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Structural Credit Risk Models and the Determinants of Credit Default Swap Spreads

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Master in Finance

Supervisor:
PhD, José Carlos Gonçalves Dias, Associate Professor, Iscte-iul, Department of Finance

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Resumo

Na sequência da inovação financeira e das consequências da recente crise financeira global de 2008-2009, o interesse e recursos alocados à medição e modelação do risco de crédito registaram um grande aumento, por parte de investigadores e profissionais ao longo das últimas décadas.

Esta tese tem como objetivo explorar os determinantes dos *spreads* de crédito. Analisando primeiro o desempenho de variáveis teóricas de risco de crédito em explicar *credit default swap* (CDS) *spreads*, introduzindo também outros fatores específicos das empresas, macroeconómicos, de liquidez e de qualidade de crédito. O conjunto de dados utilizado é composto por empresas europeias não financeiras, com um período de tempo de 2010 a 2018 e usando modelos de dados em painel para realizar a análise econométrica.

Os nossos resultados empíricos mostram que os determinantes teóricos são estatisticamente e economicamente significativos e são capazes de explicar 27% dos níveis observados de CDS *spreads*. Depois de controlarmos para a liquidez do mercado, a notação de crédito, os fatores específicos das empresas e mercado, somos capazes de explicar 57% do total dos CDS *spreads* e 21% das suas variações. Além disso, através de uma análise de robustez, concluímos que os determinantes investigados têm um melhor desempenho na explicação dos *spreads*, quando o nível de risco de crédito no mercado é maior, o que é consistente com estudos anteriores. Por último, os nossos resultados sugerem que os modelos estruturais de risco de crédito beneficiariam se fossem desenvolvidos para responder a fatores teóricos e não teóricos, como as variáveis macro-financeiras.

Classificação JEL: G33, C33

Palavras-chave: risco de crédito, modelos estruturais, credit default swap, spread de crédito, modelos de dados em painel

Abstract

Following the financial innovation and the consequences of the recent 2008-2009 global financial crisis, the interest and resources allocated into measuring and modelling credit risk has seen a major increase by researchers and practitioners over the last decades.

The main objective of this thesis is to explore the determinants of credit spreads, analysing first the performance of theoretical variables of default risk in explaining credit default swap (CDS) spreads, while introducing other firm-specific, macroeconomic, liquidity and credit rating factors. The dataset used is composed of non-financial European companies, for the period of 2010 to 2018 and we use panel data models to perform the econometric analysis. In addition, this study also analyses structural credit risk models, namely the Merton (1974) model and some of its limitations and extensions.

Our empirical results show that theoretical determinants are statistically and economically significant and are able to explain 27% of the observed CDS spreads levels. After controlling for market liquidity, credit rating, firm and market-specific factors, we are capable of explaining 57% of the total CDS spreads levels and 21% of the spreads changes. Moreover, by performing a robustness analysis, we conclude that the investigated determinants perform better in explaining credit spreads, when the overall level of credit risk in the market is higher, which is consistent with previous evidence. Lastly, our results suggest that structural credit risk models would benefit if they were further developed to account for both theoretical and non-theoretical factors, such as macro-financial variables.

JEL Classification: G33, C33

Keywords: credit risk, structural models, credit default swap, credit spreads, panel data models

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List of abbreviations

BIS: Bank for International Settlements

CDG: Collin-Dufresne and Goldstein (2001) model

CDS: Credit Default Swap

DD: Distance-to-Default

ECB: European Central Bank

FPM: First Passage Models

GBM: Geometric Brownian Motian

ISDA: International Swap and Derivatives Association

LS: Longstaff and Schwartz (1995) model

LT: Leland and Toft (1996) model

OLS: Ordinary Least Squares

ROCE: Return on Common Equity

ROE: Return on Equity

VIF: Variance Inflation Factor

VK: Vasicek-Kealhofer model

ZCB: Zero Coupon Bond

1. Introduction

Credit risk modelling and management have received an increasing importance by academics and practitioners over the last decades, as a consequence of the various credit crises that followed the 2007-2008 global financial crisis. Simultaneously, the credit derivatives market, has seen a tremendous growth and innovation with the introduction of financial products that help minimize and manage credit risk. All of this has contributed to credit risk becoming one of the most relevant topics in finance.

When it comes to modelling credit risk two of the main approaches are: structural models and reduced-form models. In this thesis we analyse and investigate structural credit risk models, that were first introduced by the seminal works of Merton (1974) and Black and Scholes (1973). In the Merton (1974) model, corporate securities are seen as contingent claims on the firm´s underlying assets and there is an explicit connection between credit risk and the fundamental variables of a firm. With the original Merton model as the foundation, many extensions have been developed over the years, as an attempt to overcome some of its unrealistic assumptions and shortcomings. As a result, three models are briefly discussed, namely the Black and Cox (1976), Longstaff and Schwartz (1995) and Zhou (2001) models, as well as a review of past empirical performance of credit risk models. On the other hand, the reduced-form approach handles default as a pure jump process, governed by an exogenous hazard-rate process.

After the analysis of credit risk models, the main objective of this dissertation is to investigate how theoretical determinants proposed by structural models perform in explaining credit spreads. Moreover, other relevant firm-specific, macro-financial and liquidity variables are also tested with the purpose to identify other important determinants. In order to identify the most relevant factors, an econometric study is performed using panel data regression models, where we use credit default swap spreads as the proxy for the firm´s credit spreads, due to advantages this financial product presents when compared to bond prices.

These regressions are performed on a sample that includes 49 non-financial firms from the STOXX Europe 600 Index. The time period of the study consists of monthly observations from 2010 to 2018 and when performing the regression analysis, we apply both data in levels and changes.

From an academic perspective, this dissertation will contribute to the existing literature on credit risk, especially on structural models and the determinants of credit spreads, by providing valuable theoretical insights on the subjects of credit risk models, credit default swaps and how different variables and measures influence and determine these spreads. The understanding of these factors is crucial for both the financial industry and policy makers. Moreover, from an empirical stand we look to analyse how theoretical variables proposed by the structural approach and other non-theoretical factors, related to macro-financial factors, firm-specific factors and relevant measures of credit quality and market liquidity, are able to explain credit spreads, while also investigating how the estimated correlation signs compare with previous empirical evidence. In addition, we introduce a new dataset of variables, extending the existing literature by only using data from the European credit derivatives market, since previous studies use mostly data from U.S firms.

The present thesis is divided into chapters with the following structure. Chapter 2 analyses the most relevant literature and some important concepts on credit risk models and credit spread determinants. Furthermore, it provides an overview of past studies that have a similar objective to our study but use different credit risk proxies and different datasets of explanatory variables.

Chapter 3 presents an overview on credit derivatives, with a specific focus on credit default swaps since it represents our proxy for the firm´s credit spreads. Chapter 4 presents a theoretical analysis of the Merton (1974) model and three of the main extensions to it, while also reviewing the empirical performance of several credit risk models using bond data and CDS data.

In chapter 5 we describe the data used, namely the dependent variable and the sets of explanatory variables investigated. Chapter 6 explains the methodology that will be used, in particular the econometric methods applied and the specification of the regressions performed. It also presents the main problems faced when applying panel data models. In chapter 7 we present the empirical results from all regressions, while also performing a robustness analysis to get further insights on how the results vary according to the financial and economic context. Finally, in chapter 8 we present the main conclusions from the thesis and possible suggestions for further studies.

2. Literature review

2.1 Credit risk and default

Credit risk can be described, according to Duffie and Singleton (2012, pg.4) as the "risk of default or of reductions in market value caused by changes in the credit quality of issuers or counterparties". Credit risk has several components, but the most important, as identified by Schönbucher (2003), are: arrival risk, that is related to a firm defaulting or not, measured by the probability of default; timing risk that refers to the uncertainty about the exact time of default; recovery risk alludes to the risk of the extent of the losses suffered in case of default; market risk is related to a different type of risk, as it represents the risk of changes in the market price of a defaultable asset, even when there is no default.

Default risk constitutes the uncertainty associated with a firm or a debtholder´s ability to meet its debts in time (Crosbie and Bohn, 2003). There are several events that can occur and lead to a firm´s default, such as bankruptcy, a bond default, debt restructuring, changes in bond rating and credit rating, among others. A firm´s default, even though infrequent, it is extremely costly especially for capital suppliers, so firms are required to pay a yield spread over the risk-free interest rate to compensate lenders for the risk. This spread is proportional to their default probability (Crosbie and Bohn, 2003) and an increasing function of the probability of default, serving as a measure to evaluate credit risk.

The assessment and management of credit risk has always been essential for financial institutions and banks, and in the last decades due to financial innovation and globalization it has received more attention from both practitioners and researchers. Moreover, the global increase in the number of credit crisis and the recent 2008-2009 financial crisis have brought the need for more precise measurements for credit risk.

As stated by Hull, Nelken and White (2004) the increase in resources and interest in the task of credit risk assessment by banks and financial institutions, is also due to the proposals in the Basel II accord, where regulatory capital requirements can be determined using a bank´s internal analysis of its counterparties default probability.

2.2 Credit risk models

As pointed by Chatterjee (2015), credit risk models were created from the need to measure the capital requirements necessary to support a bank´s exposures. The objective of these models is to take as input both variables from the economy and from a specific firm and provide as output a credit spread that reflects the credit risk associated with that firm.

Two of the most relevant types of credit risk models are: structural models and reduced-form models. The structural approach was first introduced by the seminal work of Merton (1974) and applies the option pricing framework of Black and Scholes (1973) to price capital structure elements of a firm, since corporate liabilities can be decomposed as a combination of options. This approach, by taking as underlying asset the value of a firm, allows corporate securities within the firm´s capital structure to be regarded as contingent claims on the value of the firm. Under the original Merton (1974) model, the firm´s asset value follows a geometric Brownian motion, while having a very simple capital structure, composed only by debt as a single zero coupon bond (ZCB) and equity composed only of common stock.

Under these assumptions it is possible to price both the firm´s equity and debt. Structural models are then able to relate credit risk with firm´s fundamental variables such as the asset value and volatility.

The seminal work of Merton (1974) has been the basis for structural credit risk models and has had major contributions to the literature with the development of many extensions to the model, in attempts to overcome some of its shortcomings. The original Merton (1974) model has also been the foundation to some of the most important credit risk management models in the financial industry, namely the Moody´s KMV model, CreditGrades and CreditMetrics.

The structural model of Merton (1974) is very attractive in theory due to its ease of implementation, the direct use of the option pricing framework of Black and Scholes (1973) and the explicit relation between the firm´s economic variables and the risk of default. However, the model has some shortcomings and unrealistic assumptions, such as the simplistic capital structure it assumes, and the restriction of default only possible at the maturity of the debt, among others.

As a result, there has been an effort in the literature to overcome the shortcomings of the original Merton model, resulting in multiple extensions to the model, which incorporate more realistic assumptions, and consequently are able to generate credit spreads more consistent with the ones observed in corporate debt markets.

In order to overcome the assumption of default only at maturity, Black and Cox (1976) introduced first passage models (FPM), allowing a firm to default at any time and not only at the maturity of the debt. In the Black and Cox (1976) model, debt contracts accommodate for safety covenants that allow bondholders to take control of the firm and force it into bankruptcy or capital restructuring. FPM treat default as a barrier option, meaning that default occurs when the asset value falls below a specific default barrier.

Longstaff and Schwartz (1995) developed a model that expands the Black and Cox (1976) model by trying to overcome two shortcomings: constant interest rates and the fact that assets are allocated among corporate claimants with strict absolute priority in default. According to Jones, Mason and Rosenfeld (1984) there is evidence that the introduction of stochastic interest rates would improve the performance of the original Merton (1974) model, since they account for the connection between the firm´s asset value and the short rate (Elizelde, 2006).

Over the years, multiple extensions of the Black and Cox (1976) and the Longstaff and Schwartz (1995) models were introduced in the literature. Some of the most important include: Leland and Toft (1996) introduced a first passage time model with an endogenously fixed barrier due to stockholders' efforts to introduce a default threshold that maximizes the firm´s value. Collin-Dufresne and Goldstein (2001) developed a stationary leverage model where firms adjust their capital structure to reflect changes in asset value; this framework accounts for both stochastic interest rates and mean-reverting leverage ratios. Zhou (2001) extended the Longstaff and Schwartz (1995) model by incorporating jump risk in the asset value process. As a result, default becomes unpredictable because the asset value can suddenly drop into default. Lastly, Huang and Huang (2012) developed a double exponential jump-diffusion barrier model that has the ability to capture both high default risks and high stochastic discount factors.

Another important extension of the Merton (1974) model in the literature is the compound option approach introduced by Geske. The Geske (1977) model introduces a more complex capital structure, by observing that corporations issue risky coupon bonds, each coupon payment can be seen as a compound option (an option on an option). In the model, equity is seen as a compound call option on the firm´s assets, with a strike price equal to the coupon payments. In this framework, shareholders have the option of paying the bondholders at each coupon payment date, receiving the firm´s assets and ownership of the firm until the next payment. In the model, default is then endogenously computed at every coupon payment date, and it occurs when shareholders decide not to make the coupon payment.

In contrast with structural models, reduced-form models do not take into account the explicit relation between the firm-specific variables and default, modelling default as a jump process governed by a hazard-rate process. In these models, default is assumed to be unpredictable and driven by an exogenously given default intensity, which is a function of exogenous variables extracted from market data. This approach models default as a random event, uncorrelated with any firm-specific variables allowing for a simpler process since it does not require complete information about the firm´s assets and liabilities. However, since information from the firm's balance sheet is not accounted, there is no economic explanation for default.

Within the literature of reduced-form models some of the more relevant ones were introduced by Litterman and Iben (1991), Jarrow and Turnbull (1995), Duffie and Singleton (1999), among others.

Structural and reduced-form models have their advantages and disadvantages, and both rely on different modelling mechanisms and assumptions to measure credit risk. In the literature there is some debate on which approach does a better job at modelling and measuring credit risk (see Rogers, 1999;

Lando, 2009). Structural models are especially useful for professionals in the credit portfolio and credit risk management areas due to its intuitive economic interpretations, whereas, reduced-form models, due to its easier mathematical tractability and flexibility, have gained popularity among the credit trading field (Arora, Bohn and Zhu 2006).

The work of Jarrow and Protter (2004) represents a new comparison between both approaches from an information-based perspective. They defend that these models are not separated, but that in fact they are the same model just with different informational assumptions. Structural models assume that the modeller possesses full knowledge of the firm´s assets and liabilities, causing default to be predictable. On the other side, in reduced-form models the modeller has the same information as the markets (incomplete knowledge about the firm’s assets and liabilities), resulting in an unpredictable default time.

Based on the unlikely scenario of a modeller having complete knowledge about a firm, they defend that the reduced-form approach is more appropriate to price and hedge credit risk in an information based context (Jarrow and Protter, 2004). Other authors have favoured reduced-form models due to the general consensus in the literature that the asset value process in not observed continuously by the market (Duan, 1994; Ericsson and Reneby 2003, 2005), making its estimation very difficult, and a firm’s default time inaccessible (Jarrow and Protter, 2004). However, this is not enough to prefer one approach over the other, as the choice should depend on the purpose intended for the model and its strengths or weaknesses in real world scenarios (Arora, Bohn and Zhu 2006).

2.3 Determinants of credit spreads

There is an extensive literature about the determinants of corporate yield spreads. Some important examples include Jones, Mason and Rosenfeld (1984), Longstaff and Schwartz (1995), Duffee (1999), Collin-Dufresne, Goldstein and Martin (2001) and Eom, Helwege and Huang (2004), among others. All these previous studies were limited to the use of bond data, however with the growth and innovation of the credit derivatives market, researchers were able to directly measure default in corporate spreads with the use of these new credit derivatives (Longstaff, Mithal and Neis, 2005).

The use of credit derivatives, such as CDS spread, as a direct measure of credit default spreads has some advantages when compared to the use of corporate bond spreads. As stated by Hull, Predescu and White (2004), CDS spreads are quotes from dealers, while bond yields are indications from dealers, causing them to not necessarily reflect actual trading prices. Also, Longstaff, Mithal and Neis (2005) found evidence that a significant percentage of bonds spreads are influenced by liquidity factors, such as the bid-ask spread, that might not reflect the associated default risk. Moreover, the studies of Blanco, Brennan and March (2005) and Zhu (2006) show that, while in the long run CDS and bond spreads are very similar, in the short run CDS spreads appear to respond faster to new information and changes in credit conditions.

As a consequence, the credit derivative market leads the bond market in price discovery (Blanco, Brennan and March, 2005) and in general is more liquid (Huang, Shi and Zhou, 2020). One last advantage is that CDS spreads do not require the specification of a benchmark risk-free rate, which can be a difficult task (Ericsson, Jacobs and Oviedo, 2009).

Collin-Dufresne, Goldstein and Martin (2001) performed a study on the determinants of credit spread changes using data from the U.S. bond market. In a first attempt they run a regression to test the power of theoretical determinants proposed by structural models (leverage, risk-free rate and volatility), in explaining credit spread changes. Results indicate that these variables are statistically significant and with the predicted signs for the estimated coefficients. Nevertheless, these variables can only explain twenty-five percent of the changes. Results also imply that the residuals are highly correlated and a principal component analysis indicates that they are mainly driven by a single factor. In an attempt to identify this factor, another regression is performed with the inclusion of multiple financial and macroeconomic factors, yet none were able to explain this systematic component. This leads them to conclude that credit spread changes are mostly influenced by supply/demand shocks in the bond market and not credit risk factors.

