCHE TELEKOM	Telecommunications	DE	2006-2016
E.ON	Utilities	DE	2006-2016
ENEL	Utilities	IT	2006-2016
ENGIE	Utilities	FR	2006-2016
ENI	Oil & Gas	IT	2006-2016
ESSILOR INTERNATIONAL	Health Care	FR	2006-2016
FRESENIUS	Health Care	DE	2006-2016
GRP SOCIETE GENERALE	Banks	FR	2006-2016
IBERDROLA	Utilities	ES	2006-2016
INDUSTRIA DE DISENO TEXTIL	Retail	ES	2006-2016
ING GRP	Banks	NL	2006-2016
INTESA SANPAOLO	Banks	IT	2006-2016
L'OREAL	Personal & Household Goods	FR	2006-2016
LVMH MOET HENNESSY	Personal & Household Goods	FR	2006-2016
MUENCHENER RUECK	Insurance	DE	2006-2016
NOKIA	Technology	FI	2006-2016
ORANGE	Telecommunications	FR	2006-2016
PHILIPS	Health Care	NL	2006-2016
SAFRAN	Industrial Goods & Services	FR	2006-2016
SAINT GOBAIN	Construction & Materials	FR	2006-2016
SANOFI	Health Care	FR	2006-2016
SAP	Technology	DE	2006-2016

SCHNEIDER ELECTRIC	Industrial Goods & Services	FR	2006-2016
SIEMENS	Industrial Goods & Services	DE	2006-2016
TELEFONICA	Telecommunications	ES	2006-2016
TOTAL	Oil & Gas	FR	2006-2016
UNIBAIL-RODAMCO	Real Estate	FR	2006-2016
UNILEVER NV	Personal & Household Goods	NL	2006-2016
VINCI	Construction & Materials	FR	2006-2016
VIVENDI	Media	FR	2006-2016
VOLKSWAGEN PREF	Automobiles & Parts	DE	2006-2016

Source: Own elaboration (2018).

TABLE 2 - Variable Description

This table presents the description of the variables taking into consideration in this paper and their respective abbreviations:

VARIABLES	DESCRIPTION OF VARIABLES
TA	Total Assets
TE	Total Equity
BVL	Book Value of Liabilities
WC	Working Capital
STCKPX	Price of the Stocks
MKTCAP	Market Capitalization
EAR	Earnings
EBIT	Earnings Before Interest and Taxes
RET	Retained Earnings
YIELD	Dividend 12 month Yield
CVENT	Current Value of the enterprise
EPS	Earnings Per Share
GNP	Gross National Product
CDSPX	CDS Spread
LOGCDS	CDS premium Performance
VOLACDS	Annualized Daily volatility of the CDS
ZSCORE1	Z-Score=1.2*Tt1+1.4*T2+3.3*T3+0.6*T4+0.999T5
ZSCORE2	Z-Score'=0.717*T1+0.847*T2+3.107*T3+0.420T4+0.998*T5
ZMODEL	Z-Model= 6.56*T1+3.26*T2+6.72*T3+1.05*T4
TL	Total Liabilities
CA	Current Assets
CL	Current Liabilities
NI	Net Income
OCF	Operational Cash Flow
OSCORE	OS=(-1.33)-(0.407*O1)+(6.03*O2)-(1.43*O3)+(0.076*O4)-(2.37*O5)-(1.83*O6)+(0.285*O7)-(1.72*O8)-(0.521*O9)

Source: Own elaboration (2018).

TABLE 3 - Sample Statistics

Presents all the general statistics employed in the variables used to explain and control de ZSCORE1, ZSCORE2, ZMODEL and OSCORE:

Stats	Mean	P50	Sd	N	Range	Min	Max	Skewness	Kurtosis
WC	13493.49	1839.55	107885.8	550	1755679	-644881	1110798	2.258715	30.72812
TA	239980.9	71097.5	434242.8	550	2201963	459.559	2202423	2.698537	9.910437
TE	28746.64	22156	22441.64	550	105073.1	146.896	105220	1.026423	3.505617
TL	211234.4	43276.25	419887.9	550	2170223	286.357	2170509	2.759739	10.23935
NI	2769.627	2304	2980.375	550	30910	-9198	21712	0.61346	8.03975
CL	79718.21	16980	190047.2	547	1376476	175.782	1376652	3.804021	17.92993
CA	93619.01	18254.17	199766.7	545	1658162	309.576	1658472	3.814744	21.25171
RET	13611.76	10924	14622.86	550	110824	-38944	71880	0.827147	5.722852
EBIT	4663.707	3647	4295.797	550	32319	-6663	25656	1.456571	6.851678
MKTCAP	42482.02	35403.83	27923.3	549	193921.7	511.9963	194433.7	1.231677	5.558138
BVL	211234.4	43276.25	419887.9	550	2170223	286.357	2170509	2.759739	10.23935
GNP	1909549	2106703	811848.1	549	3057270	139922	3197192	-0.55127	2.348209
OCF	7253.973	4327	12781.75	549	180435	-46972	133463	3.264048	28.86058
EAR	46695.22	39142	37184.05	550	216760.8	506.222	217267	1.468122	5.835909
CDSPX	46.28446	33.2845	41.22155	548	243.467	1.283	244.75	1.618701	5.938159
LOGCDS	-0.000038	-0.00049	0.01607	549	0.130976	-0.06448	0.0665	0.033388	5.003518
VOLDCDS	30.75834	27.2075	11.93122	540	64.208	13.875	78.083	1.281262	4.389221

Source: Own elaboration (2018).

