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The Determinants of Credit Default Swap Spread:

An Analysis of the CDS Market during the Financial Crisis of 2007-2009

Gunnar Winther Eliassen

Advisor: Jørgen Haug

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The Norwegian School of Economics and Business Administration (NHH)

Abstract

In this paper the linear relationship between theoretical determinants of default risk and default swap spread is examined and adds to general literature using multivariate regression to explain the development of the CDS spread. The paper yields new insight on the relationship between traditional credit variables and the CDS spread during periods of financial turmoil; After running multivariate regressions on 140 000 CDS spreads for 181 large-cap companies in the period from January 2007 to December 2009, historical volatility was rejected on an average basis as an explanatory factor for the CDS spread, contrary to previous findings in academic literature. Furthermore, only two variables, *firm-specific implied volatility* and *leverage* had a significant impact on an average basis for the CDS spread. The results were tested by running cross-sectional regression for 10 different business sectors resulting in the yield on corporate bonds being included as a third variable with a statistical significant impact on the CDS spread.

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Table of contest

1. Introduction

This paper aims at revealing which factors best explain the CDS spread of 181 companies during the Financial Crisis of 2007-2009. The paper adds to general literature using traditional credit variables in multivariate regression analyses to explain the development of the CDS spread.

Empirical work focusing on CDS has increased in the recent decade and provides a natural analytic framework when performing an analysis of the CDS market from 2007 to 2009.

Zhang et a.l (2006) focused on equity volatility in their analysis and found that volatility risk alone could predict 50% of the CDS spread variation. The volatility variable was examined in more detail in Cao et al. (2010) where they concluded that the information content of option-implied volatility exceeded the historical volatility when it came to explanatory power for the CDS spread. Ericsson et al. (2009) also concurred on volatility being an important determinant and included leverage as another significant variable. Hull et al. (2004) focused on the implications of credit ratings with regards to the rating announcements and showed how these announcements affect the CDS spread. Finally, Davies and Pugachevsky (2003) showed how bond spreads could be a proxy for the CDS spread and should be included in a model trying to explain the CDS spread.

This paper differs from prior research on credit default swaps as the sample period of this paper represents a period where the average CDS spreads of the financial markets reached unprecedented levels and the entire financial system was close to a global meltdown. Emphasize will therefore be put on explaining the market fundamentals which caused the financial turmoil and illustrate why this analysis of the derivative market differs from analogous CDS analyses prior to the Financial Crisis of 2007-2009.

The majority of the empirical work on credit-sensitive instruments has evolved around traditional "credit-variables" such as leverage, historical volatility and market returns and applied multivariate time-series regressions in the CDS spread analyses (Cao et al. 2010, Ericsson 2010). This traditional framework was also applied in this paper. However, other variables were also included in the regressions; firm-specific implied volatility, market return and volatility (both historical and implied volatility), trading volume of options, yield on Baa-corporate bonds, and 10 year swap rates, to test whether these variables could help explain the extreme fluctuations which took place in the CDS markets in 2008 and 2009.

A total of 10 variables were extracted on a daily basis from January 1. 2007 to December 31 2009, and multivariate time-series regressions of the CDS spread for 181 companies were conducted. The results are presented on an average basis, with the number of companies where each variable had a significant impact also included. Additional regressions were performed for 10 different business sectors, to reveal whether the different variables had explanatory power varying across the different industry sectors.

In the first section of the paper, credit default swap as a derivative will be presented before the development of the CDS spread throughout the Financial Crisis of 2007 -2009 is presented, and give grounds for the paper's hypothesis.

1.1 Credit Default Swap and its mirror image; the Spread

A credit default swap (CDS) is a privately negotiated bilateral contract where the underlying credit risk is hedged trough a swap agreement with a seller of protection; a CDS is de facto an insurance against default from a debtor. The buyer of a CDS pays an annual premium to the seller of protection in return for a payoff equal to the loss-given-default on bonds if a credit event (defaulting on coupon payments, bankruptcy, restructuring etc.) occurs. The annual payment from CDS buyer to CDS seller is based on the CDS spread, which is expressed in basis points (1/100-percentage points) of the notional value. A CDS written on a bond with face value of USD 1m and a spread of 50bs, equals an annual payment of USD 5 000 for protection of the notional amount of USD 1m. The CDS spread is considered one of the purest credit measures as it is not inferred form a benchmark yield curve, but represents the market's perception of default probability of a company; the higher the spread, the higher the risk of default.

Throughout the financial crisis, the CDS spread fluctuated widely. Figure 1 shows the weighted average of the CDS spreads from January 2007 to December 2009 for all 181 companies included in the data sample together with the S&P500 index, and illustrates the volatility jumps experienced.
The average spread was below 100bs until the start of 2008. On March 14. 2008 the investment bank Bear Stearns was overtaken by J.P. Morgan in a "merger" fully orchestrated by the US Government (Lowenstein 2009). Fear gripped the market and the CDS spreads peaked the following trading day at 204bs. Nevertheless, the spread fell just as rapidly as the market believed the failure of Bern Stearns marked the peak of the sub-prime crisis.
The next volatile jump is seen in September when Lehman Brothers declared bankruptcy and the largest corporate failure in history was a fact. Again, the unraveling of the financial markets caused the credit spreads

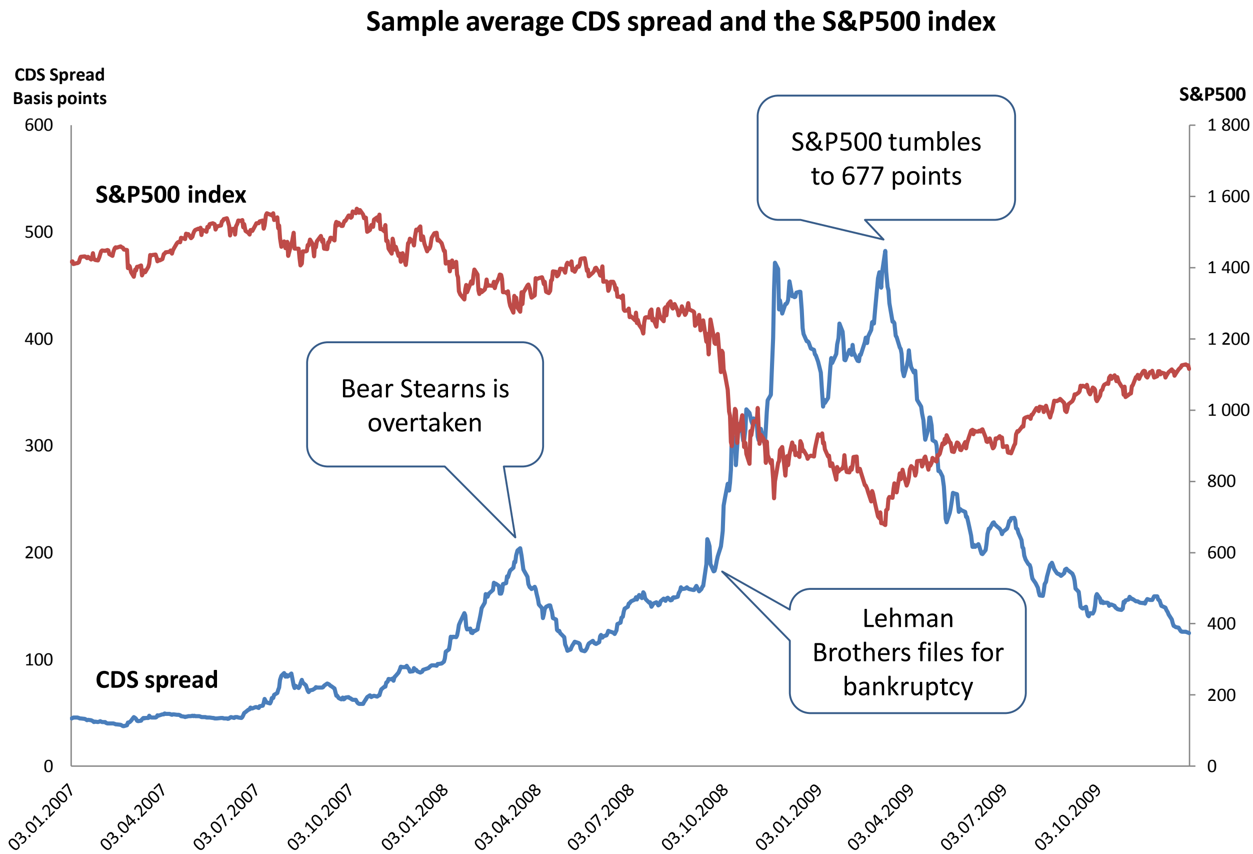


Figure 1.

Primary axis and the blue line show the weighted average of the CDS spreads for the 181 companies in the sample, expressed in basis points. Secondary axis and the red line show the S&P 500 index. The sample period extends from January 2007 to December 2009

to spike; the average CDS spread of the sample went from 169bs to 213bs in just two trading days, an increase of 26%. The S&P500 plunged almost 28% the next 4 weeks and CDS spreads continued to soar. The next couple of months were a hectic time for the Wall Street power houses and for the decision makers in Washington with government bailouts, financial institutions toppling at an unprecedented rate and large Main Street companies demanding access to emergency government funds. The average CDS spread reached a temporary peak November 21. at 471bs. The average spread decreased somewhat over the next months before fear gripped the market again in March 2009, and the CDS market peaked at 483bs on March 9. On this day, the S&P 500 index tumbled to 677, its lowest level since September 12. 1996 and represents the bottom low (high) of the financial turmoil in terms of market return and credit spreads. The next 3 months the average CDS spread fell from 471bs to under 200bs as investors regained their confidence in the financial system. The average CDS spread continued to fall throughout the sample period, ending at an average spread of 125bs on December 2009. [1]

1.2 Hypothesis and the paper's objective

As Figure 1 shows, a model trying to explain the extreme fluctuations in the CDS market faces a daunting task. With the CDS spreads fluctuating widely, it is expected that some variables traditionally assumed as statistical applicable for explaining the CDS spread, are too "slow-moving" to reflect the fluctuations. The hypothesis of the paper is therefore that the financial turmoil created such havoc in the markets that the traditional credit variables, *historical volatility* and *leverage* should "break down" and yield limited explanation power for the CDS spread. However, the paper's sole focus is not just to reject conventional "academic truths". By including additional firm-specific and market-specific variables, the paper aims at revealing which variables that *do have* explanatory power for the CDS spread during periods of severe financial distress. To further back the findings of the paper, additional regressions are conducted to test whether the results are upheld, regardless of the industry a company operates in by comparing 10 different business sectors.

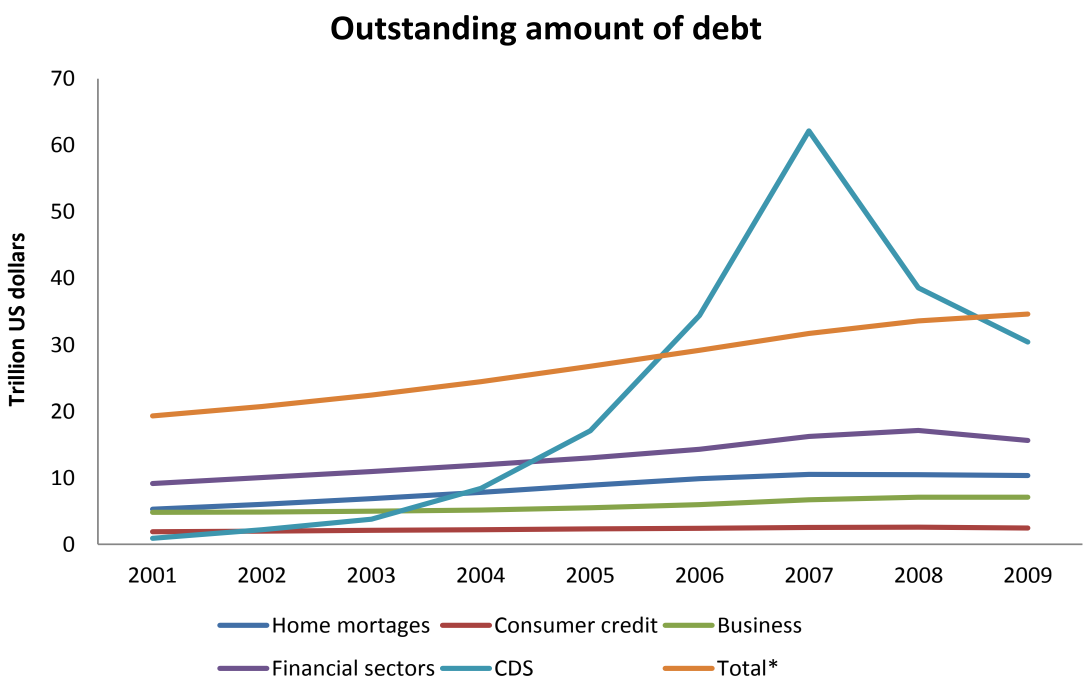
To enable a discussion of the paper's findings, and understand why a somewhat discouraging hypothesis was developed, it is important to understand the underlying factors that caused the market to unravel, with the biggest recession since 1929 as result. The market fundamentals leading up to the crisis are therefore presented in section 2, where 4 different market dynamics are highlighted as the fundamental cause of the near breakdown of the financial markets. The 4 market dynamics will illustrate an inherent systemic risk in the markets, and explain how the extreme fluctuations in the CDS spreads could take place.

The rest of the paper proceeds as follows; the methodology of the analysis and the motivation for the different variables included in the regression model is explained in section 3, sample selection and descriptive statistics follow in section 4 before time-series analyses are conducted and a discussion of its implications are presented in the next sections.

[1] Figure 1 indicates that the fluctuations of the S&P500 index were modest compared to the average CDS-spread. However, comparing the index with historically fluctuations, another truth is revealed; from January 2000 to January 2010, the index had a daily change exceeding +-5% occurring on 25 trading days. 18 of these changes took place in less than 3 months, from 29.09.2008 to 16.12.2008.