Ericsson, Jacobs and Oviedo (2009) performed a similar study, but using data from credit default swaps. Results show that theoretical determinants of default risk are also statistically and economically significant. The explanatory power of these variables for the levels of credit default swap premium is around sixty percent, and for differences in premiums around twenty-three percent. When performing an analysis on the residuals, results differ from Collin-Dufresne, Goldstein and Martin (2001), because there is not enough evidence for the presence of a residual factor.

Zhang, Zhou and Zhu (2009) also use CDSs in their analysis of credit spread determinants, with a specific focus on equity volatility and jump risks of individual firms, while including other control variables like credit rating and macro-financial factors. Results from a regression with only volatility and jump risks explain fifty-four percent of credit spreads and when controlling for all the other variables, the R-squared increases to seventy-seven percent. Lastly, they conclude that the sensitivity of credit spreads to volatility and jump risk is higher for investment grade firms than high-yield ones, which has repercussions for the management of riskier credit portfolios.

Other relevant work in the literature include: Corò, Dufour and Varotto (2013) who study the role of credit and liquidity factors in explaining changes in CDS prices during normal and crisis periods. Their results indicate that liquidity risk is more relevant than firm-specific credit risk. Galil et al. (2014) examine the determinants of CDS spreads focusing on U.S. firms. In their study, they include different sets of explanatory variables, such as firm-specific variables, common economic factors, Fama and

French (1989) factors and also Chen, Roll and Ross (1986) factors. Results show that three variables namely, stock return, change in stock return volatility and change in the median CDS spread in the rating class outperformed the rest (Galil et al., 2014). Alexander and Kaeck (2008) study on CDS concludes that interest rates, stock return and implied volatility significantly impact CDS spreads and are dependent on market conditions; during periods of CDS market instability, spreads are more sensitive to implied volatility, while during normal conditions stocks returns have a higher influence.

Moreover, Longstaff, Mithal and Neis (2005) use CDS data to directly measure the size of default and nondefault components in corporate spreads. They find that the default component represents the majority of corporate spreads across all credit ratings, and that the nondefault component varies over time and is highly related to measures of bond-specific illiquidity and macroeconomic variables of bond market liquidity. Hull, Predescu and White (2004) analyse the relation between CDS spreads and credit rating announcements. Results show that reviews for downgrade have relevant information, but downgrades and negative outlooks do not. They are also able to prove that the CDS market anticipates all three types of rating announcements and is able to absorb new information quicker.

3. Credit derivatives

A credit derivative, according to Schönbucher (2003), is a derivative security mainly used to transfer, manage or hedge credit risk and whose underlying asset is a credit-sensitive asset or index. The payoff of these securities is materially affected by the credit risk of a reference entity, which could be a firm or a country. These financial instruments allow market participants to manage their exposure to the credit risk of these entities. For example, an investor (the protection buyer) can buy a credit derivative to transfer the credit risk to the protection seller.

Moreover, the payoff of these instruments is conditioned on the occurrence of a credit event. A credit event is a precisely defined default event, usually related to the credit reference and credit assets. Such events include bankruptcy, restructuring, payment failures or obligation default (Schönbucher, 2003).

There are different types of credit derivatives. Following Bielecki and Rutkowski (2013), it is possible to make the distinction based on the payoffs:

- Default products: these instruments are exclusively connected to default events and their payoff only occurs in such case. Examples include CDSs and default options.
- Spread products: credit derivatives whose payoffs are determined by changes in the credit quality of the underlying asset, e.g., credit spread swaps or credit spread options.
- Total return instruments: these derivatives enable the transfer of the total risk of an asset from one party to another, transferring not only the credit risk but also the market risk. As examples we have total return swaps.

The credit derivatives market was created by the International Swap and Derivatives Association (ISDA) in 1992. Since then, according to ISDA market surveys, there has been an exponential growth over the years, with a notional amount of \$631.497 billion in 2001 to more than \$45 trillion in mid-2007. However, after the 2008 global financial crisis there has been a downward trend in the market, decreasing from a notional amount of \$68.68 trillion in 2008 to \$12.64 trillion in 2016 and \$8.12 trillion in the first half of 2020. This sharp decline occurred because of the role credit derivatives played in this financial crisis, whose main cause is attributed to the lack of regulation in the derivatives market, aggravated by the wrongful use of these credit derivatives.

As a result, regulators and governments tried to solve this issue by implementing multiple financial reform legislations, the main one being the Dodd-Frank Wall Street Reform and Consumer Protection Act (2009), whose main objective was to promote financial stability in the United States by increasing accountability and transparency in the financial system, while introducing heavier regulation in the derivatives market, prohibiting banks from using customer deposits to invest in CDSs and other derivatives.

3.1 Credit default swaps

A credit default swap is a simple derivative contract that is responsible for the revolution of credit risk trading. Its main purpose is to enable the transfer of credit risk between market participants. This financial instrument is essentially a contract that provides insurance against the default of a reference entity.

In a CDS contract we have a buyer, named protection buyer, whose objective is to protect himself against the default on a loan or bond of a reference entity. On the other side, the seller of the contract, referred as protection seller, is willing to take on the credit risk of the reference entity defaulting, in return of periodic payments.

Therefore, the payoff from a CDS is equal to the loss-given-default on the underlying asset of a reference entity, triggered by a credit event. The periodic payments from the protection buyer to the protection seller, known as the premium leg, are expressed as a percentage of the notional value of the underlying asset, also referred as the CDS spread. If a credit event occurs prior to the expiration of the contract, the protection seller pays to the protection buyer the default payment agreed in the contract, known as the protection leg. The normal frequency of the premium leg is usually quarterly, and in case the credit event occurs between two payment dates the protection buyer still has to pay the fraction of the next premium payment that has accrued until the default date (accrued interest).

In order to better understand the concepts and payoffs behind a CDS, let us assume that at time $t = 0$ entity A (protection buyer) and entity B (protection seller) enter a 5-year CDS contract on a firm C (reference entity). Thus, A is taking a long position in the CDS and B a short position, with the goal of transferring the credit risk of entity C from A to B. The contract has the maturity of 5 years, with a notional amount of \$5 million and a CDS spread of 200 basis points.

- Premium payments: Assuming the payments are made quarterly, the protection buyer A has to pay to the protection seller B:

  200bp x \$5m/4 = \$25,000 at each time t_i with $i \in \{0.25; 0.5; \dots; 5\}$

- Credit events: The credit events are specified in the CDS contract with respect to a wide set of bonds issued by the reference entity C.
- Default payment: Assume that the reference entity C has failed to pay a coupon payment from a bond listed in the CDS contract at time $t = \tau$. If default occurred two months after the last payment date, A is required to pay the accrued interest to B equal to:

  $$\$25{,}000 \times \frac{2}{3} = \$16{,}666.67$$

  There are two alternatives for the default payment: if in the CDS contract is agreed a physical settlement, the protection buyer A delivers the bonds of the reference entity C to the protection seller B with a notional value of \$5m and B must pay the full notional of the bonds

$5m. If instead a cash settlement has been agreed, it is necessary to evaluate the market value of the bonds after default. To prevent liquidity and market manipulation problems several dealers are asked to value these bonds. Once the price of the defaulted bonds is determined, e.g. $430 for a bond of $1,000 notional, the protection seller B has to pay the difference between the price and the par value for a notional of $5m:

$$\frac{1{,}000 - 430}{1{,}000} \times \$5m = \$2.85m$$

Equally, using the concept of recovery rate (R) the default payment can be determined as the difference between the face value and the recovery value of the reference entity: the protector seller pays $(1 - R) \times \$5m$ with $R = 430/1{,}000 = 43\%$.

A CDS contract can also be regarded has a transfer of credit risk. This way, the protection buyer is selling the credit risk to the protection seller, instead of just selling the underlying asset to minimize his exposure to the credit risk of the reference entity. Thus, CDSs contracts allow investors to increase or decrease their vulnerability to the credit risk of a reference entity, which can be less costly than buying or selling the underlying asset.

As a result, CDSs have become the most popular credit derivative, and since they were introduced by JP Morgan in 1994 the CDS market has grown exponentially, reaching a notional amount outstanding of $61.24 trillion in 2007. Due to the 2008 global financial crisis this amount has decreased to $8.81 trillion in 2020 (see figure 1).

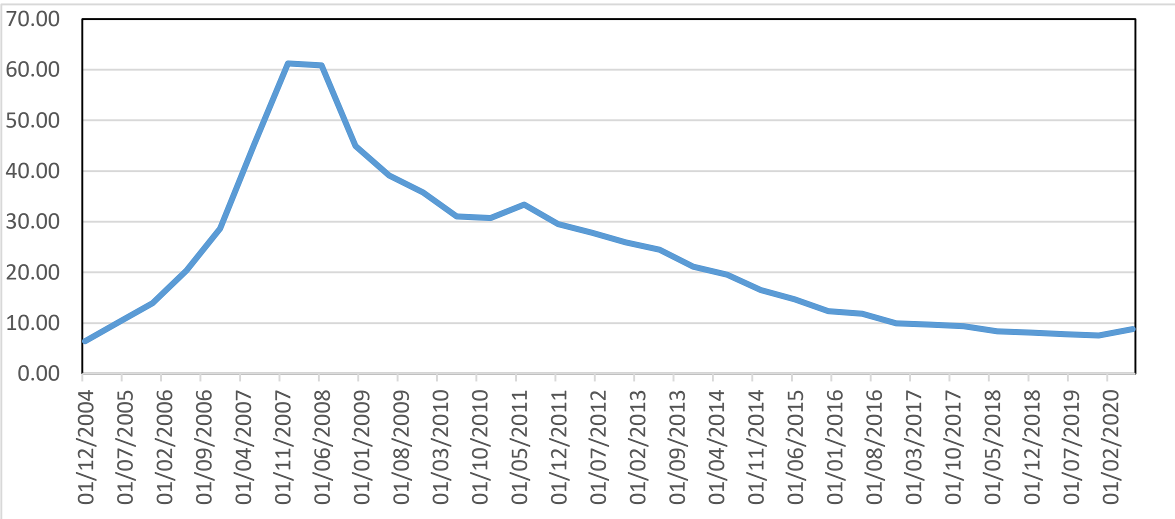

Figure 1: CDS notional amount outstanding (expressed in trillions of USD). Source: Bank for International Settlements (BIS)

3.3 Advantages and disadvantages of CDS

CDS are very useful financial instruments that since their introduction have been widely used in the financial industry by banks, insurance companies, hedge funds, etc. As already mentioned, a CDS contract allows market participants to manage, hedge and diversify their credit risk exposure.

According to Culp, Van der Merwe and Staerkle, (2016) and the ISDA CDSs have four potential benefits to their users:

- Credit risk transfer: the main objective of a CDS is to provide a risk management solution for lenders to control their credit exposures. The introduction of this innovative derivative allowed investors to customize their risk profile more efficiently than rebalancing a whole portfolio. There are two main risk management applications for CDS: the first one is to provide credit protection to cover losses in case of a credit event; and the second is to manage the interim market-to-market risk.
- Increase the credit supply: The creditor´s ability to hedge their credit exposures, allows financial institutions (before the Basel III, 2010) to free up economic/regulatory capital enabling lenders to increase their supply of loanable funds to borrowers.
- Synthetic bond investments: CDSs do not oblige the protection buyer to own the underlying asset, referred as naked CDSs. Therefore, firms can use CDSs to take positions on the credit risk of the underlying reference entity, to increase or reduce their credit exposure.
- Price discovery: CDS spreads reveal the market participants' expectations about their assessment of a reference entity probability of default and credit risk. In other words, CDS spreads are indicative of the market expectations about a firm´s likelihood of suffering a credit event, during the life of the CDS contract.

Prior to the 2008-2009 global financial crisis the literature on CDSs was shifted towards the benefits of these derivatives, but after the role they played in the crisis there has been more focus to their costs and disadvantages. According to the ISDA and Culp, Van der Merwe and Staerkle (2016) there are four main costs involved with CDS:

- Increase in risk-taking and decreased monitoring: The use of CDSs can potentially give banks incentives to take more risks, because by using these instruments banks can easily protect themselves from the risk of a borrower defaulting, which can serve has an incentive to give out riskier and larger loans. Moreover, banks by hedging their credit risk exposures are more likely to take part in insufficient monitoring of the borrower´s credit risk (Morrison, 2005).
- Empty creditor problem: The empty creditor problem occurs when a debtholder acquires credit protection through a CDS but retains control rights in the bankruptcy. As a consequence, these empty creditors lose their incentives to renegotiate the debt or make concessions even if it would be efficient for them, in an attempt to force the borrower into inefficient bankruptcy or liquidation.
- High volatility caused by speculation**:** As seen before, CDSs buyers are not required to own the underlying asset issued by the CDS reference entity. As a result, these instruments can be used

for speculation or “naked shorting” which can cause higher market volatility. The use of CDSs for speculation has been blamed for aggravating the European sovereign debt crisis which lead to the ban of naked shorting of sovereign debt through sovereign CDS in November, 2012. However, empirical evidence does not support this regulation as shown by Duffie (2010), and Silva, Vieira and Vieira (2016).

- Systemic Risk**:** Although there is not enough empirical evidence to blame CDSs for the credit and European sovereign debt crisis, these crises have revealed that they can increase systemic risk in the financial system. According to a document from the European Central Bank (2009), the CDS market is highly concentrated, which increases the counterparty risk in CDS contracts. In Europe the top ten counterparts of the surveyed banks accounted for 62% to 72% of its CDS exposures. The problem with having these high levels of counterparty and concentration risk is that if one dealer defaults, the systemic risk substantially increases generating uncertainty in the market. The 2008-2009 financial crisis is a good example of how complex credit derivatives can increase the systemic risk in the markets and lead to a credit crisis.

4. Structural credit risk models

The structural approach analyses the elements of a firm´s capital structure, such as the assets and liabilities values, in order to endogenously model credit risk. As a result, these models are able to provide an explicit relation between default and the firm´s fundamental economic variables.

4.1 Merton (1974) model

Structural credit risk models were first introduced by the works of Merton and Black and Scholes, with the pioneering Merton (1974) model, that uses the Black and Scholes (1973) and Merton (1973) option pricing framework to price capital structure elements.

This approach was first developed when it was recognized that the payoff structure of risky debt and equity of a levered firm, resembles the structure of call and put options. As a result, the model is able to apply option pricing formulas to value the various capital structure elements by decomposing corporate liabilities into a combination of financial options.

As a consequence, regarding the structure of corporate liabilities as contingent claims on the value of the firm, resulted in the contingent claim analysis that was then applied to a variety of finance fields.

4.1.1 Corporate liabilities as options

The original Merton (1974) model makes the simplistic assumption that a firm´s liability structure is only composed by debt, as a single zero coupon bond with face value *X* and maturity *T*, and equity as common stock. It also assumes that the asset value is not influenced by the capital structure of the firm.

Therefore, the Merton (1974) model is considered to be the simplest credit risk model to price corporate equity and debt due to the assumptions about the capital structure, and the simple default conditions it assumes. Within the model, the firm value (V_t) is given by:

$$V_t = E_t + D_t, \tag{4.1}$$

where E_t represents the equity value and D_t the debt value. In the model, in order to simplify the bond contract, it is assumed that the firm promises to pay at maturity the face value of the ZCB (*X*), and if *X* cannot be paid the firm enters bankruptcy and the ownership of the firm is transferred from stockholders to the bondholders. It is also assumed that there are no dividends and the firm cannot issue new securities while there is outstanding debt.

Under these specific assumptions, the firm´s equity can be regarded as a European call option on the firm´s value. Hence, the equityholders have the right, but not the obligation, to buy the firm from the debtholders by paying the strike price *X* at maturity *T*.

Using the put-call parity relationship to demonstrate the claims that both the equityholders and bondholders have on the firm´s value, we consider the following equality: the payoffs of the firm´s value (V_t) plus a put option written on it (P_t) are equal to the payoffs of a default-free ZCB (X_t), plus a call option written on the risky asset that constitutes the shareholder´s equity ($C_t \equiv E_t$). This is illustrated by the equation:

$$V_t + P_t = X_t + E_t <=> V_t = E_t + (X_t - P_t). \tag{4.2}$$

Using the market-value balance sheet identity in equation (4.1) that the firm value is equal to the equity value plus the debt value, we have:

$$D_t = Xe^{-r(T-t)} - P_t = X_t - P_t. \tag{4.3}$$

As a result, the firm´s value is composed by two claims: a riskier claim corresponding to the shareholder´s equity and is formally represented by a call option on the firm´s value with a strike price equal to *X* and maturity *T*; and a less risky claim represented by a default-free debt minus a European put option with a strike price equal to *X* and maturity *T*, equivalent to the bondholder's claim.