TABLE 4 - OLS Regressions between Z-Score Models and CDS Spread

Presents the results of the individual regressions of the CDS SPREAD variable regarding the ZSCORE1, ZSCORE2, ZMODEL and O-SCORE:

		ZSCORE1	(SD)	ZSCORE2	(SD)	ZMODEL	(SD)	OSCORE	(SD)
(1)	CDSPX	-0.000804	(0.00196)	0.00345***	(0.00118)	0.00856***	(0.00309)	-0.00294	(0.00232)
(2)	CDSPX	2.95e-05	(0.00183)	0.00353***	(0.00113)	0.00913***	(0.00297)	-0.000856	(0.00111)
(3)	CDSPX	-0.000804	(0.00405)	0.00345*	(0.00188)	0.00856*	(0.00495)	-0.00294*	(0.00171)
(4)	CDSPX	2.95e-05	(0.00366)	0.00353*	(0.00186)	0.00913*	(0.00484)	-0.000856	(0.000973)
(5)	CDSPX	-0.000804	(0.00405)	0.00345*	(0.00188)	0.00856*	(0.00495)	-0.00294*	(0.00171)
Observations		547		547		547		540	
R-squared		0.160		0.121		0.162		0.175	
Number of firms		50		50		50		50	
(1) Fixed Effects Regression *(4) Random Effects Regression Robust*				*(2) Random Effects Regression* *(5) Fixed Effects Regression VCE(Robust)*			*(3) Fixed Effects Regression Robust* *** p<0.01, ** p<0.05, * p<0.1		

Source: Own elaboration (2018).

TABLE 5 - OLS Regressions between Z-Score Models and CDS Volatility

Presents the results of the individual regressions of the CDS VOLATILITY variable regarding the ZSCORE1, ZSCORE2, ZMODEL and O-SCORE:

		ZSCORE1	(SD)	ZSCORE2	(SD)	ZMODEL	(SD)	OSCORE	(SD)
(1)	VOLACDS	-0.000276	(0.000171)	-0.000397***	(0.000120)	-0.000897***	(0.000319)	-2.78e-05	(0.000247)
(2)	VOLACDS	-0.000301*	(0.000172)	-0.000419***	(0.000120)	-0.000939***	(0.000318)	0.000133	(0.000219)
(3)	VOLACDS	-0.000276*	(0.000161)	-0.000397***	(0.000108)	-0.000897***	(0.000297)	-2.78e-05	(0.000203)
(4)	VOLACDS	-0.000301*	(0.000157)	-0.000419***	(0.000111)	-0.000939***	(0.000301)	0.000133	(0.000162)
(5)	VOLACDS	-0.000276*	(0.000161)	-0.000397***	(0.000108)	-0.000897***	(0.000297)	-2.78e-05	(0.000203)
Observations		549		549		549		542	
R-squared		0.164		0.125		0.162		0.171	
Number of firms		50		50		50		50	
1) Fixed Effects Regression				*(2) Random Effects Regression*			*(3) Fixed Effects Regression Robust*		
(4) Random Effects Regression Robust				*(5) Fixed Effects Regression VCE(Robust)*			*** p<0.01, ** p<0.05, * p<0.1		

Source: Own elaboration (2018).

TABLE 6 - OLS Regressions between Z-Score Models and CDS Performance

Presents the results of the individual regressions of the CDS PERFORMANCE variable regarding the ZSCORE1, ZSCORE2, ZMODEL and O-SCORE:

		ZSCORE1	(SD)	ZSCORE2	(SD)	ZMODEL	(SD)	OSCORE	(SD)
(1)	LOG CDS	-3.543*	(1.805)	-2.704**	(1.329)	-6.180*	(3.514)	-3.581	(2.645)
(2)	LOG CDS	-3.677**	(1.821)	-2.794**	(1.334)	-6.341*	(3.508)	-3.445	(2.580)
(3)	LOG CDS	-3.543**	(1.746)	-2.704*	(1.575)	-6.180*	(3.672)	-3.581	(2.869)
(4)	LOG CDS	-3.677**	(1.818)	-2.794*	(1.627)	-6.341*	(3.739)	-3.445	(2.838)
(5)	LOG CDS	-3.543**	(1.746)	-2.704*	(1.575)	-6.180*	(3.672)	-3.581	(2.869)
Observations		548		548		548		541	
R-squared		0.166		0.113		0.154		0.175	
Number of firms		50		50		50		50	
(1) Fixed Effects Regression				*(2) Random Effects Regression*			*(3) Fixed Effects Regression Robust*		
(4) Random Effects Regression Robust				*(5) Fixed Effects Regression VCE(Robust)*			*** p<0.01, ** p<0.05, * p<0.1		

Source: Own elaboration (2018).