2. The Fundamentals of the CDS market

The CDS market experienced an unparalleled growth in the last decade. This is expressed in Graph 1 where the notional amount (face value) of CDS is compared to total debt outstanding in various US markets.



Graph 1. Total outstanding debt, US market, trillion USD.

*Total debt includes: Total household debt, Business debt (both financial and non-financial), State and local Government debt, Federal Reserves debt, and Foreign debt. *Source; International Swaps and Derivatives Association* and *Federal Reserves*

In 2001 the notional amount written on CDS was US 919bn. However, in 2003 the CDS market took off and peaked in 2007 after increasing to US 62 173bn. The CDS market of some 62 trillion in 2007 was twice the size of the total outstanding amount of debt in the US, and illustrates the massive dimension of the CDS market.

The swelling of the CDS market will be explained through 4 different market dynamics

1. Securitization of (subprime) mortgages
2. Flawed credit rating
3. Naked bets
4. Lack of federal oversight

which all lead up to the underlying cause for the fluctuations in the CDS spreads witnessed; systemic risk!

2.1. Securitization of mortgages

J.P. Morgan is often cited as the architect of the modern CDS after its escapades following the Exxon Valdes disaster in 1989 to circumvent the capital to risk-weighted asset restriction imposed by the Basel Accords[2] (Tett, 2009). The idea of swapping credit risk was well received by the underwriters at Wall Street and the CDS market grew over the next years. Yet, it was the housing boom in the early 2000s that lay the real groundwork for the swelling of the derivative market.

In the early 2000s, banks and credit institutions abandoned the traditional banking philosophy and started a securitization of mortgages; the "originate and hold" model was abandoned and the "originate and distribute" model was created[3]. Home mortgages, credit card loans, student loans and all other types of mortgages were taken "off the books" and sliced up in different tranches based on their creditworthiness and pooled into Collateralized Debt Obligations (CDO) whose values and payments were derived from the repayment ability of the initial borrowers[4]. This securitization was combined with credit institutions aggressively making loans to consumers previously regarded as too risky (sub-prime), and the market for asset-backed securities (ABS) ballooned. Through securitization, credit institutions got their liabilities "off their books" which increased the ability to extend even more loans. The housing market was booming and risky, low-income borrowers were given huge loans based on the assumption of ever inflating housing prices.

2.2 Flawed Credit Ratings and Naked Bets

Since the pools of mortgages were based on payments from consumers spread all over America, the pools were assumed to be adequately diversified; a failure of payments from a California resident was by no means correlated with a failure of a New York resident. The idea of the housing market plunging all

[2] The first pillar of the Basel Committee on Banking Supervision from 1988 sets out a required capital to risk-weighted asset ratio of minimum 8%. This pillar puts a strain on the amount of debt a credit institution can issue as the credit institution has to hold minimum a reserve capital of 8%. (Bank for International Settlements, 23.11.2010).

[3] "Originate and hold" refers to the traditional banking philosophy where loans extended to customers were kept on the balance sheets of the banks. "Originate and distribute" refers to the process of securitization of traditional mortgages in off-balance vehicles like asset-backed-securitizes.

[4] A CDO is a type of an Asset-Backed Security (ABS). The value of, and payments from an ABS are backed by a specific pool of underlying assets (often private homes) functioning as collateral for the lenders. CDOs have therefore many of the same attributes as a corporate bond; they are backed by private assets (instead of not an institution) and receives payments in form of installments (instead of coupon payments) from private borrowers.

over America simultaneously was not considered to be a realistic situation (Lewis 2010). The credit rating agencies therefore uncritically relayed on their rating models and rated most of the CDOs with the highest credit rating, triple A.[5] Even CDOs based on tranches of the least creditworthy borrowers could be rated triple A[6] (Lewis 2010). With triple A rating, risk averse funds (money market funds, pension funds, insurance funds), could invest in the housing market by buying a CDO, and the derivative market expanded even further.

Even though the triple A rated CDOs were initially considered almost riskless, the financial players wanted to hedge their credit risk. Since buying a collateralized debt obligation had many of the same characteristics as buying a corporate bond, the buyers of a CDO were exposed to default risk. By buying a credit default swap on a CDO, investors hedged against a default from one or more of the borrowers. If the predetermined installments were not made, the collateralized debt obligation had by definition defaulted, and the issuer of the credit default swap had to cover the loss and compensate the CDO investor. The CDS market was an efficient market for the distribution and diversification of risk and the CDS market grew together with the pooling of new loans. The CDO market peaked in early 2007 with a global issuance volume of ~ US 1.2 trillion since 2004 (Barnett-Hart, 2009) and the CDS market peaked along with it. In addition investors started buying CDSs on companies as well to hedging against defaults in their bond portfolios. Since the CDS came with a low premium (spread), buying a CDS was considered an efficient and cheap hedge. Market participants could freely issue and buy CDS on a CDO without actually having a stake in the CDO or the pool of mortgages the CDO was built on. The market participants could make these "naked bets" on various companies as well[7]. If investors doubted the creditworthiness of an obligor, the new CDS market made it possible to take short positions by buying a (naked) CDS. These sorts of naked positions could be taken on every security or CDO the investors wanted, and worked as rocket fuel for the CDS market[8].

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[5] A financial paper rated as triple A is regarded to have *"extremely strong capacity to meet financial commitments"* and represent a financial paper with the best possible creditworthiness (Standard & Poor's, 23.11.2010).

[6] A tranche refers to the creditworthiness of a borrower. Different CDOs could be backed by the same type of assets (private homes) but sliced into different tranches representing different creditworthiness of the (home mortgage) borrowers.

[7] Investors taking naked positions are separated from the obligor and creditor but their payoffs are derived from the ability of the original debtor to meet its financial commitments.

[8] However, it is important to note that naked positions on credit instruments will also increase the market efficiency; expressing a negative view of a company through shorting a cash bond is difficult and time consuming (Gordon 2010). By allowing to buy naked CDSs, trades which before were unprofitable (shorting cash bonds) could now be traded with a profit through naked CDSs

In figure 2, the fundamentals of the derivative market are illustrated;

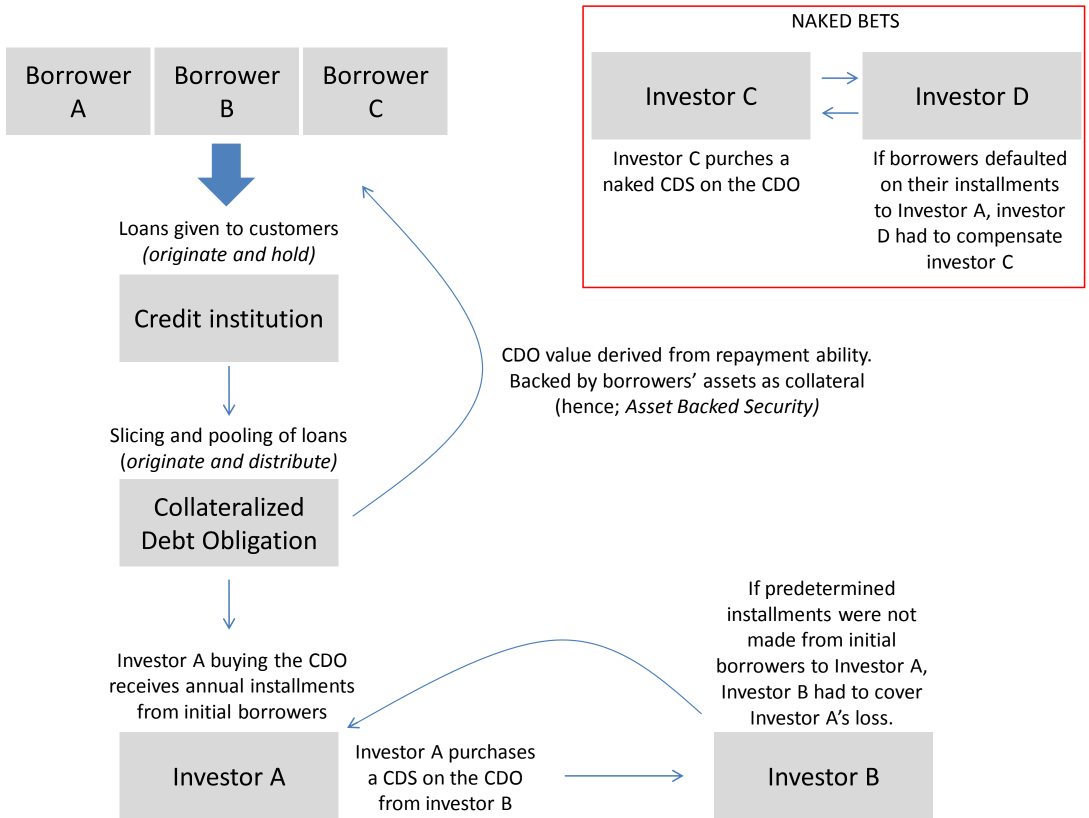

Figure 2. Banks made loans to consumers but pooled these loans into a CDO which investors invested in and received annual installments. The credit risk in the CDO was hedged by buying a CDS where the issuer of the CDS bore the cost of a credit event from the initial borrowers. Additional investors speculated on the solvency of the initial borrowers through naked trades.

2.3 Federal oversight

The federal oversight regulating the derivative market has come under public scrutiny in the wake of the financial crisis and several shortcomings have been highlighted[9].In 2000 Congress removed the 100 year old injunction on "bucket shop activities" after the Commodity Futures Modernization act of 2000 (CFMA) came into effect[10]. The CFMA clarified that most over-the-counter (OTC) derivatives transactions

[9] The Dodd-Frank Bank reform bill signed into law on July 21. 2010 by US President Barack Obama clearly pinpoints flaws in the regulatory oversight leading up to the financial crisis of 2008. The bill introduced 8 different programs all seeking increased regulatory of the financial markets. One of the 8 programs' sole focuses was to curb the credit default swap market. The new law requires CDSs to be traded in central clearinghouses and is directly regulated by the Security and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC). (USECONOMY, 03.12.2010)

[10] Bucket Shops were small front store operations where brokers allowed people to bet on price fluctuations during market hours without owning the actual securities. When the stock market crash of 1907 was investigated, exacerbated bucket shop

would not come under the Commodity Exchange Act regulatory or be regulated as futures. CDS was not considered traditional insurance securities either so nor did standard insurance regulatory apply. This meant that sellers of CDSs were not required to maintain any capital reserves and could freely issue any amount of CDS regardless of collateral assets within the firm. With the CFMA, OTC operations would only by supervised indirectly by the supervision of the firms trading CDSs.

The absence of federal oversight made is possible for all market participants to take all sorts of positions on any security they wanted. If the assumed the creditworthiness of some institutions was deteriorating, they could by a CDS from any market participant willing to guarantee for the institution. If they believed an explicit tranche of a CDO was mispriced, they could take short positions in this tranche by buying a CDS on this particular tranche. If investors were really pessimistic and believed all the assets backing the CDO were mispriced, they could take short positions in the entire CDO. Hence, the opportunities were unlimited.

2.4 Systemic risk

Because of the slicing and pooling of *all* sorts of loans, it was extremely difficult to comprehend which assets and which borrowers actually backed the different CDOs. Different CDOs could be backed by the same type of assets but vary with the creditworthiness (tranches) of the different borrowers. Different CDO could be backed by different assets but have the same creditworthiness as they were based on the same tranche of borrowers[12]. A mortgage could also be sliced up multiple times and placed in new different pools of loans which again were securitized into a CDO. Soon it was impossible to understand what collateral backed which CDO and when the investors realized that the ratings applied to the securities were in best of cases misleading, the investors regarded the asset backed security market as *one* market. The systemic risk increased!

With the use of (covered) CDSs on CDOs, the number of investors indirectly taking positions on the solvency of the different obligors, doubled. For each CDS, two positions had to be taken; one long (issuer) and one short (buyer) and with a zero-sum game, somebody was doomed to loose. The systemic risk doubled!

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activities were widely cited as the main contributor of the crash because of the speculative nature of the bets (60 minutes, August 30, 2009) and bucket shop operations were prohibited and the term defined under the criminal law.

[12] That is, one CDS based on a trance of the most secure borrowers could be backed by one asset class (cars loans) while another "similar" CDS based on a trance of equaling secure borrowers could be backed another asset class (private homes).

Naked CDS made investors place bets on the solvency of securities they did not own and indirectly betting on the solvency of an unknown borrower. Naked bets could again be placed on companies which already had made naked bets or relied on other naked or covered bets. If you add the fact that different institutions and investors directly or indirectly had bets on both outcomes through various combinations of CDOs and (naked) CDS, some of the complexity behind the swelling derivative is probably starting to loom. In addition, because of the flawed regulatory oversight it was unclear if the issuers of the CDSs had sufficient funds available to cover potential losses. The systemic risk went through the roof!

The final piece in the puzzle is the nature of the bets, which turned out to be extremely asymmetric; in a naked CDS, the issuer has little to gain but everything to lose. Since the entire system was built upon the long bet prevailing, it turned out disastrous when the housing bubble burst and sub-prime borrowers started to fall behind on their mortgage payments. A deadly chain of credit events evolved;

- Buyers of CDOs did not receive their predetermined installments, and called upon the issuers of the CDS they had bought to cover their losses.
- The issuers of CDSs had not been required to set aside capital reserves and got into a liquidity squeeze.
- The assets (private homes) backing the securities plunged in value as an economic recession seemed increasingly more likely; more borrowers fell behind on their payments and the chain of events were repeated.

Havoc occurred in the markets as nobody could grasp the implications of a mortgage meltdown; how much bad debt has been securitized? Which CDOs have the most toxic mortgages? Who has underwritten CDSs and guaranteed for their solvency?

