Explaining the variation in CDS spreads using market and accounting-based volatility measures

Bruno Martinho

Dissertation written under the supervision of professor Nuno Silva.

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, June 2023.

Abstract

The objective of this thesis is to study whether introducing fundamental measures of volatility in a model already accounting for market-based volatility can contribute to better explain the variation in credit default swap spreads. The accounting-based measures of volatility considered are (i) volatility of the return on net operating assets and (ii) volatility in the dispersion in analysts' forecasts of earnings per share. When only the market volatilities are modelled together, it produces a r-square of around 67.5%. When considering the market-based volatilities and the volatility of the return on net operating assets in the same model, the explanatory power increases to around 73.5%. In the instance where all the market-based volatilities, the volatility of the return on net operating assets, and volatility in the dispersion in analysts' earnings forecasts are considered, there is a slight decrease in r-square to around 73.0%. The results suggest that accounting measures help increase the explanation of the variation in credit default swap spreads, however adding the volatility in the dispersion in analysts' forecasts of earnings, as a second accounting-based measure, does not add any explanatory power to the model. In further robustness tests, all volatilities measures are untouched except the return on net operating assets, which is replaced firstly by return on assets and secondly by return on equity. The robustness test results fall in line with the original findings. This corroborates that the analysis of credit default swaps can be increased by introducing accounting-based information into the models.

Tittle: Explaining the variation in CDS spreads using market and accounting-based volatility measures

Author: Bruno Martinho

Keywords: credit default swaps, asset volatility, credit risk, credit spreads

Resumo

O objetivo desta tese é estudar se a introdução de medidas contabilísticas de volatilidade num modelo, que já contabiliza volatilidade de mercado, contribui para explicar melhor a variação dos spreads de credit default swaps. As medidas de volatilidade contabilísticas consideradas são (i) volatilidade da rendibilidade dos ativos líquidos de exploração e (ii) volatilidade da dispersão das previsões dos analistas dos resultados por ação. No modelo em que apenas as volatilidades de mercado são consideradas é obtido um r-quadrado de cerca de 67.5%. Ao modelar as volatilidades de mercado em conjunto com a volatilidade da rendibilidade dos ativos líquidos de exploração, verifica-se um aumento do poder explicativo para cerca de 73.5%. Quando todas as volatilidades de mercado, a volatilidade da rendibilidade dos ativos líquidos de exploração e a volatilidade da dispersão das previsões de resultados são consideradas, verifica-se uma ligeira diminuição do r-quadrado para cerca de 73.0%. Os resultados sugerem que medidas contabilísticas ajudam a aumentar a explicação da variação dos spreads de credit default swaps; no entanto, a adição da volatilidade da dispersão das previsões de resultados, não acrescenta poder explicativo ao modelo. Em testes de robustez, todas as medidas de volatilidade mantêm inalteradas, exceto a rendibilidade dos ativos líquidos de exploração, que é substituída, primeiramente, pela rendibilidade dos ativos e, segundamente, pela rendibilidade dos capitais próprios. Os resultados dos testes de robustez vão de acordo com as conclusões iniciais. Isto corrobora que a análise dos credit default swaps pode ser melhorada através da introdução de informação contabilística.

Título: Explicar a variação de CDS spreads usando medidas de volatilidade de mercado e contabilísticas.

Autor: Bruno Martinho

Palavras-chave: credit default swaps, volatilidade do ativo, risco de crédito, spread de crédito

Acknowledgement

First and foremost, I would like to sincerely thank my family for all the great support you gave me throughout my academic journey. Without it I would have not been able to reach this point. Second, I would like to thank my friends and colleagues that were alongside me during the master's degree. In this year and half I had the chance to share great experiences with you that I will cherish for the rest of my life. Third, I want to acknowledge all the professors I encountered during this master program. The knowledge, expertise and advise shared explains why Católica Lisbon School of Business & Economics is a world renowned institution. Lastly, I would like to express my gratitude to professor Nuno Silva for the knowledge passed on to me during this dissertation. His support, patience, guidance, insight and availability made it possible for me to reach this final stage and, I am truly grateful! In a short note I would also like to express my appreciation to the portfolio management support and guarantee calls unit of the European Investment Bank.

Table of Contents

Abstract 2
Resumo 3
Acknowledgement 4
1. Introduction 7
2. Literature Review 9
2.1 Credit default swaps (CDS) 9
2.1.1Structural Models 9
2.1.2 Reduced Form Models 11
2.2 Credit Risk Determinants 12
3. Data 16
3.1 Company selection 16
3.2 Credit default swap market data 17
4. Correia, Maria, Johnny Kang, and Scott Richardson (2018) model 18
4.1 Volatility measures 18
4.1.1 Market-based measures 18
4.1.1.1 Historical asset return volatility 18
4.1.1.2 Implied asset return volatility 18
4.1.2 Accounting-based measures 19
4.1.2.1 Volatility of the returns of net operating assets (RNOA) 19
4.1.2.2 Dispersion of analysts' forecasts 19
4.2 The regression model 20
5. Cross-sectional variation in credit default swap spreads 23
5.1 Empirical results 23
6. Robustness tests 28
6.1 Return on assets as the fundamental measure 28
6.2 Return on equity as the fundamental measure 31
7. Conclusion 34
References 36
Appendix 38
Appendix 1. Variables definitions 38
Appendix 2. RNOA quantile regression table 40
Appendix 3. ROA quantile regression table 41

Appendix 4. ROE quantile regression table 43
Appendix 5. Stata code 45

Table of tables

Table 1: Industry Composition 16
Table 2: Descriptive statistics for credit default swap spread 17
Table 3: Descriptive statistics for measures of volatility 20
Table 4: Descriptive statistics for non-volatility measures 23
Table 5: Heteroskedasticity test 26
Table 6: Pooled regression of credit default swaps on market and accounting-based measures 27
Table 7: Pooled regression of credit default swaps on market and accounting-based measures. Return on assets robustness test. 30
Table 8: Pooled regression of credit default swaps on market and accounting-based measures. Return on equity robustness test. 33

Table of equations

Equation 1 Historical asset return volatility 18
Equation 2: Implied asset return volatility 18
Equation 3: Volatility of the returns of net operating assets 19
Equation 4: Volatility of dispersion of analysts' forecasts 19
Equation 5: Cross-sectional regression model 21
Equation 6: Skewness 21
Equation 7: Kurtosis 21
Equation 8: Quantile regression 22
Equation 9: Volatility of return on assets 28
Equation 10: Volatility of the return on equity 31

Table of figures

Figure 1: CDS spread distribution 17

1. Introduction

Credit default swap market has, in 2022, reached a volume of around thirty trillion US dollars, the highest since 2009. Understanding what explains the variation in spreads is thus crucial for many players in the market. Credit default swaps can be seen as insurance or hedge against credit risk by bondholders of a specific company or an instrument speculators use to cash in on a potential credit event by a certain firm. With a market size for this instrument, investors and agents in financial markets should not rely only on market-based data to explain the variation in credit default swap spreads. With this comes this this thesis main goal and hypothesis. Can fundamental accounting-based data complement market-based data to better understand a certain financial instrument, specifically credit default swaps in this thesis.

Market-based measures may leave a substantial part of the spread left unexplained. Accounting-based measures can be used to better explain spreads. This dissertation aims to determine if a model combining market-based and accounting-based measures can explain credit default swaps better than a model using only market-based measures, adjusting the model of Correia, Maria, Johnny Kang, and Scott Richardson (2018) to explore whether an explanatory power improvement happens. The model of Correia, Maria, Johnny Kang, and Scott Richardson (2018) revolves around explaining variation of option adjusted spreads of bonds, this thesis centres around explaining the variation of credit default swap spreads.

Correia, Maria, Johnny Kang, and Scott Richardson (2018) framework combines historical, implied and forecasted data present in the equity and credit default swap markets with fundamental accounting data specific for each company analysed. The results from the cross-sectional regression models will demonstrate whether incorporating accounting-based volatility measures with market-based asset volatility measures increase the explanatory power of models. Whether the results go along with the initial hypothesis of this thesis, investors and financial markets agents of credit default swaps will be able to look at the work produced in this thesis and see if their approach to price and understanding of credit default swaps is the best or should they incorporate more into their models.

This thesis is organized the following way. Section 2 reviews the literature on credit default swaps and structural and reduced-form models assessing credit risk. Section 3 presents the data used, and the selection of the sample of companies to be analysed in this thesis. Section 4 breaks down the regression model to be produced in this thesis and an in-detail analysis of each variable and measure of asset volatility to be inputted in the model. Section 5 reports and analyses the results from the regression models produced. Section 6 presents robustness tests intending to check the model's validity for different variables. And Section 7 presents a conclusion and possible further research in this topic.

2. Literature Review

2.1 Credit default swaps (CDS)

Widely known as insurance on an underlying asset, CDSs are over-the-counter bi-lateral contracts that transfer credit risk from one party to another. The buyer of a CDS is buying protection while the seller of a CDS is selling protection. Buyers of a CDS can be either, a holder of the underlying asset to mitigate its exposure to credit risk, or a speculator, which believes the company will experience a credit event.

A CDS can be broken down into cash flows. The buyer seeks to buy protection agree with the protection seller to pay premium, call the CDS spread, in exchange of protection against a credit event. The default swap spread is usually expressed as a percentage of the notional of the swap. This default swap spread is paid by the protection buyer to the protection seller at a certain time of the year, previously agreed in the contract. The default swap spread can be broken down by the asset swap spread, the funding cost, and the optionality cost.

A CDS contract is triggered when a credit event happens within the maturity agreed in the contract. The credit event is typically established in the CDS contract and generally considers failure to pay any obligation by the underlying asset company, bankruptcy, or restructuring. When one of these events occurs the protection buyer no longer has the obligation to pay the spread. Instead, it delivers the underlying asset to the protection seller, which must deliver a cash payment equal to the notional value of the contract. When a credit event does not occur, the protection buyer pays the spread for the whole duration of the contract while the protection seller does not have to deliver anything to the protection buyer.

The literature on credit default swaps and credit risk pricing is organized around two main approaches: reduced-form intensity-based models and structural models.

2.1.1Structural Models

Structural models started with the seminal work of Black & Scholes (1973) and Merton (1974). Merton (1974) considers that firms finance themselves through equity and a zero-coupon bond, whose nominal value must be paid at one specific point in time. On the other side of the balance sheet, assets are assumed to be traded and follow a geometric Brownian motion. The firm is assumed to be liquidated at the date of bond maturity with all assets being sold to pay nominal debt. The remaining accrues to the shareholders. Through Black & Scholes (1973), it is possible to view a firm's balance sheet structure as a combination of European call and put options. Shareholders have a call option, which they exercise if the value of assets at debt maturity is higher than the firm's liabilities.

One of the most well-known outputs of Merton model is the so-called distance-to-default (or distance-to-distress), which measures the distance between the market value of company's assets from the default barrier. Intuitively, the distance to distress tells the analyst how many standard deviations of the asset returns the assets from the default barrier are, which in the case of Merton's model equals the nominal value of the bond. Evaluating the symmetric of the distance-to-default on the Normal distribution one can compute the probability of default. This corresponds to the probability of the call option not being exercised, or in other words, the probability of the asset's value being lower than the liabilities, which triggers a default. With this estimate of default probability, it is possible to have a sense of how much default, or credit, risk a firm implicitly has. Taking the probability of default and combining it with a recovery rate, that is usually assumed to 40%, a credit spread notion is derived. The credit spread allows to understand how much above the firms implicit credit spread is above the risk-free alternative. Firms that showcase a high credit spread, assuming a 40% recovery rate for all firms, necessarily means a higher probability of default and so they are, on principle, closer to the default barrier. One can deconstruct credit spreads into probability of default and default barrier by using the data on the markets or, one can construct credit spreads using accounting data from inside the company.

