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The Relation Between the Credit Default Swap and Corporate Bond Market

A study of European companies with different credit ratings

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Abstract

The European credit default swap (CDS) market has experienced noticeable changes and remarkably developed over the last decades. Today, the relation between the CDS and corporate bond market is a prominent topic in the financial literature. According to the arbitrage argument, the CDS spread equals the corresponding credit spread of a corporate bond. However, substantial deviations between the markets are found in the short run. Because of that, researchers try to grasp the importance of the CDS market in the context of the price discovery process of credit risk. To contribute to the literature, this study attempts to explain the gap between the markets for 84 European companies with different credit ratings over the period 2013 to 2017. Credit ratings are added as an additional dimension as they contribute with valuable information and thus have a strong impact on capital markets. By dividing the sample into subsamples, the results for different credit rated companies are analyzed. The results suggest that the arbitrage argument do not hold in the short run since credit risk at the CDS market are found to be overestimated or underestimated in relation to the corporate bond market. Moreover, the sensitivity to structural and market factors are found to differ between the rating groups.

Keywords: credit default swap, corporate bond market, credit risk, arbitrage argument, credit ratings

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1. Introduction

The credit default swap (CDS) market has remarkably developed over the last decades, trades at the CDS market have rapidly increased and CDS data have become more publicly available. Due to this, researchers try to examine how the CDS market affects the overall financial market. The importance of CDS spreads in the context of the price discovery process of credit risk is a recurrent topic in the literature (The board of the international organization of securities commissions 2012). Some of the previous research regarding the price discovery process of credit risk focuses on the CDS market and the corporate bond market in order to examine the relationship between different market drivers and the price of the insurance of corporate default (Alexopoulou et al. 2009; Blanco et al. 2005; Norden and Weber 2004; Zhu 2006). The studies investigate both structural variables, based on the Merton (1974) Model, and market variables in order to determine the overall effect of different variables on the CDS and corporate bond market.

Furthermore, credit rating agencies have become more important regarding financial decisions. Today the rating systems have a strong impact on the capital markets since the rating agencies provide investors with information about the trade-off between risk and return (Langohr & Langohr 2008). Cossin et al. (2002) and Krylova (2016) found that the credit rating effect is one of the major drivers of the CDS spread and the credit spread. However, issuers have questioned if credit ratings affect a company's reputation and whether the credit rating action affect a company's creditworthiness (Langohr & Langohr 2008). In order to answer the question regarding the relationship between credit ratings and a company's creditworthiness it is crucial to investigate if pricing credit risk differ between companies with different credit ratings. According to the arbitrage argument, the credit spread corresponds to the CDS spread for the same entity and this study attempts to examine what variables could contribute to mispricing at the CDS market between different credit ratings (Alexopoulou et al. 2009). In other words, the CDS spread should correspond to the credit spread, regardless of the credit rating of a company.

This paper is applied to the European market and investigates the pricing dynamics between the CDS market and the corporate bond market. The data sample is divided into two subsamples that consist of companies with different credit ratings over the sample period March 2013 to December 2017. Previous research has found similar results regarding the relationship between the determinants of the CDS and corporate bond market. To extend existing literature, this study attempts to explain the gap between the CDS spread and the credit spread of companies with different credit ratings. The purpose is further to contribute to the literature with valuable information regarding what variables could cause the market to underestimate or overestimate the risk at the CDS market.

The remainder of this paper is structured as follows: the second chapter provides an overview of how to measure credit risk, credit pricing models and the arbitrage argument. In chapter three some of the most central and relevant articles in the credit risk literature are reviewed. The fourth chapter describes the modelling framework of this study which includes data descriptions, variable descriptions and the empirical model. Chapter five show descriptive statistics and in chapter six the empirical results are presented and analyzed. Chapter seven consists of the conclusion based on the empirical findings and the last chapter, chapter eight, outlines suggestions for future research.

2. Theoretical Framework

There are a number of ways to estimate and measure credit risk. One main approach is the credit ratings, computed by the credit rating agencies, which are conducted to determine the creditworthiness of an issuer or instrument. Another measure of credit risk is the financial market credit spread resulting from investment decisions of bond investors (Langohr & Langohr 2008). It is also common to use the prices of credit default swaps as a measure (Hull 2012). Descriptions of credit risk measures and models are presented in the following subsections.

2.1. The Importance of Managing Credit Risk

Credit risk can be defined as the risk of a financial loss when a counterparty fails to meet its obligations within an agreed term. This risk is commonly estimated by the probability of default, which is a financial term for the likelihood of default of an entity at a particular time (Hull 2012).

For most financial institutions, loans are the largest and most obvious source of credit risk. However, they are increasingly facing credit risk in various financial instruments including interbank transactions, trade financing, foreign exchange transactions, futures, swaps, bonds, equities and options. This makes it crucial for banks to manage credit risk exposure both inherent in their entire portfolio and in individual credit transactions. Thereby, the management and estimation of credit risk is a critical component to the overall risk management and essential to the long-term success of an organization (Basel 2000).

2.2. Measuring Credit Risk

2.2.1. Credit Ratings

A credit rating is used to benchmark the probability of default for a company and the mission of the credit rating agencies is to evaluate to what extent poor performance might cause financial distress. The important role of credit rating agencies has expanded, and they have become the link of information between issuers and investors. Because of that, credit rating agencies have a strong impact on capital markets since their credit ratings contribute with valuable information to institutional investors regarding the trade-off between risk and return. However, credit rating agencies are widely criticized for failing to predict credit crises and credit ratings do not account for market risk. Because of that, bond prices tend to fluctuate regardless of the credit ratings. In the long run, credit ratings and yields are only synchronized during some periods because ratings change discretely while bond yields are continuous. Moreover, issuers are questioning whether the rating action affects the reputation of a company and thereby the creditworthiness (Langohr & Langohr 2008).

The main components of rating analysis are business and financial risk analysis. Business risk analysis is determined based on the country-specific risk, industry-specific risk and company-specific risk. Country-specific risk and industry-specific risk are taken into account in order to limit the ratings of companies in high-risk countries which means that in high-risk countries or industries it is impossible for companies to achieve the highest ratings. By also taking the industry dynamics into account, which strongly affect the company performance, it is possible to study the structure and trend of the industry which is crucial in order to understand the pricing power of the companies at a specific market. Lastly, the company is analyzed to determine the volatility of its business performance by identifying key competitive factors such as price, quality and service. Business risk analysis provides a basis for the quantitative measurement of financial risk. Financial risk consists of analyzing the company’s balance sheet, profitability, cash generation and liquidity, which are all measures of the ability of a company to repay its obligations (Langohr & Langohr 2008).

Credit ratings are based on structural company factors that do not change with the business cycle. This means that credit ratings are not systematically adjusted during recessions or expansions. The fact that credit ratings are cycle-neutral prevents a security from being downgraded due to temporarily short-run bad performance caused by market fluctuations (Langohr & Langohr 2008). One of the largest and most well-known credit rating agencies is Standard & Poor’s Global (S&P’s) (Langohr & Langohr 2008). S&P’s credit ratings are presented and explained in Table 1.

Table 1 Long-term issue credit rating scale descriptions by Standard & Poor’s.

Credit Rating	Standard & Poor's Description
Investment-grade Rating	
AAA	**Extremely Strong** capacity to meet financial commitments - Highest rating.
AA	**Very Strong capacity** to meet financial commitments.
A	**Strong capacity** to meet financial commitments, but somewhat more susceptible to adverse economic conditions and changes in circumstances.
BBB	**Adequate capacity** to meet financial commitments, but more subject to adverse economic conditions.
Sub-investment Grade Bond Status	
BB	**Less vulnerable** in the near-term but faces major ongoing uncertainties and exposures to adverse business, financial and economic conditions.
B	**More vulnerable** to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments.
CCC	**Currently vulnerable** and dependent on favourable business, financial and economic conditions to meet financial commitments.
CC	**Currently highly** vulnerable.
A Marked Shortcoming has Materialized	
C	A bankruptcy petition has been filed or similar action taken but payments or **financial commitments** are **continued**.
D	Payment **default** on **financial commitments**.