Using the put-call parity principle it is also possible to rewrite the bondholder´s claim as owning the firm and having a short European call option on the firm´s value with an exercise price equal to the face value of the bond:

$$D_t = V_t - C_t = V_t - E_t. \tag{4.4}$$

In summary, the payoff to the equityholders and bondholders are formally represented by:

$$E_t(V, X, T) = \max(V_t - X, 0) \tag{4.5}$$

and

$$D_t(V, X, T) = \min(V_t, X) = X - \max(X - V_t, 0). \tag{4.6}$$

In order to illustrate the payoffs of both type of investors at maturity, we have the following table:

Table 1: Stakeholder´s Payoffs

	Default ($V_t < X$)	**Survival** ($V_t > X$)
Shareholders' position:		
Call option	0	$V_t - X$
Payoff	0	$V_t - X$
Bondholders' position:		
Default-free bond	X	X
Short put option	$V_t - X$	0
Payoff	V_t	X

In case of survival, the equityholders will pay the face value of the bond X to the bondholders receiving control of the firm. As a consequence, the equity value is positive and represented by $V_t - X$, and the value of debt is equal to X. In contrast, if the firm defaults at maturity, shareholders declare bankruptcy giving control of the firm to the bondholders, meaning that the equity value is zero and the value of debt is equal to V_t, which is less than the promised payment of the bond X. After this analysis it is possible to observe the existence of a lower boundary to the equityholder's losses and an unlimited upside to their gains. This asymmetry occurs due to the limited liability nature of equity.

4.1.2 Merton model assumptions

In order to develop the Merton (1974) model for valuing corporate liabilities as contingent claims some specific assumptions have been made:

1. Perfect capital markets, which means that there are no transactions costs or taxes, there is also complete and symmetric information to all investors. Moreover, the assets are perfect divisible and investors are price-takers. Additionally, there are no limits to borrowing or lending.
2. Perfect liquidity, so firms are free to buy or sell assets to perform the necessary cash pay-outs and short selling is allowed.
3. Continuous asset trading in time.
4. Modigliani and Miller Theorem (1958) proposition I: The firm´s market value does not change according to its capital structure when there are no corporate income taxes and other market imperfections.
5. Shareholder wealth maximization is the main objective of managers.
6. Bankruptcy is only possible at the maturity of the debt *T*, and occurs when the asset´s market value falls below the face value of the debt ($V_t < X$). There are no bankruptcy costs and the absolute priority rule holds.
7. The risk-free interest rate is constant over time and non-stochastic.
8. The firm´s market value follows a geometric Brownian motion (GBM) given by:

$$dV_t = (\mu V_t - \bar{P})dt + \sigma V_t dW_t^p$$

where V represents the assets value, μ the expected rate of return on the firm´s assets value per unit of time, $\bar{P}$ the pay-out ratio, σ^2 is the variance of return per unit of time, and dW_t^p is a standard Gauss-Wiener process under P.

4.1.3 Option pricing model

Under the Merton (1974) model assumptions, it is possible to apply the Black-Scholes option pricing framework in order to provide a general formula for the time-t equity value of a levered firm, as:

$$E_t(V, X, T) = V_t N(d_1) - X e^{-r(T-t)} N(d_2), \quad (4.7)$$

where

$$d_1 = \frac{\ln\left(\frac{V_t}{X}\right) + (r + 0.5\sigma^2)(T-t)}{\sigma\sqrt{T-t}} \quad (4.7a)$$

and

$$d_2 = \frac{\ln\left(\frac{V_t}{X}\right) + (r - 0.5\sigma^2)(T-t)}{\sigma\sqrt{T-t}} = d_1 - \sigma\sqrt{T-t}, \quad (4.7b)$$

and E_t represents the market value of equity, X the promised principal of debt, V_t the asset´s market value, $T - t = \tau$ the time to maturity of the debt, r the risk-free interest rate and $N(.)$ the cumulative standard normal distribution function.

Using the same capital structure assumptions, the previous option pricing framework and the equality from equation (4.4), the model provides a general formula to price the value of a risky discount bond at time-t, given by:

$$D_t(V, X, T) = V_t N(-d_1) + X e^{-r(T-t)} N(d_2) \quad (4.8)$$

Alternatively, we can value risky debt as a portfolio that combines riskless debt and a short put option on the firm´s value (equation 4.3):

$$D_t(V, X, T) = X e^{-r(T-t)} - [X e^{-r(T-t)} N(-d_2) - V_t N(-d_1)] \quad (4.9)$$

Moreover, following the market-value balance sheet identity in equation (4.1) and equation (4.3), the value of the firm is given by:

$$V_t = E_t + X e^{-r(T-t)} - P_t \quad (4.10)$$

The final equation represents the put-call parity principle used to price European-style financial options, that can be expressed in the contingent claim analysis as:

$$assets = equity + (PV(face\ value\ of debt) - \text{"risk premium"}) = equity + debt \quad (4.11)$$

To conclude this section, one of the core concepts from the Merton model is that holding a defaultable bond is similar to having a portfolio that combines a riskless bond and a short put option, with the firm´s assets value as the underlying asset.

4.1.4 The implied risk structure of interest rates

In the real world there are many examples of credit crisis, whether by a firm or a sovereign defaulting. As a result, financial institutions have the need to evaluate the risks they are taking when lending money, which involves measuring the default probability of that specific entity and based on the likelihood of that scenario, they require the firm to pay a yield spread over the risk-free interest rate in order to compensate the risks they are taking. As predicted, this spread is proportional and an increasing function to the firm´s probability of default.

Under the same assumptions, the Merton model can be used to compute this credit spread. Once the cash flows of corporate bonds are similar to those of treasury bonds it is possible to use yields instead of bond prices to model credit spreads.

Assuming that a firm does not default and that the yield to maturity on risky debt is represented by $y(t,T)$, we have:

$$X = D_t e^{y(t,T)(T-t)}, \tag{4.12}$$

which is the same as expressing the yield to maturity at date t of a bond with maturity T as:

$$y(t,T) = \frac{1}{T-t} ln \frac{X}{D_t}. \tag{4.13}$$

Moreover, the yield to maturity on a defaultable bond is equivalent to the risk-free interest rate plus a credit spread that accounts for the default risk. We can then define the credit spread as:

$$s(t,T) = y(t,T) - r = \frac{1}{T-t} ln \frac{X}{D_t} - r = -\frac{1}{T-t} ln \frac{D_t}{X} - r \tag{4.14}$$

Applying equation (4.8) to price the value of a risky discount bond, we get the following formula for the credit spread:

$$\begin{aligned} s(t,T) &= -\frac{1}{T-t} ln\left(\frac{V_t N(-d_1) + Xe^{-r(T-t)} N(d_2)}{X}\right) - r \\ &= -\frac{1}{T-t} ln[e^{-r(T-t)}\left(\frac{V_t N(-d_1)}{Xe^{-r(T-t)}} + N(d_2)\right)] - r \\ &= -\frac{1}{T-t} \times \left(-r(T-t)\right) - \frac{1}{T-t} ln\left(\frac{V_t}{Xe^{-r(T-t)}} N(-d_1) + N(d_2)\right) - r \\ &= -\frac{1}{T-t} ln\left(\frac{V_t}{Xe^{-r(T-t)}} N(-d_1) + N(d_2)\right). \end{aligned} \tag{4.15}$$

A different but equivalent approach to value credit spreads in the Merton model consists of using the debt-to-firm value ratio, also referred as leverage, defined as:

$$d = \frac{Xe^{-r(T-t)}}{V_t}. \tag{4.16}$$

The leverage concept can then be integrated in formula (4.8) to calculate the value of debt as:

$$D_t = Xe^{-r(T-t)}\left[\frac{1}{d} N(-d_1) + N(d_2)\right]. \tag{4.17}$$

Using the same concept, we are also able to rewrite the credit spread value as a function of the firm´s leverage, given by:

$$s(t,T) = y(t,T) - r = -\frac{1}{T-t}\ln\left(\frac{1}{d}N(-d_1) + N(d_2)\right). \tag{4.18}$$

To conclude, by analysing the formula provided by the Merton (1974) model to value credit spreads, it is possible to identify the three major theoretical determinants of credit spreads proposed by structural models, namely the leverage, the asset volatility and the risk-free interest rate.

4.1.5 Default in the Merton model

In the Merton (1974) model, default occurs if at the maturity of the debt, the firm´s assets value (V_T) is less than the liabilities book value (X). Therefore, the firm´s default probability is the probability of the firm´s assets value falling below the default point, that in this case is the liabilities book value, illustrated in figure 2.

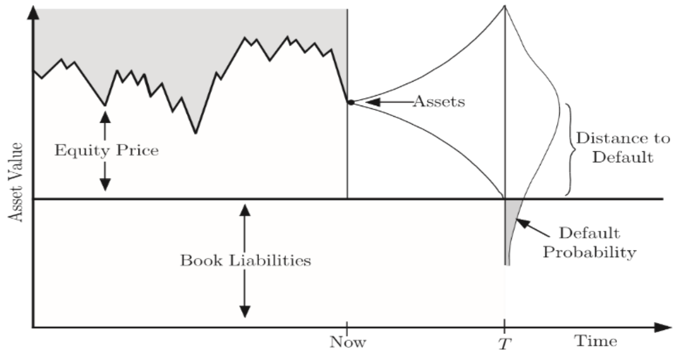

Figure 2: The Merton structural model of default, Duffie and Singleton (2012)

The probability of default can be formally described as:

$$PD(t,T) = Prob(V_T < X|V_t) = Prob(\ln(V_T) < \ln(X)|V_t)\,. \tag{4.19}$$

Additionally, since the asset value follows a GBM it is possible to define the distance-to-default (DD), which represents the number of standard deviations by which the firm´s assets surpass the liabilities (Duffie and Singleton 2012), as:

$$DD = \frac{\ln\left(\frac{V_t}{X}\right) + (\mu - \frac{\sigma_V^2}{2})(T-t)}{\sigma_V\sqrt{T-t}}. \tag{4.20}$$

Under the Merton (1974) model by simply replacing the drift μ with the risk-free interest rate r, the formula for the DD is equal to equation (4.7b), that represents the parameter d_2 in the model. As we can expect, when the distance to default increases, the firm´s default probability decreases.

To conclude, using the theoretical distribution implied by the Merton (1974) model, we are now able to formally define the risk-neutral probability of default within the model as:

$$PD(t,T) = N(-DD) = N(-d_2) = 1 - N(d_2). \tag{4.21}$$

4.1.6 Merton model limitations

The Merton (1974) model provides an attractive and intuitive approach to evaluate a credit risk, while also valuing a firm´s equity and debt values. The use of the Black-Scholes (1973) option pricing framework allows for its easy implementation, while also providing relevant insights on a firm´s default risk. However, in order to do so there is a trade-off between the model´s practical implementation and its assumptions.

As a result, the model has received criticism due to its several limitations and unrealistic assumptions; starting with the simplistic capital structure, in reality the debt structure of a firm is more complex than just a ZCB, often including other features like coupons, safety covenants and pay-out restrictions. As a result, other structural credit risk models have been developed, such as the Geske (1977) model, that accounts for more complex capital structures.

The assumption of costless bankruptcy and perfect capital markets is unrealistic, since in reality, defaulted firms have to pay court or reorganization costs and are required to pay several taxes.

Furthermore, the model assumes a known and flat risk-free interest rate term structure, something that does not correspond to the structure observed in the markets. Some extensions to the Merton model have incorporated stochastic interest rate, such as the Longstaff and Schwartz (1995) model, in order to account for interest rate risk and the correlation between credit risk and interest rates.

Another drawback of the model is the limitation is only possible at the maturity of the debt. Insinuating that a firm´s assets value could be close to zero, but recover in time to meet the debt´s obligations before maturity, without ever defaulting. This assumption is unrealistic, since in practice this firm would have defaulted before reaching the maturity of the debt. As a consequence, FPM were introduced by the Black and Cox (1976) model, treating default as a barrier option and accounting for the behaviour of the asset’s value before maturity.

Finally, the last shortcoming of the Merton (1974) model, that also applies to structural model in general, is the inability to directly observe the firm´s asset value process. By having as inputs the asset value and asset volatility, these models are required to estimate these variables using other processes.

These limitations can partially explain the poor empirical performance of the Merton (1974) model in predicting and explaining credit spreads. Previous studies by Jones, Mason and Rosenfeld (1984), Eom, Helwege and Huang (2004) and Huang, Shi and Zhou (2020), among others, have showed that the Merton model provides credit spreads smaller than the actual spreads observed in the markets. As stated by Elizalde (2006), modelling the firm´s asset value as a GBM and the assumption that default can only occur at maturity, causes the default time to be predictable and the model to under predict credit spreads, as shown by Jones, Mason and Rosenfeld (1984) and Franks and Torous (1989). The empirical performance of structural credit risk models is discussed in depth in section 4.5.

Due to the model´s shortcomings and limitations, many structural models have been developed over the years, incorporating more realistic assumptions in order to generate credit spreads more consistent with those observed by debt markets. In the next section, three of the main extensions to the Merton (1974) model will be analysed, namely the Black and Cox (1976), the Longstaff and Schwartz (1995) and the Zhou (2001) model.

4.2 Black and Cox (1976) model

In the Merton (1974) model default can only occur at maturity when the firm´s assets value fall below the face value of debt. In reality default can occur unexpectedly and due to several reasons. As a result, Black and Cox introduced the concept of FPM by extending the Merton (1974) model in altering the default conditions, relaxing the assumption of default only possible at maturity, while allowing for a more complex debt structure with safety covenants, debt subordination and asset sale restrictions.

In FPM default is treated as a barrier option, meaning that default occurs when the firm´s assets value falls for the first time, below a specific default barrier (Beem, 2010). This barrier can be exogenous or endogenously determined, whether it is defined outside or inside the model respectively. Since default can occur at any time until maturity, the implied default probabilities and credit spreads generated by FPM are closer to the ones observed in the markets, and are higher than the spreads generated by the Merton (1974) model.

The Black and Cox (1976) model follows the Merton (1974) model, also assuming that the asset dynamics of the firm is governed by a GBM:

$$dV_t = (r - q)V_t dt + \sigma V_t dW_t^Q, \tag{4.22}$$

where q is a positive constant representing the firm´s pay-out ratio.

The model includes safety covenants on the value and behaviour of the firm´s assets, that allow bondholders to force the firm into bankruptcy or reorganization. This can occur if the stockholders fail the interest payments on the debt. However, if stockholders can simply sell some assets to meet the firm´s debt obligations, the safety covenants are not effective (Black and Cox, 1976). As a consequence, the safety covenant of the model assumes that if the value of the firm´s assets fall to a specified value, the bondholders have the right to force the firm into bankruptcy, receiving the firm´s assets. This way, interest payments do not have the same critical role (Black and Cox, 1976).

Therefore, the model assumes an exogenous default barrier, modelling the safety covenants as a time-dependent variable with an exponential form. Black and Cox (1976) specified the bankruptcy level as $Ke^{-\gamma(T-t)}$, resulting in a time-dependant deterministic default barrier given by:

$$H(t) = \begin{cases} Ke^{-\gamma(T-t)} & \Leftarrow t < T \\ X & \Leftarrow t = T \end{cases}, \tag{4.23}$$

where K and γ are positive parameters and $Ke^{-\gamma(T-t)} < Xe^{-r(T-t)}$.

In the Black and Cox (1976) model the distribution of the first passage time

$$\tau_H := inf\{t \in [0,T]: V_t \leq H(t)\} = inf\{t \in [0,T]: V_t = H(t)\}, \tag{4.24}$$

is obtained as:

$$\mathbb{Q}(\tau_H \leq T|\mathcal{F}_t) = N\left(\frac{\ln\left(\frac{H(t)}{V_t}\right) - \tilde{v}(T-t)}{\sigma_V\sqrt{T-t}}\right) + (\frac{H(t)}{V_t})^{2\tilde{a}}\, N\left(\frac{\ln\left(\frac{H(t)}{V_t}\right) + \tilde{v}(T-t)}{\sigma_V\sqrt{T-t}}\right), \tag{4.25}$$

where $\tilde{v} = r - q - \gamma - \frac{1}{2}\sigma_V^2$ and $\tilde{a} = \tilde{v}/\sigma_V^2$.

The probability in a risk neutral world, that the firm never hits the default barrier before time T is given by:

$$\mathbb{Q}(\tau_H \leq T|\mathcal{F}_t) = N\left(\frac{\ln\left(\frac{H(t)}{V_t}\right) - \tilde{v}(T-t)}{\sigma_V\sqrt{T-t}}\right) + (\frac{H(t)}{V_t})^{2\tilde{a}}\, N\left(\frac{\ln\left(\frac{H(t)}{V_t}\right) + \tilde{v}(T-t)}{\sigma_V\sqrt{T-t}}\right), \tag{4.26}$$

In summary, the Black and Cox (1976) model is able to improve the original Merton (1974) model by generating higher default probabilities and credit spreads that are more consistent with those observed in debt markets. However, this approach is more complex and still shares some of the shortcomings of the Merton model, namely the constant interest rates and the strict absolute priority rules in default.

4.3 Longstaff and Schwartz (1995) model

Longstaff and Schwartz (1995) developed a model that aims to extend the Black and Cox (1976) model by focusing on two of its shortcomings. First, it incorporates both default risk and interest rate risk by assuming stochastic interest rates, and secondly, the model allows deviations from the strict absolute priority rule.

In order to incorporate stochastic interest rates, the model uses the term structure model developed by Vasicek (1977) for the interest rate process. The interest rate (r) dynamics following Vasicek, are given by:

$$dr = (\zeta - \beta r)dt + \eta dZ_{2,} \tag{4.27}$$

where ζ, β and η are constants and Z_2 is a standard Wiener process.

According to Longstaff and Schwartz (1995), this term structure is consistent with many of the observed interest rate properties, but has the disadvantage of allowing negative interest rates. However, the probability of negative interest rates occurring is rather low for the parameter values applied (Longstaff and Schwartz, 1995).

Following Black and Cox (1976) the model assumes that there is a threshold value K that triggers the firm into default. Default is then triggered when $V = K$ and bankruptcy or reorganization is just a mechanism where the total assets value are allocated to the respective classes of corporate claimants (Longstaff and Schwartz, 1995).