Amongst the inputs of the Merton (1974) model, asset volatility takes special importance. The volatility of a company's asset is directly linked to the distance-to-default barrier, meaning that when the volatility grows the distance between the company's assets and the default barrier gets smaller. This can be exemplified by firms operating in, generally speaking, riskier industries, that by having unreliability will then experience higher rates of default. Example of this type of firms are mining companies, which have extremely high operating costs, as well face external risks, ranging from natural disasters to poor extractions. What this means is when external and internal factors of firms push them closer to default, the spreads present in the market will have to reflect this information.

Since Merton seminal model, several other structural models have been developed. The main idea behind all structural models is that default occurs when a certain stochastic variable representative of the fundamental data of a company goes below a determined level, the default barrier. According to each model, the default barrier is determined in different ways. The stochastic process determining the firm fundamental value also differs among models. However most models consider that assets follow a geometric Brownian model, Zhou (2001) and Chen and Kou (2009) consider the possibility of jumps. These two papers show that by utilizing a jump-diffusion model they can better explain various shapes of the term structures of credit spreads and several empirical regularities regarding the probability of default, recovery rates, and credit spreads. Also, Fouqué, Sircar, and Solna (2006) introduce stochastic volatility and study the impact of volatility times scales on the yield curves. They show that the combination of first-passage default models with multiscale stochastic volatility can produce yield spreads more realistically. The models before are important expansions and relevant to this work but the paper by Goldstein, Ju and Leland (2001) should get a bit more of relevancy considered that this thesis has a common tread with this paper, the use of a fundamental measure of asset volatility. This identified that modelling a firm's optimal capital structure through earnings before interest and taxes (EBIT) could produce positive results, such as the ones seen by Black and Scholes (1973) when modelling the capital structure with the use of both equity and debt, instead of only using equity. The main reason to use EBIT was that this fundamental measure does not varies from the changes of capital structure. This means that when producing this model, the authors no longer face problems with levered and unlevered equity and how leverage effects the capital structure of the company. Goldstein, Ju and Leland (2001) find that by using EBIT to model companies' capital structures they not only produce optimal capital structures, but the model has the capacity to predict the optimal debt levels. This is an interesting finding by the team as it shows the potential of the use of fundamental measures of asset volatility has in modelling capital structures in this work, but it shows the possibilities of the use of fundamental measures in other research topics, in specifically the one in this thesis.

2.1.2 Reduced Form Models

Reduced-form models were originally developed as an alternative approach to the structural model for pricing derivatives securities that are subject to credit risk. The key assumption behind reduced-form CDS valuation model is that defaults are described as an exogenous jump process. Specifically, defaults do not occur because of basic market observables but due to being an exogenous variable that is independent of the default's free market information. In contrast to structural models, there is no specific economic cause that leads the firm to default.

The work done by Jarrow and Turnbull (1995) is one of the flagship models in the literature. Jarrow and Turnbull (1995) developed a model on which a Fractional Recovery of Treasury assumption is made. This means that upon default the security has a fractional value different than the present value of the security and its cash flows are discounted at the risk-free rate. Here the authors introduce a payoff ratio, based on the spot rates observable on the market that could be considered recovery rates. The reason this happens is due to the introduction of pseudoprobabilities to determine if a default occurs or not, based on arbitrage-free rules and risk-neutral probabilities.

Jarrow and Turnbull (1995) demonstrate that there are exogenous factors of a firm term structure, and that default can occur at any time, hence why the present value of a security will defer from the expected value of the security through this model. This conclusion was also verified by the work done by Cooper & Martin (1996). They also assume a company's capital structure is not directly related to bankruptcy.

Jarrow, Robert A., David Lando, and Stuart M. Turnbull (1997) extended and refined the original work of Jarrow and Turnbull (1995), by developing a Markov model based on the term structure of credit spreads built by Jarrow and Turnbull (1995). In this extended model, the authors introduce ratings as a measure of default probability and included the seniority of the debt as a factor to determine the payoff ratio in case of default.

Reduced-form models are extremely suited to model credit spreads and because of their basic formulation, they are easy to calibrate to credit default swaps. By only taking data observable in the market reduced-form models became a valuable tool in risk management, as Jarrow & Protter (2004) concluded.

2.2 Credit Risk Determinants

Present in the existing literature, the so-called traditional statistical models were the first methods introduced to value and express credit risk The work produced by Altman (1968) was a pioneer as a method of assessing credit risk through discriminant analysis of the quality of ratios. The paper focused on two groups of companies, one consisting of bankrupt companies and another non-bankrupt. The five variables selected were considered the best overall, to predict bankruptcy when combined in the model. It was important to check for the variable's statistically significance, evolution of the inter-correlation between variables, the predictive accuracy of the variables, and the judgment of the analyst. The selected variables were i) the ratio of working capital to total assets, as a measure of liquidity, ii) retained earnings to total assets, as a measure of cumulative profitability, iii) earnings before interest and taxes to total assets, as a measure of profitability, iv) market value equity to book value of total debt, as a measure of leverage and, sales to total assets as a measure of the firm efficiency in generating sales.

To test each variable's discriminating ability the author performed an “F-test” to check for the variable’s significance. This test measures the relationship between the average values of the variables in each of the two groups to the variability of the values of the variables within each group. Then they determine the relative contribution of each variable to the overall discriminating power of the model. Altman (1968) started by estimating the scaled vectors of each variable to determine the relative contribution of each variable, followed by an empirical study of the models in both the non-bankruptcy and bankruptcy groups to check the model's validity in determining bankruptcy. This model continues to be used both in the academia and by practitioners in the industry. A few years ago, Altman, et al. (2017) showcased that the model still holds its validity, consistency, and simplicity in measuring bankruptcy.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi (2008) is a more recent study that investigates what are the main determinants of credit risk. The authors produced a reduced-form default forecasting model targeted at forecasting the probability of bankruptcy over six months, one, two, and three years. The authors incorporated in the model both accounting and market observable explanatory variables which this dissertation looks to do as well. They found that firms with higher leverage, lower profitability, lower market capitalization, lower past stock returns, more volatile past stock returns, lower cash holdings, higher market-book ratios, and lower prices per share tend to default at a higher rate. Also, Campbell, John Y., Jens Hilscher, and Jan Szilagyi, (2008) realize that forecasting defaults in shorter periods, one-month windows, could deviate the results of the forecast. They find equity returns should not be forecasted in a one-month window as the previous month equity return influences the current month, creating an autocorrelation issue that could deviate the forecasting power of models.

As many other papers in the literature, Campbell, John Y., Jens Hilscher, and Jan Szilagyi, (2008) take into account equity volatility, but leave out the volatility that is observed in fundamental data. A notable example to this pattern is Konstantinidi, Theodosia, and Peter F. Pope (2016), which look to the risk embedded in earnings. They consider however that measuring risk in earnings through the historical standard deviation of earnings to be inadequate as the distribution of earnings is often far from being normal-distributed. As an alternative, the authors use quantile regressions to forecast the quantiles of the distribution of futures earnings through current accruals, cash flow, special items, and a loss indicator. Their approach reveals dependencies between the conditional shape of the futures earnings distribution and the earnings components. Based on the forecasted distribution they compute a measure of dispersion, skewness, and kurtosis and associated them with equity return volatility, credit risk and credit spreads. Konstantinidi, Theodosia, and Peter F. Pope (2016) conclude that their risk metrics capture important new risk information.

Following Konstantinidi, Theodosia, and Peter F. Pope's (2016) methodology, Correia, Maria, Johnny Kang, and Scott Richardson (2018) show that using simultaneously accounting and market data can contribute to (i) predict bankruptcies, in an out-of-sample, (ii) to explain cross-sectional variation in credit spreads and, (iii) to explain future credit excess returns. The authors take inspiration from the Merton (1974) model and how this structural model accounts for asset volatility in determining default risk. Structural models like Merton (1974) model the distance that a company is to the default threshold through variables such as, the expected difference between its assets and liabilities, and the asset volatility. It is the latter, where they find their main topic of this paper. They identify that asset volatility should be measured not only through market-based measures but also through fundamental accounting-based measures.

Their first analysis, in Correia, Maria, Johnny Kang, and Scott Richardson (2018) . focus on a regression model to predict bankruptcy over the next 12 months. They use a discrete time-hazard model, where they included three observations, non-bankrupt companies, years before bankruptcy for bankrupt companies, and years of bankruptcy.

In their second analysis, the authors run a cross-sectional regression model to explain the option-adjusted spreads of corporate bonds based on several explanatory variables, notably the dollar distance to default barrier (i.e. the non-standardized distance between the asset level and the barrier), the excess equity returns over the market, and implied asset volatility, and accounting measures like net operating assets or sales. They document an improvement in out-of-sample forecasting of defaults and a better explanation of cross-sectional variation in credit spreads when combining measures of fundamental and market-based asset volatility. Correia, Maria, Johnny Kang, and Scott Richardson (2018) shed light on the lack of literature that uses fundamental measures of asset volatility when compared to the use of market-based measures of asset volatility. They continue by pointing out that combining fundamental and market-based measures of asset volatility outperforms models, in terms of explanatory power, that only take into account market-based measures of asset volatility.

Finally, Correia, Maria, Johnny Kang, and Scott Richardson (2018) compute a measure of mispricing based on comparing the difference between the credit spreads expressed in the markets and the theoretical credit spreads produced by the authors. They identify that through the usage of fundamental and market-based measures of asset volatility, they are able to produce superior forecasts than the ones implicit in the markets and consequently they are able to obtain excess returns based on their model.

3. Data

3.1 Company selection

The firms that are the focus of this dissertation have been selected from the S&P 500 Investment Grade Corporate Bond Index and the S&P U.S. High Yield Corporate Bond Index. The analysis spans from January 2007 to December 2022. Table 1 breaks down firms by industry according to the global industry classification standard. The companies with SIC codes comprised between 6000 and 6999 were excluded due to being financial firms. Both indices were used with the solely purpose of identifying the companies and no bond data from the indices is used.

Table 1 : Industry Composition

	%
Utilities	13.91
Materials	11.01
Energy	9.86
Capital Goods	8.99
Food, Beverage & Tobacco	6.38
Consumer Durables & Apparel	5.80
Consumer Discretionary Distribution & Retail	4.35
Technology Hardware & Equipment	4.06
Consumer Services	4.06
Health Care Equipment & Services	4.06
Transportation	3.77
Pharmaceuticals, Biotechnology & Life Sciences	3.48
Media & Entertainment	3.19
Software & Services	2.90
Commercial & Professional Services	2.61
Automobiles & Components	2.61
Telecommunication Services	2.32
Consumer Staples Distribution & Retail	2.03
Semiconductors & Semiconductor Equipment	1.74
Personal Care Products	1.74

Table 1 reports the industry composition of the sample, using the global industry classification standard, as per the S&P

The resulting list of constituents comprises of 1504 unique firms, split trough 20 industries. Approximately 14% of the companies are in the Utilities industry. Materials represent 11% and Energy around 10% of the firms.