Source: S&P Global (2017)

2.2.2. Credit Default Swaps

Credit default swaps (CDS) is a commonly used credit derivative and is like other derivative instruments used for hedging, speculation and arbitrage. CDS contracts are originally thought of as a way for bondholders to protect them self against a bond default. The purpose of a CDS contract is therefore to convert a corporate bond into a risk-free bond and a risk-free investment. One key difference between a regular insurance policy and a CDS contract is that the buyer of credit protection does not have to own the underlying instrument that the contract is written on. The market price of the CDS, the CDS spread, thereby reflects the market assessments of the likelihood of a credit event and the expected value of the reference security after the credit event. If the issuer of the bond does not default during the term of the contract, the investor pays a periodical amount called the CDS spread as a protection against such an event. On the other hand, if the bond does default during the term of the contract, the investor earns a percentage up to the bond value at the time of default. This implies that the excess of the bond yield over the risk-free rate approximately equals the CDS spread according to the arbitrage theory. However, if the credit spread excess the CDS spread, an investor can earn more than the risk-free rate by buying the corporate bond and a CDS contract as protection. In turn, if the credit spread is less than the CDS spread an investor can borrow at less than the risk-free rate by shorting the corporate bond and selling CDS protection (Hull 2012).

Today CDS contracts are traded over-the-counter (OTC), mostly facilitated by inter-dealer brokers. Thereby the CDS contract reflects the market's view of the probability of default since it provides a market measure and price for credit risk. In other words, the CDS contract can be seen as a key indicator of the credit quality of corporations, banks and sovereigns (Langohr & Langohr, 2008).

2.3. Credit Risk Models

There are two main approaches in the literature of credit risk modeling, the structural and the reduced-form model. The main difference between these two approaches is that default risk is determined exogenously in the reduced-form model, and as an endogenous process in the structural model (Alexopoulou et al. 2009). Under structural models a default event is deemed to occur for a firm when its assets reach a sufficiently low level compared to its liabilities (Hull 2015). Moreover, the two approaches differ regarding the information assumption of the models since the structural model assumes that there is full information about the asset value of the firm, in contrary to the reduced-form model (Alexopoulou et al. 2009). A groundwork for the structural model is laid by Merton (1974). The model used in this study is based on the Merton (1974) Model. In the following subsections, the Merton (1974) Model is presented and explained more in detail.

2.3.1. The Merton Model

The Merton (1974) Model is one of the most well-known structural credit risk models. The model relies on the structural characteristics of the firm; the total asset value[1], equity volatility as a measure for business risk and leverage as measure for financial risk. The model is based on the same principles as the Black-Scholes Model for option pricing but with redefined variables.

In this study, the structural characteristics are used as explanatory variables for the CDS spreads and the credit spreads. The firm's leverage ratio is defined as the ratio of the debt to the firm value. Equity price volatility is measured as the standard deviation of day to day logarithmic historical price changes. This equals the annualized standard deviation for the relative price changes for the 30 most recent trading days closing price expressed as a percentage (Bloomberg 2018). Moreover, equity price is used as a proxy for firm asset value since it is assumed to contain information about the market's expectations about the future of the firm. An increase in the equity price increases the market value of equity and thereby the total asset value, which decreases the probability of default (Hull 2015; Merton 1974).

The Merton (1974) Model assumes that default occurs when the firm's value falls below its debt value. This means that if the debt increases relatively to the firm's asset value, *ceteris paribus*, the credit spread increases suggesting that the probability of default increases. Thereby, the insurance against default increases which is reflected by a higher CDS spread. Moreover, a higher leverage ratio reflects a higher CDS and credit spread. The same holds for the second theoretical determinant in the Merton (1974) Model, the volatility of the firm. This is because the price of the underlying asset increases with volatility. Increased volatility makes it more probable that the asset defaults. Since the probability of default increases, the cost for insurance increases. This is reflected by a higher CDS spread (Hull 2015).

[1] A firm's total asset value is unobservable and consists of the market value of debt and the market value of equity. The market value of equity is calculated as the firm´s current asset price multiplied by the number of outstanding shares.

Theoretically deriving the determinants of the probability of default in the Merton (1974) Model one can make the log-normal assumption in the Black-Scholes Model, shown in Equation (1):

$$lnA_T \sim N\left[lnA_0 + \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T, \mu_A \times \sqrt{T}\right] \tag{1}$$

This implies that the logarithmic value of the asset value at time T is normally distributed with the mean: $lnA_0 + \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T$, and the standard deviation: $\mu_A \times \sqrt{T}$. From this assumption, it is possible to derive the probability of default (PD) based on the assumption that probability of default occurs when the asset value of the firm falls below the debt value. This is theoretically described in Equation (2) to Equation (5), where $Z \sim N(0,1)$.

$$PD = \Pr(A_T < K) = \Pr\,(lnA_T < lnK) \tag{2}$$

$$= \Pr\left(\frac{\ln\left(\frac{A_t}{A_0}\right) - \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T}{\sigma_A \times \sqrt{T}} < \frac{\ln\left(\frac{K}{A_0}\right) - \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T}{\sigma_A \times \sqrt{T}}\right) \tag{3}$$

$$= \Pr\left(Z < \frac{\ln\left(\frac{K}{A_0}\right) - \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T}{\sigma_A \times \sqrt{T}}\right) \tag{4}$$

$$= \mathrm{N}\left(\frac{\ln\left(\frac{K}{A_0}\right) - \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T}{\sigma_A \times \sqrt{T}}\right) \tag{5}$$

By inspection of Equation (5), we see that a higher leverage, $\frac{K}{A_0}$, and a higher asset volatility, σ_A^2, leads to a higher probability of default which in turn implies a higher CDS spread.

2.4. The Arbitrage Argument

The corporate bond spread is obtained by calculating the difference between the yield on the entity's outstanding bonds and the risk-free rate. The spread reflects the credit risk and is referred to as the credit spread (Berk & DeMarzo 2013).

Financial market theory suggests that the CDS spreads and the credit spread for the same entities are bounded by a no-arbitrage condition. By ignoring differences in liquidity and assuming that the maturity of the corporate debt equals the maturity of the CDS spread, an investor who acquires a corporate bond and buys protection for the same reference asset in the CDS market is hedged against the default of this particular firm. While the credit spread is calculated using the difference between the bond yield and the risk-free rate, the CDS spread is determined on the market and is the price of insurance against default. The implied no-arbitrage assumption between the two markets suggests that the price of buying such a protection against default in the CDS markets equals the observed corporate bond yield (CBY) minus the risk-free rate (RR), referred to as the credit spread. This is shown in Equation (6) (Alexopoulou et al. 2009).

$$CDS\ Spread = CBY - RR = Credit\ Spread \tag{6}$$

Despite the above-mentioned arbitrage condition, recent developments in financial markets research show that substantial deviations between the CDS spreads and the credit spreads can occur over a prolonged period of time. In theory, there are some explanations for the on average slightly higher CDS spreads. For instance, it is easier to short credit by buying credit protection in the CDS markets, which increases the CDS spreads, *ceteris paribus*. Shorting credit in the corporate bond markets is, however, difficult as the liquidity is not optimal for these types of transactions. Furthermore, investors usually hold a number of various assets and use them as collateral for funding purposes. In this sense, corporate bonds are the preferred instrument, rather than CDS contracts. This feature tends to decrease the credit spreads relative to CDS spread (Zhu 2006).

3. Previous Research

The CDS market and the corporate bond market are prominent topics in the financial literature. During the last two decades, the European corporate bond market has experienced noticeable changes in its composition and the bond market volume has grown rapidly. Even though the European corporate bond market still lags the US corporate bond market in terms of size, evidence from previous studies find significant similarities between the US and European bond market (Boss et al. 2002). In this section, some of the central and most relevant articles within the field, covering the European and US corporate bond market, are reviewed.

Several previous studies investigate the relationship between the CDS market and the corporate bond market in the short and the long run. Alexopoulou et al. (2009) analyze the credit risk pricing dynamics of the CDS market and corporate bond market of European financial and non-financial firms. This study finds that the explanatory power of changes in systematic credit risk tend to be greater for the CDS spread compared to the credit spread, while corporate bonds seem to be more sensitive to structural factors and liquidity. Also, a long-term relationship between the two markets is detected, which means that there is a long-run no-arbitrage equilibrium. This support the results in Blanco et al. (2005), Norden and Weber (2004) and Zhu (2006). However, according to these studies substantial deviations between the CDS spread and the credit spread arise in the short run.