Contrary to previous analysed models, the Longstaff and Schwartz (1995) model deviates from the strict absolute priority rule due to the studies of Franks and Torous (1989, 1994), among others, that provide evidence that this rule is frequently overstepped on corporate reorganizations. Additionally, previous research shows that the payoff to bondholders depends on multiple exogenous variables, such as the firm size and bargaining power (Longstaff and Schwartz, 1995). Longstaff and Schwartz rather than attempting to model the difficult bargaining process during bankruptcy, they assume the allocation of the firm´s assets as an exogenous variable.

Therefore, the model assumes that if a reorganization occurs, the security holder will receive $1 - w$ times the face value of the security. The factor w is constant and represents the percentage write-down that occurs when a firm enters a reorganization process (Longstaff and Schwartz, 1995). In general, w changes according to the bond issue or the class of the security. The value for w can be computed using actuarial information, for example, Altman (1992) found that the average w for secured and senior debt from 1985 to 1991 was 0.395 and 0.477, respectively.

The framework developed by Longstaff and Schwartz (1995) for valuing risky corporate debt has some advantages when compared with other structural models. Firstly, by incorporating both default risk and interest rate risk they conclude that the correlation between the firm´s assets and changes in the interest rate level are significant and implies that credit spreads are negatively related to the interest rate level. Secondly, for investment-grade bonds the changes in interest rates are able to explain a higher percentage of credit spreads changes than changes in the firm´s assets value (Longstaff and Schwartz, 1995). Moreover, the model has the ability to be directly applied to value risky debt of firms with more complex capital structures. However, the disadvantages of including stochastic interest rates in the model are the increase in complexity.

4.4 Zhou (2001) model

The Merton (1974) model and the two previously mentioned extensions developed by Black and Cox (1976) and Longstaff and Schwartz (1995), all share the same critical assumption that the evolution of the firm´s assets value follows a diffusion process. Under this assumption, default becomes predictable, because unexpected drops in the firm´s value are impossible (Zhou, 2001). As a result, firms that are not in financial difficulties have a close to zero probability of defaulting and credit spreads much lower than those observed by markets (Beem, 2010).

The model developed by Zhou (2001) solves this problem by incorporating the risk of random jumps in the asset value process. The implementation of a jump-diffusion process allows default to occur due to changes in the firm´s assets value or from random jumps.

According to Zhou (2001), a jump-diffusion model has many advantages: firstly, it has the flexibility to generate a wide variety of term structures for credit spreads that match with those observed in the markets. Secondly, the inclusion of jump risk allows for non-zero probability of default for short time-to-maturity bonds of financially secure firms. Lastly, the model assumes that the remaining value of a firm at default is a random variable, thus generating stochastic recovery rates that are linked to a firm´s capital structure and asset value at default.

In summary, the structural model with a jump-diffusion process developed by Zhou (2001) is able to combine the advantages of both structural and reduced-form models. In one hand, the model is capable of capturing random default events; on the other hand, the model also provides conceptual insights on the economic mechanism of default risk. However, the drawback of including a jump-diffusion process is that the parameter estimation becomes more complex and less attractive for practical implementations (Beem, 2010).

4.5 Empirical performance analysis of structural credit risk models

In the previous section several extensions to the Merton (1974) model were analysed from a theoretical point of view. The objective of this section is to analyse the empirical performance of structural models in generating credit spreads similar to those observed in the markets.

4.5.1 Performance of the Merton (1974) model

The first study on the empirical performance of the original Merton model was performed by Jones, Mason and Rosenfeld (1984). Their main objective was to test the model´s ability to price corporate bonds and results showed that the model generates prices much lower than the actual market spreads. Similarly, the study performed by Eom, Helwege and Huang (2004) also concludes that the predicted spreads by the Merton model are too low.

Huang, Shi and Zhou (2020) performed a similar study but using CDS data and their results strongly reject the Merton (1974) model in estimating CDS spreads. However, the model does well in describing the sensitivity of CDS spreads to equity returns and also outperforms the others analysed models in hedging.

4.5.2 Performance of structural credit risk models using bond data

Eom, Helwege and Huang (2004) test the ability of five structural models in predicting credit spreads in the bond market. Those models are: Merton (1974), Geske (1977), Longstaff and Schwartz (LS) (1995), Leland and Toft (LT) (1996) and Collin-Dufresne and Goldstein (CDG) (2001).

Overall they conclude that all the models have some form of pricing error and underpredict credit spreads for bonds with shorter maturities. Similarly to previous studies, their results indicate that the Merton and Geske model generate spreads lower than the actual market spreads. However, the LS, LT and CDG model generate spreads that are too high on average (Eom, Helwege and Huang, 2004). In addition, all the models have the problem of overestimating the credit spreads on risky bonds (high levels of leverage and volatility), while underestimating the spreads of bonds considered safe (Eom, Helwege and Huang, 2004). According to the authors this is caused by liquidity factors not accounted in the models.

Moreover, Huang and Huang (2012) study how structural models perform in explaining corporate yield spreads. The models investigated include: a base case for the Longstaff and Schwartz (1995) model with constant interest rates, the original LS model with stochastic interest rates, models with endogenous default boundaries like the LT model, strategic default models such as the Anderson-Sundaresan (1996) model and lastly the CDG model.

Their results indicate that applying stochastic interest rates in the model decreases the implied credit spreads, while the original LT model, strategic default models and the CDG model generate, on average, higher spreads than the base LT case. In the study the authors propose a double exponential jump-diffusion model which allows for analytical tractability, while providing higher credit spreads than the base case of their study (Beem, 2010).

4.5.3 Performance of structural credit risk models using credit default swap data

Ericsson, Reneby and Wang (2015) investigate how structural models perform in estimating credit spreads from credit default swap data compared with corporate bond data. The three models investigated are: Leland (1994) model, where debt is perpetual and promises a continuous coupon stream, the Leland and Toft (1996) model and the Fan and Sundaresan (2000) model, which is similar to the Leland (1994) model, but debtholders and shareholders can renegotiate in financial distress to prevent inefficient liquidations.

The results for the bond market are consistent with previous evidence, since the models underpredict bonds spreads when treasuries are used as benchmark. Specifically, the Leland (1994) and the Fan and Sundaresan (2000) models underestimate bond spreads by 91 and 67 basis points, respectively; while the Leland and Toft (1996) model underestimates by 59 basis points (Ericsson, Reneby and Wang, 2015). However, when the swap curve is used as benchmark, the results are similar to those for credit default swaps. This suggests that previous evidence of underestimation of bond spreads can be influenced by the choice of the benchmark risk-free curve (Ericsson, Reneby and Wang, 2015).

Contrarily, results from the CDS market are more promising, with the Leland (1994) and the Fan and Sundaresan (2000) models underestimating CDS spreads by 43 and 19 basis points, respectively. The Leland and Toft model performs the best out of the three models, underestimating CDS spreads by, on average, 2 basis points (Ericsson, Reneby and Wang, 2015).

Huang, Shi and Zhou (2020) conduct a study comparing the performance of five structural models in estimating CDS spreads. The five models analysed are the original Merton (1974), the Black and Cox (1976), LS, CDG and the Huang and Huang (2012) model. They propose a new approach to testing these models based on model-implied variables, like credit spreads and equity volatility, that applies the generalized method of moments of Hansen (1982) to perform the parameter estimation and the specification analysis of the models.

Their results reject the Merton (1974), Black and Cox (1976) and LS models, with the Huang and Huang (2012) outperforming these three models and the CDG performing the best among all models. When analysing the pricing error results the authors conclude that incorporating jumps and dynamic leverage can improve the overall model fit for investment grade and high-yield issuers, respectively (Huang, Shi and Zhou, 2020). However, all the models tested have difficulties representing the behaviour of CDS spreads and equity volatility. Huang, Shi and Zhou conclude that based on their empirical findings including stochastic asset volatility and jump-risk in the original Merton (1974) model can improve its performance in estimating CDS spreads, equity volatility and hedge ratios of CDS spreads (Huang, Shi and Zhou, 2020).

4.5.4 Conclusions from empirical analysis on structural credit risk models

After analysing the performance of structural credit risk models, we are able to conclude that spreads implied by the original Merton (1974) model are much smaller than the observed market spreads, especially for lower maturities. This disparity can be caused by the previously mentioned shortcomings and unrealistic assumptions of the model, however there is not a consensus around the main reasons for the model´s poor performance.

Nonetheless, the Merton (1974) model is not the only model with this problem, as all the extensions presented in this chapter also suffer to a degree the same problem of underestimating credit spreads, or overestimating in some cases.

Many authors have tried to explain this phenomenon, concluding that one explanation is the liquidity premium component incorporated in credit spreads. Longstaff, Mithal and Neis (2005) found that even though the default risk component represents the majority of corporate CDS spreads, the nondefault component is significant and strongly related to bond-specific illiquidity. Similarly, Chen, Lesmond, and Wei (2007) find that liquidity is priced in yield corporate spreads, where illiquid bonds have higher yield spreads and bonds without liquidity issues have significant lower yield spreads.

The issue is that in general, market credit spreads from bonds or CDSs are higher than the ones implied and estimated by credit risk models, which leads to an overcompensation of credit risk. This is commonly referred in the literature as the credit spread puzzle.

4.6 Reduce-Form models

The alternative approach from structural models to model credit risk is the reduced-form approach. Reduced-form models or intensity models are developed to account for the unexpected nature of default, thus modelling default as a pure jump process governed by an exogenous hazard-rate process, also referred as default intensity process. Therefore, these models use an exogenous default intensity obtained from market prices of financial instruments, such as bonds and CDSs, to model the default event.

As a result, reduced-form models do not use information from the capital structure of a firm which simplifies the process, but does not provide economic interpretation for the default event since the relation between the firm´s economic variables and default is not taken into account.

As stated by Schmid (2004), reduced-form models, unlike structural models, can be applied in cases where the underlying asset value and volatility are not observable. Moreover, the use of a default intensity process generates an unpredictable default time and therefore the implied credit spreads from the models are more realistic. In addition, this approach offers more flexibility to generate spreads that are more consistent with the observed credit spreads (Schmid, 2004).

4.6.1 Empirical performance of reduced-form models

The first empirical analysis on the performance of reduced-form models was presented by Duffee (1999). The model tested is an adaptation from the Duffie and Singleton (1997,1999) models; the results indicate that on average the model fits corporate bond yields well, with a mean squared error lower than 10 basis points. Moreover, the model´s parameter estimation demonstrates that a firm´s financial health can substantially improve without driving yield spreads to zero, this suggests that the model is capable of capturing a liquidity component, in other words a nondefault component in credit spreads (Duffee, 1999). Lastly, the model generates a steeper spread term structure for lower quality firms than for higher ones, which represents a relevant attribute of the observed spreads.

Houweling and Vorst (2005) perform a similar study but analyse how market prices of CDSs compare with those implied by reduced-form models. They investigate a simple reduced-form model close to the Jarrow and Turnbull (1995) model. Results reveal that the model does quite well in explaining the spreads of investment grade issuers, while also performing better in pricing CDSs than bond yields.

Arora, Bohn and Zhu (2005) compare the performance of two structural models and one reduced-form model on predicting and explaining credit spreads in the CDS market. The structural models analysed are the original Merton (1974) model and the Vasicek-Kealhofer (VK) model, while the reduced-form model is the Hull and White (2000) model. Results show that the VK model outperforms the rest, except when the issuer has more than 10 bonds in the market, in which case the Hull and White (2000) model performs better in explaining variations of CDS spreads.

5. Data

This chapter of the thesis presents the data required for the empirical analysis on the determinants of credit spreads, from the sample selection to the choice and analysis of the variables tested in the regressions.

In order to perform the econometric study part of this dissertation, we have chosen to specifically investigate the determinants of credit default swap spreads using data from the European credit derivatives market. Also, since information about stock prices will be needed, all the companies selected are listed companies that integrate the STOXX Europe 600 Index. In this sample only non-financial firms are included, so we have companies with comparable balance sheet information. Moreover, the sample period consists of monthly observations during the time period from 01.01.2010 to 31.12.2018. This time interval was selected because it represents the peak of the European sovereign debt crisis and also the recovery period after it, so we are able to analyse credit spreads during a crisis period and also during a positive economic cycle.

All the required data was collected from the Bloomberg Terminal. The study uses panel data models, combining both time-series and cross-section data from the firms in the sample and investigates the power and effects of the explanatory variables with data in levels and changes.

5.1 Dependent variable

In the econometric study, as the dependent variable we use credit default swap spreads as the proxy for the firm´s credit spreads. Specifically, the monthly quotes on 5-year CDS contracts of the firms in the sample. This maturity was chosen because it represents the most liquid contracts in the CDS market (Ericsson, Jacobs and Oviedo, 2009); Zhang, Zhou, and Zhu, 2009). The quotes used are the mid-spreads which represent the average bid and offer quotes.

The choice of using CDS spreads as the proxy for the firm´s credit spread relies on the advantages presented in the literature review chapter, when compared to the use of bond yields. Moreover, CDS spreads are regarded as a relatively pure pricing measure of a firm´s credit risk (Huang and Zhou, 2008).

After selecting from the STOXX Europe 600 index, the firms with a 5-year CDS contract available for the analysed period, without any missing information at any point from 2010 to 2018, the final sample includes 49 European companies, identified in Appendix A.

5.2 Explanatory variables

Following the studies of Collin-Dufresne, Goldstein and Martin (2001) and Ericsson, Jacobs and Oviedo (2009), we will start by investigating the power of theoretical determinants proposed by structural credit risk models in explaining credit spreads, namely the firm´s leverage, risk-free rate and historical volatility.

In addition, other non-theoretical variables will be included in the regressions with the objective of testing other explanatory variables and their impact on credit spreads. These determinants will include variables with proven explanatory power and statistical significance, and also consider some different variables that account for firm´s financial conditions, market liquidity, credit quality, and economic and market conditions.

Compared to previous studies, we will analyse some explanatory variables applied in the Moody´s KMV Expected Default Probability (EDF) RiskCalc model, which is a premier model to evaluate default probabilities and credit risk. These variables are financial ratios that represent relevant risk factors of financial performance, such as profitability and firm liquidity (Dwyer, Kocagil and Stein, 2004).

The explanatory variables will be divided into groups: theoretical determinants, firm-specific variables, market-specific variables and other relevant variables. Theoretical determinants include the firm´s leverage, risk-free rate and historical equity volatility. The firm-specific variables include the equity return, implied volatility, return on equity (ROE) and the current ratio. Market-specific variables include the slope of the yield curve, the market return and market volatility. Finally, there are other relevant variables such as the bid-ask spread and credit rating.

5.2.1 Theoretical determinants

As we have seen before there are three main theoretical determinants proposed by structural credit risk models: the firm´s leverage, the risk-free rate and the historical volatility. In this section we explain each explanatory variable and its expected impact on credit spreads.

- Leverage

Starting with the firm’s leverage, this variable is central to all structural models because if the firm´s assets value falls below the firm´s liabilities value, the firm defaults. As a result, leverage has a crucial role in modelling default risk.

As expected, a firm with higher levels of leverage is more likely to default, as such, ceteris paribus, the higher the leverage, the higher the price of protection against default, resulting in higher credit spreads. Previous studies such as Collin-Dufresne, Goldstein and Martin (2001), Ericsson, Jacobs and Oviedo (2009) and Zhang, Zhou and Zhu (2009) confirm this positive and significant correlation.

For each of the firms in the sample we compute the monthly leverage ratio according to Collin-Dufresne, Goldstein and Martin (2001) as:

$$lev = \frac{Book\ Value\ of\ Total\ Liabilities}{Market\ Value\ of\ Equity + Book\ Value\ of\ Total\ Liabilities}. \qquad (5.1)$$

Since book value of debt is only available quarterly and in some cases semi-annually, we use a linear interpolation method to obtain monthly values.

- Risk-free rate

The second theoretical determinant is the risk-free rate, which according to the Merton (1974) model is negatively related to credit spreads. As explained by Longstaff and Schwartz (1995), the static effect of a higher risk-free rate is to increase the risk-neutral drift of a firm value process, which reduces the probability of default and the firm´s credit spreads. This negative relation has been shown in previous studies by Collin-Dufresne, Goldstein and Martin (2001), Duffee (1998) and Longstaff, Mithal and Neis (2005), among others.

However, from a macroeconomic perspective, higher interest rates can represent a tighter monetary policy marked by higher borrowing costs. In this case, the relation between credit spreads would be positive due to the increase in the funding costs for investors. This positive correlation has been identified in the studies of Leland and Toft (1996), Zhang, Zhou and Zhu (2009) and Corò, Dufour and Varott (2013).

Contrarily to most previous studies, our study will use as proxy for the risk-free interest rate, the 5-year Euro swap rate. The obvious alternative would be governments bonds, however as stated by Blanco, Brennan and March (2005) these are no longer adequate proxies due to taxation treatments, repo specials and scarcity premia. Moreover, Houweling and Vorst (2005), Zhu (2006) and Hull, Predescu and White (2004) conclude that market participants, both in the bond market and CDS market, use swap rates as the proxy for risk-free rates. Lastly, Ericsson, Reneby and Wang (2015) argue that the swap curve is a more appropriate benchmark for corporate bond spreads because it is closer to the cost of funding for traders.

- Historical volatility

The last theoretical determinant is the firm´s volatility. However, this variable is not directly observed in the markets, which requires modellers to use other volatility proxies, being the most common the historical volatility.