3.2 Credit default swap market data

In the secondary market exists multiple credit default swaps for each company from different sellers. Credit default swaps come in different maturities, ranging from a one-year maturity to thirty-year maturity. In the dissertation, only five years credit default swaps contracts are retrieved and used. The monthly credit default swaps spreads are from the refinitv eikon EOD – SNRFOR database. This database only tracks the credit default swaps spreads starting in January 2007, so the whole database of the spreads is being used.

Table 2 Descriptive statistics for credit default swap spreads

	Mean	**Std. Dev.**	**P1**	**P25**	**Median**	**P75**	**P99**
CDS Spread	1.1630	1.8883	0.0000	0.3180	0.6251	1.2360	8.0089

Table 2 reports the descriptive statistics for credit default swap spreads.

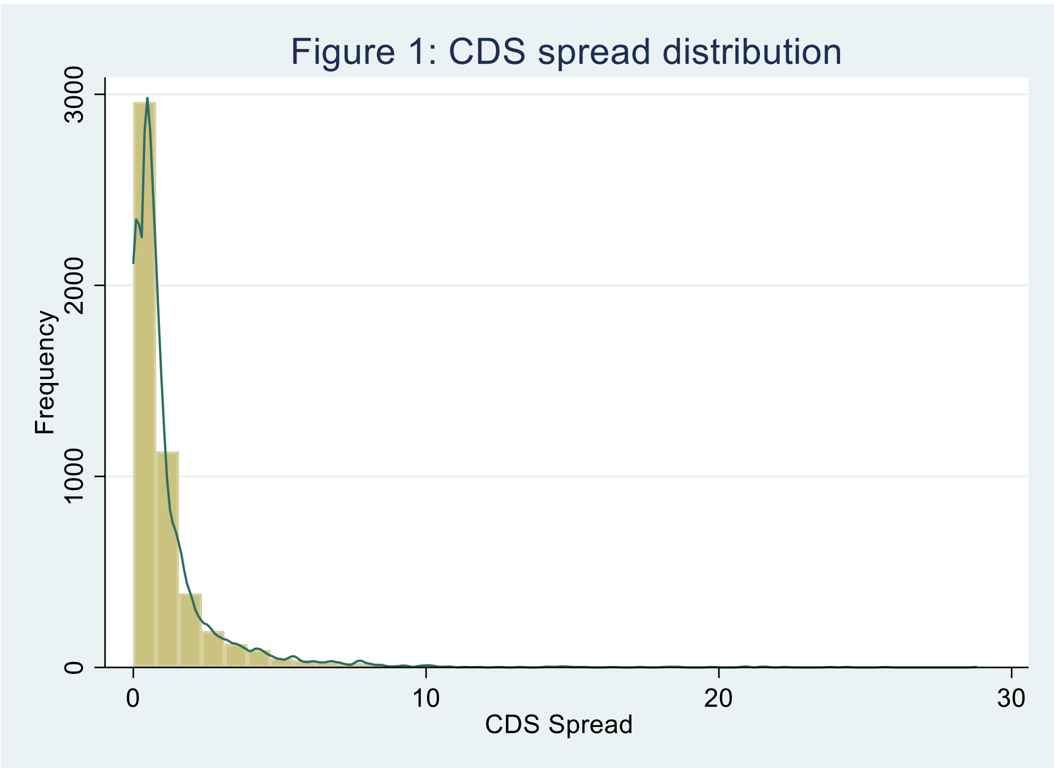

Figure 1 reports the distribution of credit default swap spreads, from January 2007 until December 2022.

The dataset of monthly credit default swap spread shows that the average spread from 2007 until the end of 2022 was around 116%. This high average spread can be explained by looking at the distribution of spreads. It resembles a Snedecor's F distribution, where the lowest possible observation is 0 and, it has a long right tail. The median credit default swap spread is around 6%.

4. Correia, Maria, Johnny Kang, and Scott Richardson (2018) model

Correia, Maria, Johnny Kang, and Scott Richardson (2018) examine whether fundamental measures of volatility are incremental to market-based measures of volatility in i) predicting the rates of bankruptcies, in an out-of-sample setting, ii) explaining cross-sectional variation in credit spreads (based on bonds data), and iii) explaining future credit returns. This dissertation reproduces their analysis on the cross-sectional variation in credit spreads using credit default swaps data.

4.1 Volatility measures

4.1.1 Market-based measures

4.1.1.1 Historical asset return volatility

Asset return volatility is computed as a weighted average of historical equity and debt volatility. Historical equity volatility corresponds to the annualized standard deviation of CRSP realized daily stock returns over the past 252 days. Regarding debt, the analysis is done using credit default spreads and not bond spreads. Mathematically, σ_A^{ω}:

$$\sigma_A^{\omega} = \sqrt{\omega^2\sigma_E^2 + (1-\omega)^2\sigma_{CDS}^2 + 2\omega(1-\omega)\rho_{CDS,E}\sigma_E\sigma_{CDS}}\,, \qquad (1)$$

where ω stands for the of ratio of the market value of the firm's equity to the total firm value, σ_{CDS} is the annualized standard deviation of the monthly credit default swap spread, and $\rho_{CDS,E}$ is an estimate of the correlation between equity returns and the credit default swap spreads.

4.1.1.2 Implied asset return volatility

Trough the Black-Scholes model an estimate of implied volatility was obtained for at-the-money 91-day options. The data was retrieved from the OptionMetrics Ivy DB standardized database. This was done to both call and put options and the average of both was calculated. This is denoted by σ_I. An estimate of the asset volatility is then computed using the same approach as in (1). I will call this as implied asset volatility and denote it as σ_{AI}^{ω}.

$$\sigma_{AI}^{\omega} = \sqrt{\omega^2\sigma_I^2 + (1-\omega)^2\sigma_{CDS}^2 + 2\omega(1-\omega)\rho_{CDS,E}\sigma_I\sigma_{CDS}}, \qquad (2)$$

where ω stands for the of ratio of the market value of the firm's equity to the total firm value, σ_{CDS} is the annualized standard deviation of the monthly credit default swap spreads, and $\rho_{CDS,E}$ is an estimate of the correlation between equity returns and the credit default swap spreads.

4.1.2 Accounting-based measures

4.1.2.1 Volatility of the returns of net operating assets (RNOA)

The accounting measure considered is the return of net operating assets (RNOA), as a representative measure for profitability. The return of net operating assets is obtained as the operating income to the net operating assets for the quarter.

Based on the RNOA estimate, fundamental volatility, σ_{RNOA}, is then measured trough the historical volatility of quarterly RNOA:

$$\sigma_{RNOA} = \sum_{k=1}^{4} \frac{Std(RNOA_k)}{4}, \qquad (3)$$

where Stdk(RNOAitk) stands for the standard deviation of RNOA for quarter k calculated over the previous 20 quarters, with a necessary minimum of 10 quarters of data to be considered. It is then divided by 4 to remove effects of seasonality across the quarters. The fundamental volatility measure is then annualized by multiplying the obtained standard deviation by √4.

4.1.2.2 Dispersion of analysts' forecasts

The second approach to estimate a fundamental volatility measure is based on the analysts forecasts of companies earnings per share. This can be considered as a proxy for future earnings uncertainty. This is calculated trough the standard deviation of analysts EPS (earnings per share) forecasts for the following 2 fiscal years, σ_{FEPS_1} and σ_{FEPS_2} from the IBES summary database. The final volatility measure is then computed by the weighted average of both standard deviations:

$$\sigma_{FEPS} = \alpha\sigma_{FEPS_1} + (1-\alpha)\sigma_{FEPS_2}, \qquad (4)$$

where α represents the number of months remaining until the end of the current fiscal year weighted by 12 months.

Table 3: Descriptive statistics measures of volatility

Panel A: Descriptive statistics of volatility measures

	Mean	**Std. Dev.**	**P1**	**P25**	**Median**	**P75**	**P99**
σ_E	0.3258	0.1845	0.1214	0.2067	0.2738	0.3824	1.0105
σ_{CDS}	0.3316	1.0246	0.0000	0.0343	0.0989	0.2826	3.6959
σ_A^ω	0.3041	0.6472	0.0260	0.1099	0.1729	0.3040	2.2349
σ_I	0.3284	0.1451	0.1550	0.2355	0.2914	0.2914	0.8726
σ_{AI}^ω	0.3036	0.6391	0.0101	0.1201	0.1789	0.2992	2.2033
σ_{RNOA}	0.1074	0.2801	0.000	0.0216	0.0518	0.0970	1.1935
σ_{FEPS}	0.2720	0.4396	0.0133	0.0671	0.1342	0.2850	2.3312

Panel B : Volatility measures correlation matrix

	σ_E	σ_{CDS}	σ_A^ω	σ_I	σ_{AI}^ω	σ_{RNOA}	σ_{FEPS}
σ_E	1						
σ_{CDS}	0.4189	1					
σ_A^ω	0.4833	0.9482	1				
σ_I	0.8222	0.3732	0.4086	1			
σ_{AI}^ω	0.4399	0.9531	0.9959	0.4042	1		
σ_{RNOA}	-0.0320	-0.0190	-0.0129	-0.0311	-0.0115	1	
σ_{FEPS}	0.2428	0.1123	0.1090	0.2109	0.1010	-0.0265	1

Panel A reports the descriptive statistics for the different market and fundamental volatility measures. Panel B reports Pearson (Spearman) correlations across volatility measures.

From the correlation matrix it is possible to determine that between the historical volatility and the volatility of credit default swap and the volatility of the dispersion of analysts' forecasts there is a mild to medium level of positive correlation, while there is a high level of positive correlation between the historical and implied equity volatilities. The credit default swap volatility presents a low to mild positive correlation with the implied and forecasted volatilities. The implied volatility has a low level of positive correlation with the volatility of the dispersion of analysts' forecasts. In the opposite direction of the rest is the volatility of the return on net operating assets that presents low levels of negative correlation with the rest.

4.2 The regression model

In the paper on which this dissertation is based, the authors introduce a cross-sectional regression model with the dependent variable of option adjusted spreads of bonds. As a possible extension to this original model, the authors introduce the possibility of switching from the use of option adjusted spreads from bonds to credit default swaps spreads. The authors view the credit spread in CDS as a cleaner representation of credit risk. They also identified the smaller sample of data that was available to them as an issue, around 8 years of data. In this dissertation this issue is mitigated, as the data sample will be of 16 years which will bring additional validity to the results.

The cross-sectional regression model has now a new dependent variable, five years CDS spreads, $CDS5Y_{it}$. **Because this are five years CDS, it is no longer needed to control for age and duration in the regression**. Also, all the CDS contracts are specified to have the same seniority, time since issuance and the same tenor (already shown to be five years). With this the estimation are prepared from the following models:

$$CDS5Y_{it} = \alpha_1 \ln\left(\frac{V_{it}}{X_{it}}\right) + \alpha_2 Exret_{it} + \alpha_3 \ln(E_{it}) + \alpha_4 P_{5,it} + \alpha_5 Skew_{it} + \alpha_6 Kurt_{it} + \sum_{k=1}^{K} \alpha_{k+6}\sigma_{k,it} + \varepsilon_{it}. \quad (5)$$

where $\ln\left(\frac{V_{it}}{X_{it}}\right)$ is the dollar distance to default, $Exret_{it}$ is the excess equity return over the value weighted market returns over the last 12 months, calculated as the annualized monthly S&P 500 returns. $\ln(E_{it})$ is the logarithmic value of the market capitalization of each firm at the beginning of the month, $P_{5,it}$ is an estimate of the fifth percentile of the distribution of RNOA, $Skew_{it}$ is an estimate of skewness of the distribution of RNOA, and, finally, $Kurt_{it}$, is an estimate of skewness of the distribution of RNOA. All these variables are at the issuer level. The measures of volatility are included in the model in $\sum_{k=1}^{K} \alpha_{k+6} + \sigma_{k,it}$. Time fixed effects are included in all models.