Some discussed variables affecting the CDS and corporate bond market are the structural variables; leverage, volatility and the risk-free rate. Also, several market-specific variables are present in the literature. Ericsson et al. (2009) investigate the theoretical determinants of the CDS spread based on the structural form model, following the Merton (1974) Model. In this study, leverage and volatility have a positive relationship with the CDS spread while the ten-year yield has a negative impact on the CDS spread. Another study based on the structural model is performed by Galil et al. (2013) and investigate the determinants of changes in the CDS spread. As an additional dimension market-risk factors are added to this analysis and the results show that both structural and market-specific factors have a significant effect on changes in the CDS spread. Agreeing with Ericsson et al. (2009), volatility has a positive relationship to the CDS spread, while the stock return has a negative relationship. Similar to these studies, Collin-Dufresne et al. (2001) examine the determinants of credit spread changes by taking several macroeconomic and financial variables into account. The conclusion of this study is that the main drivers of credit spread changes are local economic shocks, independent of credit risk and liquidity.

Some articles in the literature focus on how market or macroeconomic variables affect the CDS and corporate bond market. Chodnicka-Jaworska et al. (2017) find that CDS spreads are closely connected with business models, earnings potential and especially macroeconomic conditions. Ang and Piazzesi (2003) describe the relationship between bond yields and macroeconomic variables by imposing a no-arbitrage assumption. According to this study, the macroeconomic factors explain up to 85% in the short and middle-part movements of the yield curve but explain only approximately 40% of movements at the long-end movements of the bond-yield curve. Macroeconomic variables are also discussed in the context of CDS spreads. Kim et al. (2015) investigate the relationship between the business cycle and pricing dynamics at the CDS market. The results show that macroeconomic variables significantly explain the CDS spread changes and that investment grade companies are more sensitive to macroeconomic factors in comparison to non-investment grade companies. According to this study, macroeconomic variables have a higher explanatory power before and after an economic crisis period. During the crisis period 67% of the CDS spread changes are explained by leverage ratio, volatility and the risk-free rate while the explanatory power of the macroeconomic variables are weak.

Apart from structural variables and market variables credit ratings are discussed as one of the factors affecting the CDS spread and the credit spread. Krylova (2016) investigates the properties of the euro-denominated corporate bond market before and after the financial crisis by looking at different credit spread determinants such as rating, sector, country attribution, coupon rate, maturity and liquidity. The conclusion of this study is that the rating effect is the major driver of credit spreads during the pre-crisis period. Cossin et al. (2002) find similar results regarding the credit ratings at the CDS market. This study aims to examine how much of the variation in the CDS spread that can be explained by credit ratings. Again, the results show that credit ratings are the most important source of information on credit risk. However, some of the variables in this study have a larger impact than credit ratings for certain groups. Moreover, the variance of the equity price is negatively correlated with the CDS spread and in line with structural form models, leverage positively influence on the default swap rates (Cossin et al. 2002).

4. Methodology

The modelling framework of this study is based on previous research and the structural credit risk model, the Merton (1974) Model. According to the literature within the field, the assumption of the modelling framework is that several factors affect the price of credit risk and because of that, the variables in the model are categorized as structural variables and market variables.

4.1. Data Description

The five-year euro-denominated CDS spreads are obtained from Datastream (2018) and the initial sample includes 184 A-rated and B-rated companies. 71 of the companies are financial companies and 113 are non-financial companies. Since CDS data is scarce the countries in the sample are chosen based on the availability of CDS data: France, Germany, Italy, Netherlands, Spain, Sweden and United Kingdom. Moreover, to eliminate potential effects of the financial crises in the end of the 2000s and to get a substantial long-time period during an economic expansion the sample period is from 29 March 2013 until 29 December 2017.

After collecting the credit spreads from Datastream (2018), for the corresponding corporate bond, as well as equity price, implied price volatility and leverage from each reference entity the final sample consists of 84 companies, 39 A-rated and 45 B-rated, presented in Appendix A. Since finding corporate bond data that exactly correspond to the CDS data in terms of maturity and characteristics is difficult, the following approach is conducted when collecting the final credit spread sample: It was primarily a search process to find corporate bond spreads with issue date 2013 and maturity date later than December 2017 in order to cover the 5-year period of the CDS data obtained. For a number of corporations, a second screening process was required due to limited number of outstanding corresponding credit spreads during the sample period. For these companies, the time of issuance was extended to between 2011 to 2013 and maturity date to between 2017 to 2019.

Furthermore, the data is divided into two subsamples for the CDS and the credit spread respectively with regards to the reference entities credit rating obtained by S&P Global Ratings. This is done in order to investigate if potential mispricing is affected differently by companies of different creditworthiness. The information about the credit ratings is obtained from Bloomberg (2018). According to previous research, companies with higher ratings tend to be more sensitive to market factors and because of that, only companies rated A or B are included in the sample (Kim et al. 2015). Group A reflects companies with strong to extremely strong capacity to meet financial commitments while the group B is more of a subject to adverse economic conditions. Companies that changed credit rating from B to A or from A to B during the measurement period are excluded from the sample in order to avoid down or upgrading errors.

4.2. Variables

Based on previous research, the assumption is that investors make use of a broad range of information and factors when pricing credit risk. This information includes both structural factors and market factors.

The variables are presented in Table 2. Each variable is explained in detail in respectively subsection.

Table 2 Summary of the dependent and independent variables.

Variable	Notation	Expected Sign
Dependent Variables		
Credit Spread	CS	
Credit Default Swap Spread	CDS	
Structural Variables		
Equity Price	EP	Negative
Price Volatility	PV	Positive
Leverage	LEV	Positive
Market Variables		
Market Price Index	MPI	Negative
Market Implied Volatility	MIV	Positive
Government Bond Yield	GBY	Positive

4.2.1. Dependent Variables

4.2.1.1. The CDS Spread and the Credit Spread

Weekly observations of the CDS spreads, data type “SM”, for the companies included in the dataset are collected from Datastream (2018). The CDS spread is the mid-rate spread between the entity and the benchmark curve, expressed in basis points. Similarly, weekly observations of the credit spread, data type “SWSP”, are collected from Datastream (2018). This swap spread is a measure of the credit spread of a corporate bond and is calculated using the yield of a corporate bond and the country specific swap rate. The credit spread corresponds to the yield difference, which is the corporate bond yield minus the swap rate, expressed in basis points. Since the corporate bonds do not exactly match the maturities of the available swap rates the credit spread is computed by Datastream (2018) using linear interpolation as an estimation method.

The CDS spread follows the trend of the credit spread of the corresponding underlying asset, according to the arbitrage argument (Alexopoulou et al. 2009), and because of that, a positive correlation between the two variables is expected. In this study, the credit spread is considered to be the true value of credit risk thus the price of a CDS should equal the credit spread. However, the market is not fully efficient which means that there are deviations between the credit spread and the CDS spread in the short run (Alexopoulou et al. 2009).

4.2.2. Structural Variables

The structural variables of the model in this study are chosen according to the structural approach of credit risk pricing, based on the Black-Scholes option pricing theory, and corresponds to the three factors included in the Merton (1974) Model; price volatility, equity return and leverage. These variables are company-specific and are collected from the reference entity of the corporate bond and the CDS spread.

4.2.2.1. Equity Price

The equity price depends on how risky a stock is and reflects the markets expectation of future company performance (Hull 2015). In this study, equity price is used as a proxy for firm asset value. An increase in equity price reflects an increase in the firm’s asset value which decreases the probability of default (Merton 1974). In this study, weekly observations of the equity price are obtained from Datastream (2018). The Merton (1974) Model suggests that higher asset value decreases the probability of default. When the probability of default decreases, the CDS spread decreases and thus the expected relationship between the CDS spread and the equity price is negative. Again, we expect the credit spread to have a negative relationship to the equity price due to the no-arbitrage condition between the CDS and the credit spread (Hull 2012).

