Master Thesis Financial Economics

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The Determinants of CDS Spreads Around a Financial Crisis and The Changed Effect of Company and Economic Fundamentals

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Executive summary

This paper shows that there is a clear relationship between credit default swap spreads and the selected determinants leverage, volatility, stock return, credit rating, spot rate, slope of the yield curve, VIX index and return on the S&P 500. Moreover, the crisis had a significant impact on this relationship.

For my research, I use a random-effects GLS regression on the dataset obtained from Datastream, COMPUSTAT, CRSP, CBOE and FRED. The dataset contains 5-year CDS spread information of 153 North-American companies with matching company data and market information.

By extending my standard model for explaining variation in CDS spreads, comprised of leverage, volatility and risk-free rate, I find that stock return, spot rate, slope of the yield curve, VIX index, credit rating and return on the S&P 500 have significant explanatory power for the variation in CDS spreads.

It is argued that many people perceived risk in a wrong way preceding the global financial crisis. When investigating this assumption, I conclude that there is a clear difference in the performance of my model when comparing the pre-crisis results to the results during the crisis. The proportion of variation in CDS spreads explained by the model increases drastically during the crisis.

After the crisis, this pattern continues and the model is able to explain up to 41 percent of the variation in CDS spreads. In addition, there is a clear difference in coefficient levels before and after the crisis. The differences before, during and after the crisis could indicate a change in attitude of the market towards risk, put forward through CDS spreads.

Lastly, a comparison between industries and credit rating classes shows that the model has a better fit with certain industries and that large differences in rating classes are apparent when looking at the period before and after the crisis

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1. Introduction

The introduction of credit derivatives in 1993, gave investors the possibility to take or reduce credit exposure, generally on bonds or loans of a sovereign or corporate entity (J.P. Morgan, 2006). There are many forms of credit derivative contracts, such as single-name credit default swaps, full index trades, and synthetic CDOs.

On September 26, 2017 Bloomberg published an article with the headline: “Citi Is Bringing Back One of the Most Infamous Bets of the Credit Crisis”. The article covers the tracks of a 35-year-old Citigroup Inc. director who is becoming the face for the resurgent market of synthetic CDO’s, one of the forms of the over the counter (“OTC”) credit default swap (“CDS”) contracts. Credit default swap contracts are regarded as one of the factors that caused the exacerbation of the global financial crisis. During the crisis, these contracts let to, the downfall of, amongst others, Citibank Inc. and forced the bank into a taxpayers bailout after large losses on similar securities. Surprisingly, many in the industry say that Citigroup is responsible for over half the deals in synthetic CDOs that come to market, currently. (Bloomberg, 2017)

A credit default swap (“CDS”) contract, the most frequently traded type of credit derivative, is an over the counter contract that links returns to the changes in the credit quality of a reference entity (Hull et al., 2004). Since the introduction of the credit default swap in 1994, a growing body of research has emerged on CDS contracts and their corresponding spreads. There is still no consensus on what the drivers are for the price changes of the contracts and the current increase in activity in the CDS market shows the relevance of the subject.

The foundations for the current CDS contracts are based on the ideas of a normal swap. During an off-site weekend in Boca Raton in 1994, a J.P. Morgan swaps team came up with the idea of swapping the risk of default instead of normal interest rate or currency risk. The first CDS contract involved a credit facility from J.P. Morgan to Exxon for covering potential damages resulting from an oil spill. Since the risk of the loan was sold to a third party, the loan was now risk-free. This construction led to the situation where J.P. Morgan did not have to reserve capital for the risk of the loans going bad, which was required by the Basel rules, but the reserved capital was now available for putting out extra loans. After the origination of this first CDS contract in 1994 and the standardization of documentation for CDS contracts by the International Swaps and Derivatives Association ("ISDA") in 1999, the CDS derivatives market has grown from $631 billion by June 2001 to $62.2 trillion by the end of 2007(notional amounts) (ISDA market survey, 2010)

A CDS is an over-the-counter contract between two parties where one of the two wishes to buy insurance against the possible default on a bond issued by a third party. The CDS spread is a representation of the market's views on the credit risk of bonds, measured in basis points. Hull et al. (2004) argue that CDS spreads are an interesting alternative to bond yields for two reasons. First, bond yield data usually consists of indications from dealers, with no commitment to trade at the specified price. Where CDS spreads are bid and offer quotes provided by dealers with a commitment from the dealer to trade at the specified price. Second, bond yields require a specification of the risk-free rate before they can be converted to spreads, where CDS spreads are already spreads and do not require a benchmark risk-free rate. (Hull et al., 2004)

Previous research shows that the CDS market is more efficient in estimating default risk than credit spreads and credit ratings. Amongst others, Longstaff et al. (2005) and Blanco et al. (2005) find that CDS prices lead credit spreads. One of the reasons for this is that the CDS market benefits from being the easiest place in which to trade credit risk (Blanco et al., 2005). Other researchers, e.g. Hull et al. (2003) and Norden and Weber (2004), looked into the relationship between credit ratings and CDS spreads and find that CDS prices are effective in predicting credit rating changes.

Several researchers have looked into the variation in CDS spreads, but they were only able to explain around 50 percent of the variation (e.g. Galil et al., 2014; Di Cesare and Guazzarotti, 2010). Stulz (2010) argues that the CDS contracts contributed to the size of the financial crisis. Since CDS spreads appear to be a strong measure for default risk, but they worsened the crisis and their variation is difficult to explain, previous research leaves unexplained questions on this subject. The goal of my research is to extend the knowledge on the factors causing the variation in CDS spreads and to explain what role the crisis played in the development of the CDS spreads. Therefore, my research question is:

What is the relationship between CDS spreads and company & economic fundamentals before, during, and after the recent financial crisis and did the importance of these fundamentals change over time?

Based on the variables presented by Black and Scholes (1973) and Merton (1974) for explaining default probabilities, I will construct a similar standard model to explain variation in CDS spreads. This model will be based on the variables leverage, stock volatility, and the risk-free rate. I want to analyse whether extending this model with variables presented by other literature (e.g. Ericsson et al., 2009; Di Cesare and Guazzarotti, 2010) will improve the ability of the model to explain variation in CDS spreads. The variables I will add to the standard model are stock return, spot rate, slope of the yield curve, VIX rate, credit rating, return S&P 500, and square two-year yield. By combining these variables deemed important in previous research, my goal is to construct an objective and encompassing model for explaining variation in CDS spreads.

Many (e.g. Stulz, 2010) argue that the financial crisis was exacerbated by the presence of CDS contracts. Flannery et al. (2010) conclude that CDS spreads did not identify accumulating risk exposures before 2007. These contracts caused counterparty risks, great dealer exposure and risks of large price changes. Also, in the fall of 2008, many executives were claiming that the CDS market was being manipulated. This would be difficult in a highly liquid market, but the financial markets were not always liquid in this period (Stulz, 2010). In this research, the extended model will be used to compare its effectiveness in explaining variation in CDS spreads before, during and after the financial crisis. The extended model should be able to better explain variation in CDS spreads during and after the crisis, then before the crisis. Since the default risks of companies were poorly estimated (not based on fundamentals) before the financial crisis, I expect that my model will perform less during this period. However, during and after the crisis, I expect that investors and rating agencies started to base their risk projections on company fundamentals, most likely resulting in a better performance of the extended model. To test these assumptions, the extended model will be tested on company and market data before the crisis (Q1 2004 - Q2 2007), during the crisis (Q3 2007 – Q2 2010), and after the crisis (Q3 2010 – Q4 2016).

After the distinction in time period, I will look into the differences of variation in CDS spreads between industries and credit rating classes. I expect that there will be differences in the size of the coefficients of different company and economic variables between industries. Differences in leverage levels or stock volatility between industries could have a large impact on the model's ability to explain variation in CDS spreads. By using Standard Industrial Classification ("SIC") codes, I will be able to make a distinction between different industries and use the extended model on industry specific data. Di Cesare and Guazzarotti (2010) find that, for several economic sectors, differences are found in the proportion of variation explained. Also, I think that there will be differences in coefficient sizes for investment grade and high-yield credit ratings. Especially when looking at the economic factors, I think the variables will show different results between rating classes. Galil et al. (2014) find differences in their model's ability to explain variation in CDS spreads before, during, and after the financial crisis.

This research presents a unique view on the CDS market before, during and after the global financial crisis. Especially the period after the financial crisis presents new insights into the variation of CDS spreads and its determinants. The approach of comparing a combination of determinants with the traditional model for calculating default risk by Black and Scholes (1973) and Merton (1974) is one I have not found in previous research when combined with post-crisis data. Moreover, using the same model for comparing different industries and rating classes has not been done in recent literature on the subject of CDS spreads to this extend. This paper presents the next step for empirical research in explaining the variation in CDS spreads and the determinants this variation is based on. By presenting a model with promising variables, I will get closer to making the pricing of CDS contacts more efficient. A more efficient CDS market could mitigate or prevent a crisis of the size of the recent global financial crisis.

This paper proceeds as follows. In section 2, the theoretical foundation will be constructed using several papers related to this research. Section 3 will include the hypotheses for this research on CDS spreads. The methodology and data description will be presented in section 4. In section 5, the results of the empirical research will be shown and the conclusion and remarks on future research will be presented in section 6.

2. Literature review

During recent years, there has been a lot of research on the market of credit ratings ("CR") and the credit default swap ("CDS") market. Moreover, the interaction between the two markets has been studied extensively.

Since the early 1900s, when John Moody started rating securities, the market of measuring default risk has grown to a multi-billion dollar market. The first measures of default were credit ratings. The credit rating is a measure created by professionals focusing exclusively on the permanent component of credit quality, a through-the-cycle methodology (Altman and Rijken, 2006). Credit ratings are measured on a scale of AAA to default, where bonds with a AAA rating have almost no chance of defaulting in the near future. Three firms, Standard & Poor's, Moody's, and Fitch control this market.

More recently, a new instrument for measuring default risk has been introduced and gains popularity. The CDS market has transformed from a niche market to a large market for credit risk transferring in the last 20 years comprising an amount of 62.2 trillion US dollars in 2009, decreasing after the crisis to around 10 trillion US dollars currently. A CDS is an over-the-counter contract between two parties where one of the two wishes to buy insurance against the possible default on a bond issued by a third party. The CDS spread is a representation of the market's views on the credit risk of bonds, measured in basis points.

The credit default swap

The credit default swap is the most widely used instrument of the credit derivatives market. A credit default swap is an agreement between two parties and provides protection against default on a loan by a company (the reference entity) to the buyer of the swap. Based on the amount of risk being transferred (the notional amount), the buyer of the swap pays a predetermined periodic fee (the spread) to the seller (JP Morgan, 2006). In a standard CDS contract the buyer pays a quarterly premium, in arrears, throughout the life of the transaction, which is called a running (CDS) premium. When the reference entity has a deteriorating credit quality, the mechanics of the credit default swap contract are based on one cash flow payment to the seller at inception of the trade, called an upfront (CDS) premium (Merrill Lynch, 2006).

The protection buyer pays the seller a fixed periodic fee, the CDS spread, until there is a credit event or the swap contract matures. Credit events triggering a contingent payment on a credit default swap are usually i) bankruptcy, ii) failure to make a payment on a debt obligation, iii) restructuring due to a change in the agreement, iv) repudiation / moratorium and, v) obligation acceleration (Greatrex, 2008). Upon default, there are two ways of settlement: physical or cash. In a physical settlement, the protection buyer delivers defaulted bonds or loans with a face value amount equal to the notional amount of the credit default swap contact (pari passu) to the seller of protection. Then, the seller of protection delivers the notional amount on the CDS contract in cash to the buyer of protection. In a cash settlement, the seller of protection pays the par value less recovery rate to the protection buyer. In both physical and cash settlement, the buyer of protection pays the accrued spread from the last coupon payment date up to the day of the credit event, then the coupon payments stop and the contract is terminated (JP Morgan, 2006).

Previous research found that it is apparent that CDS spreads quickly reflect available information. Acharya and Johnson (2007) find that the credit default swap markets appear to be transmitting non-public information into publicly traded securities such as stocks. Blanco et al. (2005) find that the credit default swap market leads the bond market, resulting in the fact that most price discovery occurs in the credit default swap market. Longstaff et al. (2005) are noting that CDS premiums can provide direct measures of the size of the default and the non-default components in corporate yield spreads. Norden and Weber (2004) conclude that CDS markets anticipate rating downgrades and reviews for downgrade by the three major credit rating agencies (Standard & Poor's, Moody's, and Fitch). Some researchers have studied the relationship between the CDS market and financial crises. Hart and Zingales (2011) show increasing credit default swap spreads for several major financial institutions leading up to the most recent financial crisis. Flannery et al. (2010) confirm that many crisis related events led to dramatic increases in the average CDS spread from financial institutions. Moreover, throughout 2006 the stock returns considerably led CDS spread changes, where during 2007 and 2008 the ability of CDS spreads to predict stock returns increased.