The $Skew_{it}$ variable is estimated trough the expression:

$$Skew_{it} = \frac{(P_{75} - P_{50}) - (P_{50} - P_{25})}{IQR}, \quad (6)$$

where IQR represents the interquartile range of $(P_{75} - P_{25})$. This means that $Skew_{it}$ will range between -1 and 1. $Kurt_{it}$ is then estimated as:

$$Kurt_{it} = \frac{(P_{87.5} - P_{62.5}) - (P_{37.5} - P_{12.5})}{IQR}. \quad (7)$$

To produce each quantile used to estimate Skew, Kurt and IQR a quantile regression is produced. For each period t, the estimated regression follows the equation:

$$QUANT_q(RNOA_{it}|\cdot)= \beta^q_{0t}+ \beta^q_{1t}RNOA_{it-1}+ \beta^q_{2t}LOSS_{it-1}+ \beta^q_{3t}(LOSS_{it-1}* RNOA_{it-1})+ \beta^q_{4t}ACC_{it-1}+ \beta^q_{5t}PAYER_{it-1}+ \beta^q_{6t}PAYOUT_{it-1}. \quad (8)$$

In the regression model the variables considered are: $RNOA_{it-1}$, one year lag RNOA; $LOSS_{it-1}$, a dummy variable that is 1 if the $RNOA_{it-1}$ is negative; $PAYER_{it-1}$, a dummy variable that is 1 if the RNOA is positive; if the $RNOA_{it-1}$ is 0 both dummy variables are equal to 0; ACC_{it-1}, accruals scaled by the average $RNOA_{it-1}$; $PAYOUT_{it-1}$, dividends paid scaled by the average RNOA.

Shown in the appendix 2, the coefficients for the 5th,12.5th, 25th, 37.5th, 50th, 62.5nd, 75th, 87.5th. In a brief analysis of the median quantile regression, it is possible to view the relationships between the dependent variable and each of the independent variables. β^{50}_1 is 0.92, an expected strong positive relationship between the period t RNOA with the previous period; β^{50}_2 is -0.08, a small negative relation between RNOA and the dummy variable for negative RNOA, which shows consistency with loss makers having lower levels of profit in the future; β^{50}_3 is -0.86, a strong negative relationship between RNOA and the product of the dummy variable $LOSS_{it-1}$ with RNOA; $\beta^{50}_4$is 0.02, a small positive relation between RNOA and accruals, which goes in an opposite direction from what is expected due to accruals being historically negatively related to future profitability; β^{50}_5 is 0.02, a small positive relation between RNOA and the dummy variable for positive RNOA; β^{50}_6 is 0.00 shows a no relation between the dividend pay-out and the RNOA, a surprising coefficient given that firms that have higher dividend pay-outs have higher future profitability.

Looking at each independent variable across all regressed percentiles, the relation $RNOA_{it}$ and $RNOA_{it-1}$ is shown to be a strong positive at all percentile levels, as expected, a part from the 5th percentile. At the 5th percentile level the coefficient between the current RNOA and the previous period RNOA is -0.02. A possible explanation for this could be the fact that companies that have RNOA in the left tail of the RNOA distribution are usually negative RNOA. When a firm presents a negative RNOA, by this point the firm has been experiencing a decline in profitability until it became negative, and thus explaining the negative relation. The relation between $RNOA_{it}$ and $LOSS_{it-1}$ is, across all regressed percentiles, a negative relation, an expected relationship and already explained previously. When looking at the relation between $RNOA_{it}$ and $LOSS_{it-1}* RNOA_{it-1}$ the relationship is similar at what is seen between $RNOA_{it}$ and $RNOA_{it-1}$. At the 5th percentile level, the coefficient is negative, while the rest of the percentiles present a strong positive relation. Because this independent variable comes from the product of $RNOA_{it-1}$and $LOSS_{it-1}$ only the negative instances of RNOA will have value different than zero, so at the 5th percentile level this independent variable will present a close relation with the $RNOA_{it-1}$ variable. The relation between $RNOA_{it}$ and $\beta^q_{4t}ACC_{it-1}$ is different from the bottom percentiles and the upper percentiles. At 5th, 12.5th, 25th, 37.5th and, 50th percentiles the relation is shown to be a weal negative relation, which as explained previously comes from a documented relation between accruals and futures profitability. But for percentiles 75th and 82.5nd the relation is shown to weak and positive. This could be explained by companies with higher accruals are approaching a possible default, as they are incurring in more unpaid expenses and so a snowball effect on accruals could explained the positive relation at the higher percentiles level. The dummy variable $PAYER_{it-1}$ presents across all the regressed percentiles a weak positive relation. Lastly, the relation between $RNOA_{it}$ and $PAYOUT_{it-1}$ is for percentiles 5th, 12.5th, 25th, 37.5th and, 50th a weak negative, close to zero, relation. This could be explained by companies that have smaller dividends or no dividends tend to have lower future profitability. At the 62.5th and above percentile, the relation turn to a weal positive, also close to zero. This could be explained by companies that pay higher dividends tend to expected future profits.

Table 4: Descriptive statistics for non-volatility measures

	Mean	Std. Dev.	P1	P25	Median	P75	P99
Exret	0.1723	0.4778	-1.1614	-0.0240	0.1838	0.3911	1.4662
$\ln\left(\frac{V}{X}\right)$	1.8940	1.0152	0.0526	1.3985	1.9562	2.5044	4.6648
$\ln(E)$	9.5693	1.4438	6.2299	8.6250	9.6228	10.5744	12.7898
ω	0.4484	0.3259	0.1017	0.3322	0.3387	0.5342	1.3857
Skew	0.0129	0.3851	-0.8022	-0.2732	0.0023	0.2806	0.8062
Kurt	-0.0739	0.7571	-2.1068	-0.3856	-0.0211	0.2711	1.6629

Table 4 reports the descriptive statistics of non-volatility measures.

5. Cross-sectional variation in credit default swap spreads

5.1 Empirical results

Table 5 presents the output from all regression models assessed. Across all regression models estimated, a first conclusion can be drawn. The relationship between distance to default $\ln\left(\frac{V}{X}\right)$ and credit default swap spreads shows an consistently decreasing relation. The same relation is seen between credit default swap spreads and the firm size, $\ln(E)$. This is an expected relationship, as companies presenting a higher distance to default, will then be farther away from a credit event and so credit default swap spreads will be lower. In the same line of thought, companies that are larger in size, will benefit from a negative relationship to credit default swaps, in a notation that some companies are too big to fail and so the credit default swap market will have to price the spreads in the downside. The excess equity return presents an increasing relation in all models, an intriguing yet comprehensible relationship. Generally, when equity markets are down more than usual companies are more likely to go under distress leading upwards credit default swap spreads. Each of the three variables are consistently statistically significant at any conventional level, whether is at 1% (***), 5%(**) or 10% (*).

P5 presents a negative relation to credit default swaps for six of the models. In the five models that include the volatility of the return of net operating assets this independent variable presents a positive relation to the dependent variable. This may come from multicollinearity between the variables P5 and volatility of the return of net operating assets, given that P5 is estimated by the quantile regression approach, based on the return of net operating assets. This measure is across all regressions not statistically significant at any level.

The measure of kurtosis follows the opposite direction as the measure of the 5^{th} percentile as it presents a positive relation with the credit default swaps spreads at any regression model. When a company showcases an increasing kurtosis level through the months and years, this means that its tail levels of the return on net operating assets are increasing. With this increase, one might point out that the left tail risk increases and so the spreads of credit default swaps. In spite of this, just like the variable P5, the kurtosis variable is not statistically significant at any given level.

Lastly, the measure of skewness has a positive relation with credit default spreads. This relation can be explained by observations on the right tail of the credit default swap spreads distribution that skew the distribution to the right. Although the measure of skewness used in here is estimated through the estimation of RNOA percentiles, the distance between percentiles will be larger in right side of the distribution than in the middle and left side. This difference will explain higher values of skewness and so explain the positive relation to the credit default swap spreads. In all regressions this independent variable is statistically significant at any level.

The models (1) trough (6) examine each of the measures of volatility separately. Individually all but one measure is statistically significant at any level above 5%. The only case that is not significant is fundamental volatility σ_{RNOA} i.e. the volatility of the returns of net operating assets.

Model (1), which incorporates only the historical asset volatility measure, has a 50.30% r-squared meaning that 50.30% of the credit default swap spreads variation can be explained by the independent variables. A similar figure (approximately 51%) is obtained in model (2) using the implied asset volatility measure. Examining model (3), the volatility of the returns of credit default spreads is used and as expected the explanatory power of this model is higher than the latter two, this model has a r-squared of 62.98%. Models (4) and (5) present substantially lower r-squared values than the previous three, registering 18.42% and 18.75% respectively.

After producing a model with a single measure of volatility, it is presented another six models with combinations of the measures. In each combination only two measures of volatility are not incorporated in the regression model, being the historical return volatility and the implied volatility. This comes from the fact that one is the volatility of the past equity returns, as it is characterized of historical, and the other is looking forward at the possible level of equity volatility. So, combining both measures of volatility could deviate the results.

Model (6) combines measures of the volatility of credit default swaps spreads and historical volatility. The non-volatility measures maintain the same relation with the credit default swap spreads, except the kurtosis variable. This variable goes from a coefficient of 0.01 to -0.01 but remains not statistically significant at any level. The coefficient associated with the volatility of credit default swaps remains the same as in model (3). Both coefficients are around 1.79 and statistically significant at any standard level. The historical volatility measure presents a shift on its coefficient. In model (1), the coefficient was of 1.27 while in model (6) changes the type of relation with the credit default swaps spreads, with a coefficient of -1.33. In this model by combining market-based measures of volatility from the equity and credit default swap markets it is possible to see an increase in the explanatory power as compared with the case where only market-based measures are considered. Model (1) presents a r-square of 50.39%, being able to explain a bit more of the variation of credit default swaps spreads. In model (6), incorporating both historical asset volatility and credit default swap volatility, the explanatory power of the model is now of 67.49%. A 34% increase in the r-square credit default swaps spread through the independent variables, compared to model (1).

The next step is to introduce the volatility of RNOA and the volatility of analysts' earnings forecasts. In model (7), adding the volatility of RNOA, the r-squared goes from 67.49% to 73.52%, an increase of around 9% in the explanatory power, compared to model (6). Lastly when incorporating σ_{FEPS} in model (8), the r-squared drops slightly, from 73.52% to 73.45%. When adding the volatility of analysts' earnings forecasts to the model, along with the other three volatility measures, the explanatory power slightly drops. This does not necessarily means that the volatility of analysts' earnings forecasts cannot explain any part of the variation of credit default swap spreads. What this means is that when combined with other variables, the volatility of analysts' earnings forecasts some of the variation that this variable explains could be already explained by other variables.