The systemic risk made investors (over)react to every piece of information resulting in the spiking of CDS spread and the tumbling of the S&P500 index, as outlined in the section 1.

After comprehending the complexity of the derivative market it only seems natural to repeat the questions raised in the paper’s introduction; Will slow-moving variables like historical volatility and leverage be able to grasp this level of complexity and explain the CDS spreads? If not, which variables *are* able to coop with the systemic risk and explain the fluctuations? To answer the questions above, the paper now turns to the methodology used to test the initial hypothesis.

3. The methodology

This section outlines the methodology used when applying a model to test the initial hypothesis. A model will be presented before the motivation for all variables included in the model is discussed in greater detail.

3.1 Structural approach vs. reduced form

A substantial amount of empirical work on credit sensitive instruments has developed in the last decade[13]. The models applied in these surveys could be broadly divided into two different categories based on the theoretical frameworks they rely on.

The *structural approach* starts from deductive theories of economy and relies on a specific model. Models evolving around Black and Scholes (1973) are typical approaches when it comes to the structural approach towards credit-sensitive instruments. These models typically imply that that the determinants of the likelihood of default are leverage, volatility and the risk-free return structure. The other approach is *reduced form models* which rely on an assumed statistically dependency between some handpicked variables, typically abstracted from the firm value process; return depends on volatility, credit risk depends on leverage, firm specific return depends on market return etc.

However, a third approach could be taken that combines the two methods. When determining the variables explaining the bond spread, Collin-Dufrense et al. (2001) used a structural approach to identify the theoretical determinants of the spread. Instead of putting these variables into a specific model (and take the structural approach), regression analyses were run on these variables to try to explain the changes in bond spread (the reduced form method). A similar approach was also used by Ericsson et al. (2009) and Cao et al. (2010) when doing analogous studies of the CDS spread and motivates the methodology applied in this paper.

[13] See for example; Collin-Dufrense et al. 2001), Berndt et al. (2004) and Cao et al. (2010),

3.2 The regression-model

By combining the structural approach with the reduced form model, a total of 10 independent variables assumed to have statistical influence on the CDS spread were extracted and yielded the following model applied in the paper;

$$\mathbf{CDS}_{it} = \alpha_i + \beta_1\mathbf{HV}_{it} + \beta_2\mathbf{IV}_{it} + \beta_3\mathbf{Lev}_{it} + \beta_4\mathbf{Ret}_{it} + \beta_5\mathbf{MHV}_t + \beta_6\mathbf{MIV}_t + \beta_7\mathbf{MRet}_t + \beta_8\mathbf{Vol}_t + \beta_9\mathbf{Baa}_t + \beta_{10}\mathbf{Swap}_t + \varepsilon_{it}$$

CDS_{it} is the CDS spread for company *i* at time *t* where *t* runs from January 1. 2007 to December 31. 2009, α is the coefficient of the CDS, *HV* is the firm-specific historical volatility, *IV* is the firm-specific implied volatility, *Lev* is the firm-specific leverage, *Ret* is the daily firm specific return, *MHV* is the historical market volatility, *MIV* is the implied market volatility, *MRet* is the daily market return, *Vol* is the total number of options traded, *Baa* is the yield on corporate bonds rated as Baa, *Swap* is the difference between 10 year swap and 10-year Treasury yields, and ε is the standard error.
The model implies that a change in one of the selected 10 independent variables should result in a change in the CDS spread.

The motivation for selecting each of the independent variables will now be discussed in more detail.

3.3. Firm-specific variables

Historical volatility, implied volatility, leverage and daily return are firm-specific variables; i.e. the variables were extracted for each of the 181 companies on a daily basis.

3.3.1 Volatility

In the structural option models, it is assumed that default is trigged when the firm value falls below a certain threshold. This threshold is a function of the amount of debt outstanding. In the Black and Scholes option-model, volatility is an important variable; the higher the volatility of a security is, the higher the value of an option written on the security becomes[14]. CDS has similar attributes as issuing (selling) a put option as the potential downside is the entire debt claim (if obligor defaults), while the potential profits are limited (the annual payments). The cost of buying a CDS is therefore likely to increase as the volatility of the underlying security increases. With increased volatility the chances of falling below the (bankruptcy) threshold increases and the price for default-protection should increase, i.e. the CDS spread should increase when volatility increases.

Variance of return is unobserved, so volatility has to be estimated. Two different approaches could then be taken; Realized volatility of a stock over a given time period is the historical volatility i.e. an expression for the historical fluctuations of the security. Historical volatility's impact on credit sensitive instrument has been well documented in prior researches.[15] These findings are also confirmed in studies focusing on the CDS spread (Zhang et al. 2006) and underline why historical volatility should be included.

Another measure of variance is *implied volatility* which also is a theoretical (unobserved) measure of the variation of a security. Implied volatility is the volatility *implied* by the market price of an option based on an option model. This can be better understood through a simple example;

The price of an European put option on a security trading at USD 100 (S), with strike at USD 120 (K), 30 days to expiration (t) and a risk free rate of 5% (r) might be trading at USD 9.5. Applying the most commonly used option pricing model, the Black & Scholes model, the volatility which yields a price of USD 9.5, is 10%[16].

The implied volatility of the security is 10%

The implied volatility could be a more interesting variable than the conditional historical volatility of the security if it reveals important information not subsumed in the conditional volatility. Latande and Rendleman (1976), Chiras and Manaster (1978) and Beckers (1980) all suggested that the implied volatility explains more of the cross-sectional variations in the future standard deviation of individual security returns than the conditional standard deviation. This conclusion is also confirmed in more recent

[14] Since an option is a one sided bet trigged at a certain threshold, the buyer of an option gains as the deviation from mean of the security increases.

[15] See Campel & Tasker (2003), Cremers et al. (2004), Ericsson et al. (2009)

[16] For the theory behind the groundbreaking Black & Scholes model, see Black & Scholes; "*The Pricing of Options and Corporate Liabilities"* (1973)

literature, through the analysis of the implied volatility of Nifty index options[17] (Kumar 2008). It's worth noting that other studies have come to contrary conclusions[18]. However, when it comes to the information content of option-implied volatility for the explanation of credit default swap spreads, Cao et al. (2010) came to the unambiguous conclusion that implied volatility dominates historical volatility in explaining CDS spreads, and motivates the inclusion of implied volatility in the CDS-model.

3.3.2 Capital structure

Different variables could have been applied in order to express the differences in capital structures and asset values between companies. The popular Fama-French three factor model is one typical approach (Fama and French 1993). The market behavior of firms were analyzed and it was concluded that two classes of stocks tended to do better than the market as a whole; *small caps* (growth companies) and stocks with *high book-to-market ratio* (value stocks).

There is abundant research documenting the robustness of book-to-market values of equity in explaining stock returns[19]. However, there is a considerable debate whether the book-to-market ratio is a proxy for risk (focus on the risk of financial distress) or if the factor is a result of mispricing (undervalued book-values).[20] For the purpose of this analysis, the book-to-market ratio becomes relevant only if the variable is a risk proxy. As the academic literature disputes over the B/M factor, this variable was left out and replaced by a variable widely regarded as significant risk proxy; leverage.

Holding a debt claim through a CDS is equivalent to holding a similar risk free claim and issue a put option on the same debt; potential gain is limited while the potential downside is the entire debt claim. The important aspect of the debtor is that earnings and market value do not fall below a certain threshold. As leverage increases relatively to the equity of the stock, the stock could become more sensitive to dipping below the bankruptcy threshold and lenders demand a higher risk-weighted return.

[17] Nifty is a nickname for The Standard & Poor's CRISIL NSE Index 50 which is a leading index for large companies on the National Stock Exchange Index of India

[18] See Day and Lewis (1992) and Caninia and Figlewski (1993

[19] See Hahn et al. (2010), Lam et al. (2010) and Homsud et. al (2009)

[20] Gharghori et al. (2007) concludes that "default risk is not priced in equity returns" and "the Fama-French factors are not proxying for default risk". These conclusions were also confirmed by Daniel and Titman (1997). Lewellen (1999) on the other hand came to contradicting conclusions; "*After controlling for risk, B/M provides no incremental information about expected returns"*.

The higher risk-weighted return should be reflected in a higher cost of protection and consequently the CDS spread should increase.
This feature is confirmed through the finding of Ericsson et al. (2009) and Cao et al. (2010) and further motivates leverage as a variable in the paper's CDS-model.

3.3.3 Daily return

The intuition for including the daily stock return as a variable is straightforward; with a negative daily return, the stocks equity is reduced and the market value of the stock is reduced. Holding all other variables constant, the stock is now closer to the threshold line for default, the risk for bankruptcy has increased and the price for protection against a default should increase. Hence, the CDS spread should increase when stocks experience negative daily return.
The daily return is therefore included as a variable in the model and is expected to be negatively correlated with the CDS spread.

3.4 Market-specific variables

Even though the probability of bankruptcy of a company remains constant in terms of firm-specific variables, changes in the broad market is likely to impact investors' perception of each individual firm. The importance of market specific-variables is further motivated by the systemic risk presented in section 2; After Lehman Brothers filed for bankruptcy, the average CDS spread soared 26% within two trading days. Investors' perception of the inherent systemic risk had changed, affecting the perception of the creditworthiness of each individual firm, with firm-specific CDS spread spiking as result.

6 market-specific variables are assumed to reflect the overall business climate; historical volatility, implied volatility, market return, market-level credit risk, trading volume and market liquidity. These variables were extracted on a daily basis and the same variables were applied to all of the 181 companies in the regression analyses.

3.4.1 Market volatility

Increased volatility in the overall market is often a result of increased uncertainty and fear. Investors' perception of the overall risk in the market will affect each individual company. If the entire market is

gripped by fear and highly sensitive to market moving news, this will also affect investors' perception of each individual firm. Market volatility is therefore included as an independent variable, both the historical volatility and the implied volatility.
Increased market volatility is assumed to be positively correlated with firm-specific CDS spread.

3.4.2 Market return

The broad view of the economy will be reflected in the overall performance of the markets. During stock rallies optimism dominates and the optimism is likely to be reflected on each investor's perception of an individual company. Increased optimism reflected in positive daily market return in the markets is assumed to reduce the investors' perception of company-specific default risk, thus reducing the CDS spread. Market return is therefore included in the model and assumed to be negatively correlated with the CDS spread.

3.4.3 Market-level credit risk

The perception of the overall market credit-risk is assumed to be reflected in the firm-specific risk. Especially in a market with severe systemic risk, changes in the market level risk will have great effect on each company, even though the firm-specific variables remain unchanged. As the complexity of the derivative market was discovered, investors realized it was close to impossible to comprehend the amount of "toxic-assets" each firm was exposed to. The overall awareness of market-level credit risk soared, affecting every company, regardless of industry.

The CDS spread is assumed as one of the purest measurements of both company and market-specific risk, but as it is the CDS spread we are aiming at analyzing, we must include an alternative market level risk proxy. A natural approach would then be to turn to the bond market due to the many similarities between the CDS spread and the bond yield; when buying a bond, investors require a risk-weighted return, reflected in the bond-yield. The higher the risk, the higher return demanded. When the perceived creditworthiness of an obligor deteriorates, the bond yield is expected to increase.
The development of the yield demanded on different credit ratings could indicate the development of the overall market-level credit risk. If the perceived risk in the market increases, the yield on all corporate bonds increases and reflects the higher assumed market risk. The bond yield is therefore included as a proxy for the market risk and is expected to be positively correlated with the CDS spread.

3.4.4 Trading volume

Different levels of trading volume could be used to interpret the future development of the markets. During times of severe financial distress, fire sale of securities often occurs as traders are forced to liquidate positions sooner than originally planned. But if the liquidity dries up, the distressed sellers may have problems finding buyers, even though the securities are heavily discounted. Interpreting a linear relationship between total trading volume and market liquidity is therefore problematic.

However, the volume of put and call options on securities tends to increase during times of financial distress (Alexander 2000) as investors speculate on the volatility of different securities. During times of financial turmoil, people tend to use options as means of speculation rather than trading the actual securities, as speculating in options could be less risky. Ni et al. (2005) also showed that increased option trading volumes are positively related to the subsequent realized volatility of the underlying stocks.

It is therefore assumed that if the total volume of options increases, the CDS-spread increases as the uncertainty in the markets has increased. Option volume is therefore included in the CDS-model, and assumed to be positively correlated with the CDS spread.

3.4.5 Market liquidity

Two securities with identical characteristics, but traded in two markets with different liquidity is expected to be traded at two different prices. The difference between the prices is assumed to be the liquidity premium. Also yield spread on credit-sensitive instruments incorporates a liquidity premium (Tarek 2009). The total evaporation of the liquidity in the financial markets during the financial turmoil in 2008 was one of the major concerns and eventually triggers for the bailout by the US Congress in 2008 (60 minutes ,September 29. 2008), and underlines the importance of a liquidity proxy in the CDS-model.

There is no single definition of liquidity in financial markets so various proxy indicators are often used. The yield spread between different securities is one commonly used proxy. Yield spread is the difference between two securities with different risk, often a riskless security, and a security with a default risk. As turmoil unravels in the markets, investors tend to seek to safe havens. As more investors flee risky assets, the yield on these assets is expected to increase, and the yield on riskless assets is expected to decrease, thus resulting in a higher yield-spread. The higher yield spread is expected to coincide with a higher CDS spread, and is therefore included in the CDS-model.

4. Sample Selection and Descriptive Statistics

The following section outlines the data that has been extracted, and used as proxy for the 10 variables presented together with a discussion of their accuracy as proxies. A table summarizing the variables is presented at the end of the section.

4.1 The sample

The sample consists of 181 large-cap publicly traded companies, all listed at the S&P500 index, representing 10 different industry sectors[22];

Sector	# of companies
Consumer Discretionary	33
Financials	24
Industrials	21
Health Care	20
Consumer Staples	19
Energy	18
Utilities	16
Materials	15
Information Technology	11
Telecommunications	4

The companies were selected based on the volume of CDSs traded in the time span of the analysis. It's highly complicated to find accurate data on CDS traded on various securitized ABS, so the CDSs in the data sample are company specific swaps only. However, due to the interconnected derivative market, spreads for company specific CDSs indirectly reflect spreads on securitized ABSs.