4.2.2.2. Equity Price Volatility

Weekly observations of equity price volatility are obtained from Bloomberg (2018) for the reference asset of each company. The estimated price volatility of a stock measures the uncertainty of equity price. The volatility of the stock price cannot be observed directly but can be estimated using various variance estimation techniques using historical stock prices. The measure used in this study is the 30-day volatility. This is the standard deviation of day to day logarithmic historical price changes, which equals the annualized standard deviation for the relative price changes for the 30 most recent trading days closing price expressed as a percentage (Bloomberg 2018).

The relationship between the price volatility and the CDS spread is expected to be positive. In other words, if the price volatility increases the probability of corporate default increases. This is reflected in a higher CDS spread (Merton 1974). According to the arbitrage argument we expect the relationship between the credit spread and the equity price volatility to be positive (Alexopoulou et al. 2009).

4.2.2.3. Leverage

In this study, the leverage ratio is measured as the total debt[2] as a percentage of total capital[3] for each company (Datastream 2018). Yearly observations of leverage are obtained from Datastream (2018) and we use a linear interpolation in excel in order to estimate leverage as weekly observations instead. We assume that the yearly observations of leverage correspond to the last observation of each year. As an example, weekly observations of leverage for year 2013 is estimated using a linear interpolation between the last observation of 2012 and the last observation of 2013.

[2] Total debt is measured as long-term debt plus short-term debt.
[3] Total capital is measured as total capital plus short-term debt and current portfolio of long-term debt.

The expected relationship between leverage and the CDS spread is expected to be positive due to the Merton (1974) Model because higher leverage indicates a higher probability of default. As mentioned, higher probability of default increases the CDS spread and the same relationship is expected between the credit spread and leverage because of the arbitrage argument (Hull 2012).

4.2.3. Market Variables

4.2.3.1. Market Price Index

Market price index is a measure for the company's current and expected future dividends. This means that movements in price indices consist of information about the market beliefs about future economic activity in the economy (Alexopoulou et al. 2009). A negative relationship is expected for the market price index and the CDS spread, as well as for the credit spread, because the expectations of a good economic future decreases the probability of default for the firms. Data on the market price index is extracted from Datastream using weekly observations of the data type "TOTMKEM" (Alexopoulou et al. 2009; Datastream 2018).

4.2.3.2. Market Implied Volatility

Market implied volatility is derived from real time option prices and reflects the market expectation of volatility. Market implied volatility is a standard measure for the overall market uncertainty. Increased movements in market implied volatility tend to be a good indicator of recessions. As an empirical example, the market volatility in the European and the US market have increased prior to or during all periods of recessions since 1973 (Alexopoulou et al. 2009). This suggests a positive relationship between the market implied volatility and the credit spread. The same relationship is expected for the market implied volatility and the CDS spread. Monthly observations from the EURO STOXX 50 real time option prices is obtained from Datastream (2018). The data type is called "VSTOXXI" and measure the square root of the implied variance across all options at a given time to expiration. (Datastream 2018). Due to the fact that the "VSTOXXI" data obtained consists only of monthly observations, linear interpolation is used to transform the data into weekly observations.

4.2.3.3. Government Bond Yield

In order to capture the effect of a long-term risk-free rate on the credit spread and CDS spreads a ten-year generic government bond index, GECU10YR, is chosen as a proxy for the risk-free interest rate. The GECU10YR index consists of generic government bonds with a maturity of ten years, mainly issued by the governments of Germany and France (Bloomberg 2018). Government bond yields can be assumed as a measurement for the overall economic outlook. According to the Fisher hypothesis, government bond yields can be broken down into a real rate component and expected inflation. The real rate component is positively related to economic-growth prospects which means that higher bond yields signal optimistic expectations about the future economic activity. This in turn result in a lower expected default risk for the firms. Because of that, a negative relationship between government bond yields and credit spreads is expected. The same sign of the government bond yield in relation to the CDS spread is expected (Birch Sørensen et. al. 2010).

5. The Econometric Model

The dataset used in this study comprises both time series and cross-sectional data, known as panel data. This means that it keeps the same objects and measures the quantity of them over time. Two of the estimator approaches in financial research is the fixed effects model and the random effects model. To test if it is appropriate to use a fixed or random effect model a Hausman Test can be performed. If the probability value of the Hausman Test is less the chosen level of significance a fixed effects specification is preferred (Brooks 2008).

Based on the results obtained from the Hausman Test, see Appendix B, a fixed effects model is used in this study. The fixed effect model allows the regression to change cross-sectional but not over time (Brooks 2008). The cross-section units in the dataset are the companies while the sample periods, the same length of period for all companies, accounts for the time series part. Moreover, the fixed effects model is used when the sample objectives are not assumed to be stochastically drawn from the underlying population which is usually true when the observations are represented by countries, companies or industries (Verbeck 2004).

One of the advantages of using panel data, instead of time series or cross-sectional data, is that panel data makes it possible to analyze individual level changes. Panel datasets tend to be large and since the explanatory variables vary over both individual and time dimensions, the estimates often become more accurate compared to other sources of data. Because of that, panel data often yield efficient estimators (Verbeck 2004).

The statistical structure of the fixed effects model is a linear regression model with a fixed intercept, α_i, varying over the individual units *i*. ϵ_{it} is the disturbance term for unit *i* at time *t* and β is the average contemporaneous effect of the independent and dependent variables (Verbeck 2004). Usually the assumption is that the explanatory variables are independent of the error terms.

All six regressions performed are specified below. First, Equation (7) and Equation (8) are the statistical models for the first two regressions when including companies from rating group A and rating group B.

$$CDS_{it} = \alpha_i + \beta EP_{it} + \beta PV_{it} + \beta LEV_{it} + \beta MPI_{it} + \beta MIV_{it} + \beta GBY_{it} + \epsilon_{it} \tag{7}$$

$$CS_{it} = \alpha_i + \beta EP_{it} + \beta PV_{it} + \beta LEV_{it} + \beta MPI_{it} + \beta MIV_{it} + \beta GBY_{it} + \epsilon_{it} \tag{8}$$

Equation (9) and (10) are the models for the regression including companies from the first subsamples, rating group A.

$$CDS_{it}^{A} = \alpha_i + \beta EP_{it}^{A} + \beta PV_{it}^{A} + \beta LEV_{it}^{A} + \beta MPI_{it}^{A} + \beta MIV_{it}^{A} + \beta GBY_{it}^{A} + \epsilon_{it} \tag{9}$$

$$CS_{it}^{A} = \alpha_i + \beta EP_{it}^{A} + \beta PV_{it}^{A} + \beta LEV_{it}^{A} + \beta MPI_{it}^{A} + \beta MIV_{it}^{A} + \beta GBY_{it}^{A} + \epsilon_{it} \tag{10}$$

Equation (11) and Equation (12) show the regression models including companies from the second subsample, rating group B.

$$CDS_{it}^{B} = \alpha_i + \beta EP_{it}^{B} + \beta PV_{it}^{B} + \beta LEV_{it}^{B} + \beta MPI_{it}^{B} + \beta MIV_{it}^{B} + \beta GBY_{it}^{B} + \epsilon_{it} \tag{11}$$

$$CS_{it}^{B} = \alpha_i + \beta EP_{it}^{B} + \beta PV_{it}^{B} + \beta LEV_{it}^{B} + \beta MPI_{it}^{B} + \beta MIV_{it}^{B} + \beta GBY_{it}^{B} + \epsilon_{it} \tag{12}$$

When interpreting the results from the fixed effects model one should be aware that the model focuses on differences in the objectives thus the parameters are identified in the dimension of data. However, changes in the explanatory variables have the same effect independent of changes between periods or individuals (Verbeck 2004).

5.1. Model Diagnostics

In order to evaluate the validity and the characteristics of the variables in the models a number of diagnostic tests are performed before running the regressions. Each of the diagnostic tests are explained in the following subchapters.

5.1.1. Heteroscedasticity and Autocorrelation

Heteroscedasticity is a statistical issue that arises when the variance of the error terms in a regression is dependent of the values of the independent variables. If heteroscedasticity is present, the regression estimators will be unbiased but inefficient. This is because the true variance and covariance is underestimated (Verbeck 2004). To detect heteroscedasticity when using fixed effect regression models a modified Wald Test can be performed. The null hypothesis states that the errors are homoscedastic and if the null hypothesis is rejected the test implies heteroscedastic errors. It is possible to correct for heteroscedasticity by specifying the model with robust standard errors (StataCorp 2017).