The first option of pricing CDS spreads is using asset swap spreads. Asset swaps are related to credit default swaps because the buyers of either one have a similar exposure to credit risk. Asset swaps combine a fixed-rate bond with an interest rate swap with the same maturity. The asset swap counterparty adjusts the LIBOR part of the swap for the difference between the bond coupon rate and de swap rate. The difference is called the asset swap spread and compensates the investor for the credit risk on the bond (Mengle, 2007). Therefore, under certain circumstances, selling protection in a credit default swap has the same risk profile as investing in an asset swap. In practice, the supply and demand, as well as the arbitrage relationship with asset swaps, tends to be the dominant factor driving the price of default swaps (Merrill Lynch, 2006).

The second option of pricing CDS spreads is using the expected CDS cash flows. This method is used for valuating default swaps off-market to be able to for instance unwind them. In essence, unwinding means terminating the existing contract by paying the counterparty an unwind premium and cancelling all future cash flow streams. The expected CDS cash flow models calculate the implied default probability of the reference entity for means of discounting the cash flows in a default swap (Merrill Lynch, 2006).

Research on credit default swaps

The annual spread of a CDS contract is determined by the supply and demand of the market, which should be resulting in a fair representation of the market-perceived credit risk of an entity. Similar to bonds, if the market’s perceived credit risk has increased (decreased), credit default swap spreads widen (tighten). There are two frameworks where researchers have focused on when modelling credit spread: structural models and reduced-form models. The first group of empirical research has focused on structural models. Using this approach, the liabilities of a firm are seen as a contingent claim on the assets of the firm itself and default occurs when the market value of the assets, which is modelled as a stochastic process, reaches some limit (Di Cesare and Guazzarotti, 2010). The first structural models have evolved following Black and Scholes (1973) and Merton (1974). According to the Merton model, a default occurs when the market value of a firm is below the face value of the outstanding debt at the debt’s maturity. These models attribute financial leverage, volatility, and risk-free term structure as main determinants of default. The second, more recent, group of research focuses on reduced-form models, also called intensity-based models. These models assume that the default of a firm occurs randomly and is caused by external factors. These factor's probability of occurring is modelled by a jump process using market data (De Wit, 2006).

The first research on credit risk has looked at corporate spreads, since the CDS market has developed only recently.

The first group of empirical research look at factors that can explain the difference between corporate spreads and what the spread would be when predicted by using historical rates of default and recovery rates, the so called credit spread puzzle. Elton et al. (2001) show that taxes and risk premiums explain a substantial portion of the premium in corporate rates over treasuries, while expected default accounts for only a small portion. Driessen (2005) decomposes corporate bond returns into several factors, including a jump-risk premium, liquidity and tax effects, and a risk premium on market-wide credit spread movements, which found to be important determinants of the expected returns of investment grade bonds. Amato and Remolona (2005) suggest that the most commonly used variables (taxes, liquidity, and systematic risk) are inadequate. They argue that idiosyncratic default risk accounts for the major part of spreads. Because return distributions are highly skewed, diversification would require very large portfolios. In practice, that level of diversification is not possible so idiosyncratic risk is unavoidable, resulting in higher spreads through additional premia (Amato and Remolona, 2005).

The second group of empirical research aims at explaining credit spreads in a statistical way by regressing (changes in) observed spreads on (changes in) variables that theoretical models suggest are relevant in determining both default and non-default components of credit spreads (Di Cesare and Guazzarotti, 2010). This group of research has been initiated by Collin-Dufresne et al. (2001). The advantage of these models is that the effect of any given variable on the CDS spread can be estimated directly. Collin-Dufresne et al. (2001) find that variables that should in theory determine credit spread changes have rather limited (25 percent) explanatory power. They imply that the residuals from this regression are mostly driven by a single common factor. They conclude that monthly bond spread changes are principally driven by local supply and demand shocks that are independent of both credit-risk and liquidity factors. Campell and Taksler (2003) explore the effect of equity volatility on corporate bond yields, showing that idiosyncratic firm-level volatility can explain as much cross-sectional creation in yields as can credit ratings. Cremers et al. (2008) find that equity volatility is an important determinant of bond spreads, and that option-based volatility contains useful information for credit spreads and improve on historical volatility when explaining variations in bond spreads. Avramov et al. (2007) use a set of common factors and company-level fundamentals, inspired by structural models, and were able to explain more than 54 percent (67 percent) of the variation in credit-spread changes for medium grade bonds (low-grade). They found no clearly dominant factor left in the unexplained variation.

One of the first empirical researches on CDS spreads was conducted by Aunon-Nerin et al (2002). They investigated the influence of various fundamental variables on a cross-selection of CDS transaction data. Their results show the importance of structural variables, equity market information, interest rates, and credit ratings. Greatrex (2008) uses variables suggested by structural models to explain 30 percent of the variation in CDS spread changes. Key determinants, being leverage and volatility, can explain almost half of the variation in monthly CDS spreads. Ericsson et al. (2009) find that estimated coefficients for a minimal set of theoretical determinants of default risk are consistent with theory. When using a principal component analysis of residuals and spreads, they find that there is limited evidence for a residual common factor. Di Cesare and Guazzarotti (2010) use the theoretical CDS spreads predicted by the Merton model to account for possible non-linear effects. Explaining more than 50 percent of CDS spread variation before and during the financial crisis, they argue that leverage becomes a much more important variable for CDS spread, and volatility much less important since the onset of the crisis. Galil et al. (2014) find that market variables have explanatory power after controlling for firm-specific variables inspired by structural models. They also show that credit ratings explain cross-sectional variation in CDS spreads even after controlling for structural model variables.

The evolvement of the structural and reduced-form frameworks have led to the testing of additional factors influencing credit spreads. An increasing amount of empirical literature is using CDS spread data for testing these variables because using CDS quotes has a number of advantages with respect to bond quotes. Blanco et al. (2005) provide evidence that due to important non-default components (illiquidity) in bond spreads, changes in the credit quality of the underlying entity are likely to be reflected more quickly in the default swap spread than in the bond yield spread. Ericsson et al. (2009) argue that trading in default swaps has increased resulting in daily data for default swap spreads, while studies using corporate bonds usually use monthly spreads. Di Cesare and Guazzarotti (2010) stress that CDS contracts are relatively standardised compared to bonds regarding amongst others maturity, coupon and options, making CDS contracts easier to compare. Also, CDS contracts should be less prone to supply and demand effects than the bond market due to the physical nature of bonds, according to Di Cesare and Guazzarotti (2010). Moreover, multiple researchers argue that CDS spreads do not require the specification of a benchmark risk-free yield curve, avoiding adding a misspecified model, which can be subject to its own specific factors (e.g. Ericsson et al. (2009), Di Cesare and Guazzarotti (2010)).

Theoretical determinants of the CDS spread

In recent literature on CDS spreads, there have been a variety of papers that focus on trying to fully explain the CDS spreads using different mixtures of determinants. The models used in these papers have proved to explain a substantial part of the variety in the CDS spreads. Leverage and volatility have been tested extensively using different sets of data and found to be essential in determining CDS spreads according to multiple researchers (e.g. Aunon-Nerin et al., 2002; Ericsson et al., 2009). Related to the paper of Collin-Dufresne et al.(2001), Ericsson et al. (2009) use swap spread data for investigating credit risk. They look into the linear relationship between theoretical determinants of default risk and default swap spreads. Their basic model comprised of leverage, volatility and the risk-free rate, is extended with the slope of the smirk, the return on the S&P 500, the square of the two-year yield, the slope of the yield curve, and the yield on short maturity bonds. Their basic model finds that the variables (leverage, volatility, risk-free rate) are statistically significant and economically important. Moreover, the estimates are relatively similar whether using levels of CDS spreads or CDS spread changes. The extension of the model, factors mentioned in Collin-Dufresne et al. (2001), results in an increase of the r-squared of 7.5 percent for CDS spread changes. They find that the term structure variables are often insignificantly estimated, perhaps suggesting some multicollinearity between them, or high correlation with another explanatory variable. The return on the S&P 500 has a significantly estimated negative impact on the spread. The slope of the smirk seems to have a minor impact on the spread. Finally, the point estimates of leverage and volatility are very similar to those estimated before extending the model, concluding that the magnitude of the effects discussed is robust to the inclusion of a number of other variables.

Di Cesare and Guazzarotti (2010) test four different models, estimated by first differences, running pooled OLS regressions with standard errors that allow for time correlation at firm level. Their first model is to test the capacity of the Merton model to explain observed CDS spreads using risk-free interest rate, nominal outstanding amount of debt, firm value, and asset volatility. This results in a theoretical CDS spread using the Merton model. Their second model is a three-factor linear model which has been used in other researches on CDS spreads (e.g. Ericsson et al., 2009). The three factors are implied volatility, leverage, and the 5-year zero-coupon rate on US government bonds. In their third model they combine their first and second models. Their last model extends the third model with the (log) returns of the firms' stocks, the slope of the yield curve, an index of the premium required by investors to hold riskier assets, an equity market index, and an index of market uncertainty (VIX). Di Cesare and Guazzarotti (2010) use implied volatility as a proxy of equity volatility because of its superiority in explaining CDS spreads (Campbell and Taksler, 2003) and to partially correct for the backward-looking nature of the historical volatility of share prices. Di Cesare and Guazzarotti (2010) compare their results by splitting them into two periods, pre-crisis and after the onset of the crisis. In the pre-crisis period, their fourth model shows that all determinants have the expected signs and all but the VIX index have significant effects on CDS spreads. The r-squared of this model is 54 percent, which is a small increase compared to their third model results (52 percent). Di Cesare and Guazzarotti (2010) argue that the interest rate loses its significance during the crisis, possibly in favour of the slope of the yield curve. The positive coefficient on the slope of the yield curve seems to indicate that the CDS market has been looking at short-term interest rates as a better indicator of economic activity than longer-term interest rates (Di Cesare and Guazzarotti, 2010). During the crisis period, the ability of the model to explain variation only decreased slightly, from 54 percent to 51 percent. This shows that the variables deemed important for explaining CDS spread by economic theory have maintained their explanatory power during instable times. A principal component analysis on CDS spread changes and regression residuals suggest that, during the crisis, spread changes are less driven by firm-specific factors and increasingly by common or systematic factors (Di Cesare and Guazzarotti, 2010). By adding indicators of economic activity, uncertainty, and risk aversion to their model, results suggest the presence of a market-specific factor that influenced CDS spreads during the crisis in a way that is not fully reflected in other markets (Di Cesare and Guazzarotti, 2010).

Galil et al. (2014) test several models splitting the determinants into firm-specific variables (stock return, stock volatility, leverage), common factors (spot rate, term-structure slope, market condition, market volatility (VIX)), the Fama & French (1989) factors and Pastor and Stambaugh (2003) liquidity factor, and factors researched by Chen, Roll, and Ross (1986). They find that firm-specific variables, consistent with structural models, substantially explain CDS spread changes, and after controlling for firm-specific variables, market factors can add to the models' explanatory power. Galil et al. (2014) suggest that variables consistent with structural models have limited explanatory power after common market variables and ratings are controlled for. The strongest explanatory variables of changes in CDS spreads are stock return, Δvolatility (of stock returns), and ΔMRI (median CDS spread in the rating class) according to Galil et al. (2014). However, they find that in the absence of these variables, other factors may be used to explain the CDS changes, such as ΔVIX, MP (growth rate industrial production), ΔUTS (term premium), the change in the slope of the term structure of interest rates, and the change in the spot rates. Their model is better in explaining the period of crisis and after the crisis than the period before the crisis. Finally, they argue that their results propose a structural change in the pricing of CDS spreads was caused by the crisis. Their coefficient estimates of their models changed during the crisis, but they were not fully reversed again after the crisis (Galil et al, 2014).

Selected determinants

Following previous literature, the goal of this paper is to construct a theoretical model explaining CDS spreads. Ericsson et al. (2009), Di Cesare and Guazzarotti (2010), and Galil et al. (2014) use different sets of variables in their attempt to fully explain CDS spreads. By using a selection of these variables, complementing them with promising variables from other papers, a potentially encompassing model will be created. The determinants used in the model can be divided into two groups, the standard model determinants and the extended model determinants.