The contingent-claims approach assumes that having a debt claim is similar to holding a short put option, as a result an increase in volatility causes the option price to increase. The Merton (1974) model implies that credit spreads should increase when volatility is higher due to the decrease in the debt claim value. In other words, higher volatility leads to an increase in the bankruptcy risk, which as a result increases the protection cost and credit spreads. This positive correlation has been confirmed by Ericsson, Jacobs and Oviedo (2009) and Zhang, Zhou and Zhu (2009), among others.

The data for the firm's historical volatility was directly retrieved from Bloomberg, where for each month, the historical volatility was computed based on firm´s equity prices from the last 90 trading days, similarly to Campbell and Taksle (2003) and Benkert (2004).

5.2.2 Firm-specific determinants

We will also investigate the power of firm-specific variables in explaining the credit spreads of the firms in the sample, namely the firm´s equity return and implied volatility, while also accounting for profitability and liquidity measures such as the ROE and the current ratio.

- Equity return

The equity return of a firm is considered to be a good proxy for a firm´s financial condition, consequentially the negative relationship between credit spreads and equity return is logical: a higher stock return implies that a firm is more valuable and in better financial health, which means a lower probability of default and lower credit spreads. This relationship has been applied in the studies of Collin-Dufresne, Goldstein and Martin (2001) and Cremers et al. (2008).

By using both equity returns and leverage ratio we can have some multicollinearity problems, since equity market information is already included in the leverage formula. However, according to Collin-Dufresne, Goldstein and Martin (2001) both variables provide meaningful information, since the use of equity returns allows for a more direct use of equity market data.

The equity return is represented by the monthly log-returns of each firm´s equity in the sample.

- Implied volatility

As another measure for firm volatility we include the firm-specific implied volatility, which unlike the historical volatility, represents a forward-looking metric based on traders' expectations. Similarly to the historical volatility, the implied volatility is expected to have a positive correlation with credit spreads, since an increase in volatility increases the probability of having a faster first passage time to default. This positive relationship is confirmed by the studies of Benkert (2004), Alexander and Kaeck (2008), Cao, Yu and Zhong (2010) and Cremers et al. (2008).

The inclusion of option-implied volatility is relevant since according to Benkert (2004) and Cao, Yu and Zhong (2010) implied volatility outperforms historical volatility in explaining credit spreads, due to the ability of forecasting future volatility, while capturing a time-varying volatility risk premium.

The implied volatility variable, following Cao, Yu and Zhong (2010), is represented by the 30-day at-the-money put option-implied volatility of each firm, collected directly form Bloomberg.

- Return on equity

In order to investigate how the profitability of a firm is related to its credit spread, the firm-specific ROE is included in the study. Although the analysis of the ROE alone can be misleading, since firms with a large weight of debt can default and still be very profitable. For this reason, we include other firm-specific variables to account for leverage and firm liquidity. Naturally, it is expected a negative relationship between the firm´s ROE and the respective credit spreads, because, in theory, a more profitable firm is less likely to default.

We will use the return on common equity (ROCE) as our proxy for firm´s profitability, which represents the return that common equity investors receive for their investment in the firm. Since the ROCE is only reported quarterly or semi-annually, we use a linear interpolation to obtain monthly values.

- Current ratio

In addition to profitability, we also use a firm liquidity measure, namely the current ratio, which measures the ability of a firm to pay its short-term obligations. In other words, its ability to cover its current liabilities with its current assets. As expected, the higher the ratio, the better the firm´s financial condition and liquidity, which ultimately leads to a lower default probability and lower credit spreads.

The current ratio is directly collected from Bloomberg and, similarly to the ROCE, we use a linear interpolation to obtain monthly values.

5.2.3 Market-specific Determinants

Some market related variables will also be tested in order to investigate how market conditions and expectations affect the firm´s individual credit spreads.

- Slope of yield curve

The slope of the yield curve can be used as a proxy for the expectations of futures spot rates and as a measure for economic health. Naturally, when the slope is higher we expect higher spot rates in the future and an improvement in economic activity, which ultimately leads to a decrease in credit spreads (Collin-Dufresne, Goldstein and Martin, 2001). However, according to Zhang, Zhou and Zhu (2009) the impact of an increase in the slope of the yield curve can be ambiguous, as a stepper slope can also be indicative of a future rise in inflation and a monetary tightening of credit, resulting in a positive correlation with credit spreads. Moreover, Galil et al. (2014) argue that a stepper slope can cause the number of positive net present value projects to decrease and lead to an increase in credit spreads.

Following Duffee (1998), Collin-Dufresne, Goldstein and Martin (2001) and Campbell and Taksler (2003), we define the slope of yield curve as the difference between the long-term and short-term interest rates, specifically the 10-year and 2-year German government bond yield, since we are using a European dataset.

- Equity market return

The overall market return can provide useful information about the general state of the economy. We expect a negative relationship between the market return and credit spreads, since an increase in market return leads to an improved economic environment, which causes expected recovery rates to be higher and credit spreads to be lower.

This negative correlation has been captured in the studies of Collin-Dufresne, Goldstein and Martin (2001) and Ericsson, Jacobs and Oviedo (2009), who used the return of the S&P 500 to account for the state of the economy. However, in our study, we will use the monthly log-returns of the STOXX Europe 600 Index, as a proxy for the overall condition of the European economy.

- Market volatility

As a different proxy for the overall state of the economy, we test the power of market volatility in explaining credit spreads. When the market volatility is low, there are better economic conditions, since there are less fluctuations and higher market stability, as a result the default probabilities and credit spreads are expected to be lower. This positive correlation has been teste by Zhang, Zhou and Zhu (2009) and Corò, Dufour and Varotto (2013).

As a proxy for the overall European market volatility we will use monthly data from the VSTOXX volatility index.

5.2.4 Other relevant determinants

In our analysis we will also include other variables that account for the market liquidity and the credit quality and safeness of a firm.

- Bid-Ask spread

In order to capture the relationship between liquidity and credit spreads, we will use as proxy for illiquidity the bid-ask spread. The bid-ask spread is a useful measure for liquidity and is capable of reflecting inventory costs, processing costs and asymmetric information (Corò, Dufour and Varotto, 2013). Moreover, the study of Fleming (2001) on the relationship between liquidity and the treasury market, concludes that the bid-ask spread is a relevant measure for liquidity risk and does a better job at reflecting liquidity, when compared to other market liquidity proxies.

In theory, the more liquid a security is, the narrower the bid-ask spread. In addition, in cases of market illiquidity protection sellers will demand a higher premium, rising the respective credit spreads (Corò, Dufour and Varotto, 2013). As a result, we expect a positive correlation with credit spreads.

The bid-ask spreads have been computed with the monthly differences between the ask and bid CDS spreads of the firms in the sample.

- Credit rating

Credit ratings are considered to be one of the most reliable measures to evaluate the credit quality of a debt issuer or an entity in general. The negative relationship between credit rating and credit spreads is straightforward, as a higher credit rating results in a higher credit quality, which ultimately leads to lower credit spreads. The statistical significance and correlation of the credit rating has been confirmed by the studies of Hull, Predescu and White (2004), Daniels and Jensen (2005) and Cremers et al. (2008), among others. In fact, Aunon-Nerin et al. (2002) defend that the credit rating is the single most relevant source of information in credit spreads.

Following the study of Corò, Dufour and Varotto (2013) the credit rating variable is represented by the average of the three ratings assigned by Standard & Poor´s, Moody´s and Fitch. In order to differentiate the ratings, we will assign the letter rating into a numerical scale, in which a lower credit rating correspond to a higher number (See Appendix B).

This procedure has been widely used in the literature but can introduce some bias, due to the assumption that the influence of a credit rating change is equal to all the credit rating classes. This is not true, since in practice, credit rating changes have a more significant impact for lower quality underlying's than for higher quality ones (Aunon-Nerin et al. 2002). However, working with multiple dummy variables can become problematic and cause multicollinearity issues. Moreover, since some rating classes have very few observations in our sample, the use of dummy variables is not very well suited (Aunon-Nerin et al. 2002). As a result, in our analysis we will not deal with this problem since our main objective is to only investigate the power of credit ratings in explaining credit spreads.

6. Methodology and empirical model

In this chapter, we present the methodology that we will apply to investigate the determinants of CDS spreads, based on Baltagi (2005) and Verbeek (2017). Firstly, we introduce panel data models and the main problems we can face when performing this type of regression analysis. Secondly, we define and explain the regression models we will perform, as well as the type of data used.

6.1 Methodology

For the econometric study on the determinants of credit default swap spreads, we will apply panel data models to perform our investigation, since our dataset combines cross-sectional and time series dimensions. Previous research on the determinants of credit spreads that also use panel data include Ericsson, Jacobs and Oviedo (2009), Cremers et al. (2008) and Zhang, Zhou and Zhu (2009), among others. For our analysis we will use a similar framework to these previous studies.

According to Gujarati (2003), panel data is a combination of both cross-sectional and time series data; it is essentially the movement of cross-sectional units over a period of time.

As stated by Gujarati (2003), the use of panel data has some advantages when compared to cross-sectional or time series data. Firstly, by combining both types of data it is able to provide more information, more variability, less collinearity between the variables and also more efficient estimations. In addition, panel data due to its characteristics allows us to investigate more complex financial problems, while also reducing the problem of having omitted variables.

In panel data we have the following static linear regression model:

$$Y_{it} = \alpha + \beta' X_{it} + \varepsilon_{it}\ , \quad i = 1,2,\dots,N \text{ and } t = 1,2,\dots,T\ , \tag{6.1}$$

where *i* represents the cross-sectional dimension and *t* the time. α denotes the constant in the model and β is a K x 1 vector of parameters and X_{it} represents the *it*th observation on K explanatory variables (Baltagi, 2005). Following Baltagi (2005) panel data regressions models can have cross section effects, time effects or both, and in most of the models it is assumed a one-way error component model for the errors, where only one type of effect is dealt with:

$$\varepsilon_{it} = u_i + v_{it} \text{ or } \varepsilon_{it} = \lambda_t + v_{it}\ , \tag{6.2}$$

where u_i is time-invariant and accounts for any individual-specific effect, and on the other hand, λ_t is individual-invariant accounting for time-specific effects. Their objective is to capture the effects of variables that are not included in the regression, and that are time-constant and characteristic to the *i*-th unit or cross-section-constant and peculiar to the t-th period. The component v_{it} represents the usual error in the regression that varies with individuals and time (Baltagi, 2005).

Cross section and time effects are analysed as fixed or random effects models, depending if u_i and λ_t are treated as fixed or random. When treated as random variables they are referred as random effects, and as fixed effects when they represent parameters to estimate for each individual cross section unit *i* or for each time period *t*. Hence, in panel data regression models, traditionally there are two main models: the fixed effects and the random effects model.

In the fixed effects model, we are able to incorporate unobserved individual effects that are correlated with the variables of the model. Therefore, if we have an individual specific effect not included and correlated with X_{it}, the ordinary least squares (OLS) estimator for the vector β is biased (Jakovlev, 2007). As a result, we have the following model:

$$Y_{it} = \alpha + \beta' X_{it} + v_{it} , \tag{6.3}$$

where the cross section and time effects u_i and λ_t are treated as fixed parameters and are combined with the intercept term α that now has two components. For example, in the case of a time-invariant component u_i peculiar to the *i*-th unit and a α component constant for all *i* (cross-section one-way error component model) the regression model is defined as:

$$Y_{it} = \alpha + u_i + \beta' X_{it} + v_{it} \ , \ \text{with } \alpha + u_i = a_i \ . \tag{6.4}$$

In the random effects model, u_i and λ_t are treated as random variables and not as parameters to be estimated. The model assumes that the individual and time specific effects are uncorrelated with the regressors of the model, that is, X_{it} are uncorrelated with u_i, λ_t and v_{it} (Baltagi, 2005). Moreover, v_{it} is uncorrelated with u_i and λ_t for all *i* and *t*. Consequentially we expect that the OLS estimator for u_i, λ_t and β to be unbiased and consistent (Verbeek, 2017).

In this model the error term ε_{it} has two components, an individual-specific variable u_i that is time-invariant and/or a time specific variable λ_t that is cross-section invariant, and also a remainder component v_{it} (Verbeek, 2017). For example, in the case of a two-way error component model we have:

$$Y_{it} = \alpha + \beta' X_{it} + u_i + \lambda_t + v_{it}, \quad \text{with } u_i + \lambda_t + v_{it} = \varepsilon_{it} \ . \tag{6.5}$$

In order to decide whether fixed or random effects are better suited for our model, we will use the Hausman test, which is a test for model misspecification, where the null hypothesis is that the random effects model is preferred, versus the alternative that fixed effects are more suitable. The test is making its decision based on the correlation between the errors and the regressors, thus if they are uncorrelated the random effects model is preferred.

6.2 Autocorrelation, heteroskedasticity and unit roots

When performing an econometric study, it is crucial to identify the problems that can arise. The two main obstacles in panel data models are the presence of heteroskedasticity and autocorrelation in the error term, which can lead to incorrect and biased standard errors of the estimates and t-statistics. In case we detect any of these issues, we must apply a different estimator, such as the robust standard errors method, namely the Driscoll and Kraay (1998) procedure for panel data, which is an adaptation of the Newey-West estimator.

6.2.1 Autocorrelation

Autocorrelation, also referred as serial correlation, represents the correlation between the error and its past observations. The main causes for this problem, according to Gujarati (2003), are the omission of relevant variables for the model; secondly, serial correlation can be caused by incorrect specification of the functional form of the regression and lastly the presence of non-stationarity.

In the presence of autocorrelation, the OLS estimators continue to be consistent and unbiased but they are inefficient and no longer BLUE. Moreover, the estimated variances and the standard errors become biased and inefficient (Gujarati, 2003). In order to detect serial correlation in our panel data models we will apply the Breush-Godfrey test, which has the advantage of detecting autocorrelation up to any order ρ. The null hypothesis assumes the absence of serial correlation:

$$H_0\colon\ \rho_1 = \ \rho_2 = \cdots = \rho_p = 0 \qquad (6.6)$$

6.2.2 Heteroskedasticity

Heteroskedasticity refers to a situation where the conditional variance of the error term is not constant and different that σ^2. This problem can be caused by the presence of outliers in the data or due to misspecification of the regression model applied. Moreover, another possible sources of heteroskedasticity are the skewness in the distribution of an independent variables and extreme fluctuations in the value of an explanatory variable, among others (Gujarati, 2003).

The presence of heteroskedasticity can have several consequences, namely the OLS estimators, similarly to the autocorrelation, are no longer BLUE because they are not the most efficient, which can lead to inaccurate and misleading conclusions (Gujarati, 2003).

In order to test for heteroskedasticity in the errors we will apply the Breusch-Pagan test for panel data models, in which the null hypothesis is that the errors variances are equal (homoskedasticity).

6.2.3 Unit Roots

When dealing with panel data models, with a large number of time series observations, it is crucial to test if the data is stationary, which in our case implies that the distribution of the dependent variable (CDS spread) it is not dependent of time. The presence of non-stationarity can indicate that the time-series is affected by trends, seasonality or breaks and one of its most relevant consequences is having a spurious regression, a regression that provides misleading results.

One of the main sources for non-stationarity is the presence of unit roots. Unit roots test have been widely used in time series studies, however unit root testing in panel data models is fairly recent.

In this study we apply the Levin, Lin and Chen (2002) test, which provides a panel unit root test that allows for individual specific intercepts and time trends by considering a pooling time series data. The null hypothesis is that each of the individual time series has a unit root, with the alternative hypothesis that each time series is stationary (Baltagi, 2005).

Moreover, we also apply the Maddala and Wu (1999) test which is a Fisher-type test, that gathers p-values from unit root tests for each of the cross-sections, in order to test for the presence of unit roots. The tested hypotheses are the same as in the Levin, Lin and Chen test.

6.3 Empirical model

The first step to define the empirical model is to investigate whether the dependent variable is stationary. In order to do so we apply the Levin, Lin and Chen and Maddala and Wu test, using the R software. The test results show that we reject the null hypothesis in both tests (see appendix D) and therefore the CDS data is stationary, both in levels and changes. As a result, following the study of Ericsson, Jacobs and Oviedo (2009), we investigate how the selected explanatory variables affect CDS spreads, using both levels and changes data.

It is relevant to notice that the data in changes is computed by taking the first difference of all the variables in our model. Furthermore, for the first month (January 2010) the differences are calculated based on the last month of the previous year (December 2009). For the rest of the period, the data is calculated by taking the difference between the present month and the past one.

According to Cremers et al. (2008) when performing a regression based on changes, the focus lies more on the time-series variations, since we are analysing how CDS spread changes are affected by a change in an explanatory variable over time. In addition, the use of data in differences is harder to explain but provides more interesting results from a managerial point of view. On the other hand, regressions in levels study how the possible determinants impact both cross-sectional and time-series variations in the credit spreads (Jakovlev, 2007). For example, how the credit spreads vary amongst firms, due to differences in historical volatility.

In our regression analysis we start by analysing the power of the theoretical determinants in explaining CDS spreads (regression 6.7). After, we examine the firm-specific variables (regression 6.8) and the market-specific variables (regression 6.9) and lastly the other relevant determinants (regression 6.10). Afterwards, we perform a regression based on all the independent variables and also a robustness analysis, with the objective of investigating how these determinants explain and influence CDS spreads during different economic periods: the first marked by the sovereign debt crisis in Europe (2010-2013) and the post-crisis period (2014-2018).