The following step is to switch the from the historical to the implied asset volatility. In model (9) the model incorporates the measures of implied and credit default swap volatilities. Similar to what happens in model (1), the measure of implied volatility also changes the direction of the relationship with the credit default swap spread, going from a coefficient of 1.3039, in model (1) to -1.3851 in model (8). The r-squared in model (8) is of 67.49%, an increase from the 50.39% in model (1). Adding a credit default swap measure of volatility improves the explanatory power of the credit default spreads, in line with what is seen in model (6). Model (10) introduces the volatility of RNOA. With this addition, the r-squared jumps from 67.49%, in model (9), to 73.05%, meaning that this addition successfully increases the explanatory power of the model. Model (11) adds the measure of volatility of analysts' earnings forecasts to the model. Just like what is seen in model (8), the addition of the forecast measure of volatility makes the explanatory power of the model to slightly decrease, going from 73.05%, in model (10), to 72.94%.

After performing the regressions, it is necessary to check for a few factors to better understand whether some conclusions are being deviated or not from reality. One of the tests done is for heteroscedasticity. To test for heteroscedasticity the Modified Wald statistic for groupwise heteroskedasticity in fixed effect models is being performed for all the 11 regression models.

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model:

H0: sigma(i)^2 = sigma^2 for all I.

Rejecting the null hypnotises suggests that errors are heteroskedastic.

Table 5 : Heteroskedasticity test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Chi^2	7.7e+32	8.5e+32	8.1e+31	6.0e+32	1.6e+33	9.1e+32	1.1e+32	8.7e+32	5.8e+31	4.5e+32	4.2e+32
Prob>chi^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5 reports the heteroskedasticity tests performed for all 11 regression models. The test used is the Modified Wald test.

Based on the results of each test, it is possible to determine that every regression model produced rejects the null hypnotises and so there is no presence of homoscedasticity. From this we indicate that heteroskedasticity exists. To overcome this issue, the same regressions are replicated but this time with the use of robust standard errors.

Table 6 : Pooled regression of credit default swaps on market and accounting-based measures

$$CDS5Y_{it} = \alpha_1 \ln\left(\frac{V_{it}}{X_{it}}\right) + \alpha_2 Exret_{it} + \alpha_3 \ln(E_{it}) + \alpha_4 P_{5,it} + \alpha_5 Skew_{it} + \alpha_6 Kurt_{it} + + \sum_{k=1}^{K} \alpha_{k+6}\sigma_{k,it} + \varepsilon_{it}.$$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
$\ln\left(\frac{V}{X}\right)$	-0.2442***	-0.2601***	-0.2417***	-0.3959***	-0.3837***	-0.2642***	-0.2665***	-0.2605***	-0.2459***	-0.2482***	-0.2440***
	(-7.24)	(-7.76)	(-8.05)	(-9.16)	(-8.83)	(-9.17)	(-9.25)	(-9.01)	(-8.53)	(-8.62)	(-8.43)
Exret	0.1776***	0.2183***	0.2017***	0.2733***	0.2732***	0.2388***	0.2386***	0.2386***	0.1951***	0.1948***	0.1947***
	(4.97)	(6.15)	(6.34)	(5.95)	(5.95)	(7.81)	(7.81)	(7.82)	(6.39)	(6.39)	(6.39)
$\ln(E)$	-0.4088***	-0.3980***	-0.3103***	-0.6357***	-0.6389***	-0.2638***	-0.2709***	-0.2773***	-0.2704***	-0.2776***	-0.2823***
	(-12.14)	(-11.89)	(-10.28)	(-14.75)	(-14.83)	(-9.08)	(-9.29)	(-9.46)	(-9.31)	(-9.52)	(-9.63)
P5	-0.0279	-0.0308	-0.0311	0.0103	-0.0267	-0.0342	0.0083	0.0110	-0.0312	0.0126	0.0145
	(-0.44)	(-0.49)	(-0.55)	(0.12)	(-0.33)	(-0.63)	(0.15)	(0.19)	(-0.57)	(0.22)	(0.25)
Skew	0.1006***	0.0979***	0.0900***	0.1525***	0.1595***	0.0912***	0.0854***	0.0864***	0.0932***	0.0873***	0.0880***
	(2.01)	(1.97)	(2.02)	(2.37)	(2.48)	(2.13)	(2.00)	(2.02)	(2.18)	(2.04)	(2.06)
Kurt	0.0195	0.0179	0.0072	0.0023	0.0095	-0.0080	-0.0142	-0.0135	-0.0066	-0.0129	-0.0125
	(0.73)	(0.68)	(0.31)	(0.07)	(0.28)	(-0.35)	(-0.62)	(-0.59)	(-0.29)	(-0.57)	(-0.55)
σ_{CDS}			0.9587***			1.7940***	1.7955***	1.7983***	1.8247***	1.8269***	1.8261***
			(58.74)			(34.36)	(-16.81)	(34.48)	(33.39)	(33.45)	(33.44)
σ_A^{ω}	1.2724***					-1.3316***	-1.3340***	-1.3402***			
	(16.34)					(-16.76)	(-16.81)	(-16.88)			
σ_{AI}^{ω}		1.3039***							-1.3951***	-1.3987***	-1.3986***
		(46.39)							(-16.53)	(-16.59)	(-16.59)
σ_{RNOA}				0.1721			0.1849***	0.1898***		0.1907***	0.1941***
				(1.51)			(2.44)	(2.51)		(2.51)	(2.56)
σ_{FEPS}					0.1584***			0.0975***			0.0681
					(2.29)			(2.12)			(1.48)
Obs	58,574	49,930	58,574	58,574	49,930	58,574	58,574	49,930	58,574	58,574	49,930
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.5039	0.5106	0.6298	0.1842	0.1875	0.6749	0.7352	0.7345	0.6749	0.7305	0.7294
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 6 reports the coefficients from the regression of credit default swap spreads on the different volatility measures.

6. Robustness tests

Overall the results present are in line with those in Correia, Maria, Johnny Kang, and Scott Richardson (2018) on bond spreads. To test the robustness of the model, different accounting based measures of volatility are introduced. The aim is to understand whether different accounting measures can also increase the explanation of the variation of credit default swap spreads.

6.1 Return on assets as the fundamental measure

In the original model, the first fundamental measure of volatility is created based on the return on net operating assets. In this robustness test, the accounting measure used is the return on assets. While the RNOA measures the firm's return on the revenue generating assets, the ROA captures the return on the firm's total assets. The reasoning is to try and understand whether using a more broad accounting measure can increase the explanatory power of the model when explaining the variation of credit default swap spreads. Slight changes in the way the measure of fundamental volatility is done, but the principal and structure of how the measure is calculated remains the same:

$$\sigma_{ROA} = \sum_{k=1}^{4} \frac{Std(ROA_k)}{4}, \qquad (9)$$

where $Std_k(ROA_{itk})$ stands for the standard deviation of ROA for quarter k calculated over the previous 20 quarters, with a necessary minimum of 10 quarters of data to be considered. It is then divided by 4 to remove effects of seasonality across the quarters. The fundamental volatility measure is then annualized by multiplying the obtained standard deviation by $\sqrt{4}$.

Given that the ROA is now the fundamental measure considered, one needs to recompute the 5^{th} percentile, skewness and kurtosis taking as reference the ROA distribution. This was done using the same quantile regression approach, as previously done for the RNOA. The coefficients for each of the quantiles are in appendix 3.

Overall, the inclusion of the return on assets as the first measure of accounting based volatility produces results in line with the ones seen in original model. As a stand-alone measure of volatility, in model (1) of table 6, the variable of the 5^{th} percentile of the ROA distribution presents a negative yet statistically significant relation with credit default swap spreads. In the original regression models using RNOA, the variable P5 shows a positive relation, although not statistically significant at any level. Skewness has a negative coefficient of -0.011, in contrast with the positive relation seen in the model (4) of the original models. In both models the variable is statistically significant. Kurtosis shows a positive coefficient of 0.001 although not statically significant, in accordance with what is seen in the comparable model (4) of the original models.

Regarding the volatility of ROA itself, it has a negative coefficient of -0.011 yet not statistically significant. The variable of volatility of the return on assets in this case does not match what was seen in the original model where a positive relation with credit default swap spreads with the volatility of the return on net operating assets. The regression model (1), in table 7, itself shows a r-squared of 21.72%, an increase when compared to the 18.42% r-squared seen by the regression model utilizing the RNOA as the first accounting-based measure.

Model (2) incorporates the volatility of ROA with the credit default swap volatility and the historical asset volatility. $\ln\left(\frac{V}{X}\right)$, Exret, and $\ln(E)$ present very similar coefficients and statistical significance throughout the models, similar to what is reported in the original model. Yet the measures of the 5th percentile, skew and kurtosis, present the same relation as in model (1) although none are statistically significant. The variables for credit default swap volatility and historical volatility show similarities with the original model and the volatility of ROA presents a negative coefficient yet not statistically significant. This model is capable of explaining 67.89% of the variation of credit default swap spreads variation, which is less than the 73.52% r-square that is seen in the original model.

Model (3) incorporates all measures of volatility in the model, and the results of all variables maintain very similar to model (2). The volatility of analysts' earnings forecasts variable indicates a positive yet not statistically significant relation, just like in the original model. The volatility of ROA presents an identical coefficient to the one seen in model (2). Overall model (3) has a r-square of 73.05%, a considerable increase from model (2) yet still below from the 73.45% r-square from the original model.

Models (4) and (5) replace the historical volatility with implied volatility and very similar results are presented, both in terms of the coefficients from each variable, their statistical significance and the models overall r square. Model (4) is capable of explaining 72.52% of the variation of credit default swap spreads, a drop from the 73.05% from the original model. Model (5) explanatory power of 72.50% of the credit default swap spreads variation is also below the 72.94% from the original model.

Overall, using return on assets as the accounting-based measure holds similar result to the one seen in the original model. As the stand alone variable of volatility, the return on assets volatility is able to explain more of the variation of credit default swap spreads than the volatility of net operating assets. However, when combining the volatility of ROA with the market volatilities, the ROA cannot surpass the explanatory power seen in the model that use the return on net operating assets. Using this measure comes with some flaws, mainly the fact that in none of the regression models the fundamental measure of volatility of ROA itself is statistically significant. Observing the whole picture, the regression model appears to hold itself when replacing one measure by another, showcasing the functionality of this model to explain the variation in credit default swaps.

Table 7 : Pooled regression of credit default swaps on market and accounting-based measures. Return on assets robustness test.

$$CDS5Y_{it} = \alpha_1 \ln\left(\frac{V_{it}}{X_{it}}\right) + \alpha_2 Exret_{it} + \alpha_3 \ln(E_{it}) + \alpha_4 P_{5,it} + \alpha_5 Skew_{it} + \alpha_6 Kurt_{it} + \sum_{k=1}^{K} \alpha_{k+6}\sigma_{k,it} + \varepsilon_{it}$$

	(1)	(2)	(3)	(4)	(5)
$\ln\left(\frac{V}{X}\right)$	-0.3679***	-0.2857***	-0.2859***	-0.2689***	-0.2691***
	(-7.56)	(-8.70)	(-8.70)	(-8.15)	(-8.16)
Exret	0.4903	0.3033***	0.3033***	0.2515***	0.2514***
	(10.48)	(9.52)	(9.51)	(7.89)	(7.88)
$\ln(E)$	-0.7013***	-0.3103***	-0.3104***	-0.3201***	-0.32024***
	(-15.47)	(-9.95)	(-9.96)	(-10.24)	(-10.24)
P5	-0.9478***	-0.3472	-0.3466***	-0.1832	-0.1827
	(-2.18)	(-1.18)	(-1.18)	(-0.62)	(-0.62)
Skew	-0.0867***	-0.0604	-0.0601	-0.0413	-0.0410
	(-1.56)	(-1.62)	(-1.61)	(-1.10)	(-1.09)
Kurt	0.0014	0.0108	0.0108	0.0074	0.0075
	(0.06)	(0.69)	(0.69)	(0.47)	(0.47)
σ_{CDS}		1.8457***	1.8455***	1.8547***	1.8545***
		(36.80)	(36.79)	(35.54)	(35.53)
σ_A^{ω}		-1.6084***	-1.6081***		
		(-21.36)	(-21.35)		
σ_{AI}^{ω}				-1.6380***	-1.6377***
				(-20.65)	(-20.64)
σ_{ROA}	-0.0108	-0.0027	-0.0028	-0.0208	-0.0209
	(-0.14)	(-0.05)	(-0.05)	(-0.39)	(-0.39)
σ_{FEPS}			-0.0001		-0.0001
			(-0.41)		(-0.40)
Obs	58,574	58,574	49,930	58,574	49,930
Time FE	Yes	Yes	Yes	Yes	Yes
R2	0.2172	0.6789	0.7305	0.7252	0.7250
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7 reports the coefficients from the regression of CDS spreads on the different volatility measures. Return on assets robustness test.