Moreover, when time series data is influenced by its own historical values the data is characterized by autocorrelation. Autocorrelation in linear panel data models biases the standard errors and causes the result to be less efficient (Verbeek 2012). One way to test for autocorrelation in random and fixed panel data models is to use the Wooldridge Test. The null hypothesis in the Wooldridge test states that no first order autocorrelation exists (StataCorp 2017). If autocorrelation is present in the model, robust standard errors can correct for it (Verbeek 2012).

5.1.2. Multicollinearity

Multicollinearity means high correlation between two or more explanatory variables in the model. High correlation of the parameters leads to inaccurate estimations and the sample will not provide sufficient information about the parameters. The affected variables will have high standard errors and unstable coefficient that vary between samples and thereby undermining the credibility of the variable's statistical significance. To alleviate for this sort of problem one will be forced to use more information which is commonly done by omitting those variables from the model or extend the sample size (Verbeek, 2012). To test for multicollinearity the Variance Inflation Factor (VIF), specified in Equation (13), can be calculated for each predictor.

$$VIF = \frac{1}{1 - R^2} \tag{13}$$

From the denominator in the equation above, R^2 is the coefficient of determination stating the proportion of the variance in the dependent variable predictable from the independent variables. The Variance Inflation Factor represents the proportion of variance in one predictor explained by the other predictors in the model. A VIF value equals to one indicates no collinearity between the variables, whereas increasingly higher values suggest increasing multicollinearity. A VIF-value between five and ten indicates high correlation which can be problematic. If the VIF is above ten, one can assume that the regression coefficients are poorly estimated due to multicollinearity (StataCorp 2017).

5.1.3. Stationarity

When operating with times-series data it is desirable to have stationary processes, otherwise the regression results may be spurious which means that it is possible to detect a trend that does not exists. If the processes are non-stationary the coefficient estimates, and the test statistics will be misleading and not valid (Verbeek 2012). Since panel data consists of both time-series and cross-sectional data it is substantial to test the model for stationarity, for the same reasons as when only using time-series data (Brooks 2008). For a variable to be at least weakly stationary and in order to generate efficient estimators it is crucial for the variable to contain a constant mean, variance and autocovariance. Because of that, stationarity should be examined as a first step.

To determine if the process is stationary one can test if the variables consist of a unit root process (Verbeek 2012). For panel data several test and specifications of tests can be used to perform a unit-root test, for example the Levin-Lin-Chu unit-root Test can detect non-stationary processes in panel data (StataCorp 2017).

5.2. Model Criticism

There are several reasons for why the model is not fully valid and some of the reasons are linked to the dataset and the construction of the variables. First, some of the variables in the sample are transformed from monthly to weekly observations by linear interpolation and thereby the variables become linear. This is done to fill in the gap of observations between the monthly observations. One problem with this could be that it is not possible to exactly know how the variables fluctuate during the sample period. The second issue with the data is that it is not possible to find the exact corresponding credit spread to the five-year maturity CDS spread. Because of that, there could be some differences between the credit spread and the CDS spread which could affect the results.

6. Results

6.1. Diagnostic Tests

In order to test for stationarity a panel-data unit-root test (e.g. the Levin-Lin-Chu unit-root Test) is performed, see Appendix C. The null hypotheses are rejected due to probability values of zero which implies that the processes are stationary. A Wooldridge Test and a Wald Test for autocorrelation and heteroscedasticity, see Appendix B, are conducted as well. Due to low probability values the null hypotheses are rejected hence the models suffer from autocorrelation and heteroscedasticity. For that reason, robust standard errors are used in the model. Moreover, the Variance Inflation Factors, see Appendix D, are calculated. Since the VIF-values of the variables in the models are less than five, multicollinearity is not a problem (StataCorp 2017).

6.2. Descriptive Statistics

In this section, descriptive statistics of the variables are presented. Table 3 and Table 4 table contain the sample of 9711 observations for 39 A-rated companies. Table 5 and Table 6 contain the sample of 11205 observations for 45 B-rated companies.

Table 3. Descriptive statistics of the credit spread for group A.

Variable	Obs	Mean	Std.dev	Min	Max
CS_A	9,711	88.102	98.602	-26.400	523.400
EP	9,711	326.084	644.387	3.267	3942.000
PV	9,711	23.430	9.209	7.180	87.990
LEV	9,711	52.474	21.910	14.450	92.660
MPI	9,711	3201.005	282.858	2549.482	3816.758
MIV	9,711	19.920	4.262	12.120	32.310
GBY	9,711	1.681	0.855	0.661	3.678

Table 4 Descriptive statistics of the CDS spread for group A.

Variable	Obs	Mean	Std.dev	Min	Max
CDS_A	9,711	63.776	34.050	15.030	338.714
EP	9,711	326.084	644.387	3.267	3942.000
PV	9,711	23.430	9.209	7.180	87.990
LEV	9,711	52.475	21.910	14.450	92.660
MPI	9,711	3201.005	282.858	2549.482	3816.758
MIV	9,711	19.920	4.262	12.120	32.310
GBY	9,711	1.681	0.855	0.661	3.678

Table 5 Descriptive statistics of the credit spread for group B.

Variable	Obs	Mean	Std.dev	Min	Max
CS_B	11,205	91.760	80.493	-23.800	1418.100
EP	11,205	261.855	551.911	1.021	4130.000
PV	11,205	25.381	11.961	3.018	139.486
LEV	11,205	57.614	20.148	8.630	156.830
MPI	11,205	3201.005	282.856	2549.482	3816.758
MIV	11,205	17.291	7.790	0.121	32.310
GBY	11,205	1.681	0.855	0.661	3.678

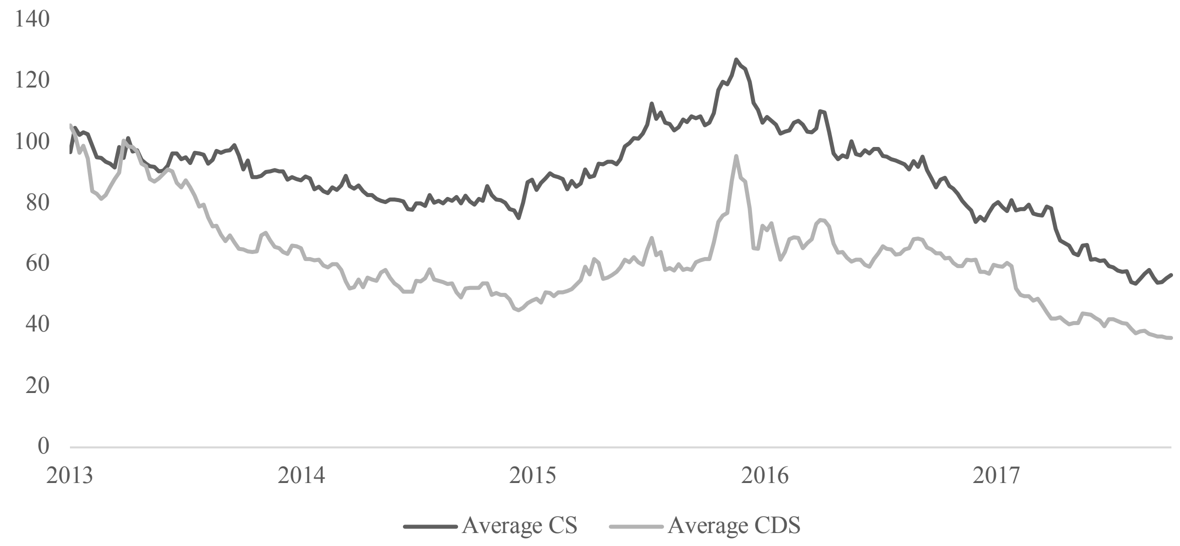
Table 6. Descriptive statistics of the CDS spread for group B.