For the data in levels the following regressions are analysed:

Regression with theoretical determinants:

$$CDS_{it} = a_i + \beta_1 Lev_{it} + \beta_2 Rf_{it} + \beta_3 HistVol_{it} + \varepsilon_{it}. \quad (6.7)$$

Regression with firm-specific determinants:

$$CDS_{it} = a_i + \beta_1 EqRt_{it} + \beta_2 ImpVol_{it} + \beta_3 ROE_{it} + \beta_3 CurrentRatio_{it} + \varepsilon_{it}. \quad (6.8)$$

Regression with market-specific determinants:

$$CDS_{it} = a_i + \beta_1 Slope_{it} + \beta_2 MktRt_{it} + \beta_3 MktVol_{it} + \varepsilon_{it}. \quad (6.9)$$

Regression with other relevant determinants:

$$CDS_{it} = a_i + \beta_1 BAspread_{it} + \beta_2 CR_{it} + \varepsilon_{it}. \quad (6.10)$$

Regression with all explanatory variables:

$$\begin{gathered} CDS_{it} = a_i + \beta_1 Lev_{it} + \beta_2 Rf_{it} + \beta_3 HistVol_{it} + \beta_4 EqRt_{it} + \\ \beta_5 ImpVol_{it} + \beta_6 ROE_{it} + \beta_7 CurrentRatio_{it} + \beta_8 Slope_{it} + \beta_9 MktRt_{it} + \\ \beta_{10} MktVol_{it} + \beta_{11} BAspread_{it} + \beta_{12} CR_{it} + \varepsilon_{it} . \end{gathered} \quad (6.11)$$

For the data in changes, two regressions will be tested: one with the theoretical determinants, in order to investigate how CDS spread changes are influenced by the changes of variables proposed by traditional credit risk models, and a second one where all explanatory variables are included:

Regression with theoretical determinants (in changes):

$$\Delta CDS_{it} = a_i + \beta_1 \Delta Lev_{it} + \beta_2 \Delta Rf_{it} + \beta_3 \Delta HistVol_{it} + \varepsilon_{it}. \quad (6.12)$$

Regression with all explanatory variables (in changes):

$$\begin{gathered} \Delta CDS_{it} = a_i + \beta_1 \Delta Lev_{it} + \beta_2 \Delta Rf_{it} + \beta_3 \Delta HistVol_{it} + \beta_4 \Delta EqRt_{it} + \beta_5 \Delta ImpVol_{it} + \\ \beta_6 \Delta ROE_{it} + \beta_7 \Delta CurrentRatio_{it} + \beta_8 \Delta Slope_{it} + \beta_9 \Delta MktRt_{it} + \beta_{10} \Delta MktVol_{it} + \\ \beta_{11} \Delta BAspread_{it} + \beta_{12} \Delta CR_{it} + \varepsilon_{it} . \end{gathered} \quad (6.13)$$

7. Empirical results

In this chapter we start by discussing the descriptive statistics of the variables used in our models, while also presenting a correlation analysis between the explanatory variables, in order to detect any multicollinearity problems. Moreover, we perform the necessary statistical test to detect any autocorrelation or heteroskedasticity issues and define which panel data models are preferred. Next, we present the results from the regressions performed, using both data in levels and changes. Lastly, we will perform a multi-period analysis by dividing our sample in two time periods, one during the European credit crisis and the other corresponding to the post-crisis period.

7.1 Descriptive statistics

The analysis of the descriptive statistics of the dependent variable and explanatory variables, by using measures of central tendency and variability, is helpful to get a better understanding on their evolution over the investigated period.

Analysing the descriptive statistics (Appendix C), the average changes in the investigated period are intuitive, and in line with the overall development of the European economy. Following the 2008-2009 crisis and the Eurozone crisis, the European Central Bank (ECB) has been practicing an expansionary monetary policy, which resulted in a decrease of interest rates, decreasing from near 3% in 2011 to -0.15% in 2016. As expected, the yield curve has changed from upward-sloping to close to flat, indicating that investors are less concerned about future inflation and anticipate interest rates to remain steady in the future. Moreover, CDS spreads have decreased on average 0.254 basis points, indicating that the markets believed that these firms have reduced their credit risk during this period.

In addition, when examining the firm-specific variables, the leverage ratio has on average decreased, while the historic volatility has slightly decreased and the implied volatility has recorded a small increase of 0.016%. As expected, both the ROE and current ratio improved on average, but interestingly the overall equity log returns have seen a small decrease of near -0.114%. It is interesting to notice that even though the mean of the equity log returns is positive (0.637%), the average change in the log returns is negative from 2010 to 2018. One possible explanation is that during the periods of higher uncertainty, the decreases in the returns were more significant than the increases recorded during the bullish ones.

Throughout our sample, similarly to the equity log returns, the market log returns have also seen a decrease of -0.1%, while the market volatility has slightly decreased. Lastly, the CDS market liquidity has on average recorded a slight improvement, similarly to the credit ratings.

In Appendix C we also present the correlation matrix between all the individual variables, which can help identify possible multicollinearity problems. Analysing the pairwise correlations, it is not surprising that the correlation between the risk-free rate and the slope of the yield curve is high (82.4%). However, a correlation matrix has limited power in detecting multicollinearity, since it only analyses the correlation between pairs of variables. As a result, we use the variance inflation factor (VIF), which measures the level of multicollinearity among a set of explanatory variables. Looking at the VIFs for each of the independent variables, the variables with the highest values are the risk-free rate and slope of the yield, with VIF of around 3.8 and 3.2, respectively. These values suggest the existence moderate correlation, but since none of the VIFs are higher than 5 there is no evidence of critical values of multicollinearity.

7.2 Statistical tests

After defining the panel data regressions that we will perform, it is necessary to run statistical tests in R, with the objective of identifying autocorrelation and heteroskedasticity problems and lastly to decide whether fixed or random effects model are better suited.

Starting with the Hausman test (Appendix E), by analysing the results we can see that for the data in levels we reject the null hypothesis (p-value<0.05), which leads to the conclusion that the fixed effects model is preferred. On the other hand, when the data is presented in changes, the results show that we do not reject the null hypothesis (p-value>0.05) and the random effects model is more adequate.

Next we performed an autocorrelation test (Appendix F), in order to detect any serial correlation in the error term, namely the Breush-Godfrey test. Since both p-values for the test in levels and changes, are lower than 0.05, we reject the null hypothesis and conclude that there is autocorrelation.

Lastly, we performed the Breush-Pagan test, in order to detect heteroskedasticity in the models. By analysing the results (Appendix G), for both types of data we reject the null hypothesis, as a result we conclude that there is heteroskedasticity in our dataset.

Considering that in our dataset we have detected autocorrelation and heteroskedasticity, we need to calculate the robust standard errors, for both the models in levels and in changes. We will use the Driscoll and Kraay (1998) standard errors, since this procedure is capable of producing heteroskedasticity and autocorrelation-consistent standard errors, while also being able to ensure a valid statistical inference in our models (Hoechle, 2007).

7.3 Results from the regressions in levels

After performing the necessary statistical test and applying the robust standard errors to control for heteroskedasticity and autocorrelation, we are now able to analyse the estimated regressions results.

7.3.1 Regression with theoretical determinants

We start by analysing the results from the regressions using fixed effects and with data in levels, presented in Appendix H. Looking at the results from regression (6.7), composed by the theoretical determinants, we can observe that all three variables are statistically significant (at the 1% level) in explaining the CDS spreads levels of the selected firms.

With respect to the sign of the coefficients, for the leverage there is a positive correlation with the CDS spreads, which is in line with predictions from structural models. Interestingly, the benchmark for risk-free interest rate applied in our model, has a positive correlation with credit spreads, contrarily to most previous literature on credit spreads in the CDS and bond markets. This change of sign can be explained by the fact that most previous studies on the determinants of credit spreads, were performed prior to the 2008-2009 global financial crisis, where interest rates were much higher. Whereas the post-crisis period was marked by a sharp decrease in interest rates, as a result of the expansionary monetary policies applied, which according to our results had a positive impact on the firm´s credit risk, since CDS spreads decreased. Moreover, this positive correlation is supported by macroeconomic theory, since higher interest rates can reflect a tightened monetary policy, resulting in higher credit spreads and default probabilities. Lastly, as expected the historic volatility is positively correlated with CDS spreads.

Additionally, when analysing the adjusted R-squared we observe that all three variables have an explanatory power of 27.1%. Since this value is not as high as in previously mentioned studies, we can conclude that the theoretical determinants predicted by structural models have limited power in explaining the CDS spreads levels in our study. As a result, there is the need to incorporate other variables that account for different measures of the default probability and macroeconomic conditions.

7.3.2 Regression with firm-specific determinants

The results of regression (6.8), which include the firm-specific determinants, are presented in Appendix H. Firstly, implied volatility and the two measures introduced to account for profitability and liquidity, namely the ROE and the current ratio, are all statistically significant. However, in our study the equity return is not statistically significant, unlike previous literature that use data from the U.S market. This points to the possible conclusion, that the equity log returns of European firms are not as good of a proxy for the financial situation of a firm as the firm´s leverage, not containing much relevant information in explaining the levels of CDS spreads.

Moreover, the weak explanatory power of equity returns can be explained by the fact that CDS spreads in levels might not be able to respond fast enough to short-term variations in equity markets, since credit spreads fluctuations are much less common than equity returns variations. One solution to this problem is the use of equity returns based on the last 180 or 360 days, instead of monthly returns.

Additionally, the signs of the coefficients are in line with theory except for the equity return, which in this regression is not statistically significant. As was foreseeable, an increase in the firm´s implied volatility by 1% leads to an average increase of 3.96 basis point on the CDS spreads, while both the ROE and current ratio have a negative correlation.

Interestingly, the explanatory power of all the firm-specific variables is 22.2%, which is lower than the power of the theoretical determinants. This suggests that there might be other firm-specific factors affecting CDS spreads, such as firm size, growth rate or recovery rates. Moreover, when comparing the explanatory power of implied volatility with historical volatility (Appendix I), the implied volatility is able to explain a much higher percentage of the CDS spreads levels, which is in line with previous studies that use both volatility measures.

7.3.3 Regression with market-specific determinants

Results from regression (6.9) are available in Appendix H. When regressing the levels of CDS spreads based on the levels of the market-specific variables, it is possible to conclude that the slope of the yield curve, the market return and market volatility are all statistically significant in explaining the CDS spreads levels.

Regarding the estimated coefficients, the slope of the yield curve has a positive correlation with CDS spreads, which is the opposite relationship predicted by theory. However, similarly to the effect of the risk-free rate in our study, this positive sign can be explained by the impact that a steeper slope can have on forecasting a future economic scenario, with rising inflation rates and a tighter credit policy. As predicted by theory, the market volatility has a positive coefficient estimate. However, the model estimates that an increase in the market return causes CDS spreads to increase, contrarily to previous literature and economic rationality.

Nonetheless, when performing a regression with only the market return (Appendix J), the coefficient sign is negative, as predicted. This coefficient sign change can be explained by the presence of some multicollinearity among the market-specific determinants. Indeed, when analysing the results for the VIFs in Appendix C some multicollinearity is detected, but not enough to be considered critical. Moreover, this sign change can be explained by the Simpson´s Paradox, which is a well-known phenomenon in regression analysis.

Looking at the explanatory power of the market-specific factors, we conclude that these variables do a slightly better job than the firm-specific factors, in explaining the levels of CDS spreads (23.2% to 22.2%). However, the market-level determinants still have a lower explanatory power when compared with the theoretical determinants (23.2% to 27.1%). Suggesting that the factors driving credit spreads proposed by theoretical models, outperform the aggregate factors (market-specific variables) in explaining CDS spreads, contrarily to the findings of Collin-Dufresne, Goldstein and Martin (2001).

7.3.4 Regression with other relevant determinants

We move now to the results from the regression (6.10) with the bid-ask spread and the credit rating, which represent liquidity and credit quality measures, respectively. Both variables are statistically significant and have a positive estimated coefficient sign, in line with theory. Since a larger bid-ask spread is indicative of less liquidity in the market, consequentially increasing credit spreads, a higher credit rating score (in our scale) is the result of a perceived lower credit quality by rating agencies, which increases spreads.

When analysing the adjusted R-squared, it is possible to conclude that both factors outperform the other set of variables, in explaining the levels of CDS spreads, with an explanatory power of 35.1%. This suggests that in our study, the credit spreads levels are more affected by liquidity risk and the respective firm´s credit quality, than firm-specific variables and macroeconomic conditions. These results are in line with previous studies that concluded that the credit rating can be one of the most relevant sources of information in credit spreads. Moreover, this points to the existence of a liquidity premium component in credit spreads, as observed by other studies in the literature, and the relevancy and strong relationship between illiquidity and credit spreads, which has important implications for corporate finance and asset pricing, due to the effects liquidity can have on security prices and cost of corporate debt (Longstaff, Mithal and Neis, 2005).

7.3.5 Regression with all determinants

Results from the regression (6.11) with all the possible determinants investigated in our study are presented in Appendix H. Starting with the explanatory power, we observe that there is a substantial increase in the Adjusted R-squared, from the regression composed only by theoretical determinants, from 27.1% to 57.3%. Thus, the inclusion of these extra variables has proven to be significant in increasing the explanatory power of the CDS spreads levels. When compared to the study of Ericsson, Jacobs and Oviedo (2009), where the additional explanatory variables, that account for market liquidity changes, nonlinear effects and economic conditions, among others, caused an increase of the R-squared in 14%, compared to the near 30% in our study.

Moreover, results show that all the explanatory variables are statistically significant in explaining CDS spreads levels, even when we compute the Driscoll and Kraay (1998) standard errors. Interestingly, the firm´s equity return is now statistically significant, contrarily to the results from regression (6.8), and has a negative relationship with CDS spreads, as predicted by theory.

When analysing the estimated coefficients, the average impact of each explanatory variable on the CDS spreads levels has decreased, which is expected when new variables are introduced in the model, due to correlations amongst independent variables and with the dependent variable. Additionally, the *t*-statistics of the coefficients also change. Regarding the coefficients signs, only the historical volatility and the market return contradict expectations from previous studies, as an increase in volatility is expected to increase credit spreads and an increase in market return should decrease spreads, ceteris paribus. These coefficients signs can be explained by the same reasons detected in regression (6.9), where the estimated coefficient sign for the market return was also positive, but when regressing the CDS spreads levels exclusively based on market return, the sing changes to negative, as expected by theory. Similarly, the estimated coefficient sign for the historical volatility was also positive when performing regression (6.7).

7.4 Results from the regressions in changes

7.4.1 Regression with theoretical determinants (in changes)

In this section we analyse the results from the random effects regressions using data in changes (1st differences), exhibited in Appendix K. Beginning with the results from regression (6.12), that includes the theoretical variables proposed by structural models, we can conclude that similarly to the regression in levels, the leverage, risk-free rate and historical volatility are all statistically significant in explaining CDS spread changes.

Regarding the estimated coefficients, the firm's leverage ratio is positively correlated with CDS spread changes, as predicted by theory. Moreover, the estimated sign for the historical volatility is positive, which is supported by theory and empirical results from previous studies. The most surprising result is the coefficient sign for the risk-free rate, which is negative when the data is in changes, but positive when in levels. This suggests that when analysing the effects of changes in the risk-free rate on CDS spreads, with a specific focus on time-series variations, we find a negative correlation. However, when we investigate the impact of time-series and cross-sectional variations in CDS spreads, caused by risk-free rate changes, a positive correlation is found. Nonetheless, this negative correlation is consistent with the empirical findings of Longstaff and Schwartz (1995) and Collin-Dufresne, Goldstein and Martin (2001).

Furthermore, the explanatory power is considerably low (approximately 5%). It was expected that regression (6.7) would generate a higher explanatory power, since data in changes is more difficult to explain than levels. However, this low adjusted R-squared suggests that theoretical determinants proposed by structural models, have difficulties in explaining the changes of CDS spreads and that non-theoretical factors should be analysed in order to obtain a better understanding of which factors influence and explain the CDS spread changes in our study.

7.4.2 Regression with all determinants (in changes)

Results for regression (6.13), that includes all the possible CDS spread changes determinants, are presented in Appendix K.

The first relevant result is that some variables are not statistically significant determinants of CDS spread changes, contrarily to the results with data in levels. Starting with the ROE and current ratio, it is not surprising that these variables are not statistically significant, due to the way they were computed. Since these financial ratios are only available quarterly and in some cases semi-annually, there was the need to use linear interpolation to have complete information across the time period, which causes the interpolated monthly values to remain almost equal when using data in changes, having no significant effect on the changes of the CDS spreads. Moreover, the credit rating of the firm is also not statistically significant when presented in differences. One possible cause for this is the fact that credit ratings are usually revised infrequently and with a lag, which results in very few variations when using data in changes, causing them to not be able to reflect and explain the current firm´s credit risk level. As a result, credit rating changes are unable to explain the differences in credit spreads. Lastly, the slope of the yield curve is found to not be statistically significant in explaining CDS spreads changes, which is in line with previous empirical results, such as Collin-Dufresne, Goldstein and Martin (2001).

After computing the robust standard errors to deal with heteroskedasticity and autocorrelation problems, the ROE interestingly becomes a statistically significant determinant, at a 10% significance level, while the opposite occurs to the historical volatility. Suggesting that this volatility measure is capable of explaining better the cross-sectional differences in CDS spreads. Additionally, this represents further evidence that implied volatility outperforms historical volatility in explaining CDS spreads.