6.2 Return on equity as the fundamental measure

The second robustness test changes the first measure of accounting volatility again, this time to the return on equity. Now using the return on equity, changing from a view of the assets to the equity the goal is to understand whether considering the assets or equity there is a significant difference in explanation of the cross-sectional variation of credit default swap spreads

Replicating the steps from the return on assets robustness test, adjusting the formula to express the volatility of the return on equity as

$$\sigma_{ROE} = \sum_{k=1}^{4} \frac{Std(ROE_k)}{4}, \tag{10}$$

where $Std_k(ROE_{itk})$ stands for the standard deviation of ROE for quarter k calculated over the previous 20 quarters, with a necessary minimum of 10 quarters of data to be considered. It is then divided by 4 to remove effects of seasonality across the quarters. The fundamental volatility measure is then annualized by multiplying the obtained standard deviation by $\sqrt{4}$.

Just like for the return on assets, the measures of the 5^{th} percentile, skewness and kurtosis are adjusted to the distribution of the return on equity. As done in the previous two accounting measures, a quantile regression is produced, the coefficient values are in appendix 4.

When using return on equity as the first accounting-based measure of volatility, the independent variables $\ln\left(\frac{V}{X}\right)$ and $\ln(E)$ both have negative relations to the credit default swaps spreads, in accordance with the results in the previous models, shown in tables 6 and 7. The variable Exret also presents a similar positive relation to the credit default swaps spreads. The variable of the 5^{th} percentile of the distribution of ROE presents a negative relation in all models, in table 8, just like what is seen if the first robustness test. The variable Skew presents a negative relation in model 1, while the rest of the models presents a positive relation to the dependent variable. When comparing to the original model, the variable Skew presents a negative across all regression models. The variable Kurt has a weak negative relation in models (1) through (3) but in models (4) and (5) it presents a coefficient of 0.00.

The volatility of return on equity variable, shows across all models, a negative relation to credit default swap spreads. This is an expected relation, as both the volatility of return on net operating assets and volatility on return on assets both show the same relation to credit default swap spreads. This negative relation comes from the fact that companies with higher returns, this case return on equity, have lower credit default swap spreads. The reasoning behind this comes from companies with higher return should be in a better position and so farther away from a credit event, reflecting a negative relation in the credit default swap spread.

Looking at the explanatory power, model (1) has a r-square of 23.83%. Comparing to r-square of 21.72% model (1), in table 7, and 18.42% model (4), in table 6, this is the higher of the three. This shows that, when only using the first accounting based measure of volatility, the measure of return on equity is the one that can explain the higher percentage of variation of credit default swaps. In model (2), combining the volatility of credit default swap spreads, the historical volatility and the volatility of return on equity, the explanatory power of the model is 67.03% . Comparing to the r-square of 67.89% in model (2), in table 7, and 73.52% model (7), in table 6, the measure of return on equity trails to the measures of return on assets and return on net operating assets. In model (3) using the volatility of credit default swap spreads, the historical volatility, the volatility of return on equity and, the volatility of the dispersion of earning per shares forecasts, the r-square is of 72.95%.In comparison, to the r-square of 73.05% in model (3), of table 6, and 73.45% model (8), of table 7, again the return on equity falls behind the other two accounting measures studied. In model (4) the using the volatility of credit default swap spreads, the implied volatility and, the volatility of return on equity, the r-square is of 72.36%.In comparison, to the r-square of 72.52% in model (4), of table 7, and 73.05% model (10), of table 6, falling behind again the other two accounting measures. Lastly, model (5) incorporating the volatility of credit default swap spreads, the historical volatility, the volatility of return on equity and, the volatility of the dispersion of earning per shares forecasts, the r-square is of 72.35%. In comparison, to the r-square of 72.50% in model (5), of table 7, and 72.94% model (11), of table 6, once again the measure of return on equity produces a lower explanatory power than the return on assets and return on net operating assets.

Table 8 : Pooled regression of credit default swaps on market and accounting-based measures. Return on equity robustness test.

$$CDS5Y_{it} = \alpha_1 \ln\left(\frac{V_{it}}{X_{it}}\right) + \alpha_2 Exret_{it} + \alpha_3 \ln(E_{it}) + \alpha_4 P_{5,it} + \alpha_5 Skew_{it} + \alpha_6 Kurt_{it} + \sum_{k=1}^{K} \alpha_{k+6}\sigma_{k,it} + \varepsilon_{it}$$

	(1)	(2)	(3)	(4)	(5)
$\ln\left(\frac{V}{X}\right)$	-0.4744	-0.3297***	-0.3300***	-0.2962***	-0.2964***
	(-10.25)	(-10.91)	(-10.92)	(-9.79)	(-9.79)
Exret	0.6599***	0.0810***	0.0810***	0.0292	0.0292
	(12.52)	(2.25)	(2.25)	(0.81)	(0.81)
$\ln(E)$	-0.5221***	-0.2560***	-0.2561***	-0.2622***	-0.2623***
	(-11.42)	(-8.54)	(-8.54)	(-8.71)	(-8.72)
P5	-0.1798***	-0.0437***	-0.0437***	-0.0583***	-0.0583***
	(-6.18)	(-2.26)	(-2.26)	(-3.02)	(-3.02)
Skew	-0.0385	0.0261	0.0263	0.0344	0.0346
	(-0.89)	(0.93)	(0.93)	(1.21)	(1.22)
Kurt	-0.0006	-0.0004	-0.0004	0.0000	0.0000
	(-0.11)	(-0.11)	(-0.11)	(0.01)	(0.01)
σ_{CDS}		2.1613***	2.1601***	2.1052***	2.1051***
		(28.19)	(-28.18)	(27.23)	(27.22)
σ_A^{ω}		-1.9485***	-1.9478***		
		(-16.99)	(-16.98)		
σ_{AI}^{ω}				-1.8853***	-1.8844***
				(-16.11)	(-16.10)
σ_{ROE}	-0.0179***	-0.0084***	-0.0084***	-0.0093***	-0.0093***
	(-3.51)	(-2.52)	(2.52)	(-2.78)	(-2.78)
σ_{FEPS}			-0.0002		-0.0002
			(-0.64)		(-0.59)
Obs	58,574	58,574	49,930	58,574	49,930
Time FE	Yes	Yes	Yes	Yes	Yes
R2	0.2383	0.6703	0.7295	0.7236	0.7235
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 8 reports the coefficients from the regression of CDS spreads on the different volatility measures. Return on equity robustness test.

7. Conclusion

This work studies whether fundamental measures of volatility can supplement market-based measures of volatility in explaining the cross-sectional variation in credit default swap spreads. Previously Correia, Maria, Johnny Kang, and Scott Richardson (2018) showed that adding fundamental accounting-based data to market-based data increases the explanatory power of the cross sectional variation of option adjusted spreads of bonds. The authors also found that the market itself lacks in not incorporating fundamental measures of asset volatility in pricing credit spreads. This dissertation extends their analysis to the case of credit default swaps.

This dissertation shows that using market-based measures of volatility can explain a great part of the cross-sectional variation of credit default swaps, notably around 63% when using historical asset volatility and the credit default swap volatility and around 67% when using implied asset volatility and the credit default swap volatility. The impact of adding fundamental measures to market-based measures depends on the specific measure used. When supplementing market-based with the volatility of the return on net operating assets in a model considering the historical asset volatility and the credit default swap volatility, the r-squared increases from 63% to 74%. These figures change to 67% and 73%, respectively, when using the implied asset volatility and the credit default swap volatility. In contrast, when adding the volatility of the dispersion of earning per shares forecasts, the r-square of both approaches slightly drops. When using historical asset volatility, the credit default swap volatility, volatility of the return on net operating assets and supplementing with the volatility of the dispersion of earning per shares forecasts the r-square drops from around 74% r-square to 73% r-square. Adding the volatility of the dispersion of earning per shares forecasts to implied asset volatility, the credit default swap volatility, and volatility of the return on net operating assets the r-square slightly drops but maintains around 73% r-square.

Two robustness tests were done. The first changed the fundamental-based accounting measure used from the return of net operating assets to the return on assets. This robustness test shows that r-square levels maintain around the same levels and that the same conclusion can be drawn. A second robustness check is done replacing the return of net operating assets by the return on equity. Once again, the results show that the model produces similar levels of r-square and so it is possible to conclude that adding fundamental-based measures do indeed increment the explanation of cross-sectional variation in credit default swap spreads.

To finalize, the credit market may lack in the pricing of credit default swap spreads by only taking in consideration market-based measures of asset volatility and as seen, it is possible to increase the explanation of cross-sectional variation in credit default swap spreads and so better price this type of instrument. In further research, other fundamental measures of volatility could be taken into consideration, examples of that could be measure of financial leverage or operating leverage. It would be an interesting expansion to identify other financial instruments and check whether the regression model can or cannot explain the variation of set financial instrument.

References

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. Journal of political economy, 81(3), 637-654.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. The Journal of finance, 29(2), 449-470.

Zhou, C. (2001). The term structure of credit spreads with jump risk. Journal of Banking & Finance, 25(11), 2015-2040.

Goldstein, R., Ju, N., & Leland, H. (2001). An EBIT-based model of dynamic capital structure. The Journal of Business, 74(4), 483-512.

Cao, D., Kou, Y., Liang, J., Chen, Z., Wang, L., & Meier, H. (2009). A facile and efficient preparation of pillararenes and a pillarquinone. Angewandte Chemie International Edition, 48(51), 9721-9723.

Fouque, J. P., Sircar, R., & Sølna, K. (2006). A first-passage-time model under regime-switching market environment. Applied Mathematical Finance, 13(3), 215-244.

Jarrow, R. A., & Turnbull, S. M. (1995). Pricing derivatives on financial securities subject to credit risk. The journal of finance, 50(1), 53-85.

Jarrow, R. A., Lando, D., & Turnbull, S. M. (1997). A Markov model for the term structure of credit risk spreads. The review of financial studies, 10(2), 481-523.

Cetin, U., Jarrow, R., Protter, P., & Yıldırım, Y. (2004). Modeling credit risk with partial information.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of finance, 23(4), 589-609.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model.

Journal of International Financial Management & Accounting, 28(2), 131-171.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. The Journal of finance, 63(6), 2899-2939.

Konstantinidi, T., & Pope, P. F. (2016). Forecasting risk in earnings. Contemporary Accounting Research, 33(2), 487-525.