Table 1
Sources of the independent variables

Variables	**Ericsson et al. (2009)**	**Di Cesare & Guazzarotti (2010)**	**Galil et al. (2014)**	**Other**
Standard model				
Leverage	X	X	X	X
Volatility	X	X	X	X
Risk-free rate	X	X		X
Extended model				
Stock return		X	X	X
Credit rating				X
Spot rate			X	X
Slope yield curve	X	X		X
VIX		X	X	X
Return S&P 500	X			
Square 2-year yield	X			

Research on selected determinants

Standard model determinants

Leverage

The first determinant included in the model for determining CDS spreads is the variable leverage. This determinant is considered to be one of the key factors in determining the value of a default-sensitive security. According to Merton (1974), firms with higher leverage ratios are closer to default barriers and have a higher chance to default. Therefore, the expected relation between a firm's leverage and CDS spreads is positive. Ericsson et al. use a dataset with a cross-sectional as well as a time-series dimension for multiple variables. Using levels of spreads and changes of spreads, they find that for leverage the time-series correlation is not very different from the cross-sectional correlation and that the relationship is always positive. Di Cesare and Guazzarotti (2010) find that when adding a theoretical CDS spread to their model, the coefficient of leverage maintains its usefulness in explaining CDS spreads. When comparing the period before the crisis and during the crisis they find that spreads have become more sensitive to changes in leverage. Ericsson et al. (2009) argue that the point estimates for lower rated firms are higher than for higher rated firms. Galil et al. (2014) analyse CDS spread changes and find that changes in leverage are not statistically significant when combined in a model with stock return and changes in volatility. According to the researchers this may reflect the high correlation between stock return and changes in leverage.

Volatility (historical)

The second determinant used to measure default risk in the structural approach by Black and Scholes (1973) and Merton (1974) is volatility. The volatility of the security's underlying assets is important for the value of a default-sensitive security because the security is actually a short put combined with a credit risk-free security. The value of this short put option is affected by volatility. Campbell and Taksler (2003) use corporate bond yield data to find that idiosyncratic firm-level volatility can explain as much cross-sectional variation in yields as can credit ratings. They find that equity volatility explains about one third of the variation in corporate bond data. Ericsson et al. (2009) find a positive relation for volatility in the cross-sectional correlation and in the time-series correlation. Similar to leverage, the cross-sectional correlation is not very different from the time series correlation for volatility, but the correlation for volatility is higher. Di Cesare and Guazzarotti (2010) use the risk-free interest rate, nominal outstanding amount of debt, firm value, and asset volatility to create a theoretical CDS spread. Moreover, they also use implied volatility as a proxy for equity volatility as a separate determinant. They find a large positive relation between CDS spreads and volatility. When including more determinants, the size of the relation decreases for volatility. Galil et al. (2014) find that three explanatory variables (including volatility) overshadow the other variables used in their model. However, in absence of these variables, other factors may be used to explain the CDS changes. Zhang et al. (2009) find that the volatility risk alone predicts 48 percent of the variation in CDS spread levels. Research implies that volatility should have a positive relationship with CDS spreads.

Risk-free rate (Treasury bond yields)

According to Merton's (1974) model, the level of the riskless rate also impacts the value of the option. This value is expected to be negative because the risk-adjusted drift of the value of a firm is determined by the risk-free rate. An increase in this determinant will decrease the risk-adjusted default probabilities resulting in a decrease in the spreads. The results of Ericsson et al. (2009) are in line with theory, finding a negative relation between the risk-free rate and CDS spreads. Longstaff and Schwartz (1995), Duffee (1998), and Collin-Dufresne et al. (2001) use bond yields and also find this negative relationship. Di Cesare and Guazzarotti use the risk-free rate to determine the theoretical CDS spread using the Merton model. Before the crisis, the theoretical CDS spread is positive and highly significant. They find that during the crisis the empirical relationship between CDS spreads and default factors is no longer described by the specific functional form of the Merton model.

Extended model determinants

Return on stock

The first extended model determinant of CDS spread used in the model is the return on stock. Galil et al. (2014) find that Δleverage and stock return are highly correlated (-0.73) in their model consisting of Δvolatility, Δleverage, and stock returns. Their model explains 16.23 percent of CDS spread changes. Di Cesare and Guazzarotti (2010) present a negative and significant relationship between stock returns and CDS spreads. Research implies a negative relationship between CDS spreads and stock return, because higher stock values could indicate higher future profit and low expectancy of not meeting financial obligations resulting in lower default risk.

Credit rating

Early research on the influence of credit rating on CDS spreads has been conducted by Aunon-Nerin et. al (2002). They find that credit ratings are a very important source of information on credit risk. Moreover, they find that credit ratings provide an r-squared of 47 percent, and when combined with structural variables, the r-squared increases to 65 percent. Hull et al. (2004) test the extent to which CDS spreads anticipate credit rating changes. They find that CDS spread levels and changes have predictive power on estimating negative rating changes. Positive rating events (changes, reviews for upgrades, outlook reports) have a lower significance than downgrades (Hull et al., 2004). Norden and Weber (2004) use a similar framework as Hull et al. (2004) and find that the market anticipates both downgrades and reviews for downgrades. Daniels and Shin Jensen (2005) find that CDS spreads react to changes in credit ratings and in particular to downgrades. They discover anticipated and lagged effects of change in credit rating and conclude that the CDS market seems to react faster and more significantly than the bond market regarding credit rating changes. Flannery et al. (2010) evaluate the viability of CDS spreads as possible substitutes for credit ratings. Focussing on financial institutions during the crisis, they show that CDS spreads incorporate new information roughly as quick as equity markets and significantly faster than credit ratings.

Spot rate

Longstaff and Schwartz (1995) conclude that a higher spot rate, reinvestment rate in their paper, reduces the probability of default and increases future value, which results in reducing credit spreads. They find that credit spreads are negatively related to interest rates. Duffee (1998) and Collin-Dufresne et al. (2001) strengthen this conclusion by finding similar results. Avramov et al. (2007) are able to explain more than 28 percent of the variation in credit-spread changes through changes in the five-year spot rate alone. Galil et al. (2014) find that the differences in spot rate are conditionally correlated with other factors in their models. By combining different variables, the differences in spot rate in their models become statistically insignificant. Galil et al. (2014) reveal that when controlling for their market factor (ΔMRI) the differences in spot rates become significant again.

Slope yield curve

The level and slope of the term structure are the two most important factors driving the term structure of interest rates according to Litterman and Scheinkman (1991). Collin-Dufresne et al. (2001) argue that an increase in the slope of the yield curve increases the expected future short rate, which should lead to a decrease in credit spreads. They also argue that a decrease in the yield curve slope might indicate a weakening economy, resulting in a decrease in expected recovery rate (Collin-Dufresne et al., 2001). Daniels and Shin Jensen (2005) show that the slope of the yield curve has significant influence on the CDS spread, suggesting that macro-economic factors play a role in the CDS market. Di Cesare and Guazzarotti (2010) come to another conclusion, finding a significant positive relation between CDS spreads and the slope of the yield curve. This could be explained by, that an increase in expected future interest rates may reduce the number of profitable projects available to the company, increasing credit spreads (Di Cesare and Guazzarotti, 2010). Their interest rate coefficient loses its significance during the crisis, possibly in favour of the slope of the yield curve. Given the negative relationship of the slope of the yield curve and short-term interest rates, they argue that the CDS market has been looking at short-term interest rates as a better indicator of economic activity.

Volatility Index (VIX)

Collin-Dufresne et al. (2001) describe the VIX index as a measure corresponding to a weighted average of implied volatility from options on equity indices. Schaefer and Strevbulaev (2004) find that the change in the VIX index of implied volatility is significant for only AAA, A, and BB ratings. Although, they explain that VIX and S&P 500 returns appear to be substitutes in explaining corporate bond returns, resulting in the fact that the effect of those variables is not consistent over time. Pan and Singleton (2008) view the VIX index, a widely used measure of event risk in credit markets, as an indicator of investor appetite for exposure to the high-yield bond credit class. A positive sign is expected for the effect of the VIX index on CDS spreads, as higher market uncertainty means higher put option value that the bondholders implicitly sell to shareholders when buying credit risk (Di Cesare and Guazzarotti, 2010). Though, Di Cesare and Guazzarotti (2010) were not able to find a significant relationship between the CDS spread and the VIX index. Tang and Yan (2012) show that the role of the VIX index remains remarkably stable before and during the crisis, suggesting that instead of market sentiment, individual firms' default risk is the driver of the co-movement in CDS spreads during the crisis. Galil et al. (2014) compensate for the lack of stock data in their dataset by adding macro-variables, like the VIX index, and finding statistically significant results in explaining CDS spread changes after controlling for the market factor (ΔMRI).

Return S&P 500

Collin-Dufresne et al. (2001) find that the return of the S&P 500 is extremely significant both statistically and economically. The return of the S&P 500 has a negative impact on bond spreads according to their results. They include lagged S&P 500 returns in their model, because research shows that lagged values of equity returns have impact on changes in bond yields (Kwan, 1996). Their results show negative significant impacts for lagged S&P 500 returns, except for higher leverage (lower rated) bonds, for which they report insignificant lagged S&P 500 returns. The economic significance is smaller for lagged returns than for current returns (Collin-Dufresne et al, 2001). Similar results are found by Ericsson et al. (2009), who look at the relation between current S&P 500 returns and CDS spreads.

Square two-year yield

Ericsson et al. (2009) add the square of the two-year yield to their model in attempting to capture nonlinearities in the relationship between term structure variables and CDS spreads.

Other factors to take into account

The results of the model can be viewed at different levels. Following Di Cesare and Guazzarotti (2010), a comparison between different industries can be made to discover in what sectors the model performs best. From their research, it appears that their model performs best for sectors with a high level of perceived risk caused by for instance high leverage. Also, a distinction can be made between investment-grade rated companies and non-investment grade rated companies. Galil et al. (2014) find that their model is best in explaining variation in CDS spreads for investment-grade rated firms, compared to high-yield rated firms.

3. Hypotheses

As stated before, literature indicates that many different variables have an impact on CDS spreads, but researchers are not able to fully explain the variation in spreads. To be able to obtain a better understanding of the variation in CDS spreads, it is interesting to create a new model based on promising variables. Since CDS contracts are a relatively new product, there is a possibility that, over time, factors become more, or less, important for explaining variation. Following literature, I construct a model based on my selection of determinants to explain CDS spread variation. I will take the recent financial crisis as a window to look into possible (permanent) changes in the importance of different variables. Moreover, comparing the differences between credit rating classes and industries can provide useful insights in the process of creating an optimal model.

Research question

The research question this paper is based on is:

What is the relationship between CDS spreads and company & economic fundamentals before, during, and after the recent financial crisis and did the importance of these fundamentals change over time?

Research hypotheses

To further specify the research questions, the following hypotheses will be researched:

Hypothesis 1

The following variables will have significant explanatory power for the variation in CDS spreads in the standard model: stock return, spot, slope, VIX, credit rating, return S&P 500, square two-year yield.

Many researchers have looked into the relationship between CDS spreads and the determinants influencing them. Different frameworks have been developed to be able to explain as much of the variation in CDS spreads as possible. The standard model is based on the structural approach following Black and Scholes (1973) and Merton (1974). This approach implies that the main determinants for default are leverage, volatility and the risk-free term structure (Ericsson, 2009). These variables have been studied extensively for bond spreads and credit spreads by Colin-Dufresne et al. (2001)

and Campbell and Taksler (2003). Following the approach of Ericsson et al. (2009), I will use this standard model and extend it to capture unidentified variation in CDS spreads. The effect on spreads of the variables slope of the yield curve, spot rate, square of the two year yield, and return on the S&P 500 have been studied relating to credit spreads by Colin-Dufresne et al. (2001) and later by Ericsson et al. (2009) on CDS spread premia. In 2010, Di Cesare and Guazzarotti looked into the effect of extending the standard model with multiple other variables including the VIX index, stock return, and an equity market index. They find promising results for the new variables added to the model. Where Di Cesare and Guazzarotti (2010) study the effects before and during the financial crisis, Galil et al. (2014) also look into the effects after the crisis. The inclusion of the variable credit rating in my model is based on the underlying value of risk presented by a certain credit rating. Daniels and Shin Jensen (2005) argue that higher corporate credit ratings are associated with lower credit spreads. I expect that the right combination of company-level and economic-level variables will be able to have significant explanatory power for the variation of CDS spreads in the standard model. Previous research lead me to think that the variables stock return, spot, slope, VIX, credit rating, return S&P 500, and square of the two-year yield will result in this significant explanatory power for the variation in the standard model.

Hypothesis 2

During the crisis, the CDS spreads of companies are to a bigger extend explained through economic/company fundamentals

Initially, CDS contracts were meant as an instrument for hedging physically owned positions in companies. While the market for CDS contracts grew, it increasingly became a market for taking speculative positions on the underlying assets of a company, or the corresponding CDS spread, without actually owning a position. Because of the enormous growth in this highly profitable market, estimating the risk of individual contracts, or packages of contracts, became harder. After the crisis, the market for CDS contracts became much smaller. One could argue that since the CDS contracts are OTC contracts without proper regulation, and that many firms came in financial difficulties during the crisis, companies involved in trading CDS contracts during the crisis would make a better estimation of risk, based on company and economic fundamentals.