Variable	Obs	Mean	Std.dev	Min	Max
CDS_B	11,205	107.107	75.891	27.560	1385.490
EP	11,205	261.855	551.911	1.021	4130.000
PV	11,205	25.381	11961	3.018	139.486
LEV	11,205	57.614	20.148	8.630	156.830
MPI	11,205	3201.005	282.856	2549.482	3016.758
MIV	11,205	19.921	4.262	12.120	32.310
GBY	11,205	1.681	0.855	0.661	3.678

Based on the descriptive statistics in Table 3 to Table 6, the mean value of EP for companies in rating group A is greater compared to rating group B. However, the mean value of LEV and PV are lower for companies in group A. The descriptive statistics of the structural variables are consistent with the rating scale descriptions from the credit rating agency Standard & Poor's. According to the credit rating agency, companies in group A have strong to extremely strong capacity to meet financial commitments while companies in group B have adequate or worse capacity to meet financial commitments (S&P Global Ratings 2017).

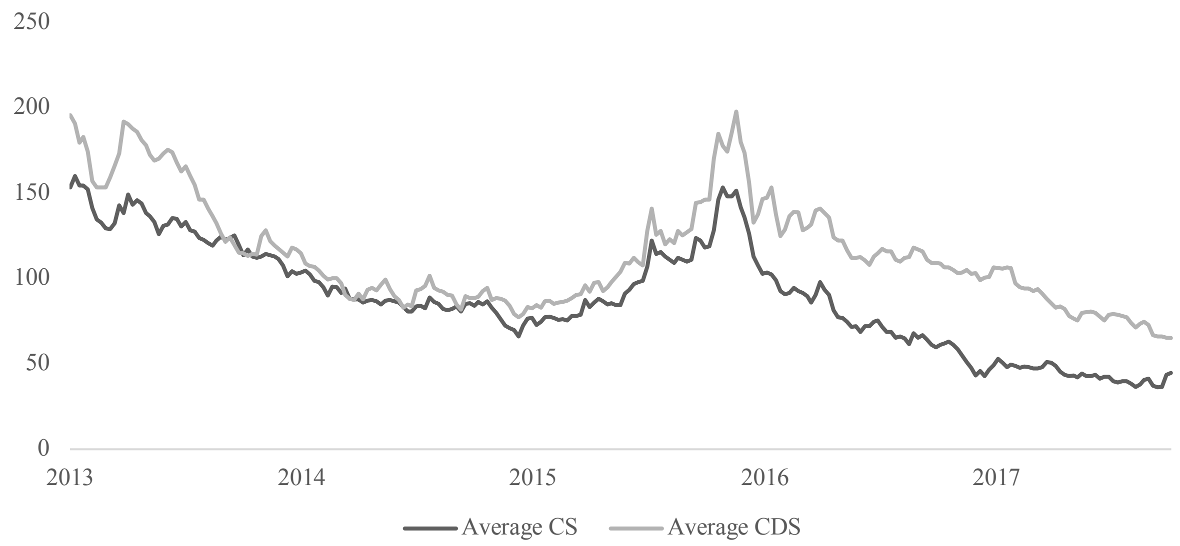
The descriptive statistics in Table 3 to Table 6 implies that, on average, the CDS spread is less than the credit spread for companies in rating group A while for companies in group B the CDS spread is on average greater than the credit spread. The mean value of the CDS spread for the companies in rating group A corresponds to approximately 72,39 % of the mean value of the credit spread. For companies in rating group B, the mean value of the credit spread corresponds to approximately 85,67 % of the mean value of the CDS spread. This implies that the gap between the CDS spread and the credit spread is on average greater for companies in rating group A. The CDS spread and the credit spread for companies in rating group A and B are illustrated separately in Figure 1 and in Figure 2. The trend of the CDS spread and the credit spread including both rating groups is illustrated in Figure 3. The size of the gap between the CDS spread and the credit spread is smaller in Figure 3 compared to Figure 1 and Figure 2.

Figure 1 The average credit spread and CDS spread for companies in rating group A.



Source: Datastream (2018)

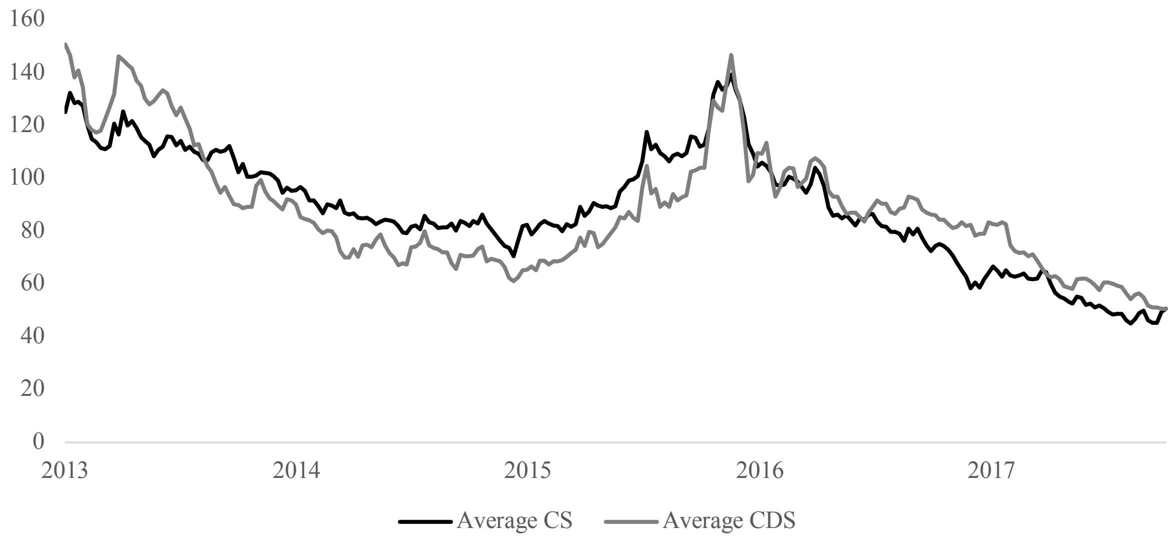
Figure 2 The average credit spread and CDS spread for companies in rating group B.



Source: Datastream (2018)

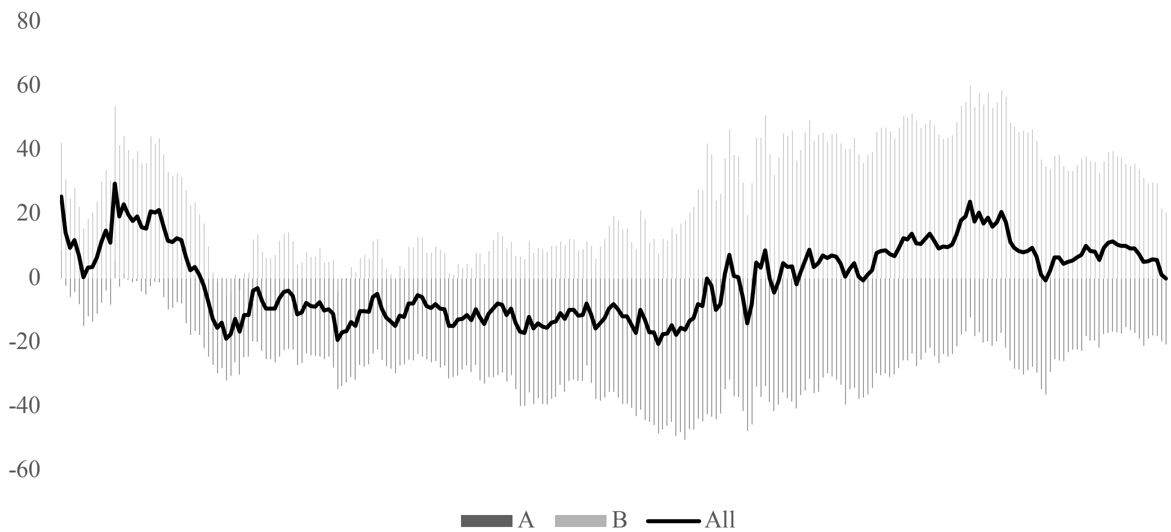
Moreover, the size of the gaps between the CDS spread and the credit spread for the companies in the two rating groups fluctuate over the sample period, illustrated in Figure 4. In the beginning and in the end of the sample period the average gap is greater for group B but from approximately early 2014 to the end of 2015 the size of the gap is greater for group A.

Figure 3 The average credit spread and CDS spread for all companies.



Source: Datastream (2018)

Figure 4 The difference between the credit spread and the CDS spread.