Correia, M., Kang, J., & Richardson, S. (2018). Asset volatility. Review of Accounting Studies, 23, 37-94.

Weistroffer, C., Speyer, B., Kaiser, S., & Mayer, T. (2009). Credit default swaps. Deutsche bank research, 27.

Stulz, R. M. (2010). Credit default swaps and the credit crisis. Journal of Economic Perspectives, 24(1), 73-92.

Hou, K., Van Dijk, M. A., & Zhang, Y. (2012). The implied cost of capital: A new approach. Journal of Accounting and Economics, 53(3), 504-526.

Penman, S. H. (1991). An evaluation of accounting rate-of-return. Journal of Accounting, Auditing & Finance, 6(2), 233-255.

Appendix

Appendix 1. Variables definitions

Variable	Description
Panel A: Volatility measures	
σ_E	Historical equity volatility, annualized standard deviation of realized daily stock returns over the previous 252 days.
σ_I	Implied volatility, average of implied Black and Scholes volatility measures for at-the-money 91-day call and put options (source: Option Metrics Ivy DB standardized database).
σ_{CDS}	Credit default swap volatility, the annualized standard deviation of total monthly credit default swap spreads, computed over the previous 12 months
σ_A^ω	Weighted historical equity volatility, $\sqrt{\omega^2\sigma_E^2 + (1-\omega)^2\sigma_{CDS}^2 + 2\omega(1-\omega)\rho_{CDS,E}\sigma_E\sigma_{CDS}}$
σ_{AI}^ω	Weighted implied equity volatility, $\sqrt{\omega^2\sigma_I^2 + (1-\omega)^2\sigma_{CDS}^2 + 2\omega(1-\omega)\rho_{CDS,I}\sigma_I\sigma_{CDS}}$
σ_F	Average standard deviation of quarterly RNOA. The standard deviations of RNOA for fiscal quarters 1, 2, 3, and 4 are computed over the previous 20 years (requiring a minimum of 10 quarters of data). The resulting quarter-specific volatilities are then averaged across the four fiscal quarters.
RNOA	Return on net operating assets, defined as operating income after depreciation (OIADP) scaled by average of the opening and closing balance of net operating assets (NOA).
σ_{FEPS}	The weighted-average volatility of analyst EPS forecasts for the following 12 months (computed based on the IBES summary files, requiring a minimum of 10 analyst forecasts).
σ_{FROA}	Average standard deviation of quarterly ROA. The standard deviations of ROA for fiscal quarters 1, 2, 3, and 4 are computed over the previous 20 years (requiring a minimum of 10 quarters of data). The resulting quarter-specific volatilities are then averaged across the four fiscal quarters.
σ_{FROE}	Average standard deviation of quarterly ROE. The standard deviations of ROE for fiscal quarters 1, 2, 3, and 4 are computed over the previous 20 years (requiring a minimum of 10 quarters of data). The resulting quarter-specific volatilities are then averaged across the four fiscal quarters.
Panel B: Non volatility measures	
CDS spread	Credit default swap spread of 5 year maturity contract. (source: refinitv eikon EOD – SNRFOR database)
Exret	Excess returns, the difference between equity returns and value weighted market returns over the last 12 months.
STD	Book value of short-term debt
LTD	Book value of long term debt
X	Book value of short-term debt + 0.5*book value of long-term debt
E	Market capitalization.
Ω	market capitalization scaled by the sum of market capitalization and the book value of debt

Variable	Description
ρ	Average correlation of monthly equity and CDS spread returns, calculated over the prior 12 months
V	Sum of Market capitalization plus the book value of short and long-term debt.
P5	5th percentile of the distribution of RNOA.
Skew	Estimate of skewness based on the distribution of RNOA. Defined as: ((P75 − P50) − (P50 − P25))/IQR. Estimated from the quantile regression. Coefficients present in appendix 2.
Kurt	Estimate of kurtosis based on the distribution of RNOA. Defined as: ((P87.5 − P62.5) − (P37.5 − P12.5))/IQR. Estimated from the quantile regression. Coefficients present in appendix 2.
IQR	Interquartile range of the distribution of RNOA, estimated from the quantile regression. Defined as: P75 – P25. Coefficients present in appendix 2.

Appendix 2. RNOA quantile regression table

rnoat	Coefficient	Bootstrap std. err.	t	P>|t|	[95% conf.	interval]
rnoat1	-0.0193	0.0263	-0.7400	0.4620	-0.0708	0.0321
loss	-0.0137	0.1740	-0.0800	0.9370	-0.3547	0.3273
rnoaloss	2.4572	1.2782	1.9200	0.0550	-0.0480	4.9625
acc	0.0923	0.0063	14.7600	0.0000	0.0801	0.1046
payer	0.0935	0.0281	3.3300	0.0010	0.0384	0.1485
payout	-0.0029	0.0004	-6.7700	0.0000	-0.0037	-0.0020
_cons	-0.0215	0.0285	-0.7600	0.4500	-0.0774	0.0343
q125						
rnoat1	0.0176	0.1185	0.1500	0.8820	-0.2147	0.2499
loss	-0.6393	0.5063	-1.2600	0.2070	-1.6317	0.3531
rnoaloss	0.8923	0.3955	2.2600	0.0240	0.1171	1.6675
acc	0.1338	0.0225	5.9400	0.0000	0.0897	0.1779
payer	0.0795	0.0229	3.4700	0.0010	0.0345	0.1244
payout	-0.0026	0.0004	-6.5100	0.0000	-0.0034	-0.0018
_cons	0.0156	0.0175	0.8900	0.3730	-0.0187	0.0499
q250						
rnoat1	0.6277	0.1765	3.5600	0.0000	0.2818	0.9737
loss	-0.8793	0.4381	-2.0100	0.0450	-1.7380	-0.0207
rnoaloss	-0.2571	0.3262	-0.7900	0.4310	-0.8965	0.3823
acc	0.0673	0.0415	1.6200	0.1050	-0.0140	0.1487
payer	0.0191	0.0217	0.8800	0.3780	-0.0233	0.0616
payout	-0.0005	0.0003	-1.3900	0.1660	-0.0011	0.0002
_cons	0.0282	0.0106	2.6600	0.0080	0.0074	0.0489
q375						
rnoat1	0.8360	0.0574	14.5700	0.0000	0.7236	0.9484
loss	-0.2241	0.0529	-4.2400	0.0000	-0.3278	-0.1204
rnoaloss	-0.6992	0.1532	-4.5600	0.0000	-0.9995	-0.3989
acc	0.0464	0.0158	2.9400	0.0030	0.0155	0.0774
payer	-0.0130	0.0097	-1.3500	0.1780	-0.0320	0.0059
payout	-0.0001	0.0001	-1.1500	0.2500	-0.0002	0.0000
_cons	0.0388	0.0052	7.3900	0.0000	0.0285	0.0491
q500						
rnoat1	0.9208	0.0258	35.7100	0.0000	0.8703	0.9714
loss	-0.0831	0.0087	-9.5100	0.0000	-0.1002	-0.0660
rnoaloss	-0.8619	0.0585	-14.720	0.0000	-0.9766	-0.7472
acc	0.0275	0.0078	3.5200	0.0000	0.0122	0.0429
payer	-0.0227	0.0070	-3.2600	0.0010	-0.0364	-0.0091
payout	0.0000	0.0000	-1.1100	0.2660	0.0000	0.0000
_cons	0.0388	0.0058	6.7200	0.0000	0.0275	0.0502
q625						
rnoat1	0.9683	0.0148	65.4300	0.0000	0.9393	0.9973

loss	-0.0595	0.0112	-5.3000	0.0000	-0.0814	-0.0375
rnoaloss	-0.9405	0.0350	-26.870	0.0000	-1.0091	-0.8719
acc	0.0066	0.0062	1.0700	0.2850	-0.0055	0.0187
payer	-0.0353	0.0105	-3.3700	0.0010	-0.0558	-0.0148
payout	0.0000	0.0001	0.4500	0.6550	-0.0001	0.0002
_cons	0.0461	0.0104	4.4500	0.0000	0.0258	0.0664
q750						
rnoat1	1.0081	0.0117	86.3800	0.0000	0.9852	1.0310
loss	-0.0717	0.0159	-4.5200	0.0000	-0.1028	-0.0406
rnoaloss	-1.0173	0.0172	-59.140	0.0000	-1.0511	-0.9836
acc	-0.0075	0.0034	-2.2500	0.0250	-0.0141	-0.0010
payer	-0.0774	0.0169	-4.5700	0.0000	-0.1106	-0.0442
payout	0.0003	0.0001	4.0900	0.0000	0.0001	0.0004
_cons	0.0867	0.0164	5.2900	0.0000	0.0546	0.1188
q875						
rnoat1	1.0962	0.0151	72.5300	0.0000	1.0666	1.1258
loss	-0.0757	0.0221	-3.4300	0.0010	-0.1189	-0.0324
rnoaloss	-1.1683	0.0625	-18.710	0.0000	-1.2907	-1.0459
acc	-0.0110	0.0039	-2.8200	0.0050	-0.0187	-0.0034
payer	-0.1297	0.0247	-5.2500	0.0000	-0.1782	-0.0812
payout	0.0006	0.0002	3.1500	0.0020	0.0002	0.0010
_cons	0.1378	0.0231	5.9600	0.0000	0.0925	0.1831

Appendix 3. ROA quantile regression table

roat	Coefficient	Bootstrap std. err.	t	P>|t|	[95% conf. interval]	
q050						
roat1	0.7531	0.0058	129.6900	0.0000	0.7417	0.7645
losst1	-0.1718	0.0138	-12.4900	0.0000	-0.1988	-0.1449
roat1losst1	-0.8816	0.0129	-68.4000	0.0000	-0.9069	-0.8563
acct1	-0.0162	0.0041	-3.9800	0.0000	-0.0241	-0.0082
payert1	0.0278	0.0008	35.4000	0.0000	0.0263	0.0293
payoutt1	-0.0001	0.0000	-3.4600	0.0010	-0.0002	-0.0001
_cons	-0.0312	0.0003	-103.3700	0.0000	-0.0318	-0.0306
q125						
roat1	0.8614	0.0022	399.6000	0.0000	0.8572	0.8656
losst1	-0.1044	0.0077	-13.5500	0.0000	-0.1195	-0.0893
roat1losst1	-0.9795	0.0082	-119.3900	0.0000	-0.9956	-0.9634
acct1	-0.0211	0.0026	-8.2300	0.0000	-0.0261	-0.0161
payert1	0.0302	0.0007	41.7300	0.0000	0.0288	0.0316
payoutt1	-0.0001	0.0000	-3.6400	0.0000	-0.0002	-0.0001
_cons	-0.0294	0.0008	-37.4200	0.0000	-0.0310	-0.0279
q250						