Hypothesis 3

After the crisis, the level of importance of the company/economic variables do not return to the pre-crisis levels, but a permanent change has taken place

Through efforts of the ISDA to reduce the risk in the CDS market, two mechanisms, netting and auctioning, were introduced. Netting is the mechanism whereby counterparties net out their obligations to each other over the range of contracts that they have (Morgan, 2010). This reduced the notional amount of outstanding CDS contracts to $39 trillion by the end of 2008 (European Central Bank, 2009). There has also been a consensus between several governments (US, UK, and Europe) that a way to lower the risk in the OTC derivatives market, and especially CDS contracts, is pushing large parts of it into central clearing houses and regulated exchanges (Morgan, 2010). A large group of companies should have drawn lessons from the crash in CDS contracts market. Therefore, I believe that the foundation on which a CDS spread is based, has permanently changed since the beginning of the crisis. In the estimation of the risk profile of CDS contracts during and after the crisis, a larger part of the variation can be explained through company/economic fundamentals.

Hypothesis 4

The proportion of variation in CDS spreads explained by the model differs by industry and credit rating class

There have been many researches that have looked into the relationship between CDS spreads and different rating and industry classes. Daniels and Shin Jensen (2005) find that most of their industry dummy variables are significant in their regression models. They argue that this could suggest that the impact of these industry dummies is not captured in the credit rating and that the CDS market may be segmented along industry type. Di Cesare and Guazzarotti (2010) find that across sectors, their model explains the highest proportion of variation for the industry classes ‘Utilities’ and ‘Consumer Cyclical’ sectors. They find that these are also the industry classes with the highest levels of leverage. Moreover, they find better results during the crisis for industry classes with relatively low levels of leverage, volatility, and CDS spreads. Because differences between and within industry classes have been found before and during the financial crisis, there may have been significant changes after the crisis accordingly.

Since there are also differences in levels of leverage, volatility and CDS spreads between rating classes, I expect to find differences in the proportion of variation explained by my model along the different rating classes. Galil et al. (2014) research the differences between speculative-grade and investment-grade firms. They find that their model is better in explaining variation for investment-grade firms than speculative-grade firms.

4. Methodology

Data gathering

The dataset for this research is based on information between January 1, 2004 and December 31, 2016. This range is used to be able to get a clear view on what changes in CDS spreads, and its determinants, were caused by the crisis. The periods in which the sample will be divided are:

- Pre-crisis: Q1 2004 – Q2 2007
- Crisis: Q3 2007 – Q2 2010
- Post-crisis: Q3 2010 – Q4 2016

Following Ivashina and Scharfstein (2010), the peak of the credit boom is set at the second quarter of 2007, followed by the subprime crisis. The focus of this study will be on firm-data of S&P 500 companies with available CDS quotes. The credit default swap dataset consists of daily mid-quotes obtained from Datastream. CDS spread levels data for the period 2004-2016 has to be computed from two sources, CMA Datavision and Thomson Reuters CDS, since CMA Datavision goes further back than Thomson Reuterd CDS but is no longer updated since 2008. In Datastream, the list of S&P 500 tickers for both sources is found. In the Datastream extranet a table is obtained to link the Thomson Reuters identifiers to the CMA Datavision identifiers. The CMA data contains quotes between January 1, 2004 and December 31, 2007. Thomson Reuters provides multiples variants of CDS spreads (AC, AR, AM, AX), of which this study works with the AX variant (no restructuring event constitutes a credit event) as it provides the most quotes for my dataset. All the quotes are in U.S. dollars and accompanied by the ISIN identifier to link them to the other data in this study. After deleting 'empty' quotes, this resulted in 789,316 unique CDS spreads. From COMPUSTAT North America the quarterly data for debt and equity of S&P 500 companies are obtained. Following common practice in finance research, through excluding firms in the utilities and financial sector, by excluding SIC codes 40-49 and 60-69, possible distortions in the analysis are limited (Fama and French, 1992) (Norden and van Kampen, 2013). The monthly credit ratings of the S&P 500 companies are also acquired from COMPUSTAT North America. Share price information of the S&P 500 companies is obtained from CRSP. The share prices are adjusted for dividends, stock splits, and right offerings. Also, the return on the S&P 500 index is obtained from CRSP. The Chicago Board Options Exchange (CBOE) keeps records of market expectations of near-term volatility conveyed by S&P 500 stock index options, the VIX index (CBOE VIX Volatility Index). The VIX Index data is obtained from the CBOE website. The 10-year, 5-year, and 2-year treasury yields used in the analysis come from the Federal Reserve Economic Data (FRED).

To be able to link all the data from different datasets, I had to find a way to connect the different identifiers. Since CRSP, COMPUSTAT North America, and Datastream use different keys for identifying companies, this took some effort. I started with the data obtained from CRSP, and matched this data with my data from COMPUSTAT. I used both the Tickers and CUSIP codes to match them in Excel. In case an observation from CRSP did not match with an observation from COMPUSTAT, I looked for the company name and suitable Ticker. If the Ticker for a company changed overtime, I changed the Ticker to the most recent one. After doing this, I started with the CDS spread data from Datastream. The Tickers obtained from Datastream were matched with the Tickers of the CRSP data. If a Datastream Ticker did not match, I manually looked for the company name and changed the Ticker manually. After matching all the Tickers, I merged the CDS spread data with the share price data in Stata. When matching CDS spreads to my CRSP output, some observations form both datasets had missing values. These observations are deleted. Hereafter, the COMPUSTAT North data was added to the dataset. Lastly, data from the CBOE (VIX) and FRED (Treasury Rates) was added.

Main variables and descriptive statistics

There are several ways in which the variables in my model influence CDS spreads. Next, I will show you how the different variables in my model are build-up and present their expected coefficient direction, which I have derived from the literature review.

Table 2
Measurement of variables

Variables	Measurement	Predicted sign
Dependent variable		
CDS spread	Daily mid-quotes (levels) in percentages	
Independent variables		
Leverage	Book Value of Debt / Total Assets	+
Volatility	250-day variance of individual stock returns	+
Risk-free rate	10-year Treasury Constant Maturity Rate	-
Stock return	Monthly stock return	-
Credit rating	Standard and Poor's corporate credit rating	-
Spot rate	Five-year Treasury Rate	-
Slope	Slope yield curve	+/-
VIX	CBOE volatility index	+
Return S&P 500	Daily S&P 500 index returns	-
Square two-year yield		-

Some of the variables in Table 2 need additional explanation to get a good understanding of them:

- *Volatility:* Following the approach of Galil et al. (2014), the firm-specific stock volatility is estimated for each firm separately as the annualised variance of the individual stock returns from the previous 250 trading days
- *Stock return:* The 30-day stock return of individual firms
- *Credit rating:* The credit ratings are scaled from 1-24, where 1 is Not Rated, 2 is Default and 24 is rated AAA+
- *Slope of the yield curve:* The term structure slope is created using the differences between the 10-year Treasury Constant Maturity Rate and the 2-year Treasury Constant Maturity Rate
- *VIX:* Market volatility representing the option implied volatility based on the S&P 500 index options
- *Square two-year yield:* According to Ericsson et al. (2009), the square of the two-year yield attempts to capture nonlinearities in the relationship between term structure variables and spreads

Descriptive statistics

There are a total of 153 companies in the sample with 106.483 CDS spreads in the pre-crisis period, 90.850 CDS spreads in the crisis period, and 224.540 CDS spreads in the post crisis period. During the crisis, the number of companies in the sample increases from 124 to 140. 153 companies have credit ratings that are transformed into an interval variable. Of these companies, 146 have at least one investment grade rating and 24 companies have at least one non-investment grade rating.

From the sample used in this research, I have dropped observations for the companies General Motors, Chesapeake Energy Corp, and Advanced Micro Devices. After research into the outliers of my sample, I decided to drop these companies due to irregular extremities in their values. For instance, General Motors had a large sell-off of their corporate bonds in 2005 due to a significant imbalance in their quotes towards sales, increasing their CDS spreads massively (Acharya et al., 2015). Deleting these observations from my dataset will improve the generalisability of my model. The exclusion of these companies resulted in a dataset with a total of 426.834 observations.

When looking at the descriptive statistics table in Appendix 1, there a few interesting things that come forward. CDS spreads appear to have significant differences in the pre-crisis, crisis, and post-crisis periods. The CDS spreads in my sample have a 5-year mean of 92 bps and a median of 60 bps. The highest CDS spread is 2925 bps (Interpublic Group Companies Inc. in December 2008) and the lowest CDS spread is 1 bps (Rockwell Collins Inc. in March 2007). During the crisis period, the average and median CDS spreads are larger than in the periods before and after the crisis (1.17 and 0.66 respectively). Interestingly, the post-crisis average and median CDS spreads are higher than the same measures before the crisis (pre-crisis: 0.49 and 0.31; post-crisis: 1.03 and 0.73). The average leverage for the entire sample is 0.59 and the median is 0.58. The company with the highest leverage is YUM Brands Inc. (lev=2.03) at the end of 2016 and the company with the lowest leverage is Mylan N.V. (lev=0.14) in 2005. It appears that the average volatility during the crisis (0.41) is a lot higher than before (0.24) and after (0.26) the crisis. The median volatility of the entire sample is 0.25 and the mean is 0.29. The lowest risk-free rate is 1.37 (July 5, 2016) and the highest is 5.26 (June 12, 2007). The stock return is the lowest and the highest in the first quarter of 2009. A company profiting from the crisis, and a company negatively being affected by the crisis could cause this. Interestingly, Textron has both the highest monthly stock return of 2.45 (=245 percent) and the lowest monthly stock return of -0.70 (=-70 percent). The downfall of the stock return could be caused by a drawdown on the balance of their $3.0 billion committed bank credit lines in February 2009 (Textron Annual Report, 2009). Quickly hereafter, on April 3, 2009, Textron sold an operating unit for $376 million in cash (Textron Annual Report, 2009). This could explain the extreme increase in 30-day stock return. The median corporate credit rating in the sample is 16, which resembles a BBB+ credit rating. The average credit rating is a little higher. The average and median CDS spreads for investment-grade rated companies during the entire sample are respectively 0.71 and 0.52, while the high-yield rated average and median CDS spreads are clearly higher, being 2.36 and 1.97 respectively. The mean spot rate is 4.19 before the financial crisis. It decreases to 2.73 during the crisis, and is only 0.02 after the crisis. The VIX and the slope of the yield curve show a similar reaction to the crisis. Their values are respectively 0.14 & 0.62 before the crisis, 0.29 & 1.89 during the crisis, and finally decreasing again to 0.17 & 1.34 after the crisis. S&P 500 index return shows both its most extreme and its lowest value during the crisis. Its lowest value is -.2646 on October 15, 2008 and its highest value is 0.1158 on October 13, 2008. It is interesting to take a look at what made the S&P 500 index return mark its best daily percentage return. On this date (October 13, 2008), U.S. Treasury Secretary Paulson, forced nine chief executives of the largest banks in the country to sell shares (for $125 billion) to the government and go along with the Treasury plan to inject $250 billion of capital into thousands of banks (Veronesi and Zingales, 2009). The loss on October 15, 2008 is the second-biggest loss, percentage wise, since October 26, 1987 (Black Monday). This was caused by weak sales report, weak forecasts of the Federal Reserve, and sober comments from FRED Chairman Ben Bernanke (CNN, 2008). The mean of the squared 2-year yield also declined from before the crisis (16.18), to 4.42 during the crisis, and finally to 0.30 after the crisis.

In Appendix 2 the descriptive statistics for different industries and rating classes are presented. For the construction industry, there is a relatively high average CDS spreads (1.94) compared to the other industries. It also has relatively high average leverage, high average volatility, and low average credit ratings. The trade and manufacturing industries have relatively low average CDS spreads (both 0.79), low average volatility, and high average credit ratings. When looking at rating classes, the numbers show what you might expect. High-yield rated companies, compared to investment-grade rated companies, have high average CDS spreads (respectively 2.36 and 0.71), high average leverage, high average volatility, and high average stock return.