Source: Datastream (2018)

6.3. Empirical Findings

The empirical analysis aims to investigate the pricing dynamics between the CDS market and the corporate bond market. According to the arbitrage argument, the CDS spread corresponds to the credit spread. In this analysis the results from the CS model are used as a benchmark against the results in the CDS model. For instance, if a variable has a larger effect in the CDS model, that variable increases the price of the CDS more than the corresponding increase in the credit spread. In other words, that variable potentially causes the market to overestimate credit risk at the CDS market relative to the corporate bond market resulting in a higher price of the CDS. Moreover, the effects of the variables are compared between two rating groups, A and B. For this purpose, a fixed effect regression for each dependent variable is performed, with correction for robust standard errors. All of the regressions are performed in the same manner and are thereby comparable.

Before running the regressions on the subsamples, two regressions containing both rating group A and B are performed. The coefficient estimates of the two regressions show similar results and are presented in Table 7. However, the variables EP and MIV are not significant in the CDS model. In the CS model all independent variables are significant. The results imply that both structural and market variables affect the CDS spread and the credit spread. Further in this section, the results from the subsample regressions are presented.

Table 7 The regression results including all companies.

Variable	ALL_CDS	ALL_CS
EP	-0.059	-0.077*
	(0.051)	(0.045)
PV	1.282**	1.084**
	(0.535)	(0.498)
LEV	1.279***	1.313***
	(0.377)	(0.468)
MPI	-0.035***	-0.021***
	(0.004)	(0.005)
MIV	0.289	1.558***
	(0.515)	(0.506)
GBY	11.070***	11.040***
	(2.136)	(2.752)
Constant	88.600***	34.160
	(21.360)	(30.720)
Observations	20,916	20,916
R-squared	0.328	0.280
Number of Companies	84	84

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the subsample regressions are presented in Table 8. Based on the regression results, all of the structural factors affect the CDS spread and the credit spread except for EP in the subsample with B-rated companies. Based on the Merton (1974) Model the relationship between EP and the dependent variables should be negative but this expectation is only supported by the regression results for rating group A. The credit spread seems to be more sensitive to changes in the EP in comparison to the CDS spread for group A. A one unit increase in EP generates a 0.031 decrease in the credit spread and a 0.050 decrease in the CDS spread. Moreover, PV has a larger effect on rating group B and according to the Merton (1974) Model the sign of the coefficients is positive, which is confirmed by the regression results. Similar to PV and in line with Merton (1974), LEV has a positive effect on both of the dependent variables. For group A LEV has a considerably higher effect on the credit spread than the CDS spread, while for group B the effect is higher for the CDS spread.

Table 8 The regression results for the subsamples.

Variable	A_CDS	B_CDS	A_CS	B_CS
EP	-0.031*	-0.082	-0.050*	-0.102
	(0.018)	(0.088)	(0.025)	(0.082)
PV	0.672***	1.527**	0.508***	1.304*
	(0.185)	(0.705)	(0.137)	(0.669)
LEV	0.734***	1.410**	1.463**	0.993*
	(0.247)	(0.562)	(0.660)	(0.502)
MPI	-0.027**	-0.044***	-0.021***	-0.025***
	(0.003)	(0.006)	(0.006)	(0.005)
MIV	0.277	0.714	1.149***	2.335***
	(0.290)	(0.572)	(0.257)	(0.591)
GBY	8.347***	12.700***	0.637	20.070***
	(2.155)	(3.844)	(3.539)	(3.918)
Constant	85.780***	112.900***	58.140*	35.350
	(17.250)	(37.510)	(32.740)	(46.210)
Observations	9,711	11,205	9,711	11,205
R-squared	0.408	0.347	0.226	0.358
Number of Companies	39	45	39	45

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

According to previous research a negative sign of MPI is expected (Alexopoulou et al 2009). This is because the expectations of a good economic future decrease the probability of default and thereby the CDS and the credit spread decreases (Hull 2015). The negative expectation is confirmed by the regression results where the coefficients for MPI are negative for the dependent variables. The effect of MPI is higher for the CDS spread, especially for group B where a one unit increase in MPI leads to a 0.044 decrease in the CDS spread. The second market variable MIV supports the findings of the regression in Table 7. Since MIV can be considered as a measure for the overall market uncertainty the positive relationship between MIV and the credit spread is expected (Alexopoulou et al. 2009). The coefficient for MIV is greater for B-rated companies where a one unit increase in MIV increases the credit spread by 2.335 while for companies in group A the one unit increase in the variable only increases the credit spread by 1.149.

Furthermore, changes in the GBY is an indication of a market reaction. Increased interest rates are a signal that worse times are to be expected. The expectation of a positive sign for GBY is confirmed by the regression results, even though there is no significant relationship between GBY and the credit spread for group A (Hull 2000). GBY has the largest coefficient estimate on the credit spread for group B where a one unit increase in GBY causes the credit spread to increase by 20.070 while the CDS spread for companies in group B increase by 12.700. For the companies in group A, the relationship between GBY and the CDS spread is positive, but the effect of a change in the market variable on the CDS spread is less for group A compared to group B.

6.4. The Pricing Dynamics Between the CDS and the Corporate Bond Market

Based on the arbitrage argument the credit spread corresponds to the CDS spread (Alexopoulou et al. 2009). Looking at Figure 1 and Figure 2 the CDS spread for companies in group A is on average less than the corresponding credit spread. This could indicate that for companies in group A credit risk tend to be underestimated at the CDS market in relation to the corporate bond market during the sample period. For companies in group B credit risk instead tend to, on average, be overestimated during the sample period since the credit spread is less than the CDS spread. The gap between the CDS spread and the credit spread is supported by previous studies, Zhu (2006) and Blanco et al. (2005) found short-run deviations between the CDS spread and the credit spread. The gap between the CDS spread and the credit spread for all companies, illustrated in Figure 3, is smaller compared to companies in group A and B separately. This implies that the size of the gap between the credit spread and the CDS spread differ among different ratings.

In line with the study performed by Alexopoulou et al. (2009) the CDS spread for group A is found to be more sensitive to market factors in relation to the credit spread. Also, the CDS spread for rating group A is less sensitive to structural factors in relation to the corresponding credit spread. However, this contradicts the regression results for rating group B. For rating group B, the CDS spread is instead less sensitive to market factors and more sensitive to structural factors, in relation to the corresponding credit spread. This implies that the sensitivity to structural and market factors differ between different rating group when comparing the results of the CDS model with the CS model. Moreover, according to Kim et al. (2015) companies with a higher rating are more affected by market factors. This cannot be concluded by only analyzing the regression results from the CDS model. However, by comparing the regression results of the CDS and CS model separately between the credit rating groups, the market variables have a larger impact on the CDS model for group A and a lower impact on the CDS model for group B. In accordance with Ericsson et al. (2009) and the Merton (1974) Model leverage and price volatility have positive relation with the CDS spread and the credit spread during the sample period.

LEV is one of the structural variables where the coefficient estimates differ between the regressions performed. The effect of LEV for group A in the CDS model corresponds to approximately 50 % of the effect in the CS model. For group B, LEV in the CS model corresponds to approximately 70 % of the effect in the CDS model. Because of that, LEV could be one of the factors driving the CDS spread to be underestimated or overestimated in relation to the credit spread. The regression results thereby suggest that financial risk in group B is overestimated at the CDS market, compared to the corporate bond market, while it is underestimated for companies in group A.

Furthermore, the effect of PV for both rating groups is larger at the CDS market compared to the corporate bond market. Because of that, PV could also be a potential driver for overall mispricing credit risk at the CDS market.

To sum up, the regression results of the structural variables for group A indicate that prices at the CDS market are too low in relation to the corresponding credit spreads. This means that the CDS market may not reflect the actual credit risk and thus credit risk becomes underestimated. For companies in group B the opposite relation is true, where credit risk becomes overestimated at the CDS market.

7. Conclusion

This study investigates the differences between the determinants of the CDS market and the corporate bond market, for different credit rated companies. This is performed based on the arbitrage argument that the CDS spread and the credit spread are equal as a backdrop. The dataset consists of 84 European companies over the sample period Mars 2013 to December 2017, using 5 years to maturity credit default swaps.