When analysing the estimated coefficients signs, the market return has a positive sign which contradicts expectations from theory. The same relationship was found when using levels instead of changes, some possible reasons for this to occur where presented and also apply here. Moreover, results indicate a positive correlation between changes in credit rating and CDS spreads changes, contrarily to previous empirical findings and economic theory, nonetheless this variable is found to not be statistically significant.

As expected, the total explanatory power of the regression with all the determinants is much lower than when using data in levels (21.5% and 57.3%). However, we can conclude that the additional variables included from the theoretical determinants regression, are able to increase significantly the explanatory power (5% to 21.5%), even when only the statistical significant determinants are included (see Appendix L). Lastly, since this value is still rather low, we conclude that there are still other variables and different proxies influencing the changes in CDS spreads.

7.5 Robustness analysis

In this section we investigate the robustness of our previous results, by performing a multi-period analysis to obtain additional information on how the selected determinants interact with CDS spreads during a crisis and post-crisis period. Thus, we divide the sample into two sub-samples, the first one from 01.01.2010 to 31.12.2013 (Eurozone crisis) and the second during 01.01.2014 to 31.12.2018 (post-crisis). For each period we estimate regression (6.11), with all the investigated variables using data in levels and applying fixed effects models.

The descriptive statistics for each period are presented in Appendix M. As expected, the data has some differences in each sub-sample. In the first period, the average CDS spread is 140.65 basis points, while in post-crisis period is 73.43. Moreover, recession periods are marked by higher uncertainty and a decline in economic activity, resulting in higher market volatility and less market liquidity.

When analysing the results presented in Appendix N, there are some interesting differences when comparing both periods. The historical volatility is not statistically significant in both periods, suggesting that even when the levels of historical volatility are higher, the impact on CDS spreads are not relevant.

Moreover, during the crisis period the risk-free rate is found to no be statistically significant, while in the following period the opposite occurs. Interestingly, in the first period, risk-free rates are much higher than in the post-crisis period, while also recording a significant decrease, reflecting the monetary policy of the ECB to fight the Eurozone crisis. From an econometric perspective, this indicates that the higher and more volatile CDS spreads are not significantly affected by these risk-free rate levels, while in the period after when the markets are more solid, CDS spreads are more sensitive to interest rates.

Lastly, the ROE is no longer statistically significant in the post-crisis period, suggesting that during the crisis period when spreads are higher, this profitability proxy is a relevant determinant of CDS spreads. While when spreads are lower and less volatile, the ROE is not taken into account when computing CDS premiums.

Regarding the coefficient estimates, we observe that when the credit risk in our sample is higher, most of the determinants have a higher impact on the CDS spreads, when compared to the post-crisis period. Additionally, the explanatory power of these variables is much higher during the Eurozone crisis, 53.4% compared to 33.2% recorded in the second subsample. These conclusions support previous empirical evidence, that credit spreads determinants do a better job in explaining credit spreads when credit risk levels are higher.

8. Conclusion

The 2008-2009 global financial crisis had severe consequences both economically and financially, that were felt worldwide and as a result one of the fields that received more attention in finance was credit risk, due to the role it played in the crisis. This led to an increase interest and innovation in credit risk modelling, assessment and management, both from financial institutions and researchers.

With this in mind, this thesis looks to contribute to the existing literature, by providing insights on which factors are able to explain and influence corporate credit spreads and, therefore, their respective credit risk. We are able to accomplish this by performing various panel data regressions models, where as a proxy for the firm´s credit risk we utilize CDS spreads, since this financial product is considered to be a better credit risk measure when compared to bond spreads, which were mostly used in previous studies. We start by investigating how theoretical determinants of default risk explain and influence actual CDS spreads. In addition, other non-theoretical variables are also analysed, which account for firm-specific, macroeconomic, credit quality and market liquidity factors, in order to identify other relevant factors influencing credit spreads.

Throughout the econometric study we use a dataset composed by 49 European non-financial firms, from the STOXX Europe 600 index, during the time period from 2010 to 2018. After performing the regressions with data in levels and changes, we also execute a robustness analysis to investigate how these determinants perform when the levels of economic instability and credit risk are higher (Eurozone crisis) compared to the post-crisis period.

Starting with the empirical results of the theoretical determinants, namely the firm´s leverage ratio, the historical volatility and risk-free rate, we find that all are statistically significant in explaining CDS spreads. Regarding the coefficient signs, only the risk-free rate contradicts previous theory, however this positive correlation can be explained by the expansionary monetary policy applied by the ECB after the 2008-2009 crisis. Nevertheless, the theoretical determinants of default risk are able to explain to some extent the credit spreads of the sampled firms, performing much better in explaining cross-sectional variations of the CDS spreads than simply time-series variations, since the adjusted R-squared is 27% with data in levels and 5% with data in first differences.

This limited explanatory power of the variables predicted by structural models, can help explain why structural credit risk models have difficulties in predicting credit spreads, as shown by previous studies on the empirical performance of these models. Our results highlight one of the shortcoming of these type of models, since excluding the risk-free rate, the structural approach predicts that the firm-specific factors (e.g. leverage and firm volatility) are the main drivers of corporate credit spreads (Collin-Dufresne, Goldstein and Martin, 2001). However, results from our analysis imply that aggregate factors, such as market liquidity also have a significant impact in explaining the levels of the observed

CDS spreads. These findings from our study, suggest that structural credit risk models would benefit from being developed towards incomplete information models, introduced by Duffie and Lando (2001) and Giesecke (2006). Once these models are capable of adjusting credit spreads to reflect variations in market data, accounting for aggregate market factors, such as market liquidity, which has proven to be an important determinant and past research as shown that most models are not able to incorporate this liquidity premium present in credit spreads. In addition, these models also apply the economic interpretation for default, provided by structural models and the respective firm-specific factors, while taking into account the unpredictability of default present in reduced-form models.

Secondly, the introduction of non-theoretical determinants in our study had a significant impact, since the explanatory power increased by 30% and 16%, for data in levels and changes, respectively. This increase in the adjusted R-squared is promising when compared to the study of Ericsson, Jacobs and Oviedo (2009), which observed that the introduction of additional explanatory variables increased the explanatory power in 14% and 7.5%, respectively. Moreover, we conclude that according to our results, the firm´s credit rating and market liquidity outperform the other variable sets in explaining the levels of CDS spreads, with an adjusted R-squared of 35%. However, the theoretical determinants have a higher explanatory power than both the firm-specific and the market-specific factors, suggesting that the variables predicted by theory contain relevant information in explaining the pricing of CDS. Additionally, we find that the two financial ratios introduced in our study, namely the ROE and current ratio, are statistically significant and with the expected coefficients signs, however when performing regressions in differences this no longer occurs. The most striking reason for this is the data availability of these ratios.

Thirdly, by performing a multi-period analysis we are able to conclude that both theoretical variables and non-theoretical variables do a better job in explaining the levels of CDS spreads when there is more uncertainty in the market and consequentially a higher degree of credit risk in the sampled companies. Moreover, it is interesting to notice, that during the crisis period the level of risk-free rate is found to not be statistically significant, suggesting that when CDS spreads are more volatile the interest rates do not influence the firm´s credit risk, as much as other firm-specific and market factors. These results can have relevant implications for managing riskier portfolios and also for monetary policy practices (Chen, Cheng and Wu, 2013)

Overall, this study is able to contribute to the existing literature in credit risk, by providing relevant insights on the determinants of credit spreads, while allowing for a better understanding of structural credit risk models. From our regression analysis we can conclude which possible credit spread determinants are actually statistically and economically significant which contributes to the important task of understanding what influences credit spreads, so that we can develop more precise and realistic credit risk models, that perform better in predicting and estimating both CDS and bond spreads, ultimately leading to a better management and assessment of credit risk, while also giving useful information for financial analysts and policy makers.

On the other hand, since we can observe which sets of variables, from manageable to external ones, have the most influence on the firm’s credit spreads, this dissertation also provides important empirical information on the sampled firm´s credit risk situation and consequentially on the European credit derivatives market, from the time period of 2010 to 2018.

However, during this thesis we encountered some challenges. The main limitation was the data availability, since from the 600 companies in the index used, only 49 had available and complete CDS information during the investigated time period. Moreover, some of the explanatory variables, namely the leverage, ROE and current ratio, only had available data quarterly and in some cases semi-annually, which required the use of linear interpolation to get monthly data.

Regarding the suggestions for future research, it could be interesting to explore different determinants of credit spreads, since there is still close to 40% of CDS spread levels unexplained by the variables used. For example, other proxies for the overall economic state, a measure for expectations about recovery rates and other firm-specific factors, since this set of variables recorded the lowest explanatory power. Moreover, the use of a different regressions forms, other than linear, could provide more insights on the interaction between credit spreads and its determinants. Lastly, it may prove worthwhile to use CDS quotes with different expiry times, in order to investigate the influence of maturity in the explanatory power of the determinants of credit spreads.

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Appendixes

Appendix A. List of companies used in regressions

Company	Country
Adecco	Switzerland
Ahold Delhaize	Netherlands
Air Liquide	France
ASSA ABLOY B	Sweden
Atlas Copco A	Sweden
BASF	Germany
Bayer	Germany
BMW	Germany
BP	UK
BT Group	UK
Continental AG	Germany
Daimler	Germany
Deutsche Telekom AG	Germany
E.ON SE	Germany
EDP	Portugal
Electricite de France	France
Endesa	Spain
Fresenius SE	Germany
Heidelbergcement	Germany
Henkel VZO	Germany
Koninklijke KPN	Netherlands
Legrand	France
Linde	Germany
Lufthansa	Germany
Melrose Industries	UK
Merck	Germany
Novartis	Switzerland
Orange	France
Peugeot	France
Porsche	Germany
Prosiebensat	Germany
Renault	France
Rheinmetall AG	Germany
Rio Tinto PLC	UK
Roche Holding AG Participation	Switzerland
SCA B	Sweden
Schneider Electric	France
Securitas B	Sweden
Siemens AG	Germany
SKF B	Sweden
Swedish Match	Sweden
Telecom Italia	Italy
Telefonica	Spain
Telenor	Norway
Telia Company	Sweden
Thyssenkrupp AG	Germany
UPM-Kymmene	Finland
Vodafone Group PLC	UK
Volkswagen VZO	Germany

Appendix B. Credit Rating Score Table

Score	Moody´s	S&P	Fitch
1	Aaa	AAA	AAA
2	Aa1	AA+	AA+
3	Aa2	AA	AA
4	Aa3	AA-	AA-
5	A1	A+	A+
6	A2	A	A
7	A3	A-	A-
8	Baa1	BBB+	BBB+
9	Baa2	BBB	BBB
10	Baa3	BBB-	BBB-
11	Ba1	BB+	BB+
12	Ba2	BB	BB
13	Ba3	BB-	BB-
14	B1	B+	B+
15	B2	B	B
16	B3	B-	B-
17	Caa1	CCC+	CCC+
18	Caa2	CCC	CCC
19	Caa3	CCC-	CCC-
20	Ca	CC	CC
21		C	C
22	C	D	D

Appendix C. Descriptive Statistics

Variable	Min	Max	Mean	St. Dev.	Obs
CDS	12.500	920.270	103.300	95.621	5292
ΔCDS	-548.390	472.219	-0.254	26.096	5292
Lev	1.186	96.574	49.610	20.013	5292
ΔLev	-20.276	15.981	-0.044	1.138	5292
Rf	-0.152	3.096	0.943	0.868	5292
ΔRF	-0.433	0.418	-0.024	0.148	5292
HistVol	13.410	67.050	27.960	9.793	5292
ΔHistVol	-23.452	7.204	-0.073	0.658	5292
EqRet	-70.004	46.426	0.637	7.330	5292
ΔEqRet	-80.138	70.069	-0.114	10.429	5292
ImpVol	7.029	105.183	26.021	9.476	5292
ΔImpVol	-64.448	54.335	0.016	5.453	5292
ROE	-107.772	437.530	17.454	29.899	5292
ΔROE	-104.420	91.464	0.091	5.271	5292
CurrentRatio	-3.563	6.574	1.261	0.696	5292
ΔCurrentRatio	-0.791	0.736	0.002	0.100	5292
Slope	0.435	2.246	1.241	0.414	5292
Δslope	-0.394	0.457	-0.011	0.134	5292
MktRet	-11.080	7.664	0.264	3.500	5292
ΔMktRet	-12.726	12.225	-0.108	4.909	5292
MktVol	11.990	46.680	21.960	6.195	5292
ΔMktVol	-13.019	11.784	-0.002	4.512	5292
BAspread	0.299	57.108	9.095	6.914	5292
ΔBAspread	-34.764	38.402	-0.00003	3.600	5292
CR	3.333	12.667	8.084	2.055	5292
ΔCR	-3.000	2.667	-0.0003	0.108	5292

Correlation Matrix

	CDS	Lev	Rf	HistVol	EqRet	ImpVol	ROE	CurrentRatio	Slope	MktRet	MktVol	BAspread	CR
CDS	1.000												
Lev	0.493	1.000											
Rf	0.259	0.121	1.000										
HistVol	0.420	0.299	0.121	1.000									
EqRet	-0.059	-0.043	0.013	0.032	1.000								
ImpVol	0.547	0.353	0.220	0.555	-0.126	1.000							
ROE	-0.159	-0.220	0.021	-0.072	0.025	-0.128	1.000						
CurrentRatio	-0.238	-0.437	-0.020	0.059	0.000	-0.056	0.053	1.000					
Slope	0.249	0.116	**0.824**	0.100	0.036	0.154	-0.003	-0.024	1.000				
MktRet	-0.023	0.001	-0.015	0.020	0.524	-0.168	-0.012	-0.017	0.041	1.000			
MktVol	0.306	0.101	0.427	0.115	-0.186	0.451	0.019	-0.036	0.268	-0.362	1.000		
BAspread	0.542	0.029	0.002	0.366	-0.011	0.341	-0.043	0.060	0.030	-0.017	0.140	1.000	
CR	0.550	0.346	-0.005	0.456	0.020	0.351	-0.094	-0.131	-0.004	0.004	-0.005	0.488	1.000

Variance Inflation Factors

Variance Inflation Factors (VIF)											
Lev	Rf	HistVol	EqRet	ImpVol	ROE	CurrentRatio	Slope	MktRet	MktVol	BAspread	CR
1.6151	3.8380	1.3236	1.4032	1.6866	1.0667	1.1669	3.2972	1.6008	2.0256	1.1527	1.2804

Appendix D.

1) Results of the unit root tests in levels

```
        Levin-Lin-Chu Unit-Root Test (ex. var.: Individual Intercepts)

data:  CDS ~ 1
z = -5.1956, p-value = 1.02e-07
alternative hypothesis: stationarity
```

```
        Maddala-Wu Unit-Root Test (ex. var.: Individual Intercepts)

data:  CDS ~ 1
chisq = 217.86, df = 98, p-value = 4.251e-11
alternative hypothesis: stationarity
```

2) Results of the unit root test in changes

```
        Levin-Lin-Chu Unit-Root Test (ex. var.: Individual Intercepts)

data:  CDSdatachanges$CDS
z = -69.212, p-value < 2.2e-16
alternative hypothesis: stationarity
        Maddala-Wu Unit-Root Test (ex. var.: Individual Intercepts)

data:  CDSdatachanges$CDS
chisq = 4132.4, df = 98, p-value < 2.2e-16
alternative hypothesis: stationarity
```

Appendix E. Hausman test

1) Results from Hausman test (Levels)

```
        Hausman Test

data:  CDS ~ Lev + Rf + Hvol + EqRet + Ivol + ROE + CurrentRatio + Slope +  ...
chisq = 48.524, df = 12, p-value = 2.533e-06
alternative hypothesis: one model is inconsistent
```

2) Results from Hausman test (Changes)

```
        Hausman Test

data:  CDS1 ~ Lev1 + Rf1 + Hvol1 + EqRet1 + Ivol1 + ROE1 + CurrentRatio1 +  ...
chisq = 0.95492, df = 12, p-value = 1
alternative hypothesis: one model is inconsistent
```

Appendix F. Autocorrelation tests

1) Results from the Breush-Godfrey test (Levels)

```
        Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  CDS ~ Lev + Rf + Hvol + EqRet + Ivol + ROE + CurrentRatio + Slope +     MkRet + Mvol + BASpread + CR
chisq = 3356.8, df = 108, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

2) Results from the Breush-Godfrey test (Changes)

```
        Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data:  CDS1 ~ Lev1 + Rf1 + Hvol1 + EqRet1 + Ivol1 + ROE1 + CurrentRatio1 +     Slope1 + MkRet1 + Mvol1 + BASpread1 + CR1
chisq = 644.47, df = 108, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

Appendix G. Heteroskedasticity tests

1) Results from the Breush-Pagan test (Levels)

```
        Breusch-Pagan test

data:  CDS ~ Lev + Rf + Hvol + EqRet + Ivol + ROE + CurrentRatio + Slope +     MkRet + Mvol + BASpread + CR
BP = 7925, df = 12, p-value < 2.2e-16
```

2) Results from the Breush-Pagan test (Changes)

```
        Breusch-Pagan test

data:  CDS1 ~ Lev1 + Rf1 + Hvol1 + EqRet1 + Ivol1 + ROE1 + CurrentRatio1 +     Slope1 + MkRet1 + Mvol1 + BASpread1 + CR1
BP = 3524.7, df = 12, p-value < 2.2e-16
```