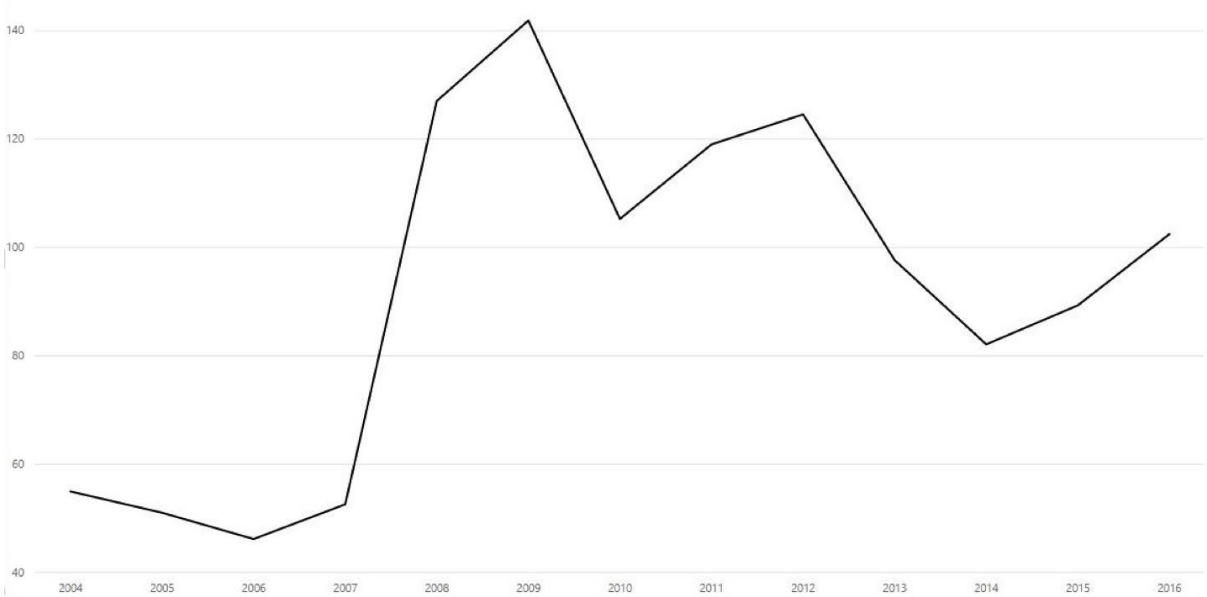

Figure 1: Average CDS spread over time

Model Specification

First, the standard model, following the approach of Black and Scholes (1973) and Merton (1974), for testing hypothesis 1 is constructed. This model will be extended to verify whether adding multiple variables, put forward by literature, will increase the explanatory power of the model. The standard model results in the following multivariate regression model:

(1) $CDS(i,t) = \alpha + \beta 1\ LEV(i,t) + \beta 2\ VOL(i,t) + \beta 3\ Rf(i,t) + \varepsilon(i,t)$

A multivariate model is estimated to investigate whether leverage, stock volatility, return of a firm's stock, credit rating, spot rate, slope of the yield curve, VIX, risk-free rate, and the square of the two-year yield are significantly related to the CDS spreads for each company *i* in period *t*:

(2) $CDS(i,t) = \alpha + \beta 1\ LEV(i,t) + \beta 2\ VOL(i,t) + \beta 3\ Rf(i,t) + \beta 4\ STOCK(t) + \beta 5\ CR(i,t) + \beta 6\ SPOT(t) + \beta 7\ TSSLOPE(t) + \beta 8\ VIX(t) + + \beta 9\ S\&P(t) + \beta 10\ Rf^{\wedge}2(t) + \varepsilon(i,t)$

The goal of this paper is to analyse the proportion of variation that is explained by the before-mentioned variables and the regression coefficients, before, during, and after the financial crisis. The explanatory power of the model will be compared for the different time-intervals to elaborate if a change in the ‘pricing’ of CDS spreads has taken place. This process is repeated for investment-grade and high-yield credit rating classes, and industry types to be able to shed light on hypothesis 4.

Validity and reliability of the model

In my panel dataset, the company ticker is used as the panel variable and the date as the time variable. The dataset appears to be unbalanced with dates ranging from 01-01-2004 to 30-12-2016, but with a few gaps. Missing observations and the use of trading days causes these gaps. To be able to decide whether to use a fixed-effects or random-effects regression on my panel data, I run a Hausman test. This test looks at whether the unique errors are correlated with the regressors; the null hypothesis is that they are not. When I run the Hausman test, a “Prob>chi2 = 0.2954“ is obtained, concluding that the preferred method is the random-effects GLS regression for the extended model. For the standard model, a fixed-effects GLS regression is preferred. After looking at the results of the Modified Wald test for groupwise heteroscedasticity for a fixed effects model, I suspect heteroscedasticity and use the “robust” option in my random effects model to correct for this. This option makes the standard error estimates robust for heteroscedasticity. Some variables in my dataset are non-normally distributed, like CDS spreads, but this is not uncommon for financial data. Moreover, adapting the data for all the outliers is unfavourable since I want to test the model during crisis years, and the financial crisis period is paired with many outliers. As discussed in the descriptive statistics section, the firms I decided to drop from the dataset are General Motors, Chesapeake Energy Corp, and Advanced Micro Devices.

Since there are a couple of variables in the model that are based on Treasury Rates, I want to check for multicollinearity. If there is multicollinearity between variables in my model, I will use the method of trail-and-error to find the best fit. After running a regression for the standard model, the levels of multicollinearity (VIF values) are within an acceptable range (VIF < 5). However, the extended model does appear to have collinearity between variables. The risk-free rate (VIF = 126), the spot rate (VIF = 124), the square of the two-year yield (VIF = 31), and the slope of the yield curve (VIF = 29) all appear to have high collinearity. After using the trail-and-error method, I conclude that deleting the variables square of the two-year yield and the risk-free rate results in the best fit for the extended model. When running the regression for the extended model without those two variables and testing it for multicollinearity, the VIF values are well below the threshold of VIF = 5. Since I will exclude the risk-free rate in my extended model (makes comparability with the standard model harder), it should be noted that using the spot rate (5-year treasury rate) is suitable for CDS spread analysis because of the same maturity of both contracts. Therefore, the extended multivariate regression model I will use for my analysis is:

(3) $CDS(i,t) = \alpha + \beta 1\ LEV(i,t) + \beta 2\ VOL(i,t) + \beta 3\ STOCK(t) + \beta 4\ CR(i,t) + \beta 5\ SPOT(t) + \beta 6\ TSSLOPE(t) + \beta 7\ VIX(t) + \beta 9\ S\&P(t) + \varepsilon(i,t)$

5. Results

Using a random-effects GLS regression, I test the relationship of several variables on CDS spreads. In this section I will take a look at the significant correlations between the variables in my model. Hereafter I will use regression (1) and (3) for testing hypothesis 1, analysing improvements of the ability to explain variation in CDS spreads of the standard model when adding new variables. After that, regression (3) is used for looking into the results in different periods of time, namely pre-crisis, crisis, and post-crisis for hypothesis 2 and 3. Lastly, regression (3) is used to distinguish between different industries and credit rating classes following hypothesis 4.

Intercorrelations

In table 3, the correlations between all the variables, CDS spreads and all the independent variables (leverage, volatility, risk-free rate, stock return, credit rating, spot rate, slope of the yield curve, VIX, return of the S&P 500, square two-year yield), are presented.

The 250-day variance of stock returns (volatility) appears to have a strong positive correlation with CDS spread of up to 50 percent. Also, it looks like there is a strong relationship between the credit rating of a company and its CDS spreads, showing a correlation of up to 45 percent. The intercorrelations between the spot rate, risk-free rate and square of the two-year yield are also indicating that multicolinearity could be a factor with these variables. Table 3 shows that the risk-free rate correlates up to 96 percent with the spot rate and it correlates up to 81 percent with the square of the two-year yield. The square of the two-year yield correlates up to 92 percent with the spot rate. These results strengthen the decision to exclude the risk-free rate and the square of the two-year yield from my regression model.

In Appendix 5, 6 and 7, three additional intercorrelation tables are presented. These contain the intercorrelations of all the variables used in the regression model, before, during and after the financial crisis. It appears that there are differences in significance levels and coefficients between the variables in the three time periods. It also appears that the level of correlation between volatility and CDS spreads over time increases. Before the crisis, the two variables are up to 31 percent correlated, where this increases to 49 percent during the crisis. After the crisis, the level of correlation further grows to 57 percent. Also, the correlation between credit ratings and CDS spreads shows an interesting development. Before the crisis, the variables were negatively correlated up to 50 percent. During the crisis, the correlation decreased to up to 42 percent, and after the crisis, it increased again to up to 52 percent. This could indicate that CDS spreads reacted faster to (negative) market information than credit ratings during the crisis. The correlation between the spot rate and CDS spreads before the crisis was 7 percent, during the crisis 23 percent, and after the crisis 12 percent. Lastly, the correlation between CDS spreads and the VIX rate showed an increase after the crisis. The correlation between the two variables was 5 percent before the crisis, 2 percent during the crisis and 13 percent after the crisis.

Table 3

Intercorrelation between variables

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	CDS spread	x										
2	Leverage	0.161***	x									
3	Volatility	0.502***	-0.080***	x								
4	Risk-free rate	-0.215***	-0.125***	-0.034***	x							
5	Stock return	-0.036***	0.011***	0.055***	-0.003**	x						
6	Credit rating	-0.457***	-0.117***	-0.313***	0.037***	-0.028***	x					
7	Spot rate	-0.241***	-0.107***	-0.097***	0.960***	-0.004***	0.043***	x				
8	Slope yield curve	0.172***	0.021***	0.231***	-0.376***	0.004**	-0.035***	-0.604***	x			
9	VIX	0.270***	-0.006***	0.460***	-0.097***	-0.261***	-0.004***	-0.191***	0.319***	x		
10	Return S&P 500	0.002	-0.000	0.009***	-0.004**	0.092***	-0.001	-0.004**	0.003**	-0.126***	x	
11	Square two-year yield	-0.232***	-0.092***	-0.179***	0.811***	0.005***	0.040***	0.917***	-0.817***	-0.275***	0.001	x

*Table 3: Significance levels: *** = 1%, ** = 5%, * = 10%.*

Extending the standard model

Hypothesis 1: *The following variables will have significant explanatory power for the variation in CDS spreads in the standard model: stock return, credit rating, spot rate, slope of the yield curve, VIX, return S&P 500, square two-year yield.*

One of the first models for predicting default was introduced by Black and Scholes (1973) and Merton (1974). They argue that leverage, volatility, and the risk-free rate are the main variables to use when estimating default risk. To get a reference point for the variation in CDS spreads, this model, as described in equation (1), is applied on CDS spread data with a fixed-effects GLS regression. By regressing leverage, volatility, and the risk-free rate on CDS spreads, the proportion of variation explained by these specific independent variables is revealed. Table 4 shows that the model introduced by Black and Scholes (1973) and Merton (1974), explains 31.7 percent of the variation in CDS spreads between 2004 and 2016. More recently, researchers argue that by adding variables to the model, the ability to explain variation in CDS spreads can be enlarged. When using the extended model (random-effects GLS regression), as shown in equation (3), the predictive power should increase compared to the 'standard' model. As shown in table 4, adding stock return, credit rating, spot rate, slope of the yield curve, VIX and the return on the S&P 500 index (excluding square of the two-year yield and the risk-free rate) to the 'standard' model increases the r-squared to 40.5 percent. These results confirm previous findings by a.o. Ericsson et al. (2009), Di Cesare and Guazzarotti (2013), and Galil et al. (2014) that adding economic and company variables can increase the ability of the model to explain CDS spreads. The risk-free rate in the standard model indicates a negative relation with CDS spreads. Similarly, the spot rate in the extended model shows a negative relation to CDS spreads. Longstaff and Schwartz (1995), Duffee (1998) and Ericsson et al. (2009) also find a negative relation between the risk-free rate and spreads, but they do not find consensus on the economic reasoning behind this (Ericcson et al., 2009). Longstaff and Schwartz (1995) argue that a higher spot rate increases future value, where Collin-Dufresne et al. (2001) reason that a higher spot rate reduces the probability of default. With the exemption of the return on the S&P 500 index, all the coefficients of the independent variables have the expected direction in their relationship to CDS spreads in the extended model. The positive relation of return on the S&P 500 index and CDS spreads is similar to the results of Di Cesare and Guazzarotti (2010). They argue that by including individual stock returns, the expectations of individual profitability are much better accounted for than with broad market measures. An increase of equity values in the market (S&P 500 index return) could signal relatively bad performance of individual firms, so that a positive effect on CDS spreads can be expected (Di Cesare and Guazzarotti, 2010). Leverage stays significant at the 5 percent level and volatility has a slightly weaker relationship in the extended model.

The r-squared that I find when testing the extended model (40.5 percent) is similar or lower than found by Di Cesare and Guazzarotti (2010) (54 percent before the crisis, 50 percent during the crisis) and Galil et al. (2014), but higher than the r-squared found by Ericsson et al. (2009). It should be noted that there are differences in the variables and methods used in this research and by the other researchers. For instance, they have focused on CDS spread changes, where I use levels of CDS spread. Moreover, I have strived to keep my data manipulation to a minimum, which could result in a lower fit.

When comparing the standard and the extended model, it appears that stock return, credit rating, spot rate, slope of the yield curve, VIX, and return on the S&P 500 index have significant explanatory power for the variation in CDS spreads. It increases the r-squared from 31.7 percent to 40.5 percent.