All data material is obtained from Bloomberg Professional.

4.2 Data extraction

4.2.1 CDS

CDSs are traded in the OTC-market and the CDS spread provided by a broker consist of a firm bid and quotes from dealers. Once a quote has been made, the dealer is committed to trading a minimum principal at the quoted price. The CDS data consists of quotes from various traders collected and categorized by Bloomberg. The vast majority of all CDS quotations are denominated in USD. The first

[22] See appendix I for the entire list of the companies included in the sample

years of CDS trading were for CDSs with very short term (less than 3 months), and for rather longer-term (more than 5 years). However, at the end of 2002 the market began to standardize contract maturity dates, and in 2001 and 2002 approximately 85% of the quotes were for contracts with 5-year maturity (Hull et al. 2004). The majority of these contracts were written on senior unsecured obligations (Cao et al. 2010). All CDSs extracted for the analyses are therefore US dollar-nominated five-years CDS contracts written on the senior unsecured debt of the obligors, expressed in basis points.

The CDSs extracted for the 181 companies are expected to yield a fitting reflecting of the broad CDS market.

4.2.2 Historical volatility

One of the most popular models for estimating historical volatility, is the rolling window (moving average) model where the sample's variance is estimated using the M most recent observations. The historical volatility applied on day *t* is then the weighted average of the *M* past trading days. However, selecting the "right" window length (number of observations) is difficult, and two factors have to be weighed against each other;

- The sample has to be as long as possible to increase the precision of the estimated variance
- The sample has to be as short as possible to increase the relevance of the observations included

Increasing (decreasing) the window length decreases (increases) the sensitivity of the rolling window variance estimator to observations that lie within the window, and decreases (increases) the volatility of the volatility estimator. A large window (>1000 trading days) could be too smooth to reveal changes in the CDS spread, while a small window (<25 trading days) could be "to noisy" to indicate any significant change in the CDS spread. For this analysis a window length of 260days was chosen and is assumed to reflect changes in the CDS being neither "too smooth" nor "too noisy".

The problems with determining the optimal window length are recognized and the 260days average could therefore be a biased proxy for stock volatility.

4.2.3 Implied volatility

As outlined in section 3, implied volatility is the volatility *implied* by the market price of an option model. To extract implied volatility, an option model has to be defined as starting point. Despite its shortcomings, the Black & Scholes (BS) option pricing model is one of the most commonly used option-pricing models[24]. In this model the value of an option depends on the risk free rate, the volatility and market value of the stock, and the strike price of the option. The BS model has been applied in this analysis when extracting implied volatility.

Put options written on a company have some of the same characteristics as a CDS; a protection against downside risk. Deep out-of-the money (OTM)[25] puts are most sensitive to the left tail of the risk-neutral stock return distribution (Cao et al. 2010) because of the increased probability of default. The implied volatility of deep OTMs puts is therefore preferred when analyzing changes in the CDS spread. However, if plotting implied volatility from the BS-model, the graph typically yields a "smile", indicating an overpricing of out of the money options. The more out of the money, the higher the skewness tends to be[26]. The level of moneyness therefore has to be weighed against the level of skewness.

For this analysis, European put-options with 80% moneyness were extracted and assumed as a reasonable balance between moneyness and skewness. Nonetheless, the implied volatility clearly is a biased estimator for the volatility of a security.

Options are also written with different maturities. The shorter the maturity, the higher the risk becomes; 30-days options represent an annual risk of 1 200% (100% risk every 30-days), while 3-months options represent an annual risk of 400%. Short dated options are therefore more sensitive to market moving news than long-dated options because of the relatively shorter time to expiration. Options with 30-days maturity are one of the most traded option maturities (Wei and Zheng 2010) and news affecting the CDS spread are more likely to be subsumed in the implied volatility of 30-days options, than longer dated options.

30-days put options with 80% moneyness were therefore chosen as the basis for the implied volatility for the data set[27].

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[24] Among the flaws often highlighted are assumed constant risk free rate and volatility, and the assumptions of continuous stock prices.

[25] Options could be sorted based on the degree to which an option is likely to have positive monetary value at its expiration. This is measured in moneyness (m) which is the ratio of the option strike price (K) compared to the spot price of the underlying security on which the option is written on (S). For put options; at-the-money: K=S, out of the money: K<S, in-the-money: K>S.

[26] Volatility smile refers to the long-observed patterns when plotting the implied volatility against different strikes prices and thus resulting in a "smile". Traditional option models assume constant volatility. However, the implied volatility from option models indicates that the volatility tends to increase as the strike of the options move out-of-the money.

[27] Note that Bloomberg's implied volatilities are sometime criticized for the way they allow for items such as dividends, bid-offer spread, and American exercise features. The data set is not adjusted for these features.

4.2.4 Leverage

The broadest definition of stock leverage is the ratio of total liabilities to total assets (Rajan & Zingales 1995). However, this does not provide a good indication of whether the firm is at risk of default in the near future as book values seldom reflect "real values". Therefore we have to include market value, which in theory should reflect true values. One of the most common view in the literature is that the ratio of total debt to capital, defined as total debt plus shareholders' equity, is the best proxy for leverage (Nivorozhkin, 2002); as book value of debt reflects the notional amount of debt outstanding, leverage will vary with the issuance of new debt and with the changing stock price.

As the stock price declines or new debt is issued, leverage will increase, bringing the company closer to the bankruptcy threshold, and thus increasing the risk of a default.

As book values often deviate from market values, using book values as a part of the proxy could be a pitfall. Corporate bonds are often traded below its notional amount because of a default premium. This default premium will not be reflected when using book values. However, in terms of leverage as a *ratio*, using book values could in fact be a more fitting proxy than market values. It is the lenders who can declare bankruptcy and they are concerned with notional amount of the loans, not the market value, as it is the notional amount they are entitled to be repaid.

By comparing the book value (notional amount) of debt with the shareholders' equity, the notional value of the debt remains unchanged, and the leverage ratio then indicates how close the company is to the bankruptcy threshold and thus reflecting the risk of default.

The ratio of total debt to capital, defined as total debt (Current and Non-Current Liabilities) plus shareholders total equity, is therefore applied as proxy for leverage.[28]

However, bankruptcy could also occur when lenders fail to meet the annual predetermined installments or breaks some of the bond covenants[29]. These features are not reflected in the proxy applied in the paper. The leverage is therefore a proxy for default risk with limitations.

[28] The balance sheet items used to calculate "Current and Non-Current Liabilities" are showed in appendix III

[29] Bond covenants are legally binding promises made by the bond issuers to the bondholders, requiring or forbidding certain actions of the issuer.

4.2.5 Daily return

Daily returns could be calculated using arithmetic return or logarithmic return. The advantages of using logarithmic return are that the results are time-additive and more mathematical convenient. However, for this analysis the concern is how each single discrete daily return affects the CDS spread on each individual observation. Since returns are not added up, but matched with corresponding daily CDS spread change, the arithmetic return is applied.

The daily return is calculated using gross dividends where all ordinary dividends that are paid, plus capital-gains distribution and nontaxable distribution received, are included. This is done to reflect the *total* return of a stock, and not just the share price change.

The daily return is expected to be an unbiased proxy for total daily profit for stockholders.

4.2.6 Market volatility and performance

The S&P 500 index is commonly considered one of the best gauges for the development of the financial markets. The index has therefore been used as a proxy for the market development when it comes to volatility and return[30].

Calculations of the market volatility have been done with the same considerations as under the company specific volatility calculations; historical volatility has been calculated based on the development of the S&P500 index using a rolling window of 260 days while the implied volatility has been calculated using put options on the S&P500 index with 80% moneyness and 30 days maturity[31].

The daily return is the arithmetic daily return of the S&P 500 index using gross dividends.

4.2.7 Market credit risk

Motivated by the findings of Davies and Pugachevsky (2003) that showed how yield on corporate bonds could be a proxy for the CDS spread, bond-yield is included in the CDS-model.

[30] Since all companies in the sample are themselves included in the S&P500 index, the performance of each firm is included twice. Ideally, each firm's impact on the S&P500 index should have been left out. However, since the volatility and return of the S&P500 is a weighted average of all 500 companies, each company's impact on the index is highly limited. The dataset is therefore not adjusted for these features.

[31] Note that this implied market volatility coincide with the VIX index, commonly referred to as the *Fear* index, with only minor differences when it comes to the mathematical approach

If the bond *spread* (between bond yield and risk-free rate) was applied, a benchmark risk-free yield curve is required which the spread is inferred from, and could render the accuracy of the proxy. A simple bond yield was therefore chosen.

The industry standard for the measuring of creditworthiness is done by the credit rating agencies. Based on the borrower's overall credit history and its ability to repay current debt, the obligor is assigned an alphanumeric symbol ranging from AAA (best) to D (worst).
Once a rating has been assigned, the rating is independent of size, industry and country of origin; two companies with the same rating should in theory have exactly the same default probability. A threshold in the rating sphere is set at the BBB/Baa rating[32]; companies above BBB/Baa are classified as I*nvestment Grade* companies with adequate capacity to meet its financial commitments while companies rated below BBB/Baa are *High Yield* companies with a much more speculating nature and higher default risk. As the majority of the companies in the data sample are rated as investment grade companies, the Baa corporate bond spread was chosen.
The increased market credit risk should be reflected in a higher Baa-yield and impact each company's CDS spread.

As a proxy for market risk the bond yield has several shortcomings as the yield includes several non-default components like taxes, illiquidity and changing risk premium (Bruche and Reneby 2004, and Elton et al. 2001). In addition, changes in perception of credit quality are reflected more slowly in the bond spread than in the CDS spread (Ericsson 2009). These features could render the variable's accuracy as market risk proxy.
The Baa-yield is therefore assumed as proxy for market credit risk with limitations.

4.2.8 Trading volume

As the volume of put and call options tends to increase during times of financial distress, and increased option trading volumes are positively related to subsequent realized volatility (Alexander 2000), (Ni et al. 2005), total option volume was included.

[32] The rating sphere refers to the discrete set of possible ratings assign to a company, ranging from AAA (best) to D (worst). BBB is the notation applied by S&P while Baa is the notation applied by Moody's.

The total volume of call and put options contracts (all strikes and all expiration dates) traded each day on the S&P500 index, or on companies included in the index, was therefore extracted and used as proxy for total trading volume.

Ideally, the data should have been on a firm-specific data and not on a combined basis as in this paper. In addition, the relationship between option volumes and CDS spread is also poorly explored in academic literature. It is therefore recognized that this is a limited proxy for volume and could yield biased results.

4.2.9 Yield spread

Various approaches could have been taken when selecting a yield spread as proxy for market liquidity.[33] In this paper the difference between 10 year swap and 10-year Treasury yields has been applied. Interest swaps involve swapping floating interest payments with fixed interest payments. The floating payments are measured as the payments from (riskless) "on the run treasuries"[34] while the fixed payments are measured as the fixed payments to (risky) banks in the interbank system. The difference between the fixed and the floating rate is the swap rate.

The perception of the creditworthiness of the bank will to a large extent determine the swap rate while the yield on (riskless) government treasuries will reflect the risk free rate in the market. The spread between the swap rate and the treasury rate (given the same maturity) could therefore be an indication of liquidity and fear in the market; when liquidity dries up, people tend to flee to riskless assets and the spread between the swap rate and treasury yields should increase. US Treasuries are assumed as one of the securities least likely to default, and investor poured into Treasuries when the liquidity dried up and fear gripped the market during the financial turmoil in late 2008 and early 2009.

This increased swap rate is assumed to be positively correlated with the CDS spread.

The problems with finding adequate proxies for the market liquidity are acknowledged and the yield spread is therefore assumed as an imperfect proxy for market liquidity.

4.3 Summarization of data extracted

As we can see from Table 1 the average company in the sample has a MCAP of USD 29bn, a CDS spread of 170bs, a historical volatility aligned with implied volatility (45% vs. 50%), a leverage of 49% and an

[33] TED-spread, LIBOR-OIS ,10-year on-the-run and first off-the-run treasury yields are 3 commonly applied proxies.

[34] On the run Treasuries are the most recently issued U.S. treasury bond or note of a particular maturity

Table 1. Cross-sectional summary statistics on an average basis for the 11 variables used as input in the analyses. In addition, market capitalization and 365 days annualized return from Jan. 07 to Dec. 2009 are included for the 181 companies. The 181 companies are split into the 10 different sectors constituting the S&P500 index and the numbers in brackets are the total number of companies included in each sector. CDS is expressed in basis points, all volatility measures expressed in percentage points and MCAP is the market value as of 31. December 2009 expressed in USD millions.