Appendix H. Results from regressions with data in levels

1) Results from regression with theoretical determinants (Regression 6.7)

```
Oneway (individual) effect Within Model

Call:
plm(formula = CDS ~ Lev + Rf + Hvol, data = PaneldataLevels,
    model = "within", index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-266.9727  -23.9105   -2.1845   16.1142  641.6955

Coefficients:
     Estimate Std. Error t-value  Pr(>|t|)
Lev   3.66712    0.11520 31.8330 < 2.2e-16 ***
Rf   16.24390    1.02609 15.8309 < 2.2e-16 ***
Hvol  1.49460    0.19364  7.7184 1.402e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 18613000
R-Squared:      0.27821
Adj. R-Squared: 0.27118
F-statistic: 673.24 on 3 and 5240 DF, p-value: < 2.22e-16
```

2) Results from regression with firm-specific determinants (Regression 6.8)

```
Oneway (individual) effect Within Model

Call:
plm(formula = CDS ~ EqRet + Ivol + ROE + CurrentRatio, data = PaneldataLevels,
    model = "within", index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-323.0329  -23.5519   -1.3147   17.3202  674.3970

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
EqRet          0.019094   0.117030  0.1632 0.8704030
Ivol           3.961773   0.111727 35.4595 < 2.2e-16 ***
ROE           -0.132402   0.039726 -3.3329 0.0008654 ***
CurrentRatio -16.690184   1.670951 -9.9884 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 19853000
R-Squared:      0.23014
Adj. R-Squared: 0.2225
F-statistic: 391.533 on 4 and 5239 DF, p-value: < 2.22e-16
```

3) Results from regression with market-specific determinants (Regression 6.9)

```
Oneway (individual) effect Within Model

Call:
plm(formula = CDS ~ Slope + MkRet + Mvol, data = PaneldataLevels,
    model = "within", index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
      Min.     1st Qu.      Median     3rd Qu.        Max.
-188.38004  -26.54042    0.28797    19.05651   621.47692

Coefficients:
      Estimate Std. Error t-value  Pr(>|t|)
Slope 38.89767    2.13107 18.2526 < 2.2e-16 ***
MkRet  2.03136    0.26077  7.7898 8.038e-15 ***
Mvol   4.43387    0.15280 29.0174 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 19596000
R-Squared:      0.24011
Adj. R-Squared: 0.23272
F-statistic: 551.918 on 3 and 5240 DF, p-value: < 2.22e-16
```

4) Results from regression with other relevant determinants (Regression 6.10)

```
Oneway (individual) effect Within Model

Call:
plm(formula = CDS ~ BASpread + CR, data = PaneldataLevels, model = "within",
    index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-292.602  -25.295   -3.556   20.180  551.850

Coefficients:
         Estimate Std. Error t-value  Pr(>|t|)
BASpread  9.85971    0.19436  50.730 < 2.2e-16 ***
CR       18.16792    1.42895  12.714 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 16568000
R-Squared:      0.35753
Adj. R-Squared: 0.3514
F-statistic: 1458.28 on 2 and 5241 DF, p-value: < 2.22e-16
```

5) Results from regression with all the variables (Regression 6.11)

```
Call:
plm(formula = CDS ~ Lev + Rf + Hvol + EqRet + Ivol + ROE + CurrentRatio +
    Slope + MkRet + Mvol + BASpread + CR, data = PaneldataLevels,
    model = "within", index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-246.73132  -23.41579    0.29226   17.43602  576.87973

Coefficients:
              Estimate Std. Error t-value  Pr(>|t|)
Lev           1.515362   0.107466 14.1008 < 2.2e-16 ***
Rf           11.355058   1.418655  8.0041 1.471e-15 ***
Hvol         -0.586291   0.164005 -3.5748 0.0003536 ***
EqRet        -0.458363   0.101757 -4.5045 6.799e-06 ***
Ivol          1.499410   0.105109 14.2652 < 2.2e-16 ***
ROE          -0.052002   0.030135 -1.7256 0.0844766 .
CurrentRatio -5.842686   1.318150 -4.4325 9.506e-06 ***
Slope        15.797404   2.750861  5.7427 9.843e-09 ***
MkRet         1.613331   0.227008  7.1069 1.346e-12 ***
Mvol          1.310581   0.144703  9.0570 < 2.2e-16 ***
BASpread      8.059115   0.168156 47.9264 < 2.2e-16 ***
CR           13.657038   1.295088 10.5453 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 10894000
R-Squared:      0.57756
Adj. R-Squared: 0.57272
F-statistic: 595.987 on 12 and 5231 DF, p-value: < 2.22e-16
```

6) Results after controlling for the autocorrelation and heteroscedasticity in the model (Driscoll and Kraay standard errors)

```
t test of coefficients:

              Estimate Std. Error t value  Pr(>|t|)
Lev           1.515362   0.184363  8.2195 2.554e-16 ***
Rf           11.355058   3.477968  3.2649 0.0011023 **
Hvol         -0.586291   0.265812 -2.2057 0.0274511 *
EqRet        -0.458363   0.170163 -2.6937 0.0070897 **
Ivol          1.499410   0.272041  5.5117 3.724e-08 ***
ROE          -0.052002   0.030396 -1.7108 0.0871720 .
CurrentRatio -5.842686   2.588826 -2.2569 0.0240563 *
Slope        15.797404   8.331084  1.8962 0.0579886 .
MkRet         1.613331   0.426973  3.7785 0.0001595 ***
Mvol          1.310581   0.382594  3.4255 0.0006184 ***
BASpread      8.059115   0.692498 11.6377 < 2.2e-16 ***
CR           13.657038   2.357738  5.7924 7.342e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix I. Historical volatility vs Implied volatility

1) Regression with only historical volatility

```
Call:
plm(formula = CDS ~ Hvol, data = PaneldataLevels, model = "within",
    index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-222.9426  -22.6092   -5.5015   13.9437  667.5105

Coefficients:
     Estimate Std. Error t-value  Pr(>|t|)
Hvol  3.26925    0.21431  15.255 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 24692000
R-Squared:      0.042506
Adj. R-Squared: 0.033555
F-statistic: 232.705 on 1 and 5242 DF, p-value: < 2.22e-16
```

2) Regression with only implied volatility

```
Call:
plm(formula = CDS ~ Ivol, data = PaneldataLevels, model = "within",
    index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-304.8629  -23.2090   -1.0353   17.2471  673.8125

Coefficients:
     Estimate Std. Error t-value  Pr(>|t|)
Ivol  4.15013    0.11033  37.614 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    25788000
Residual Sum of Squares: 20307000
R-Squared:      0.21254
Adj. R-Squared: 0.20518
F-statistic: 1414.83 on 1 and 5242 DF, p-value: < 2.22e-16
```

Appendix J. Regression with only market return

```
Call:
plm(formula = CDS ~ MkRet, data = PaneldataLevels, model = "within",
    index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-216.1402  -23.2994   -5.6741   14.0703  665.6734

Coefficients:
      Estimate Std. Error t-value Pr(>|t|)
MkRet -0.61829    0.27536 -2.2454  0.02479 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix K. Results from regressions with data in changes

1) Results from regression with theoretical determinants in changes (Regression 6.12)

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = CDS1 ~ Lev1 + Rf1 + Hvol1, data = paneldatachanges,
    model = "random", index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Effects:
                 var std.dev share
idiosyncratic 652.77   25.55     1
individual      0.00    0.00     0
theta: 0

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-548.594557   -5.727251   -0.099463    5.629943  428.166802

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)    
(Intercept)  -0.27781    0.35749 -0.7771   0.43709    
Lev1          4.28751    0.30960 13.8487 < 2.2e-16 ***
Rf1         -14.88853    2.38538 -6.2416 4.332e-10 ***
Hvol1         2.03104    0.53334  3.8082   0.00014 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    3603200
Residual Sum of Squares: 3424100
R-Squared:      0.049691
Adj. R-Squared: 0.049152
Chisq: 276.507 on 3 DF, p-value: < 2.22e-16
```

2) Results from regression with all variables in changes (Regression 6.13)

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = CDS1 ~ Lev1 + Rf1 + Hvol1 + EqRet1 + Ivol1 + ROE1 +
    CurrentRatio1 + Slope1 + MkRet1 + Mvol1 + BASpread1 + CR1,
    data = paneldatachanges, model = "random", index = c("id",
        "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Effects:
                 var std.dev share
idiosyncratic 538.69   23.21     1
individual      0.00    0.00     0
theta: 0

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-5.3145e+02 -6.8877e+00  8.7024e-03  6.7149e+00  3.8269e+02

Coefficients:
               Estimate Std. Error z-value  Pr(>|z|)
(Intercept)   -0.244758   0.325534 -0.7519 0.4521315
Lev1           2.527937   0.290091  8.7143 < 2.2e-16 ***
Rf1           -6.005078   2.571932 -2.3349 0.0195512 *
Hvol1          1.191640   0.487892  2.4424 0.0145889 *
EqRet1        -0.342144   0.035777 -9.5633 < 2.2e-16 ***
Ivol1          0.469932   0.068166  6.8939 5.427e-12 ***
ROE1          -0.061327   0.060345 -1.0163 0.3095010
CurrentRatio1 -1.992040   3.207328 -0.6211 0.5345403
Slope1        -4.259575   2.748746 -1.5496 0.1212272
MkRet1         0.367755   0.101202  3.6339 0.0002792 ***
Mvol1          1.276140   0.111266 11.4693 < 2.2e-16 ***
BASpread1      1.792852   0.089635 20.0018 < 2.2e-16 ***
CR1           -3.548904   2.944227 -1.2054 0.2280577
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    3603200
Residual Sum of Squares: 2820300
R-Squared:      0.21727
Adj. R-Squared: 0.21549
Chisq: 1465.32 on 12 DF, p-value: < 2.22e-16
```

3) Results using Driscoll and Kraay standard errors with data in changes

```
t test of coefficients:

               Estimate Std. Error t value  Pr(>|t|)
(Intercept)   -0.244758   0.302999 -0.8078  0.419252
Lev1           2.527937   0.583518  4.3322 1.503e-05 ***
Rf1           -6.005078   2.966985 -2.0240  0.043024 *
Hvol1          1.191640   0.911324  1.3076  0.191069
EqRet1        -0.342144   0.064808 -5.2794 1.348e-07 ***
Ivol1          0.469932   0.173213  2.7130  0.006689 **
ROE1          -0.061327   0.034392 -1.7832  0.074614 .
CurrentRatio1 -1.992040   3.011871 -0.6614  0.508387
Slope1        -4.259575   2.931213 -1.4532  0.146234
MkRet1         0.367755   0.123597  2.9754  0.002939 **
Mvol1          1.276140   0.188112  6.7839 1.298e-11 ***
BASpread1      1.792852   0.344573  5.2031 2.034e-07 ***
CR1           -3.548904   6.567995 -0.5403  0.588990
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Appendix L. Results from regression with only statistically significant variables (in changes)

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = CDS1 ~ Lev1 + Rf1 + EqRet1 + Ivol1 + MkRet1 + Mvol1 +
    BASpread1, data = paneldatachanges, model = "random",
    index = c("id", "Time"))

Balanced Panel: n = 49, T = 108, N = 5292

Effects:
                 var std.dev share
idiosyncratic 539.23   23.22     1
individual      0.00    0.00     0
theta: 0

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-531.302279   -6.905364    0.011392    6.652227  388.350440

Coefficients:
             Estimate Std. Error z-value  Pr(>|z|)
(Intercept) -0.344217   0.323382 -1.0644 0.2871349
Lev1         2.556522   0.287519  8.8917 < 2.2e-16 ***
Rf1         -8.226795   2.239724 -3.6731 0.0002396 ***
EqRet1      -0.342211   0.035780 -9.5644 < 2.2e-16 ***
Ivol1        0.489902   0.067814  7.2242 5.042e-13 ***
MkRet1       0.381684   0.101142  3.7738 0.0001608 ***
Mvol1        1.276045   0.111268 11.4682 < 2.2e-16 ***
BASpread1    1.787391   0.089483 19.9746 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    3603200
Residual Sum of Squares: 2826200
R-Squared:      0.21564
Adj. R-Squared: 0.2146
Chisq: 1452.73 on 7 DF, p-value: < 2.22e-16
```

Appendix M. Descriptive statistics for each sub-sample (Multi-period analysis)

1) Eurozone crisis period (2010-2013)

Variable	Min	Max	Mean	St. Dev.	Obs
CDS1	21.500	920.270	140.650	122.685	2352
Lev1	3.007	96.574	52.852	19.185	2352
Rf1	0.751	3.096	1.738	0.689	2352
HistVol1	14.650	67.050	29.450	10.319	2352
EqRet1	-46.126	45.333	1.060	7.729	2352
ImpVol1	7.029	105.183	28.371	11.243	2352
ROE1	-76.983	437.530	17.818	31.120	2352
CurrentRatio1	-3.563	6.574	1.220	0.729	2352
Slope1	1.192	2.246	1.604	0.262	2352
MktRet1	-11.080	7.370	0.535	3.655	2352
MktVol1	14.650	46.680	24.990	6.395	2352
BAspread1	0.299	57.108	9.730	8.005	2352
CR1	3.333	12.667	8.080	2.101	2352

2) Post-crisis period (2014-2018)

Variable	Min	Max	Mean	St. Dev.	Obs
CDS2	12.500	721.430	73.430	49.108	2940
Lev2	1.186	92.572	47.017	20.285	2940
Rf2	-0.152	1.015	0.308	0.258	2940
HistVol2	13.410	64.450	26.770	9.180	2940
EqRet2	-70.004	46.426	0.298	6.978	2940
ImpVol2	9.185	102.634	24.142	7.253	2940
ROE2	-107.772	281.846	17.163	28.887	2940
CurrentRatio2	-1.719	6.412	1.295	0.666	2940
Slope2	0.435	1.592	0.950	0.253	2940
MktRet2	-8.852	7.664	0.047	3.356	2940
MktVol2	11.990	32.310	19.540	4.814	2940
BAspread2	1.177	31.340	8.587	5.849	2940
CR2	3.333	12.667	8.087	2.018	2940

Appendix N. Results from the regressions of each sub-sample

1) Regression from Eurozone crisis period (2010-2013)

```
Oneway (individual) effect Within Model

Call:
plm(formula = CDS1 ~ Lev1 + Rf1 + Hvol1 + EqRet1 + Ivol1 + ROE1 +
    CurrentRatio1 + Slope1 + MkRet1 + Mvol1 + BASpread1 + CR1,
    data = Period1, model = "within", index = c("id",
        "Time"))

Balanced Panel: n = 49, T = 48, N = 2352

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-237.42740  -19.03967    0.18215   16.78414  398.21545

Coefficients:
                Estimate Std. Error t-value  Pr(>|t|)
Lev1            1.152488   0.187758   6.1382 9.810e-10 ***
Rf1            -0.501959   1.702815  -0.2948 0.7681870
Hvol1          -0.429836   0.424194  -1.0133 0.3110240
EqRet1         -0.543356   0.143258  -3.7929 0.0001528 ***
Ivol1           1.830423   0.144001  12.7112 < 2.2e-16 ***
ROE1           -0.132591   0.061786  -2.1460 0.0319811 *
CurrentRatio1  -6.138987   1.894422  -3.2406 0.0012100 **
Slope1        -29.300741   4.289305  -6.8311 1.076e-11 ***
MkRet1          1.473935   0.329166   4.4778 7.912e-06 ***
Mvol1           1.906687   0.197378   9.6601 < 2.2e-16 ***
BASpread1       6.219848   0.212102  29.3248 < 2.2e-16 ***
CR1            25.867968   2.646732   9.7735 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    10234000
Residual Sum of Squares: 4645500
R-Squared:      0.54609
Adj. R-Squared: 0.53421
F-statistic: 229.691 on 12 and 2291 DF, p-value: < 2.22e-16
```

2) Regression from post-crisis period (2014-2018)

```
Oneway (individual) effect Within Model

Call:
plm(formula = CDS2 ~ Lev2 + Rf2 + Hvol2 + EqRet2 + Ivol2 + ROE2 +
    CurrentRatio2 + Slope2 + MkRet2 + Mvol2 + BASpread2 + CR2,
    data = Period2, model = "within", index = c("id",
        "Time"))

Balanced Panel: n = 49, T = 60, N = 2940

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-92.04061  -9.37085  -0.54185   8.34093 557.66635

Coefficients:
               Estimate Std. Error t-value  Pr(>|t|)
Lev2           0.850008   0.097037  8.7596 < 2.2e-16 ***
Rf2           -7.072696   2.648300 -2.6707  0.007613 **
Hvol2          0.063993   0.124650  0.5134  0.607727
EqRet2        -0.297595   0.071336 -4.1717 3.112e-05 ***
Ivol2          0.748973   0.096087  7.7947 8.947e-15 ***
ROE2          -0.017691   0.019488 -0.9078  0.364082
CurrentRatio2 -6.323365   1.077302 -5.8696 4.867e-09 ***
Slope2        21.030259   3.023980  6.9545 4.361e-12 ***
MkRet2         0.935003   0.173414  5.3918 7.542e-08 ***
Mvol2          1.290619   0.148092  8.7150 < 2.2e-16 ***
BASpread2      3.522879   0.189834 18.5577 < 2.2e-16 ***
CR2           11.317186   1.337619  8.4607 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2219200
Residual Sum of Squares: 1451900
R-Squared:      0.34572
Adj. R-Squared: 0.33209
F-statistic: 126.773 on 12 and 2879 DF, p-value: < 2.22e-16
```