Table 4

The impact of the standard & extended model on CDS spreads

Dependent variable: CDS spread

Variables	Standard Model	Extended Model
LEV	0.629**	0.608**
VOL	2.943***	2.269***
RF	-0.166***	-
Total R^2	0.317	-
STOCK	-	-0.360***
RATING	-	-0.068***
SPOT	-	-0.150***
SLOPE	-	-0.071***
VIX	-	1.362***
S&P500	-	1.480***
Total R^2	-	0.405

*Table 4: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

The influence of the financial crisis

Hypothesis 2: *During the crisis, the CDS spreads of companies are to a bigger extend explained through economic/company fundamentals*

It can be argued that the crisis partly happened because of the wrong estimation of risk. Before the crisis, many companies were not careful enough when making risk assumptions for certain investments. The financial crisis showed them this flaw in risk estimation. I think that because a period of financial distress broke out, companies re-evaluated the way they looked at risk. I expect that companies go back to the essence of calculating spreads by more extensively evaluating firm-specific variables and market fluctuations. If this is the case, the extended model should provide a better estimation of the variation in CDS spreads during and after the crisis, than before. There is a chance that this is not the case and that the crisis has caused a general increase in CDS spreads without any matching independent variable changes, resulting in a weaker model. Table 5 presents the results of the extended model regression differentiated between the pre-crisis, crisis, and post-crisis period. Leverage and stock return become insignificant during the crisis. Volatility becomes more significant and increases drastically in terms of the coefficient. Interestingly, the variable credit rating becomes significant during the crisis and has the predicted negative effect on CDS spreads. Since the credit rating was a popular, but apparently not trustworthy estimator of risk before the crisis, one could have expected that the credit rating would become less important or insignificant of estimation variation of CDS spreads during the crisis. The negative relation and significance level of the spot rate remain the same but the size of the coefficient increases. The slope of the yield curve shows a negative sign during the crisis and becomes significant. The VIX rate and the S&P 500 index return increase in size and in stay highly significant. The various variables that show the sentiment of the market, all increase in their coefficient value. Moreover, the economic-level variables that were not significant at the 1 percent level are all significant at the 1 percent level during the crisis. Whereas leverage, a firm-level variable, becomes insignificant. This could be caused by the difference of interval from which the data of CDS spreads and leverage is available. CDS spreads are recorded daily and are able to adapt to the crisis instantly, where leverage is only recorded quarterly. Table 5 shows the impact of the crisis on the model for estimating variation in CDS spreads. There is a clear difference between the model's r-squared before and during the crisis. Before the crisis, the extended model was able to explain 19 percent of the variation in CDS spreads. Di Cesare and Guazzarotti (2010) and Galil et al. (2014) find that their models do not improve in explaining variation in CDS spreads when comparing before and during the crisis results. When looking at my results, I find that the crisis resulted in a large improvement of the model's ability to explain variation in CDS spreads. During the crisis, the model is able to explain 31.5 percent of the variation in CDS spreads. This strengthens my view that companies started to look differently at risk, and therefore CDS spreads, during the crisis.

Table 5

The impact of the extended model before, during, and after the crisis

Dependent variable: CDS spread

Variables	Pre-crisis	Crisis	Post-crisis
LEV	1.049***	0.420	0.707**
VOL	0.547*	1.321***	4.074***
STOCK	-0.122***	-0.227	-0.429***
RATING	-0.022	-0.041**	-0.029
SPOT	-0.053***	-0.407***	-0.135**
SLOPE	0.001	-0.325***	0.109***
VIX	0.732***	1.603***	0.803***
S&P500	0.922***	1.833***	1.046***
Total R^2	0.190	0.315	0.412

*Table 5: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

Permanently changed behaviour

Hypothesis 3: *After the crisis, the level of importance of the company/economic variables do not return to the pre-crisis levels, but a permanent change has taken place*

After the crisis, I expect that a change has taken place in the overall ability of the company and economic variables in the model to explain variation in CDS spread levels. When estimating risk, I think that many companies 'have learned their lesson' and started calculating CDS spreads based on company and economic fundamentals. This should result in a higher r-squared for the period after the crisis, as well as larger coefficients for the different (significant) variables. When looking at the results in Table 5, the leverage coefficient becomes larger and significant again after the crisis, but the size of the effect and the level of significance do not return to pre-crisis levels. It appears that leverage has a smaller impact on CDS spreads after the crisis. Volatility increases a lot in terms of the coefficient and stays very significant. The size of the coefficient and significance level are higher than before the crisis. The spot rate is significant at the 5 percent level after the crisis and decreases in coefficient, but does not return to pre-crisis levels. Stock return becomes significant again after the crisis and has a higher negative relation with CDS spreads than before the crisis. The credit rating becomes insignificant again after the crisis, where it was significant at the 5 percent level during the crisis. The slope of the yield curve becomes positive after the crisis and stays significant compared to an insignificant result before the crisis. The positive relation could be explained by the fact that an increase in expected future interest rates may reduce the number of profitable projects available for the company, increasing credit spreads (Di Cesare and Guazzarotti, 2010). The S&P 500 index return and the VIX rate return to pre-crisis levels again and stay very significant. For various variables, a change in coefficient size has taken place when comparing the results of the pre-crisis period to the post-crisis period. Also, the ability of the model to explain changes in the levels of CDS spreads increases dramatically from 19 percent before the crisis, to 41.2 percent after the crisis. This is a similar percentage as found by Galil et al. (2014), but they do not find an improvement in their model's ability to explain variation in CDS spreads compared to their pre-crisis results. From my results I conclude that there has been a shift in the 'pricing', the determinants explaining the variation, of CDS contracts. It seems that the CDS quotes are to a bigger extend explained through several company and economic variables after the financial crisis.

Differences across industries and rating classes

Hypothesis 4: *The proportion of variation in CDS spreads explained by the model differs by industry and credit rating class*

When running the extended model's regression for different industries and credit rating classes, interesting results come forward. It should be noted that the number of observations differs a lot between different industries, where "Manufacturing" is by far the largest (261.896 observations) and "Construction" the smallest (11.465 observations). The largest proportion of variation in CDS spreads is explained in the construction industry, for which the model has an r-squared of 67.2 percent. For this industry, the variables volatility, spot rate, and slope of the yield curve have an insignificant relationship with CDS spreads. The other variables are significant at the 1 percent level. The size of the coefficient for return on the S&P 500 index and the VIX are relatively high compared to other industries. This suggests that the construction industry is highly dependent on the economic cycle.

The mining industry shows significant results for all company-level and economic-level variables. The coefficients for leverage and spot rate are high compared to other industries, where volatility has a relatively low beta. The extended model is able to explain 49.0 percent of variation in CDS spreads in the mining industry. The manufacturing industry, the largest industry in the sample, shows significant results for the independent variables of the standard model (leverage at the 10 percent level and volatility at the 1 percent level). Stock return and credit rating have insignificant results. The industry has relatively low standardised beta's for economic variables and an r-squared of 38.9 percent. Trade, being wholesale and retail trade combined, shows an insignificant value for leverage. Interestingly, only the trade industry shows an insignificant value of the VIX index coefficient. The model is able to explain 36.7 percent of the variation of CDS spreads in the trade industry. The services industry has the highest standardised beta for volatility. Leverage and credit rating are insignificant for this industry. Also, all the independent economic variables are significant and the model produces an r-squared of 35.8 percent for the Services industry.

Although there is a large discrepancy of observations between industries, it is clear that there are substantial differences produced by the model for different industries in terms of r-squared, standardised beta levels and significance levels.

Table 6

The impact of the extended model on different industries

Dependent variable: CDS spread

Variables	Mining	Construction	Manufacturing	Trade	Services
LEV	2.051***	2.271***	0.502*	0.054	0.548
VOL	1.695***	0.127	1.971***	2.193***	4.539***
STOCK	-0.3552*	-0.731***	-0.124	-0.585**	-0.447*
RATING	-0.094***	-0.369***	-0.045	-0.177***	-0.027
SPOT	-0.257***	0.001	-0.120***	-0.207***	-0.098***
SLOPE	-0.158***	-0.104	-0.040*	-0.119*	-0.143*
VIX	1.548*	7.862***	1.250***	0.339	2.912**
S&P500	1.820***	6.059***	1.345***	0.610***	2.622**
N	42.260	11.645	261.896	58.491	43.935
Total R^2	0.490	0.672	0.389	0.367	0.358

*Table 6: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

The dataset has an ordinal scale for company credit rating from 1 to 24. The investment-grade barrier is at the BBB+ rating. In Table 7, regressions for different rating classes in show that the extended model is better, by a small difference, in explaining variation in CDS spreads for companies with a credit rating defined as high-yield than for companies with an investment-grade credit rating. The r-squared for investment-grade rated companies is 39.6 percent, where the r-squared for sub-investment grade companies is 40.3 percent. Coefficients for variables of the current state of the economy, spot rate, VIX index and S&P 500 index returns, show high standardised betas for companies with a sub-investment grade credit rating, indicating that the CDS spreads for high-yield rated companies are highly dependent on the state of the economy. Also, the stock volatility of individual firms seems to have a larger impact on CDS spreads for sub-investment grade companies. Interestingly, the standardised beta for credit ratings of high-yield companies is higher than for investment-grade rated companies. This could indicate that the level of the credit rating is more important in estimating default risk for high-yield companies than for investment-grade companies.

It is clear that, although the difference in r-squared for the two groups is not large, there are difference between the model's standardised beta's for investment-grade and high-yield companies, especially when looking at the VIX index and the S&P 500 return index.

When looking at investment-grade and high-yield ratings in the periods before during and after the crisis, the differences are more evident (Appendix 8 and 9). The r-squared for high-yield ratings in the pre-crisis period is only 8 percent, where this increases to 24 percent during the crisis. When looking at the post-crisis period for high-yield ratings, the r-squared is even higher, at 38 percent. In the pre-crisis period, the fit of the model for investment-grade ratings, at 26.5 percent, is better than the explanatory power for high-yield ratings in this period. Also, the r-squared increases during the crisis for investment-grade ratings to 36 percent. After the crisis, it decreases to 33.5 percent. It seems that, especially for high yield ratings, the CDS spreads were not based on company or economic fundamentals before the crisis. During the crisis, the process of valuing the CDS spreads started to focus more on these fundamentals. Interestingly, the variable credit rating becomes insignificant during the crisis for high-yield ratings, where for investment-grade ratings it stays significant. This supports my view that default risk, especially for high-yield rated companies, was not measured properly before the crisis and that the market changed its view on the default risks when the crisis started.

Table 7

The impact of the extended model on rating classes

Dependent variable: CDS spread

Variables	**Rated**	**Investment-grade**	**High-yield**
LEV	0.312	0.082	0.708
VOL	2.065***	1.679***	2.073***
STOCK	-0.380***	-0.296***	-0.428*
RATING	-0.210***	-0.105***	-0.461***
SPOT	-0.138***	-0.146***	-0.168**
SLOPE	-0.064***	-0.063***	-0.074
VIX	1.444***	1.015***	6.133***
S&P500	1.594***	1.209***	5.785***
N	413.427	364.066	49.361
Total R^2	0.467	0.396	0.403

*Table 7: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

6. Conclusions and implications

A credit default swap is similar to an insurance contract, compensating the buyer for losses arising from default (Greatrex, 2008). The spread in the contract is a representation of the market's views on the credit risk of bonds, measured in basis points. The protection buyer pays the seller a fixed periodic fee, the CDS spread, until there is a credit event or the swap contract matures. If the loan defaults, the protection buyer receives payoff from the protection seller. There have been various researches on the relationship between the determinants of bond spreads, CDS spreads, and credit ratings (e.g. Colin-Dufresne et al., 2001; Hull et al., 2004; Ericsson et al., 2009). Compared to the other factors for measuring default risk, the CDS spread is a relatively new one. Therefore, the main purpose of this paper is to take a look into various company and economic fundaments and their relationship with the spreads in the market for credit default swaps.

The goal of this paper is to investigate the relationship between CDS spreads and company and economic fundamentals. An important factor of this research is the influence of the recent financial crisis and to examine if the crisis (permanently) impacted this relationship. This paper uses a broad dataset of 153 U.S. companies from the S&P 500 using data from 2004 to 2016.

To test my first hypothesis, suggesting that stock return, spot rate, slope of the yield curve, VIX, credit rating, return on the S&P 500, and square of the two year yield have significant explanatory power for the variation in CDS spreads in the standard model, I first construct the standard model following Black and Scholes (1973) and Merton (1974) with the variables leverage, volatility, and risk-free rate. This standard model explains 31.7 percent of the variation in CDS spreads, where the extended model, excluding risk-free rate and square of the two-year yield due to multicollinearity, explains 40.5 percent. This hypothesis can therefore be confirmed. It appears that the variables that I added to the standard model have significant explanatory power for the variation in CDS spreads. These results are higher than the results found by Ericsson et al. (2009), but lower that the results found by Di Cesare and Guazzarotti (2010) and Galil et al. (2014).