Panel A **Firm-level variables**	**CDS**	**260D.Vol**	**30D-80%M-IV**	**Leverage**	**Daily return**	**MCAP**	**Annual return**
Consumer Discretionary (33)							
Average	271.76	48.95	57.66	0.48	0.02 %	15 196	-11.75 %
Median	128.30	40.95	50.91	0.45	-0.04 %	7 600	-9.95 %
Standard deviation	*601.75*	*26.67*	*28.76*	*0.20*	*3.53 %*	*17 483*	*16.61 %*
Consumer Staples (19)							
Average	91.99	28.69	35.91	0.41	0.01 %	34 818	-2.71 %
Median	53.42	27.09	32.27	0.38	0.02 %	13 316	-4.95 %
Standard deviation	*107.77*	*12.23*	*16.90*	*0.12*	*1.95 %*	*57 250*	*13.15 %*
Energy (18)							
Average	128.65	53.48	53.38	0.35	0.07 %	47 154	0.49 %
Median	69.32	45.19	46.53	0.34	0.13 %	16 881	3.31 %
Standard deviation	*145.71*	*25.69*	*23.05*	*0.14*	*3.53 %*	*78 927*	*14.80 %*
Financials (24)							
Average	246.11	62.50	64.13	0.73	0.04 %	25 442	-15.10 %
Median	127.39	41.23	52.77	0.80	-0.01 %	16 054	-13.14 %
Standard deviation	*344.54*	*49.76*	*40.77*	*0.21*	*5.00 %*	*35 706*	*12.35 %*
Health Care (20)							
Average	84.99	38.35	41.92	0.38	0.03 %	40 970	-2.51 %
Median	53.50	30.70	37.79	0.33	0.02 %	19 781	-4.57 %
Standard deviation	*100.55*	*22.19*	*18.06*	*0.19*	*2.46 %*	*49 236*	*13.53 %*
Industrials (21)							
Average	94.32	40.69	46.45	0.45	0.02 %	29 296	-6.46 %
Median	50.89	35.43	41.49	0.43	0.02 %	26 505	-6.28 %
Standard deviation	*129.52*	*20.51*	*20.51*	*0.16*	*2.75 %*	*34 424*	*10.74 %*
Information Technology (11)							
Average	201.84	40.15	48.59	0.35	0.02 %	61 122	-7.63 %
Median	59.00	35.47	42.96	0.34	0.00 %	28 939	-5.72 %
Standard deviation	*490.56*	*17.12*	*20.28*	*0.21*	*2.79 %*	*65 028*	*13.03 %*
Materials (15)							
Average	136.35	47.80	51.04	0.43	0.05 %	17 942	0.77 %
Median	86.40	43.13	46.38	0.43	0.06 %	14 815	-3.55 %
Standard deviation	*146.13*	*22.65*	*21.98*	*0.17*	*3.28 %*	*13 132*	*17.65 %*
Telecommunications Services (4)							
Average	254.00	46.23	50.33	0.63	-0.02 %	28 887	-21.90 %
Median	225.95	35.88	40.54	0.63	-0.03 %	9 094	-21.16 %
Standard deviation	*216.65*	*28.90*	*28.62*	*0.12*	*3.51 %*	*44 167*	*14.96 %*
Utilities (16)							
Average	176.00	33.67	35.66	0.66	0.01 %	9 493	-6.32 %
Median	102.32	26.78	30.43	0.65	0.07 %	8 220	-3.37 %
Standard deviation	*187.70*	*17.72*	*19.16*	*0.10*	*2.28 %*	*5 235*	*7.10 %*
All sectors combined (181)							
Average	169.70	44.90	49.56	0.49	0.03 %	29 094	-6.85 %
Median	74.35	35.33	42.79	0.46	0.01 %	12 863	-5.72 %
Standard deviation	*337.55*	*29.12*	*27.21*	*0.22*	*3.30 %*	*44 723*	*14.59 %*

Panel B **Market-level variables**	**30D-80%M-IV**	**260D.Vol**	**Daily retun**	**BAA - yield**	**Tot opt. Vol**	**Swap-Treasury**
Average	37.69	26.00	-0.49 %	7.02 %	641 261	0.46 %
Median	33.42	20.55	0.09 %	6.75 %	585 638	0.53 %
Standard deviation	*11.56*	*13.61*	*1.88*	1.03 %	*277 368*	0.23 %

annual return of -6.9% from Jan 07 to Dec 2009. The average size of a S&P500 company in September 2010 was USD 19bn and the larger MCAP of companies in this sample reflects the selection of large liquid companies as the basis for the analysis. Also the companies selected are more volatile than the S&P 500 index as whole (implied volatility; 50% vs. 38%, historic volatility 45% vs. 26%).
The annual return of -6.85% reflects the financial turmoil which the companies have experienced since 2007. The turmoil is also reflected in a relatively high average CDS spread of 170bs and a standard deviation of 338bs.

4.3.1 Cross sectional variances in CDS spread

During periods of financial turmoil and with the possibility of an economic recession looming in the horizon, the market perception of the solvency of firm will, among other things, depend upon the segment the company operates within. The average CDS spread is therefore expected to vary across the different sectors. The 181 companies included in the analysis have therefore been divided into 10 different business sectors based on the Global Industry Classification Standard (GICS).[35]

The Consumer Discretionary Sector is a sector made up of companies dealing with products or services which are not classified as necessities. These non-vital goods and services are expected to sell according to the fluctuations in the economy as whole. *Consumer Discretionary* companies are therefore expected to experience more difficulties during a recession than other companies. Dominating companies included in this segment in the analysis are Ford Motor, Darden Restaurants, Home Depot and Office Depot (see appendix I). As we see from Table 1, the average CDS spread of 272bs is the highest spread of all the sectors, far exceeding the average spread of 170bs.

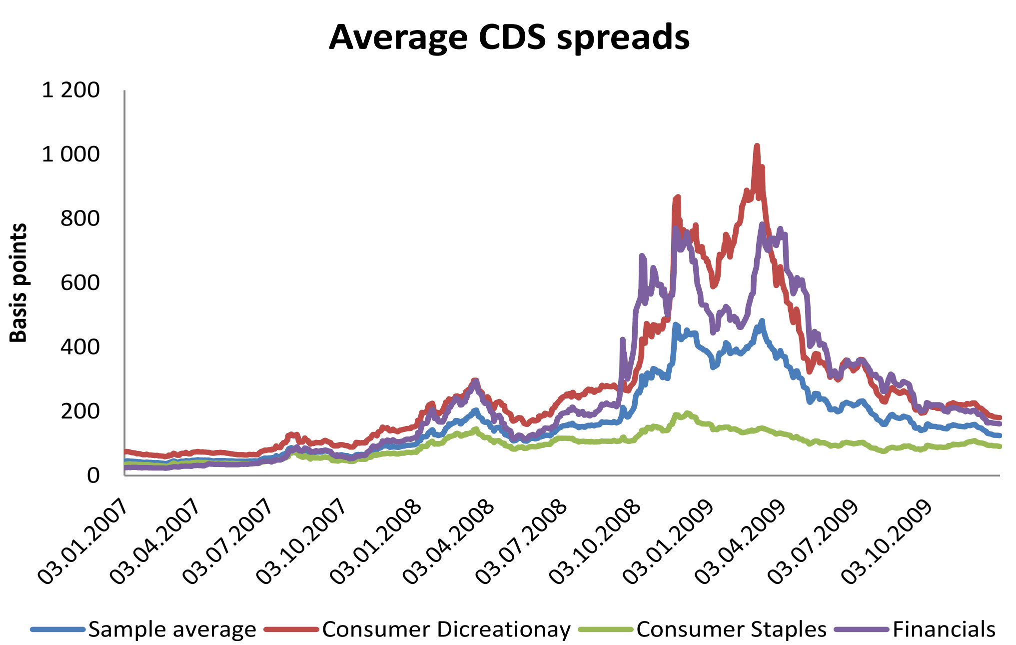
The Consumer Staples Sector, on the other hand, constitutes of companies selling goods considered as basic requirements, like food, beverages, housewares, clothing and tobacco. The performance of this sector is expected to some extent be detached from general fluctuations in the economy. Dominating companies from this sector included in the analysis are Costco, CVS, Wal-Mart and Procter & Gamble. With an average CDS spread of 92bs, *The Health Care sector (*which also represents basic fundamental

[35] The GICS is an industry classification developed by Morgan Stanley and Standard & Poor's for use by the global financial community and assigns all major public companies into one of 10 different industry sectors. For the complete classification, see appendix II.

goods) is the only sector with a lower spread, and confirms the initial assumption on the performance (and solvency) varying across the fundamentals of the different sectors.

A final observation of the CDS spreads is the average spread of 246bs from *The Financial Sector* which exceeds 7 of the other 9 segments. This sector is often hit hard in financial crises. However, during the Financial Crisis of 2007-2009 the sector was hit even harder than usual. The breakdown of Wall Street institutions has come to symbolize the backdrop of the crisis, and is reflected in the swelling of the CDS spreads.

The observation of the CDS spreads varying across the different sectors is echoed in Graph 2. The average CDS spread of the *Consumer Discretionary Sector* exceeds the sample average on every trading day, the spread of the *Consumer Staples Sectors* is below the sample average on each observation, while the *Financial Sector* experiences a significant increase in the spreads from September 2008.



Graph 2**.** Weighted average CDS for the entire sample, the Consumer Discretionary Sector, the Consumer Staples Sector and the Financial Sector. The sample period extends from January 2007 to December 2009.

5 Time-series regressions

Based on the 10 variables presented, multivariate time-series regressions were conducted. For all regressions the dependent variable was the company specific CDS spread from January 1. 2007 to December 31. 2009 while the independent variables were the 10 independent variables previously presented. We repeat the regression model;

$$CDS_{it} = \alpha + \beta_1 HV_{it} + \beta_2 IV_{it} + \beta_3 Lev_{it} + \beta_4 Ret_{it} + \beta_5 MHV_t + \beta_6 MIV_t + \beta_7 MRet_t + \beta_8 Vol_t + \beta_9 Baa_t + \beta_{10} Swap_t + \varepsilon_{it}$$

The regression model yields coefficients which indicate the expected change in the CDS spread when one variable changes with one unit. To test the statistical significance of the coefficients, a null hypothesis (H_0) and an alternative hypothesis (H_A) were computed;

$H_0 : \beta_i = 0$ and $H_A : \beta_i \neq 1$

For the daily returns variables (Ret_{it}, $MRet_t$), the alternative hypothesis is that $\beta_i = -1$, i.e. the CDS should decrease when the daily return increases. For all other variables $H_A : \beta_i = 1$

A test statistics (T) is computed to test the statistical significance of the results;

$T = (\beta_i - E[\beta_i]) / S(\beta_i)$

which is t-distributed with n-2 degrees of freedom.

When the number of observations is large (above 200 observations), the t-distribution becomes standard normal distributed. Each regression was run with 756 daily observations and the t-values extracted were therefore assumed as standard normal distributed.

A significance level of 95% was chosen when evaluating the statistical significance of each coefficient (t-value > 1.96)

5.1 Heteroskedasticity and Autocorrelation

Financial time series are inherently noisy and non-stationary and regarded as one of the most challenging applications of time series analyses (Lu et al. 2009).

The unavailability of complete information in the complex financial markets results in the error term (noise) making up a large component of the regression. In addition, the distribution of financial time series is often changing over time; the data set becomes non-stationary (Lu et al. 2009). The problem with heteroskedasticity and autocorrelation arises, and complicates the analysis.[36]

Over the last 20 years several procedures for heteroskedasticity and autocorrelation consistent (HAC) covariance estimations have been suggested in the economic literature[37]. The different procedures all correct for the HAC in the sample and aim at increasing the statistical significance of the regression results.

5.1.2 The Newey-West approach

For many data structures it is a reasonable assumption that the autocorrelations should decrease with increasing lags (l) and the vector which is used to correct for HAC (ω) should therefore decrease (Zeiles 2004). Different choices for the vector weights have been suggested in the economic literature[38]. However, the estimators presented by Newey and West (1987) to correct for HAC, have been widely applied in time-series analyses (Cao et al. 2010) since its introduction in 1987.

Newey and West suggested using linearly decaying weights; as the time between error term increases, the correlation between the error terms decreases, expressed with ;

$$\omega = 1 - \frac{l}{L+1}$$

Where L is the maximum lag, all other weights are zero.

[36] Heteroskedasticity occurs when the standard errors of the observations do not have a constant variance. Autocorrelation occurs when the standard errors of the observations correlate, i.e. a positive (negative) error term is expected to be followed by another positive (negative) error term.

[37] See White (1980), MacKinnon and White (1985) and Andrew (1991)

[38] See White and Domowitz (1984) , Newey and West (1987), Andrews (1991) and Lumley and Heagerty (1999)

The Newey-West approach does not change the regression *model*, it only corrects the standard error (and consequently the t-values); The coefficients (beta-values) will remain unchanged after running the regression through a Newey-West filter, but the t-value could be applied with a more statistical certainty.

Deciding the number of lags is difficult as this depends upon the size of the dataset and the degree of HAC. A general rule of thumb (Greene's Econometric Analysis, 5th Edition) is that the number of lags is given as the fourth power of the number of observations.

The Newey-West method was used to correct the dataset for HAC and with 756 observations for each company, five lags were chosen.

5.1.3 Prewhitening filter

In addition, the data was run through a prewhitening filter. This filter helps correct for the autocorrelation in the sample and removes observation regarded as “noise”. The prewhitening filter is a default component in the Newey-West filter in the R package used for the regressions in the paper. A unique model was built to be able to run multiple regressions with a Newey-West filter at the same time, so displaying the observations which were left out by the prewhitening filter, proved difficult.

However, the regression results both with and without the prewhitening filter is displayed in appendix IV and further discussed in section 5.4.

5.2 Regression results

The regressions were done step-wise, starting by only including firm-specific volatility variables. In R2 leverage and daily return were added, in R3 the market volatility variables were added before all macro-variables were included in R4. The results are presented in Table 2.

The first part of the table provides the average coefficients and indicates if they are significant on an average basis. However, it is problematic to conclude on an average basis as companies with relatively large/small t-values could affect the sample’s average. The number of companies where each coefficient came up as significant is therefore added in the second part of the table to yield additional insight on the results.

Table 2. Cross-sectional average coefficients and t-values (in red) for time-series regression analyses of CDS spreads. In all regressions all 181 companies are included. All regressions are with CDS as the dependent variables and the 10 independent variables presented as independent variables. Newey -West (1987) standard error with 5 lags has been used to calculate t-values. Average adjusted R^2 for the four regressions is included and the percentage of companies where the different independent variables came up significant is also showed. The sample period is from Jan. 07 to Dec 2009. Note that the coefficient counts differ; CDS is expressed in basis points, total option volume in blocks of 100 000 while other variables in %.