roat1	0.9305	0.0012	751.3600	0.0000	0.9280	0.9329
losst1	-0.0554	0.0146	-3.8000	0.0000	-0.0840	-0.0268
roat1losst1	-1.0427	0.0066	-157.3300	0.0000	-1.0557	-1.0297
acct1	-0.0141	0.0014	-9.9200	0.0000	-0.0168	-0.0113
payert1	0.0085	0.0143	0.5900	0.5530	-0.0195	0.0364
payoutt1	-0.0001	0.0000	-2.2600	0.0240	-0.0001	0.0000
_cons	-0.0068	0.0143	-0.4800	0.6330	-0.0349	0.0212
q375						
roat1	0.9656	0.0009	1113.4500	0.0000	0.9639	0.9673
losst1	-0.0202	0.0093	-2.1700	0.0300	-0.0385	-0.0019
roat1losst1	-1.0766	0.0075	-142.9500	0.0000	-1.0914	-1.0619
acct1	-0.0092	0.0009	-10.1400	0.0000	-0.0109	-0.0074
payert1	0.0057	0.0095	0.6000	0.5500	-0.0129	0.0243
payoutt1	0.0000	0.0000	-0.5900	0.5570	0.0000	0.0000
_cons	-0.0039	0.0095	-0.4100	0.6830	-0.0225	0.0147
q500						
roat1	0.9908	0.0008	1247.2700	0.0000	0.9892	0.9923
losst1	-0.0158	0.0091	-1.7300	0.0840	-0.0337	0.0021
roat1losst1	-1.1491	0.0182	-63.0700	0.0000	-1.1848	-1.1134
acct1	-0.0033	0.0005	-7.0900	0.0000	-0.0042	-0.0024
payert1	-0.0091	0.0081	-1.1200	0.2630	-0.0250	0.0068
payoutt1	0.0000	0.0000	1.5200	0.1280	0.0000	0.0000
_cons	0.0103	0.0081	1.2700	0.2030	-0.0056	0.0263
q625						
roat1	0.9905	0.0005	2112.5500	0.0000	0.9896	0.9915
losst1	-0.0074	0.0111	-0.6600	0.5070	-0.0292	0.0144
roat1losst1	-1.1937	0.0115	-103.5100	0.0000	-1.2163	-1.1711
acct1	-0.0126	0.0005	-23.1800	0.0000	-0.0136	-0.0115
payert1	-0.0145	0.0094	-1.5500	0.1200	-0.0329	0.0038
payoutt1	0.0000	0.0000	2.6800	0.0070	0.0000	0.0000
_cons	0.0180	0.0094	1.9200	0.0550	-0.0004	0.0364
q750						
roat1	0.9964	0.0010	1018.4100	0.0000	0.9945	0.9983
losst1	0.0132	0.0177	0.7400	0.4570	-0.0215	0.0479
roat1losst1	-1.1940	0.0212	-56.4000	0.0000	-1.2355	-1.1525
acct1	-0.0181	0.0008	-22.5600	0.0000	-0.0196	-0.0165
payert1	-0.0310	0.0112	-2.7600	0.0060	-0.0530	-0.0090
payoutt1	0.0000	0.0000	1.4300	0.1510	0.0000	0.0000
_cons	0.0380	0.0112	3.3800	0.0010	0.0160	0.0601
q875						
roat1	1.0069	0.0014	728.2100	0.0000	1.0042	1.0096
losst1	0.0975	0.0381	2.5600	0.0110	0.0228	0.1723
roat1losst1	-1.1372	0.0318	-35.7900	0.0000	-1.1995	-1.0749
acct1	-0.0152	0.0022	-6.9400	0.0000	-0.0194	-0.0109
payert1	-0.0271	0.0333	-0.8100	0.4160	-0.0924	0.0382
payoutt1	0.0000	0.0000	0.6500	0.5160	0.0000	0.0000

_cons	0.0427	0.0334	1.2800	0.2010	-0.0228	0.1082

Appendix 4. ROE quantile regression table

roet	Coefficient	std. err.	t	Bootstrap P>|t|	[95% conf. interval]	
q050						
roet1	0.0001	0.0348	0.0000	0.9970	-0.0681	0.0684
losst1	-0.2403	0.0364	-6.5900	0.0000	-0.3118	-0.1689
losst1roet1	1.2638	0.1813	6.9700	0.0000	0.9085	1.6192
acct1	0.0633	0.0133	4.7600	0.0000	0.0372	0.0893
payert1	0.0717	0.0114	6.2700	0.0000	0.0493	0.0942
payoutt1	-0.0071	0.0006	-12.510	0.0000	-0.0083	-0.0060
_cons	-0.0349	0.0114	-3.0700	0.0020	-0.0572	-0.0126
q125						
roet1	0.0001	0.1814	0.0000	1.0000	-0.3555	0.3557
losst1	-0.1214	0.0143	-8.5000	0.0000	-0.1494	-0.0934
losst1roet1	1.0416	0.2099	4.9600	0.0000	0.6303	1.4529
acct1	0.1268	0.0365	3.4700	0.0010	0.0552	0.1984
payert1	0.0892	0.0150	5.9600	0.0000	0.0599	0.1186
payoutt1	-0.0090	0.0022	-4.0900	0.0000	-0.0133	-0.0047
_cons	-0.0177	0.0037	-4.7400	0.0000	-0.0250	-0.0104
q250						
roet1	0.0001	0.3086	0.0000	1.0000	-0.6048	0.6050
losst1	-0.0703	0.0128	-5.5200	0.0000	-0.0953	-0.0453
losst1roet1	0.8209	0.3063	2.6800	0.0070	0.2205	1.4212
acct1	0.1596	0.0611	2.6100	0.0090	0.0398	0.2793
payert1	0.0974	0.0291	3.3400	0.0010	0.0403	0.1545
payoutt1	-0.0062	0.0025	-2.5100	0.0120	-0.0111	-0.0014
_cons	0.0028	0.0074	0.3700	0.7090	-0.0118	0.0173
q375						
roet1	0.4253	0.3028	1.4000	0.1600	-0.1682	1.0188
losst1	-0.0580	0.0099	-5.8400	0.0000	-0.0774	-0.0385
losst1roet1	0.1504	0.3236	0.4600	0.6420	-0.4837	0.7846
acct1	0.0797	0.0581	1.3700	0.1700	-0.0342	0.1936
payert1	0.0576	0.0333	1.7300	0.0830	-0.0076	0.1228
payoutt1	-0.0015	0.0012	-1.3100	0.1890	-0.0038	0.0008
_cons	0.0116	0.0089	1.3100	0.1900	-0.0058	0.0290
q500						
roet1	0.7115	0.1649	4.3100	0.0000	0.3882	1.0347
losst1	-0.0492	0.0108	-4.5400	0.0000	-0.0704	-0.0280
losst1roet1	-0.3516	0.2455	-1.4300	0.1520	-0.8328	0.1296
acct1	0.0259	0.0287	0.9000	0.3680	-0.0304	0.0821
payert1	0.0280	0.0176	1.5900	0.1120	-0.0066	0.0626
payoutt1	-0.0002	0.0003	-0.6900	0.4930	-0.0008	0.0004

_cons	0.0137	0.0088	1.5500	0.1210	-0.0036	0.0309
q625						
roet1	0.8430	0.0837	10.0700	0.0000	0.6789	1.0070
losst1	-0.0368	0.0067	-5.4600	0.0000	-0.0500	-0.0236
losst1roet1	-0.8437	0.2162	-3.9000	0.0000	-1.2675	-0.4199
acct1	-0.0044	0.0111	-0.4000	0.6890	-0.0263	0.0174
payert1	0.0182	0.0121	1.5100	0.1310	-0.0054	0.0419
payoutt1	0.0000	0.0001	-0.4000	0.6860	-0.0003	0.0002
_cons	0.0106	0.0044	2.3900	0.0170	0.0019	0.0192
q750						
roet1	0.9163	0.0487	18.8200	0.0000	0.8209	1.0117
losst1	-0.0273	0.0081	-3.3600	0.0010	-0.0432	-0.0114
losst1roet1	-0.9218	0.0783	-11.770	0.0000	-1.0754	-0.7683
acct1	-0.0219	0.0050	-4.4000	0.0000	-0.0317	-0.0122
payert1	0.0008	0.0091	0.0900	0.9270	-0.0171	0.0188
payoutt1	0.0002	0.0003	0.7600	0.4490	-0.0004	0.0008
_cons	0.0227	0.0092	2.4700	0.0140	0.0047	0.0406
q875						
roet1	0.9951	0.0365	27.2400	0.0000	0.9235	1.0667
losst1	-0.0071	0.0122	-0.5800	0.5610	-0.0310	0.0168
losst1roet1	-1.0619	0.0432	-24.610	0.0000	-1.1464	-0.9773
acct1	-0.0527	0.0061	-8.7000	0.0000	-0.0646	-0.0408
payert1	-0.0131	0.0108	-1.2100	0.2260	-0.0344	0.0081
payoutt1	0.0017	0.0002	7.2600	0.0000	0.0012	0.0021
_cons	0.0370	0.0108	3.4300	0.0010	0.0158	0.0581

Appendix 5. Stata code

```
clear
cd "\\Client\C$\Users\bruno\OneDrive\Ambiente de Trabalho"
import excel "\\Client\C$\Users\bruno\OneDrive\Ambiente de Trabalho\Volatility Master File
.xlsx", sheet("Sheet1 ") firstrow
egen Ticker1 = group(Ticker)
xtset Ticker1 Month, monthly
summarize RNOAVolatility , detail
keep if inrange(RNOAVolatility , r(p0), r(p99))
summarize RNOAVolatility , detail
keep if inrange(RNOAVolatility , r(p0), r(p99))
summarize RNOAVolatility , detail
summarize ForecastVolatility , detail
keep if inrange( ForecastVolatility , r(p0), r(p99))
summarize ForecastVolatility , detail
corr CDSSpreadVolatility EquityVolatility HistoricalequityVolatility ImpliedVolatility
ImpliedVolatilitya RNOAVolatility ForecastVolatility
summarize CDSSpread , detail
hist CDSSpread , freq kdensity title("Figure 1: CDS spread distribution")
summarize EXRET , detail
destring P5, replace
summarize lnVX , detail
summarize lnMarketCap , detail
summarize w , detail
summarize P5 , detail
summarize Skew , detail
summarize Kurt , detail
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility, fe
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya , fe
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt CDSSpreadVolatility , fe
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt RNOAVolatility , fe
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ForecastVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility , fe
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility RNOAVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility , fe
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility , fe Year
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility , fe time
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility RNOAVolatility ForecastVolatility , fe Year
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility RNOAVolatility ForecastVolatility , fe
```

```
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility ForecastVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility, fe
vc(robust)
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya , fe vc(robust)
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt CDSSpreadVolatility , fe
vc(robust)
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt RNOAVolatility , fe vc(robust)
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ForecastVolatility , fe
vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility , fe vc(robust)
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility RNOAVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility , fe vc(robust)
 xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility , fe Year vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility RNOAVolatility ForecastVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility RNOAVolatility ForecastVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility RNOAVolatility ForecastVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ROAVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility ROAVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility ROAVolatility ForecastVolatility, fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ROAVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility ROAVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility ROAVolatility ForecastVolatility, fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ROAVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility ROAVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt HistoricalequityVolatility
CDSSpreadVolatility ROEVolatility ForecastVolatility, fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ROEVolatility , fe
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility ROEVolatility , fe vc(robust)
xtreg CDSSpread lnVX EXRET lnMarketCap P5 Skew Kurt ImpliedVolatilitya
CDSSpreadVolatility ROEVolatility ForecastVolatility, fe
```

```
import delimited "\\Client\C$\Users\bruno\Downloads\Quant Reg.csv"sqreg rnoat rnoat1
losst1 losst1rnoat1 acct1 payert1 payoutt1, q(0.05 0.125 0.25 0.375 0.5 0.625 0.75 0.875)
import delimited "\\Client\C$\Users\bruno\Downloads\letstry.csv"
sqreg rnoat rnoat1 loss rnoaloss acc payer payout, q(0.05 0.125 0.25 0.375 0.5 0.625 0.75
0.875)
```