The second hypothesis of my research stated, that during the crisis, the CDS spreads of companies are to a bigger extend explained through economic/company fundamentals. This paper shows that there is a clear difference between the r-squared before the crisis and during the crisis. The extended model was able to explain only 19 percent of the variation in CDS spreads before the crisis. When comparing this number to the model’s ability to explain variation in CDS spreads during the crisis, the results show a clear difference. During the crisis the model generated an r-squared of 31.5 percent. While this is lower than results found by Di Cesare and Guazzarotti (2010) and Galil et al. (2014), my model, compared to others, does improve during the crisis and therefore I can confirm my second hypothesis.

My third hypothesis compares the period after the crisis with those before and during the crisis. It formulated that after the crisis, the level of importance of the company/economic variables do not return to pre-crisis levels, but a permanent change has taken place. Some variables show a change in coefficient size when comparing the pre-crisis results and the post-crisis results. Moreover, the ability of the model to explain variation in CDS spreads increases form 19 percent before the crisis, to 41.2 percent after the crisis, where Galil et al. (2014) do not find an improvement in their model. This could indicate that there has been a permanent change in the pricing of CDS spreads, but a definitive conclusion cannot be drawn. It is clear that, for this sample, the CDS spreads are to a bigger extend explained through economic and company fundamentals and have not (yet) returned to pre-crisis levels, confirming the hypothesis (in part).

The fourth hypothesis looks at the outcomes of the model for different credit ratings and industry classes. Different results from the model, regarding r-squared levels, were expected for different industry classes and credit ratings. The sample used in this research shows large differences in observations between industries. The largest r-squared is found for the construction industry, where the model is able to explain 67.2 percent of the variation in CDS spreads. Although, the results show many insignificant variables and combined with a large discrepancy in observations between industries, a clear conclusion cannot be drawn. For credit ratings, two groups are defined for this research, high-yield ratings and investment-grade ratings. The results show that the difference in r-squared between the two rating classes is not large. For high-yield ratings, the r-squared of my model is 40.3 percent, where the r-squared for investment-grade ratings is 39.6 percent. There are differences, especially for the VIX index and the S&P 500 return index, in coefficients when comparing the two groups, but a clear conclusion for the hypothesis cannot be drawn. However, the model's ability to explain variation in CDS spreads increases during and after the crisis for high-yield rated companies. The r-squared increased from 8 percent before the crisis, 24 percent during the crisis to 38 percent after the crisis, which could indicate that CDS spreads for high-yield rated companies were not based on economic or company fundamentals before the crisis and that the crisis resulted in a change in view. For investment-grade rated companies, the model shows an r-squared of approximately 26 percent before the crisis, 36 percent during the crisis and 33 percent after the crisis. These results indicate differences between rating classes in different periods. Overall, it seems that there are not big differences in the model's ability to explain variation in CDS spreads for high-yield and investment-grade rated companies, but more extensive research in smaller sample periods could result in a different conclusion.

This paper shows that the selected variables improve the ability of the model to explain variation in CDS spreads. Moreover, it addresses the fact that the crisis has played a large role in the development of estimating default risk through CDS spreads. Lastly, it brings forward that the importance of several determinants has changed during and after the crisis.

7. Further research

In this paper, I have tried to present a complete and relevant framework on CDS spreads. The variables included in the model were chosen after reviewing existing literature and analysing what factors could be interesting. To make the model more accurate in explaining variation in CDS spreads, future research could include additional variables. One of the factors that could provide interesting results is a measure for counterparty risk. Since there are no requirements for collateral in CDS contracts, a measure for counterparty risk may improve the ability of the model to explain variation in CDS spreads.

For the dataset of this paper, I obtained quotes from January 2004 to December 2016 to be able to make a clear comparison for the periods before, during and after the crisis. Because of the timeframe, I used Thomson Reuters and CMA data to obtain CDS spreads from Datastream. Thomson Reuters offers 4 types of credit events and I made the decision to only use one, the AX variant. Future research on the subject could improve the results by taking additional credit event variants such as AC, AR or AM. Moreover, using the Datastream CDS spread data, I was not able to link all the CDS quotes to the data I obtained from other databases. This problem could be resolved by using another sources for the CDS quotes such as Markit.

Another interesting extension of the CDS spread research would be using a broader geographic scope. In this research, I have used company data for S&P 500 companies obtained from COMPUSTAT. Using a more extensive set of North American companies, or comparing the results to another continent such as Europe, could shed light on the reliability of the results and the differences from a geographical perspective.

In addition to looking at the rating classes before, during and after the crisis, a similar view can be taken for different industry classes. This could show what industries were more severely impacted by the financial crisis. Lastly, I have used book values to calculate the leverage factor in my model. Using market value of equity for calculating leverage could provide a more accurate look on its impact on CDS spreads.

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9. Appendices

Appendix 1

Table 8: Descriptive statistics total dataset

Variable	Mean	Std.	Min	P25	P50	P75	Max	Med.	Obs.
Dependent variable									
CDS TOTAL	0.92	1.03	0.01	0.36	0.60	1.06	29.26	0.60	426834
CDS PRE	0.49	0.55	0.01	0.19	0.30	0.55	5.17	0.30	107584
CDS CRISIS	1.17	1.48	0.06	0.42	0.66	1.27	29.26	0.66	91822
CDS POST	1.03	0.93	0.11	0.46	0.73	1.27	11.33	0.73	227428
Independent variables									
LEV TOTAL	0.59	0.17	0.14	0.48	0.58	0.68	2.03	0.58	426628
LEV PRE	0.57	0.15	0.14	0.48	0.56	0.66	1.44	0.56	107584
LEV CRISIS	0.58	0.16	0.19	0.47	0.57	0.67	1.14	0.57	91740
LEV POST	0.61	0.17	0.19	0.49	0.59	0.69	2.03	0.59	227304
VOL TOTAL	0.29	0.13	0.09	0.20	0.25	0.33	2.83	0.25	425353
VOL PRE	0.24	0.07	0.10	0.19	0.22	0.28	2.83	0.22	107093
VOL CRISIS	0.41	0.20	0.11	0.26	0.35	0.51	1.46	0.35	91661
VOL POST	0.26	0.09	0.09	0.19	0.24	0.31	0.70	0.24	226599
RF TOTAL	3.14	1.07	1.37	2.16	2.96	4.12	5.26	2.96	423547
RF PRE	4.50	0.34	3.70	4.22	4.51	4.74	5.26	4.51	106972
RF CRISIS	3.65	0.56	2.08	3.36	3.68	3.91	5.19	3.68	91089
RF POST	2.28	0.51	1.37	1.88	2.20	2.63	3.75	2.20	225486
STOCK TOTAL	0.01	0.10	-0.70	-0.04	0.01	0.07	2.45	0.01	426627
STOCK PRE	0.02	0.08	-0.42	-0.23	0.02	0.07	0.55	0.02	107524
STOCK CRISIS	0.00	0.14	-0.70	-0.07	0.00	0.07	2.45	0.00	91792
STOCK POST	0.02	0.09	-0.52	-0.03	0.02	0.03	0.89	0.02	227311
RATING TOTAL	16.09	3.33	1.00	15.00	16.00	18.00	23.00	16.00	426834
RATING PRE	16.31	3.31	1.00	15.00	16.00	18.00	23.00	16.00	107584
RATING CRISIS	16.12	3.48	1.00	14.00	16.00	18.00	23.00	16.00	91822
RATING POST	15.98	3.28	1.00	14.00	16.00	18.00	23.00	16.00	227428
SPOT TOTAL	2.36	1.32	0.56	1.37	1.80	3.48	5.23	1.80	423547
SPOT PRE	4.19	0.60	2.65	3.72	4.30	4.68	5.23	4.30	106972
SPOT CRISIS	2.73	0.80	1.26	2.22	2.54	3.14	5.10	2.54	91089
SPOT POST	0.02	0.09	-0.52	-0.03	0.02	0.06	0.89	0.02	227311
SLOPE TOTAL	1.51	0.85	-0.19	0.97	1.61	2.22	2.91	1.61	423547
SLOPE PRE	0.62	0.83	-0.19	-0.02	0.19	1.23	2.24	0.19	106972
SLOPE CRISIS	1.89	0.75	0.14	1.43	1.95	2.53	2.90	1.95	91089
SLOPE POST	1.34	0.41	0.56	0.96	1.40	1.64	2.40	1.40	225486
VIX TOTAL	0.19	0.09	0.10	0.13	0.16	0.21	0.81	0.16	426834
VIX PRE	0.14	0.02	0.10	0.12	0.13	0.15	0.24	0.13	107584
VIX CRISIS	0.29	0.12	0.15	0.21	0.25	0.32	0.81	0.25	91822
VIX POST	0.17	0.06	0.10	0.14	0.16	0.19	0.48	0.16	227428

S&P500 TOTAL	0.00	0.01	-0.09	-0.00	0.00	0.01	0.12	0.00	426834
S&P500 PRE	0.00	0.01	-0.03	-0.00	0.00	0.00	0.02	0.00	107584
S&P500 CRISIS	-0.00	0.02	-0.09	-0.01	0.00	0.01	0.12	0.00	91822
S&P500 POST	0.00	0.01	-0.07	-0.00	0.00	0.00	0.05	0.00	227428
SQUARE TOTAL	5.20	8.02	0.03	0.18	0.66	6.92	27.98	0.66	423547
SQUARE PRE	16.18	7.43	2.25	9.06	18.23	22.75	27.98	18.23	106972
SQUARE CRISIS	4.42	5.73	0.37	0.83	1.19	5.95	24.90	1.19	91089
SQUARE POST	0.30	0.27	0.03	0.09	0.21	0.45	1.66	0.21	225486

Appendix 2

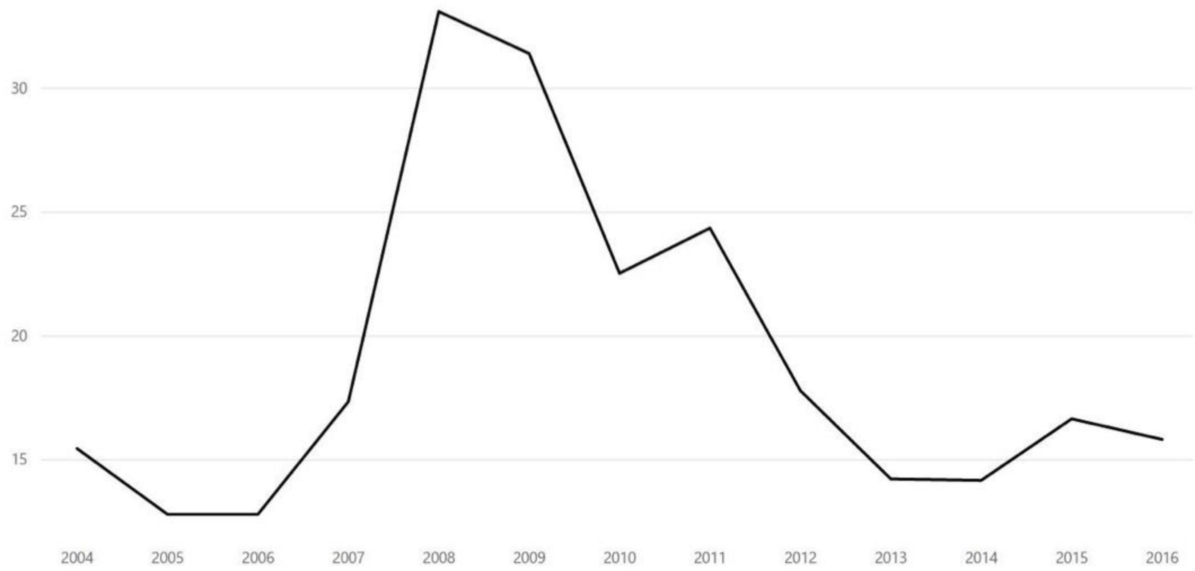
Table 9: Descriptive statistics rating classes and industries