Cross-sectional averages of regression coefficients and t-values

	R1	**R2**	**R3**	**R4**
Firm-specific variables				
Intercept (CDS)	-91	-591	-570	-587
(t-value)	-2.69	-3.26	-2.57	-3.10
260D historical volatiltiy	1.29	0.37	-0.32	-0.54
(t-value)	1.84	-0.01	-0.49	-0.58
30D, 80% moneyness, implied volatility	3.48	2.24	1.90	1.85
(t-value)	6.91	4.50	3.26	3.41
Additional firm-specific variables				
Leverage		8.96	8.71	8.84
(t-value)		2.57	2.22	2.54
Daily return		0.22	0.32	0.15
(t-value)		0.16	0.28	-0.01
Market volatility variables				
30D historical market volatility			0.80	0.89
(t-value)			0.59	0.72
30D, 80% moneyness, market implied volatility			0.51	0.33
(t-value)			0.32	0.25
Macro variables				
Total option volume				-1.62
(t-value)				-1.02
Market return				-0.05
(t-value)				0.27
BAA - yield				5.97
(t-value)				1.84
10Y swap vs 10-years Treasury yield				-0.21
(t-value)				-0.02
Adjusted R2	73 %	78 %	81 %	82 %
Percentage of t > 1.96 β1 (historical volatility)	41 %	17 %	10 %	14 %
Percentage of t > 1.96 β2 (implied volatility)	96 %	80 %	70 %	73 %
Percentage of t > 1.96 β3 (leverage)		59 %	51 %	56 %
Percentage of t <- 1.96 β4 (daily return)		4 %	7 %	5 %
Percentage of t > 1.96 β5 (hist.market.vol)			22 %	29 %
Percentage of t > 1.96 β6 (market implied vol)			16 %	16 %
Percentage of t > 1.96 β7 (total option vol.)				1 %
Percentage of t < -1.96 β8 (market return)				2 %
Percentage of t > 1.96 β9 (Baa -yield)				54 %
Percentage of t > 1.96 β10 (swap vs. Treasury)				13 %

5.2.1 R1

In R1 the firm-specific volatilities explain 73% of the variation in the CDS spread.

For 172 of the 181 companies (96%), the implied volatility comes up as significant with a t-value > 1.96, while only 78 of the companies (41%) come up with a significant coefficient for the historical volatility coefficient. On an average basis historic volatility (HV) comes up as marginal significant (t-value of 1.84) while implied volatility is highly significant (t-value of 6.91).
It's worth notice that the average IV coefficient is almost three times as large as the HV coefficient (3.48 vs. 1.29) and demonstrates a relative importance of IV when it comes to explaining the CDS spread.

5.2.2 R2

By including *Leverage* and *Daily return* the adjusted R^2 increases to 78%.

The leverage variable comes up as significant on an average basis (t-value of 2.57). However, for 74 companies (41%) in the sample it is not a significant change in the CDS spread when the leverage changes. A positive *Daily return*-coefficient (0.22) is unexpected. This result indicates that a positive daily return results in a *higher* CDS spread, and not a reduced spread, contrary to what one might expect. Even though the coefficient is positive, it is close to zero and not statistical significant, and could therefore be ignored. This is also confirmed on a company specific basis, where only 7 companies (4%) have a significant (negative) correlation between leverage and CDS spread.

The average firm-specific IV coefficient comes up significant (t-value of 4.5) but its impact on the CDS spread is reduced compared to R1 (beta reduced from 6.91 to 4.5). The IV coefficient is significant for 144 companies (80%) in the sample. Surprisingly HV comes up as insignificant with a t-value of -0.01 (and a *positive* HV coefficient). The use of cross-sectional averages results in the t-value and the coefficient differing when it comes to positive / negative numerical value. The insignificancy for HV is also confirmed on a company specific basis, where only 17% companies (31) have a t-value above 1.96.

5.2.3 R3

In the third regression, the market volatility variables are added and the adjusted R^2 increases to 81%.

As for regression 2, firm-specific IV comes up as significant on an average basis (t-value of 3.26) while firm-specific HV still is insignificant (t-value of -0.49). For both IV and HV, the number of companies with t-value above 1.96 is reduced compared to R2.
On an average basis leverage comes up significant (t-value of 2.2), and the impact of the CDS is still sizeable with a coefficient of 8.7. Yet, for almost half of the companies in the sample (49%) no such significant correlation exists.
As in R2, the daily return has an insignificant impact on an average basis, and with only 12 (7%) of the companies being significantly impacted by a negative daily return.

Both market volatilities (IV and HV) have positive coefficients (0.51 and 0.8), but both coefficients come up as insignificant. This suggests that the information content of market level volatilities is subsumed in the firm level volatilities.
However the historical market volatility has a significant impact on the CDS spread for more companies than for market implied volatility; 39 companies (22%) for MHV vs. 29 companies (16%) for MIV.
This suggests that HV relatively to IV is a more important variable on a market basis, than on a firm-specific basis.

5.2.4 R4

Regression 4 is the most exhaustive regression where all the macro variables are included. In this regression the 10 independent variables explain 82% of the variations in the CDS spread.

For 132 of the companies (73%) the IV comes up significant. The average coefficient is 1.85 and the average t-value is 3.41. Again the historical volatility comes up insignificant (t-value of -0.58) on an average basis, and the HV has statistical significant impact on only 26 (14%) of the companies.
Leverage is significant variable for 102 companies (56%) with an average t-value of 2.54 and with an average coefficient of 8.8.
For only 9 companies (5%), the CDS is significantly impacted by a negatively daily return and the daily return is rejected as a significant coefficient on an average basis.

Again, the regression results suggest that the information content of market level volatilities is subsumed in the firm level volatilities; average implied market volatility has a t-value of 0.25 and average historical market volatility a t-value of 0.72.
But as for R3, the number of companies where historical market volatility impacts the CDS spread is higher than for the implied market volatility; 52 companies (29%) for MHV vs. 29 companies (16%) for MIV.

Both total option volume and market return are insignificant on average basis.

Interestingly, the swap spread as proxy for market liquidity also comes up as insignificant. As already discussed, the evaporation of liquidity was one of the reasons behind the government bailout. This may indicate that the liquidity squeeze was isolated to the inter-bank market but reflected upon the equity and credit market in the form of increased fear and not in the form of reduced liquidity. However, it is also likely that the volume proxy applied is an inadequate liquidity proxy incapable of subsuming changes in the market liquidity. This remains an open question.

The yield on corporate bonds expressed through the Baa-yield comes up as marginal significant with an average t-value of 1.84 However, it's worth noting the relatively large impact on the CDS spread when the bond yield changes (coefficient of 5.97). The statistical significant correlation between Baa-yield and CDS spread was found for 98 companies (54%) in the sample.

5.2.5 Summary of findings

Overall, the analysis indicates that the implied volatility of put options explain a significant part of the time-series variations in the CDS spread during times of financial turmoil. The historical volatility only comes up as marginal significant in R1 and is rejected in R2,R3 and R4, while the daily return coefficient is rejected in all regressions where the variable was included. However, it's worth noting that even though the variables are rejected on a combined average basis, there is still some companies where both the HV coefficient and the daily return coefficient has a significant impact on the CDS spread.

Leverage comes up as significant, regardless of the exhaustiveness of the regression, by having an average t-value above 1.96 in R2, R3 and R4. But again, it must be emphasized that this is on an average basis and for several companies no such significance exists.

R2 and R3 suggest that that the information content of market level volatilities is subsumed in the firm level volatilities, and on an average basis the market volatilities were rejected as having significant impact on the CDS spread. Yet, the results indicate that when it comes to market volatility, the historical volatility has a bigger impact on the CDS spread than the implied market volatility.
Finally, market return, total daily option volumes, and the swap spread are neither factors explaining CDS spreads, while the yield on corporate bonds (rated as Baa) is marginal significant for changes in the CDS spread on an average basis.

5.3 Sector Comparison

By examining the second part of Table 2 in more detail, it is revealed that even though coefficients come up as significant on an average basis, there could be a relatively large number of companies where the statistical dependency is not found (see *Leverage* in R4 with an average t-value of 2.56 but where % of t > 1.96 was only 56%). In addition, section 4.3.1 showed how the average CDS spread varied across the different business sectors throughout the sample period. It could therefore be the case that the significance of the variables will depend upon the nature of the industry a company operates in.
This feature was tested for by running the same multivariate regression for each company, but this time by fitting each company to its' corresponding industry. The results are showed in Table 3. As the table contains a lot of information, the variables which came up as significant, are painted in grey and represent the key takeaways from the analysis.

5.3.1 Historical and Implied Volatility

Historical volatility comes up as insignificant on an average basis in all 10 sectors, while all sectors have an average t-value > 1.96 when it comes to the implied volatility. Hence, the results from R1-R4 are confirmed in the sector comparison.

However, it's worth noticing the *Financial Sector* where an increase in the IV will have the largest effect on the CDS spread (coefficient of 4.28) As presented, the *Financial Sector* experienced the biggest surge in the CDS spread after September 2008. The volatility spiked, and this is reflected in a large impact on the CDS spread from a change in the volatility. On the other hand, it is in *the Industrial Sector* where the number of companies with a significant IV coefficient is the highest (90%).

Table 3.Cross-sectional average coefficients and t-values (in red) for time-series regression analyses of CDS spreads split into different business sectors. The brackets indicate # of companies in each sector. All regressions are with CDS as the dependent variables and the 10 variables outlined in section 4 as independent variables. Average adjusted R^2 is included and the percentage of companies where the different independent variables came up significant, is also showed. Newey and West (1987) standard error with five lags has been used to calculate t-values. Observations painted in grey indicate coefficients with t-values of > 1.96. The sample period is from Jan. 07 to Dec 2009. Note that the coefficient counts differ; CDS is expressed in basis points, total option volume in blocks of 100 000 while all other variables are expressed in percentage points.

Sector	CDS	HV	IV	Lev	Return	MHV	MIV	Tot.opt.v	Mreturn	Baa-yield	10Yswap
Consumer Disc. (33)											
Coefficient	-2185	0.77	2.42	28.37	0.01	0.04	0.38	-2.90	-1.02	3.71	-1.27
T-value	-3.70	0.41	3.09	2.92	0.04	-0.77	0.35	-1.02	0.09	1.25	-0.60
Adjusted R2	*84 %*										
Consumer St. (19)											
Coefficient	-146	-0.99	1.15	3.79	-0.40	1.00	-0.36	0.02	-0.01	2.35	0.14
T-value	-3.30	-0.51	4.22	3.70	-1.14	0.48	-0.36	-0.42	0.38	2.18	0.02
Adjusted R2	*77 %*										
Energy (18)											
Coefficient	-143	-0.66	1.52	3.03	0.30	2.61	0.37	-1.51	-0.06	5.72	0.07
T-value	-3.07	-0.73	3.36	1.65	0.55	2.29	0.34	-1.53	-0.11	2.53	0.37
Adjusted R2	*84 %*										
Financials (24)											
Coefficient	-261	-0.08	3.70	3.52	1.74	0.74	-0.56	-1.92	-1.64	11.41	0.12
T-value	-2.38	-0.29	4.28	1.90	0.99	0.39	-0.54	-0.53	-0.49	1.30	0.38
Adjusted R2	*86 %*										
Health (20)											
Coefficient	-107	-1.76	1.22	3.08	0.07	2.25	0.04	-0.83	-0.06	4.38	-0.20
T-value	-2.41	-1.07	3.45	2.58	-0.13	1.40	0.00	-1.15	0.13	2.20	-0.73
Adjusted R2	*76 %*										
Industrials (21)											
Coefficient	-154	-1.71	1.36	3.98	0.00	1.77	-0.12	-1.39	0.48	6.66	-0.04
T-value	-2.43	-1.57	3.11	1.96	-0.02	1.23	-0.05	-1.39	0.48	2.29	-0.33
Adjusted R2	*81 %*										
IT (11)											
Coefficient	-538	1.69	1.02	10.37	-0.59	-4.72	3.72	-2.73	2.44	11.07	-0.23
T-value	-4.78	-0.14	2.13	3.30	-0.49	-0.29	1.72	-1.49	1.25	2.23	0.22
Adjusted R2	*82 %*										
Materials (15)											
Coefficient	-250	-0.87	1.88	5.91	-0.07	-0.08	-0.43	-2.02	0.21	6.18	-0.27
T-value	-4.17	-0.81	3.60	3.43	0.12	0.45	-0.04	-1.50	0.26	2.27	-0.46
Adjusted R2	*84 %*										
Telecom (4)											
Coefficient	-685	5.55	2.19	10.38	-0.43	-12.55	2.53	-3.34	1.80	10.74	1.12
T-value	-5.30	1.15	4.27	4.33	-0.51	-1.38	0.73	-1.90	0.67	2.64	1.96
Adjusted R2	*85 %*										
Utilities (16)											
Coefficient	-295	-2.92	1.01	3.99	-0.28	6.04	1.16	-0.28	1.19	3.21	0.29
T-value	-1.77	-1.59	2.65	1.27	-0.37	2.71	1.72	-0.29	1.18	0.75	1.15
Adjusted R2	*85 %*										
Total (181											
Coefficient	-587	-0.54	1.85	8.84	0.15	0.89	0.33	-1.62	-0.05	5.97	-0.21
T-value	-3.10	-0.58	3.41	2.54	-0.01	0.72	0.25	-1.02	0.27	1.84	-0.02
Adjusted R2	*82 %*										

Percentage of t>1.96 (t<-1.96 for daily returns)

	HV	IV	Lev	Return	MHV	MIV	Tot.opt.v	Mreturn	Baa-yield	10Yswap
Consumer Disc. (33)	24 %	58 %	70 %	3 %	15 %	15 %	0 %	0 %	36 %	15 %
Consumer St. (19)	11 %	79 %	68 %	16 %	21 %	11 %	5 %	5 %	68 %	11 %
Energy (18)	6 %	72 %	28 %	0 %	56 %	17 %	0 %	0 %	83 %	6 %
Financials (24)	13 %	83 %	50 %	4 %	21 %	4 %	0 %	8 %	29 %	13 %
Health (20)	15 %	75 %	45 %	10 %	40 %	10 %	0 %	5 %	60 %	10 %
Industrials (21)	0 %	90 %	48 %	0 %	33 %	0 %	0 %	0 %	67 %	5 %
IT (11)	27 %	45 %	82 %	9 %	0 %	36 %	0 %	0 %	64 %	18 %
Materials (15)	20 %	80 %	80 %	7 %	20 %	13 %	0 %	0 %	73 %	7 %
Telecom (4)	50 %	75 %	100 %	0 %	0 %	25 %	0 %	0 %	50 %	50 %
Utilitites (16)	0 %	69 %	31 %	0 %	63 %	56 %	6 %	0 %	31 %	25 %
Tot (181)	**14 %**	**73 %**	**56 %**	**5 %**	**29 %**	**16 %**	**1 %**	**2 %**	**54 %**	**13 %**

5.3.2 Leverage and Daily return

In section 5 it was concluded that leverage had a significant impact on the CDS spread on an average basis. However, in this analysis, leverage level is insignificant in the *Energy Sector,* the *Financial Sector* and the *Utility Sector.* Interpreting the capital structures variables in the *Financial Sector* and the *Utility Sector* could be difficult. Especially for the *Financial Sector* changes in capital structure could be difficult to detect and the market may respond (reflected in the CDS spread) more slowly than for changes in other sectors, and could explain the results.