This study supports previous research and finds that short-run deviations exist between the CDS and the corporate bond market. Thereby, this study confirms that the arbitrage argument does not hold in the short-run. The results imply that some of the variables are potential reasons for the market to overestimate or underestimate credit risk at the CDS market. Moreover, the regression results differ between the rating groups. This indicates a credit rating effect. The CDS spread for group A is more sensitive to market factors compared to structural factors. This contracts the findings for group B where structural factors have a larger effect on the CDS spread compared to market factors. Furthermore, the coefficient estimates of leverage differ between the models. The effect of a change in leverage for group A suggests that credit risk is underestimated at the CDS market but for group B it suggests that credit risk is overestimated. Due to this, the price of credit risk at the CDS market does not correspond to the corporate bond market.

8. Future Research

There are possibilities to expand the research performed in this paper. This paper covers companies with S&P ratings of B and above, implying that only companies with relatively good creditworthiness are accounted for. Because of that, a possible extension is to include companies with S&P ratings below B to get more dynamics in the regression results. Moreover, only companies with the same rating over the sample period are selected. This means that companies that migrated between the sample groups during the sample period are excluded. By including migrating companies, it is possible to analyze the effect of changes in credit ratings. Elaborating further on limitations of the selected sample, the companies in the sample is in the top ten of the European countries with the highest GDP. A potential expansion of the research is to investigate other countries in Europe and compare the results by accounting for a country-specific effects. Another possible extension is to choose a longer sample period in order to examine the effect of the independent variables on the CDS and corporate bond market over the business cycle. This paper only covers a period of economic expansion and the results might look different during dissimilar economic circumstances. In other words, it would be interesting to compare the effect of the variables that affects the CDS and the credit spread before, during and after a financial crisis to see if the effect fluctuates over time. Then, it would be possible to analyze if the arbitrage argument holds in the long run. It would also be possible to include more explanatory variables on both firm and market-specific levels. This may result in finding further indications of what drives the differences between the CDS and the credit spread.

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Appendix

Appendix A. Companies in rating group A respectively rating group B.

Company	Rating	Sector	Country
Aegon NV	A-	Financial	NL
Airbus Group SE	A+	Non-financial	NL
AkzoNobel NV	A-	Non-financial	SE
Atlas Copco AB	A+	Non-financial	SE
Axa SA	A-	Financial	FR
Banco Bilbao Vizcaya Argentaria	A-	Non-financial	SP
Banco Santander SA	A	Financial	SP
BASF SE	A	Non-financial	GE
Bayer AG	A-	Non-financial	GE
BNP Paribas SA	A	Financial	FR
Credit Agricole SA	A	Financial	FR
Daimler AG	A	Non-financial	GE
Deutsche Bank AG	A-	Financial	GE
Diageo plc	A-	Non-financial	UK
EnBW Energie Baden-Württenberg AG	A-	Non-financial	GE
Engie	A-	Non-financial	FR
Experian Finance plc	A-	Financial	UK
GlaxoSmithKlinge plc	A+	Non-financial	UK
HSBC Holdings plc	AA-	Financial	UK
ING Groep NV	A-	Financial	NL
Investor AB	AA-	Financial	SE
Klépierre SA	A-	FR	FR
Legrand SA	A-	Non-financial	FR
Linde AG	A+	Financial	GE
LVHM Moët Hennessy Louis Vuitton SE	A+	Non-financial	FR
Merck	AA	Non-financial	GE
Nordea Bank AB	AA-	Financial	SE
Prudential plc	A	Financial	UK
Rio Tinto plc	A	Non-financial	UK
Royal Dutch Shell plc	A+	Non-financial	NL
Sanofi SA	AA	Non-financial	FR
SAP SE	A	Non-financial	GE
Skandinaviska Enskilda Banken AB	A+	Financial	SE
Société Générale SA	A	Non-financial	FR

Svenska Handelsbanken AB	AA-	Financial	SE
Telia Company AB	A-	Non-financial	SE
Thales SA	A-	Financial	FR
Unilever NV	A+	Non-financial	NL
Vinci SA	A-	Non-financial	FR

Company	Rating	Sector	Country
Anglo American plc	BBB-	Financial	UK
Atlantia SPA	BBB+	Financial	IT
Bae System plc	BBB	Non-financial	UK
Banco de Sabadell SA	BBB	Financial	SP
Bankinter SA	BBB+	Financial	SP
Bouygues Telecom	BBB+	Non-financial	FR
Saint-Gobain SA	BBB	Non-financial	FR
Daily Mail & General Trust plc	BB+	Non-financial	UK
Danone SA	BBB+	Non-financial	FR
E.ON SE	BBB	Non-financial	GE
Enel SpA	BBB+	Non-financial	IT
Eni SpA	BBB+	Non-financial	IT
Fresenius SE & CO	BBB-	Non-financial	GE
Gas Natural Fenosa	BBB	Non-financial	SP
Heidelbergcement AG	BBB-	Non-financial	GE
Heineken NV	BBB+	Non-financial	NL
Iberdrola SA	BBB+	Non-financial	SP
Imperial Brands plc	BBB	Non-financial	UK
Intesa Sanpaolo SpA	BBB	Financial	IT
Lanxess AG	BBB-	Non-financial	GE
Lloyds Bank plc	BBB+	Financial	UK
Mediobanca SPA	BBB	Financial	IT
Orange SA	BBB+	Non-financial	FR
Koninklijke Philips NV	BBB+	Non-financial	NL
Rentokil Initial plc	BBB	Non-financial	UK
Repsol SA	BBB	Non-financial	SP
Segro pls	BBB+	Financial	UK
Sky plc	BBB	Financial	UK
Smiths Group plc	BBB+	Non-financial	UK
STD Chartered plc	BBB+	Financial	UK
Swedish Match AB	BBB	Non-financial	SE
Tate & Lyle plc	BBB	Financial	UK
Telefonica SA	BBB	Non-financial	SP

Tesco plc	BB+	Non-financial	UK
Thyssenkrupp AG	BB+	Non-financial	GE
Unicredit Bank SPA	BBB-	Financial	IT
Unione di Banche Italiane SPA	BBB-	Financial	IT
Valeo SA	BBB	Non-financial	FR
Veolia Environnement SA	BBB	Non-financial	FR
Vivendi SA	BBB	Non-financial	FR
Vodafone Group plc	BBB+	Non-financial	UK
Volkswagen	BBB+	Non-financial	GE
AB Volvo	BBB+	Non-financial	SE
Wendel SA	BBB-	Financial	FR
Wolters Kluwer NV	BBB+	Non-financial	SE

Appendix B. The results of the Hausman specification test, the Wald test for heteroscedasticity and the Wooldridge test for autocorrelation.

Model Diagnostic Test Probability Values						
Test	CDS A	CDS B	CS A	CS B	CS_ALL	CDS_ALL
Hausman Specification Test	0	0	0,003	0	0	0
Wald Test for Heteroskedasticity	0	0	0	0	0	0
Wooldridge Test for Serial Correlation	0	0	0	0	0	0

Appendix C. The results of the Levin-Lin-Chu unit-root test.

Levin-Lin-Chu Unit Root Test		
	Adjusted T-Statistic	P-Value
CS_All	-6,6376	0
ER	-2,5436	0,0055
PV	-19,3851	0
LEV	-8,1316	0
MPI	-11,3999	0
MIV	-30,2327	0
GBY	-7,9394	0

Levin-Lin-Chu Unit Root Test		
	Adjusted T-Statistic	P-Value
CDS_All	-12,6892	0
ER	-2,5436	0,0055
PV	-19,3851	0
LEV	-8,1316	0
MPI	-11,3999	0
MIV	-30,2465	0
GBY	-7,9394	0

Appendix D. The variance inflation factors (VIF).

Variance Inflation Factor						
Variables	CDS A	CDS B	CS A	CS B	CS_All	CDS_ALL
Equity Return	1,01	1	1,01	1	1,01	1,01
Price Volatility	1,48	1,21	1,48	1,2	1,24	1,29
Leverage	1,05	1,03	1,05	1,04	1,03	1,04
Market Price Index	1,74	1,72	1,74	1,52	1,57	1,72
Market Implied Volatility	1,53	1,35	1,53	1,14	1,17	1,4
Government Bond Yield	1,67	1,65	1,67	1,48	1,52	1,65