Variable	Mean	Std.	Min	P25	P50	P75	Max	Med.	Obs.
Dependent variable									
CDS INVESTMENT GRADE	0.71	0.68	0.01	0.33	0.52	0.86	16.14	0.52	367499
CDS HIGH YIELD	2.36	1.68	0.03	1.33	1.97	2.85	29.3	1.97	50808
CDS MINING	1.09	1.04	0.01	0.43	0.79	1.43	10.49	0.79	42589
CDS CONSTRUCTION	1.94	1.48	0.18	0.74	1.69	2.61	9.24	1.69	11771
CDS MANUFACTURING	0.79	0.82	0.01	0.32	0.55	0.92	16.14	0.55	264415
CDS TRADE	0.78	0.81	0.03	0.33	0.53	0.90	11.33	0.53	59314
CDS SERVICES	1.38	1.65	0.01	0.43	0.77	1.79	29.26	0.77	44938
Independent variables									
LEV INVESTMENT GRADE	0.59	0.16	0.14	0.48	0.58	0.67	1.60	0.58	367375
LEV HIGH YIELD	0.65	0.16	0.25	0.54	0.62	0.76	2.03	0.62	50754
LEV MINING	0.50	0.09	0.24	0.43	0.49	0.56	0.89	0.49	42589
LEV CONSTRUCTION	0.57	0.07	0.40	0.53	0.56	0.62	0.75	0.56	11771
LEV MANUFACTURING	0.58	0.15	0.14	0.48	0.58	0.67	1.19	0.58	264291
LEV TRADE	0.66	0.17	0.24	0.57	0.63	0.73	2.03	0.63	59314
LEV SERVICES	0.65	0.23	0.24	0.50	0.61	0.78	1.60	0.61	44856
VOL INVESTMENT GRADE	0.27	0.12	0.09	0.19	.24	0.31	2.83	0.24	367015
VOL HIGH YIELD	0.38	0.18	0.14	0.26	0.34	0.45	1.46	0.34	49812
VOL MINING	0.36	0.14	0.13	0.27	0.33	0.40	0.94	0.33	42589
VOL CONSTRUCTION	0.43	0.22	0.21	0.30	0.37	0.44	2.83	0.37	11735
VOL MANUFACTURING	0.27	0.13	0.09	0.19	0.24	0.31	1.20	0.24	264049
VOL TRADE	0.26	0.10	0.11	0.19	0.23	0.31	0.71	0.23	58948
VOL SERVICES	0.30	0.13	0.14	0.21	0.25	0.34	1.00	0.25	44357
STOCK INVESTMENT GRADE	0.01	0.09	-0.70	-0.04	0.01	0.06	2.45	0.01	367411
STOCK HIGH YIELD	0.02	0.13	-0.66	-0.05	0.02	0.09	2.07	0.02	50690
STOCK MINING	0.01	0.12	-0.60	-0.06	0.02	0.09	0.80	0.02	42589
STOCK CONSTRUCTION	0.01	0.14	-0.66	-0.07	0.01	0.09	2.07	0.01	11771
STOCK MANUFACTURING	0.14	0.09	-0.70	-0.04	0.01	0.06	2.45	0.01	264384
STOCK TRADE	0.01	0.09	-0.50	-0.03	0.01	0.06	1.12	0.01	59255
STOCK SERVICES	0.02	0.10	-0.59	-0.04	0.02	0.07	0.99	0.02	44849
RATING INVESTMENT GRADE	16.98	2.15	14.00	15.00	17.00	18.00	23.00	17.00	367499
RATING HIGH YIELD	12.24	1.04	9.00	12.00	13.00	13.00	13.00	13.00	50808
RATING MINING	15.15	3.49	1.00	14.00	16.00	17.00	22.00	16.00	42589
RATING CONSTRUCTION	13.13	2.13	10.0	11.00	13.00	14.00	17.00	13.00	11771
RATING MANUFACTURING	16.79	1.32	1.00	15.00	17.00	18.00	23.00	17.00	254415
RATING TRADE	16.53	2.22	10.0	15.00	16.00	18.00	23.00	16.00	59314
RATING SERVICES	13.22	5.47	1.00	1.00	15.00	16.00	23.00	15.00	44938
SPOT INVESTMENT GRADE	2.36	1.32	0.56	1.37	1.80	3.51	5.23	1.80	364669
SPOT HIGH YIELD	2.31	1.30	0.56	1.34	1.80	3.39	5.23	1.80	50414
SPOT MINING	2.30	1.30	0.56	1.36	.173	3.35	5.23	1.73	42260

SPOT CONSTRUCTION	2.44	1.37	0.56	1.37	1.93	3.70	5.23	1.93	11681
SPOT MANUFACTURING	2.38	1.32	0.56	1.38	1.83	3.53	5.23	1.83	262385
SPOT TRADE	2.38	1.32	0.56	1.37	1.84	3.52	5.23	1.84	58854
SPOT SERVICES	2.29	1.29	0.56	1.35	1.73	3.36	5.23	1.73	44591
SLOPE INVESTMENT GRADE	1.50	0.85	-0.19	0.96	1.60	2.22	2.91	1.60	364669
SLOPE HIGH YIELD	1.55	0.83	-0.19	1.03	1.66	2.26	2.91	1.66	50414
SLOPE MINING	1.52	0.83	-0.19	0.99	1.61	2.21	2.91	1.61	42260
SLOPE CONSTRUCTION	1.48	0.87	-0.19	0.90	1.61	2.23	2.91	1.61	11681
SLOPE MANUFACTURING	1.51	0.85	-0.19	0.96	1.61	2.22	2.91	1.61	262385
SLOPE TRADE	1.50	0.85	-0.19	0.96	1.60	2.22	2.91	1.60	58854
SLOPE SERVICES	1.52	0.82	-0.19	1.01	1.61	2.20	2.91	1.61	44591
VIX INVESTMENT GRADE	0.19	0.09	0.10	0.13	0.16	0.21	0.81	0.16	367499
VIX HIGH YIELD	0.19	0.09	0.10	0.14	0.16	0.22	0.81	0.16	50808
VIX MINING	0.19	0.09	0.10	0.14	0.16	0.21	0.80	0.16	42589
VIX CONSTRUCTION	0.19	0.09	0.10	0.13	0.16	0.21	0.81	0.16	11771
VIX MANUFACTURING	0.19	0.09	0.10	0.13	0.16	0.21	0.81	0.16	264415
VIX TRADE	0.19	0.09	0.10	0.13	0.16	0.22	0.81	0.16	59314
VIX SERVICES	0.19	0.09	0.10	0.13	0.16	0.21	0.81	0.16	44938
S&P500 INVESTMENT GRADE	0.00	0.01	-0.09	-0.00	0.00	0.00	0.12	0.00	367499
S&P500 HIGH YIELD	0.00	0.01	-0.09	-0.00	0.00	0.01	0.12	0.00	50808
S&P500 MINING	0.00	0.01	-0.09	-0.00	0.00	0.00	0.12	0.00	42589
S&P500 CONSTRUCTION	0.00	0.01	-0.09	-0.00	0.00	0.00	0.12	0.00	11771
S&P500 MANUFACTURING	0.00	0.01	-0.09	-0.00	0.00	0.00	0.12	0.00	264415
S&P500 TRADE	0.00	0.01	-0.09	-0.00	0.00	0.00	0.12	0.00	59314
S&P500 SERVICES	0.00	0.01	-0.09	-0.00	0.00	0.00	0.12	0.00	44938

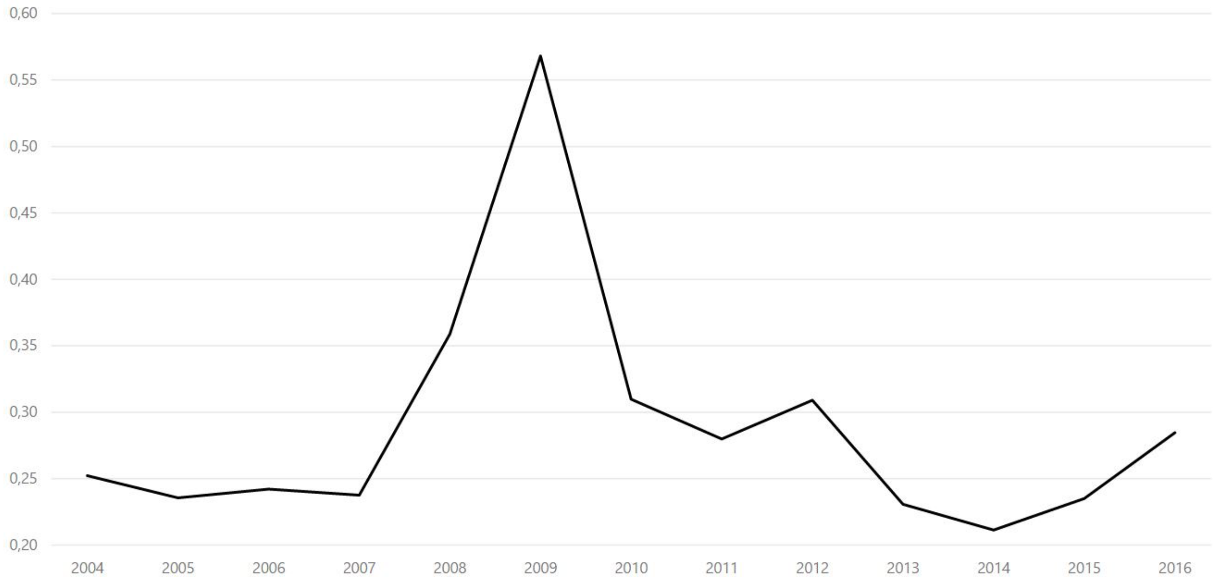
Appendix 3

Line graph 1: average VIX over time



Appendix 4

Line graph 2: average volatility over time



Appendix 5

Table 10: intercorrelations

Table 10

Intercorrelation between variables before the crisis

	Variables	1	2	3	4	5	6	7	8	9
1	CDS spread	X								
2	Leverage	0.187***	X							
3	Volatility	0.311***	-0.181***	X						
4	Stock return	-0.000	-0.007**	0.057***	X					
5	Credit rating	-0.501***	-0.054***	-0.419***	-0.042***	X				
6	Spot rate	-0.071***	-0.039***	-0.074***	-0.035***	0.008***	X			
7	Slope yield curve	0.068***	0.045***	0.093***	-0.000	-0.002	-0.855***	X		
8	VIX	0.051***	0.023***	0.051***	-0.222***	0.003	-0.350***	0.563***	X	
9	Return S&P 500	0.004	0.000	0.003	0.057***	-0.000	0.016**	-0.022**	-0.223***	x

*Table 10: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

Appendix 6

Table 11: intercorrelations

Table 11

Intercorrelation between variables during the crisis

	Variables	1	2	3	4	5	6	7	8	9
1	CDS spread	X								
2	Leverage	0.209***	X							
3	Volatility	0.492***	-0.005	X						
4	Stock return	-0.035***	0.005	0.145***	X					
5	Credit rating	-0.424***	-0.053***	-0.309***	-0.030***	X				
6	Spot rate	-0.233***	-0.028***	-0.460***	-0.064***	0.026***	X			
7	Slope yield curve	0.057***	0.009**	0.349***	0.078***	-0.030***	-0.698***	X		
8	VIX	0.266***	0.039***	0.292***	-0.343***	0.004	-0.459***	0.068***	X	
9	Return S&P 500	0.003	-0.001	0.033***	0.108***	-0.002	0.018***	0.010***	-0.135***	x

*Table 11: Beta’s are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

Appendix 7

Table 12: intercorrelations

Table 12

Intercorrelation between variables after the crisis

	Variables	1	2	3	4	5	6	7	8	9
1	CDS spread	X								
2	Leverage	0.123***	X							
3	Volatility	0.572***	-0.112***	X						
4	Stock return	-0.019***	0.022***	0.056***	X					
5	Credit rating	-0.525***	-0.161***	-0.435***	-0.024***	X				
6	Spot rate	-0.128***	-0.014***	-0.197***	-0.009***	0.008***	X			
7	Slope yield curve	-0.032***	0.110***	-0.123***	0.039***	-0.018***	0.490***	X		
8	VIX	0.138***	-0.033***	0.176***	-0.237***	-0.000	-0.204***	0.056***	X	
9	Return S&P 500	0.005**	-0.002	0.010***	0.082***	-0.000	0.012***	0.026***	-0.151***	x

*Table 12: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

Appendix 8

Table 13: regression model investment-grade ratings before, during and after the crisis

Table 13

The impact of the extended model before, during, and after the crisis

Investment-grade ratings

Dependent variable: CDS spread

Variables	**Pre-crisis**	**Crisis**	**Post-crisis**
LEV	0.483***	-0.021	0.294
VOL	0.379**	1.060***	3.163***
STOCK	-0.110***	-0.212	-0.327***
RATING	-0.034**	-0.246***	-0.086***
SPOT	-0.043***	-0.334***	-0.122***
SLOPE	0.000	-0.239***	0.061*
VIX	0.546***	1.349***	0.368**
S&P500	0.605***	1.592***	0.610***
N	92.514	77.762	193.790
Total R^2	0.265	0.362	0.335

*Table 13: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*

Appendix 9

Table 14: regression mode high-yield ratings before, during and after the crisis

Table 14

The impact of the extended model before, during, and after the crisis

High-yield ratings

Dependent variable: CDS spread

Variables	Pre-crisis	Crisis	Post-crisis
LEV	1.738***	1.003	0.838
VOL	0.033	1.261	3.352***
STOCK	-0.313*	-0.219	-0.638***
RATING	-0.290***	0.039	-0.245*
SPOT	-0.122	-1.067***	-0.267
SLOPE	0.045	-0.840**	0.221
VIX	1.913**	4.144***	4.654***
S&P500	0.093***	4.764***	5.204***
N	11.971	11.013	26.377
Total R^2	0.080	0.243	0.383

*Table 14: Beta's are standardized regression coefficients. Significance levels: *** = 1%, ** = 5%, * = 10%.*