The Consumer Discretionary Sector is the most sensitive to leverage changes with a coefficient of 28. Four of the other sectors have leverage coefficients below 6, and the second highest leverage coefficient observed, is 10.38, indicating a relative high importance of leverage in the D*iscretionary Sector* compared to the other sectors.

Market return and firm-specific return are both insignificant variables for all sectors on an average basis and confirms the results from R1-R4.

5.3.3 Market volatility, Baa-yield and 10 Year Swap spread

In R1-R4 it was concluded that the information content of market level volatilities was subsumed in the firm level volatilities. The historical market volatility and the implied market volatility coefficients were therefore rejected as having impact on the CDS spread. In this analysis we see that in *the Utility Sector* and the *Energy Sector,* the historical market volatility has a significant impact on the CDS spread (t-values of 2.71 and 2.29) and contradicts R1-R4. We must therefore be cautious to reject the historical volatility as an insignificant variable on a general basis.

In R4, the Baa-yield was rejected on a 5% significance level (t-value of 1.84).
Another truth is revealed in this analysis where 7 of 10 sectors have a statistical dependency between the bond yield and the CDS spread. This could indicate that the average results presented in R4 are somewhat misleading and that the Baa-yield *does* have impact on the CDS spread.

The Telecom Sector is the only sector where the swap vs. treasury yield has statistical significant impact on the spread. Only 4 companies are included in this sector, and represents only 2% of the total sample. The conclusion from R4 is therefore upheld.

5.3.4 Summary of sector comparison

The findings from R1-R4 are mostly confirmed; historical volatility is rejected in all sectors while implied volatility is the supreme variables for explaining the changes in the CDS spread.
However, leverage as a significant variable is challenged with the CDS spread for 3 of 10 sectors being insignificantly impacted by a leverage change. Interpreting the complex capital structure in these 3 sectors is assumed as the cause for these findings. The conclusion from R2-R4 when it comes to leverage as a significant variable is therefore upheld.
Furthermore, the analyses show that Baa-yield has a significant impact on 7 of 10 industries, indicating a strong relationship between the Baa-yield and the CDS spread. The Baa-yield is therefore added as a third variable explaining the CDS spread.

The tendency of historical market volatility being a more important factor for the CDS spread than implied market volatility is also found in the sector comparison; two sectors with a total of 34 companies had a on an average basis significant correlation between the historical market volatility and the CDS spread while none sectors had a significant impact from changes in the market implied volatility.

Finally, the conclusion from R2-R4 when it comes to daily returns, option volume and the swap rate being insignificantly variables, are upheld after the sector comparison.

5.4 Robustness – are the results reliable?

All data used as input in the analyses are extracted from Bloomberg. As the Bloomberg database is a highly comprehensive database, commonly regarded as the standard bearer for the financial industry, the data extracted have not been tested for flaws and unexplainable outliners, but rather assumed to be correct.

For regression analyses some basic assumptions have to apply for the results to be statistical applicable: 1) the standard error of the error term is constant, 2) the error term is independent for all observations, and 3) the error term is normally distributed.
Since the analyses were based on thousands of firm-specific regressions, analyzing each individual regression would have become vastly time consuming. 10 randomly selected companies were therefore selected and the residual plots were analyzed. For all 10 residual plots, the pattern was the same. The

residual plot for a randomly selected company is shown in appendix IV. The plots indicate positive (right) skewness with long tail to the right. In theory the CDS spread could increase to an infinite number (no upper bond) but could never fall below 0 (lower bond) so a positive skewness is expected. However, the plot indicates more skewed data than expected and could render the analysis' statistical accuracy. In addition the pattern of HAC in the sample is confirmed with non-constant, correlated variances of the error term. This does not bias the regression coefficients, but the standard errors tend to be underestimated and resulting in an overestimation of the t-values. This has been adjusted for through the Newey-West approach (5-lags), and with a prewhitening (PW) filter. Appendix V indicates that the t-values are nearly independent of the number of lags so the decision of using 5 lags in this analysis do not affect the statistically accuracy.
"Pure" OLS regressions (no filter) are compared with regressions using NW and with regressions including both NW and a PW-filter in appendix VI. As expected, the t-values are greatly reduced by including a NW-filter and a PW-filter. As the NW approach is regarded as one of the most effective tools for handling HAC, it is assumed that the assumptions for the regression analysis are met, despite the obvious fact of auto-correlated data with a time varying variance in the sample.

6. Implications

The results of the analyses indicate that part of the paper's hypothesis should be rejected;
On an average basis leverage came up as significant for 7 of 10 industries and as significant on an overall basis. With the $\beta_3 Lev$ being the variable with the largest coefficient (8.84), the analyses proved that the CDS spread is sensitive to changes in the level of leverage. This is contrary to the paper's hypothesis but aligned with previous academic work. The results indicate therefore that the leverage variable is a significant factor for the CDS spread, regardless of the state of the financial markets.

Firm-specific historical volatility was on an average basis rejected as a significant variable, aligned with the hypothesis. This contradicts the findings of Zhang et al. (2006) and Cao et al. (2010).
Cao et al. (2010) conducted similar multivariate regression analyses for the CDS spread for 301 companies from January 2001 to December 2006 and firm-specific historical volatility came up as significant regardless of the exhaustiveness of the regression. In the data set of the analyses conducted by Cao et al., similar instant hikes in the CDS were not experienced and a historical volatility based on a

260 days weighted average was therefore more likely to subsume the more smooth changes in CDS spread.
By rejecting the historical volatility variable, the results confirm the hypothesis on historical volatility being an inadequate variable for explaining the CDS spread during periods of financial turmoil.

When it comes to the variables that *did explain* the CDS spread (in addition to the leverage variable) the results are aligned with Davies and Pugachevsky (2003) when it comes to bond yields. Bond yields were rejected on an average basis in R4, but additional sector analyses challenged this result with 7 of 10 industries being significant affected by changes in bond yields. The paper therefore concludes that the bond yield has significant impact on the CDS spread during financial turmoil.

The variable which turned out as the supreme explanatory factor for the CDS spread was the firm-specific implied volatility. On an average basis implied volatility was significant for all 10 industries and significant regardless of the exhaustiveness of the regression analysis (R1-R4). As the implied volatility was extracted on a daily basis and reflected the de facto risk (volatility) in the market, this finding is not surprising. This finding is also aligned with Cao et al. (2010) and the paper thus concludes that implied volatility explains the CDS spread independent of the state of the financial markets.

Finally, the results of the analyses also motivate further research. The market liquidity proxy came up as insignificant and could indicate: 1) that the liquidity squeeze was isolated to the inter-bank and credit market but reflected upon the derivative market in form of increased fear and not in form of reduced liquidity *or* 2) the volume proxy applied was an inadequate liquidity proxy incapable of subsuming changes in the market liquidity. The paper does not answer this question.
In addition, an interesting observation was done when it came to market specific volatility. The historical market volatility had a more significant impact on the CDS spread than the implied market volatility on an average basis. In addition, the sector comparison showed that two sectors had a significant positive correlation between the CDS spread and the historical market volatility. This is interesting as the conclusion was reversed when it came to firm-specific volatilities with implied volatility being the dominating variable. The paper was unable to explain the rationale behind this finding.

7. Conclusion

In this paper the Credit Default Swap market from 2007 to 2009 has been analyzed. Four market dynamics have been presented to explain the soaring CDS spread in late 2008 and early 2009; 1) *securitization of mortgages*, 2) *flawed credit rating*, 3) *naked bets*, and 4) *lack of Federal oversight,* and motivated a hypothesis that slow-moving credit variables like historical volatility and leverage should yield limited explanation power for the changes in the CDS spread during times of severe financial distress. After multivariate regressions on 140 000 CDS spreads for 181 large-cap companies in the period from January 2007 to December 2009 were run, historical volatility was rejected on an average basis as an explanatory factor for the CDS spread, contrary to previous literature but aligned with the paper's hypothesis. Furthermore, only two variables, *firm-specific implied volatility* and *leverage* had significant impact on an average basis for the CDS spread, partly contradicting the paper's hypothesis, but aligned with previous analyses of the CDS market. After the results were tested for 10 different business sectors, the conclusions were upheld, but the bond yield was included as third statistical significant factor explaining the CDS spread.

The conclusions have yielded new insight on the relationship between historical volatility and the CDS spread during periods of financial turmoil, by rejecting the historical volatility as a significant variable for the CDS spread. However, implied volatility, leverage and Baa-yield having a significant impact on the CDS spread is aligned with previous academic research, and indicate that the determinants for the credit default swap premia remain partly unaffected by the state of the financial markets.

8. Literature

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Appendix I: List of Companies

List of all 181 companies included in the analyses, split by sector.

Company	Sector
AutoZone Inc	Con. Discr.
Block H & R Inc	Con. Discr.
CBS Corp B	Con. Discr.
Darden Restaurants	Con. Discr.
Eastman Kodak Co	Con. Discr.
Expedia	Con. Discr.
Ford Motor	Con. Discr.
Gannett Co.	Con. Discr.
Goodyear Tire & Rubber Co.	Con. Discr.
Hasbro Inc.	Con. Discr.
Home Depot	Con. Discr.
Interpublic Group	Con. Discr.
Johnson Controls	Con. Discr.
Lennar Corp.	Con. Discr.
Limited Brands Inc.	Con. Discr.
Lowe's Cos.	Con. Discr.
Macy's Inc.	Con. Discr.
Marriott Int'l.	Con. Discr.
McDonald's Corp.	Con. Discr.
New York Times Cl. A	Con. Discr.
Newell Rubbermaid Co.	Con. Discr.
Nordstrom	Con. Discr.
Office Depot	Con. Discr.
Penney (J.C.)	Con. Discr.
RadioShack Corp	Con. Discr.
Staples Inc.	Con. Discr.
Target Corp.	Con. Discr.
Time Warner Inc.	Con. Discr.
TJX Inc.	Con. Discr.
V.F. Corp.	Con. Discr.
Viacom Inc.	Con. Discr.
Walt Disney Co.	Con. Discr.
Whirlpool Corp.	Con. Discr.
Campbell Soup Co	Cons. St.
Clorox Co.	Cons. St.
ConAgra Foods Inc.	Cons. St.
Constellation Brands Inc.	Cons. St.
Costco Co.	Cons. St.
CVS Caremark Corp.	Cons. St.
Dean Foods	Cons. St.
General Mills	Cons. St.
Heinz, H.J. Co.	Cons. St.
Hershey Foods Corp.	Cons. St.
Kellogg Co.	Cons. St.
Kimberly-Clark	Cons. St.
Kraft Foods Inc-A	Cons. St.
Kroger Co.	Cons. St.
Procter & Gamble	Cons. St.
Safeway Inc.	Cons. St.
Sara Lee Corp.	Cons. St.
Tyson Foods Inc A	Cons. St.
Wal-Mart Stores	Cons. St.
Apache Corp	Energu
Baker Hughes Inc	Energy
Chevron Corp.	Energy
ConocoPhillips	Energy
Devon Energy Corp.	Energy
Diamond Offshore Drilling	Energy
Exxon Mobil Corp.	Energy
Halliburton Co.	Energy
Hess Corp.	Energy

Company	Sector
Marathon Oil Corp.	Energy
Massey Energy Company	Energy
Murphy Oil	Energy
Nabors Industries Ltd.	Energy
Noble Energy Inc	Energy
Occidental Petroleum	Energy
Peabody Energy	Energy
Pioneer Natural Resources	Energy
Valero Energy Corp.	Energy
ACE Limited	Financials
Allstate Corp	Financials
American Express Co	Financials
American Intl Group Inc	Financials
Aon Corp	Financials
AvalonBay Communities Inc	Financials
Boston Properties Inc	Financials
Capital One Financial	Financials
Chubb Corp.	Financials
Goldman Sachs Group	Financials
Host Hotels & Resorts Inc.	Financials
JP Morgan Chase & Co	Financials
Kimco Realty	Financials
Lincoln National	Financials
Loews Corp.	Financials
Metlife Inc.	Financials
Morgan Stanley	Financials
Prologis	Financials
Prudential Financial	Financials
Simon Property Group	Financials
SLM Corp.	Financials
Unum Group	Financials
Vornado Realty Trust	Financials
XL Group Plc.	Financials
Aetna Inc	Health Care
Allergan Inc	Health Care
AmerisourceBergen Corp	Health Care
Amgen Inc	Health Care
Baxter Intl Inc	Health Care
Bristol-Myers Squibb	Health Care
Cardinal Health Inc.	Health Care
Carnival Corp	Health Care
CIGNA Corp	Health Care
Coventry Health Care Inc.	Health Care
Health Care REIT Inc.	Health Care
Hospira Inc.	Health Care
Johnson & Johnson	Health Care
Lilly (Eli) & Co.	Health Care
McKesson Corp.	Health Care
Medco Health Solutions Inc.	Health Care
Merck & Co.	Health Care
Pfizer Inc.	Health Care
Quest Diagnostics	Health Care
Unitedhealth Group Inc.	Health Care
Caterpillar Inc.	Industrials
Corning Inc.	Industrials
CSX Corp	Industrials
Dover Corp.	Industrials
Emerson Electric	Industrials
FedEx Corp.	Industrials
General Dynamics	Industrials

Company	Sector
General Electric	Industrials
Goodrich Corp.	Industrials
Honeywell Inc.	Industrials
Lockheed Martin Corp.	Industrials
Masco Corp.	Industrials
Norfolk Southern Corp.	Industrials
Pitney-Bowes	Industrials
Raytheon Co.	Industrials
Ryder System Inc.	Industrials
Southwest Airlines Co.	Industrials
Textron Inc.	Industrials
Union Pacific Corp.	Industrials
United Parcel Service Inc B	Industrials
United Technologies Corp.	Industrials
Advanced Micro Devices	IT
Altera Corp	IT
Cisco Systems	IT
Computer Sciences Corp.	IT
Dell Inc.	IT
Hewlett-Packard Co.	IT
Intl Business Machines Corp	IT
Motorola Inc.	IT
Oracle Corp.	IT
Texas Instruments Inc.	IT
Xerox Corp.	IT
Alcoa Inc	Materials
Dow Chemical	Materials
DuPont, E.I. de Nemours	Materials
Eastman Chemical	Materials
Freeport McMoRan Copper & Gold	Materials
Intl Paper Co	Materials
Monsanto Co.	Materials
Newmont Mining Corp. (Hldg. Co.)	Materials
Nucor Corp.	Materials
Owens-Illinois Inc	Materials
Pactiv Corp.	Materials
PPG Industries	Materials
Praxair Inc.	Materials
Sealed Air Corp.	Materials
Weyerhaeuser Co.	Materials
Frontier Communications	Telecom
Qwest Communications Inc.	Telecom
Sprint Nextel Corp.	Telecom
Verizon Communications	Telecom
AES Corp	Utilities
Allegheny Energy Inc	Utilities
American Electric Power	Utilities
Centerpoint Energy	Utilities
CMS Energy Corp	Utilities
Constellation Energy Group	Utilities
DTE Energy Co.	Utilities
Duke Energy Corp.	Utilities
Edison Intl.	Utilities
NRG Energy	Utilities
Pepco Holdings Inc.	Utilities
PPL Corp.	Utilities
Progress Energy Inc.	Utilities
Sempra Energy	Utilities
Wisconsin Energy Corporporation	Utilities
Xcel Energy Inc	Utilities

Appendix II: Global Industry Classification Standard

The Global Industry Classification Standard was applied when dividing the 181 companies into 10 different business sectors. Below is an overview of the different industry groups which is included in the 10 sectors.

Sector	**Industry Groups**
Energy	*Energy*
Materials	*Materials*
Industrials	*Capital Goods* *Commercial & Professional Services* *Transportation*
Consumer Discretionary	*Automobiles and Components* *Consumer Durables and Apparel* *Consumer Services* *Media* *Retailing*
Consumer Staples	*Food & Staples Retailing* *Food, Beverage & Tobacco* *Household & Personal Products*
Health Care	*Health Care Equipment & Services* *Pharmaceuticals, Biotechnology & Life Sciences*
Financials	*Banks* *Diversified Financials* *Insurance* *Real Estate*
Information Technology	*Software & Services* *Technology Hardware & Equipment* *Semiconductors & Semiconductor Equipment*
Telecommunication Services	*Telecommunication Services*
Utilities	*Utilities*

Appendix III: Calculation of total liabilities

For the analysis *Total Liabilities* was defined as

Current Liabilities + Non-Current Liabilities

For Banks, Financial institutions and Insurance underwriters interpreting the capital structure variables could be difficult.
The following formulas was applied;

Banks
Customers' Acceptance and Liabilities
+ Total Deposits
+ ST Borrowings
+ Other ST Borrowings
+ Sec Sold with Repo Arguments
+ Long-term Borrowings
+ Other Long-term Borrowings

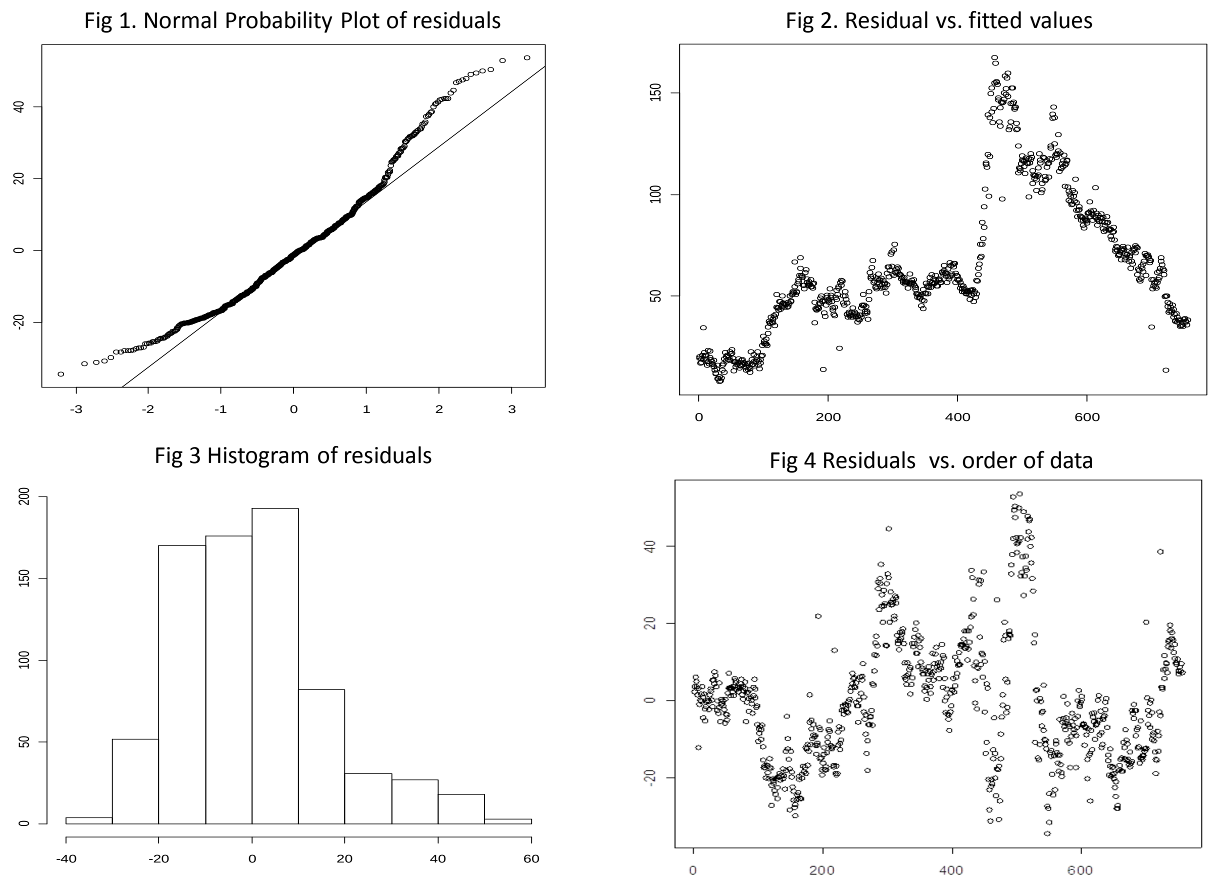
Financials
Total deposits
+ ST Borrowings
+ Other ST borrowings
+ Sec Sold with Repo Agreements
+ Long-term borrowings
+ Other Liabilities

Insurances
Total insurance Reserves
+ Short term Borrowings
+ Current position of Long-term Debt
+ Other Short-term liabilities
+ Long-term Borrowings
+ Other Long-term Liabilities

Appendix IV: Residual plot

A residual plot for a randomly selected company;

Residual plots



If the residuals were normally distributed figure 1 would have been a straight line and the histogram would have showed the traditional Bell curve. This is not the case as the figures indicate positive (right) skewness with long tail to the right. In theory the CDS spread could increase to an infinite number (no upper bond) but could never less than 0 (lower bond) so a positive skewness is expected. However, this plot indicates more skewed data than expected and could render the analysis' statistical accuracy. Figure 2 clearly indicates a sample with heteroskadesicity and figure 4 further confirms the autocorrelation which was assumed present in the dataset. The Newey-West approach (5-lags) and a prewhitening filter have been used to adjust for HAC.

Appendix V: Robustness 1

Table 4. Cross-sectional average coefficients and t-values (in red) for time-series regression analysis of CDS spreads. In all regressions, all 181 companies are included. All regressions are with CDS as the dependent variables and the 10 independent variables presented as independent variables. Newey -West (1987) standard error has been used to calculate t-values. The regression are done with 4 different lags; 0lags, 5lags, 10 lags and 15lags. The sample period is from Jan. 07 to Dec 2009. Note that the coefficient counts differ; CDS is expressed in basis points, total option volume in blocks of 100 000 while other variables in %.

	0lags	5lags	10lag	15lags
Firm-specific variables				
Intercept (CDS)	-587	-587	-587	-587
(t-value)	-2.97	-3.10	-2.91	-2.78
260D historical volatiltiy	-0.54	-0.54	-0.54	-0.54
(t-value)	-0.53	-0.58	-0.53	-0.51
30D, 80% moneyness, implied volatility	1.85	1.85	1.85	1.85
(t-value)	3.31	3.41	3.16	3.02
Additional firm-specific variables				
Leverage	8.84	8.84	8.84	8.84
(t-value)	2.41	2.54	2.41	2.33
Daily return	0.15	0.15	0.15	0.15
(t-value)	0.00	-0.01	-0.01	-0.01
Market volatility variables				
30D historical market volatility	0.89	0.89	0.89	0.89
(t-value)	0.66	0.72	0.66	0.62
30D, 80% moneyness, market implied volatility	0.33	0.33	0.33	0.33
(t-value)	0.26	0.25	0.26	0.27
Macro variables				
Total option volume	-1.62	-1.62	-1.62	-1.62
(t-value)	-1.03	-1.02	-1.00	-1.00
Market return	-0.05	-0.05	-0.05	-0.05
(t-value)	0.25	0.27	0.28	0.29
BAA - yield	5.97	5.97	5.97	5.97
(t-value)	1.83	1.84	1.76	1.71
10Y swap vs 10-years Treasury yield	-0.21	-0.21	-0.21	-0.21
(t-value)	-0.04	-0.02	-0.01	-0.01
Adjusted R2	82.36 %	82.36 %	82.36 %	82.36 %

As we can see from Table 4, the t-values are almost independent of the number of lags. A general rule of thumb was applied (forth power of the number of observations) and 5 lags was used in the analysis. However, changing the number of lags have an insignificant impact on the t-values; i.e. the paper's conclusions are unaffected by the number of lags.

Appendix VI: Robustness 2

Table 5. Cross-sectional average coefficients and t-values (in red) for time-series regression analyses of CDS spreads. In all regressions all 181 companies are included. All regressions are with CDS as the dependent variables and the 10 independent variables presented as independent variables. In *OLS1* no filter has been added and is the result from a "pure" OLS regression. In *OLS2*, Newey -West with five lags *without* a prewhitening filter has been added to calculate t-values. In *OSL3* Newey-West with 5 lags and a prewhitening filter has been added and represent the regression results the paper has applied in the analyses. The sample period is from Jan. 07 to Dec 2009. Note that the coefficient counts differ; CDS is expressed in basis points, total option volume in blocks of 100 000 while other variables in %.

	OLS1	OLS2	OLS3
Firm-specific variables			
Intercept (CDS)	-587	-587	-587
(t-value)	-9.70	-4.86	-3.10
260D historical volatiltiy	-0.54	-0.54	-0.54
(t-value)	-1.74	-0.94	-0.58
30D, 80% moneyness, implied volatility	1.85	1.85	1.85
(t-value)	10.34	4.68	3.41
Additional firm-specific variables			
Leverage	8.84	8.84	8.84
(t-value)	10.14	4.49	2.54
Daily return	0.15	0.15	0.15
(t-value)	0.13	-0.02	-0.01
Market volatility variables			
30D historical market volatility	0.89	0.89	0.89
(t-value)	2.17	1.20	0.72
30D, 80% moneyness, market implied volatility	0.33	0.33	0.33
(t-value)	0.77	0.34	0.25
Macro variables			
Total option volume	-1.62	-1.62	-1.62
(t-value)	-2.31	-1.37	-1.02
Market return	-0.05	-0.05	-0.05
(t-value)	0.28	0.29	0.27
BAA - yield	5.97	5.97	5.97
(t-value)	3.35	2.23	1.84
10Y swap vs 10-years Treasury yield	-0.21	-0.21	-0.21
(t-value)	0.08	-0.01	-0.02
Adjusted R2	82.36 %	82.36 %	82.36 %

Regressions with HAC do not bias the regression coefficients but the standard errors tend to be underestimated and resulting in an overestimation of the t-values and hence the statistical significance of the results. As expected, the t-values are greatly reduced by including a NW-filter and a PW-filter. As the NW approach is regarded as one of the most effective tools for handling HAC, it is assumed that the assumptions for the regression analysis are met, despite the obvious fact of auto-correlated data with a time varying variance in the sample.