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Credit Default Swaps and CreditGrades

Evidence from the Nordic markets

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Abstract

This study examines and compares theoretical CDS spreads created by a structural framework with empirical CDS spreads. The model employed is the CreditGrades model based on the Merton framework from 1974 which calculate default probabilities and credit spreads from balance sheet and equity data. The aim is to measure how well the model can explain the observed CDS spreads and if it has any predictive ability. The model is tested for 22 companies in the Nordic market. Regression analysis is used to measure the explanatory power of the model. It is tested for the period between 2005 and 2009 and for two subperiods, 2005-2007 and 2007-2009.

The model was found to have limited explanatory power with R-square value ranging from 0 to 21 percentages. Even though the explanatory value is low the CDS spreads obtained through CreditGrades are significant for 19 companies during 2005-2009 and 21 companies during 2007-2009. The predictive ability of the model is inconclusive with about a third yielding significant results for the one day lagged model and third of the companies' CDS spreads are significantly autocorrelated with its lagged variable.

The residuals were found to be highly cross-correlated. Principle component analysis reveals that 20-50 % of the variation in the residual can be explained by a systematic component not related to the company specific information. We propose the use of a counterparty risk index. With the inclusion of the index the R-square value is strengthened. The index is significant for 21 companies during the entire sample period and all of the companies during the second half of the sample.

Keywords: CDS spread, Credit default swap, CreditGrades, Credit risk, Structural model, Nordic market.

1. Introduction

The recent financial crises have taught the world at least one new acronym; CDS. A CDS or credit default swap is a financial derivative that help lenders manage credit risk, and as the recent crises have shown it is also a mean of speculating on the financial health of others.

The financial crises originated in the bond market in the middle of 2007. The first classes of bonds affected were mortgage backed securities (MBS), especially those backed by subprime loans i.e. loans to people with poor credit histories. Subprime loans were often packed together in collateralized debt obligations (CDO) which made up the MBS. A CDO is a special purpose entity which is securitized into different risk classed, called tranches. This structure made it attractive to a broad range of investors. Risk adverse actors could invest in the senior tranche, which often was rated with an AAA rating and investors which preferred higher returns, with additional risk, could invest in the equity tranche.

In mid 2007 the first signs of distress were evident, when two prominent hedge funds which had invested heavily in mortgage backed securities were shut down. The primary cause for this was defaulting subprime loans which had deteriorated the credit health of the hedge funds. Further deterioration of the financial system followed when house prices in the US declines and more mortgages defaults, this is further aggravated by cross ownership between different MBS's. This led rating agency to review the credit rating on many of the MBS's leading to downgrades of their rating (BIS, 2008b). During this period the TED (Treasury Eurodollar) spread increased. Taylor and Williams (2009) demonstrates that this can be seen as an increase in counterparty risk in the financial sector which also is apparent from the rise of systematic risk in the financial system during this time period.

During 2008 the crises worsened even more, in March Bear Stearns were bought by JP Morgan Chase in order to avoid bankruptcy. In September Lehman Brothers declares bankruptcy. Both were the result of too large holdings of risky tranches of mortgage backed securities.

One of the most important insurance contracts for debt is the credit default swap contract. A CDS can be seen as a bilateral insurance agreement where the buyer pays the seller periodic fees in return for the contingent claim i.e. depending on whether or not the underlying asset defaults the buyer of the CDS contract have a claim on the seller of the contract. If the underlying asset defaults the seller is obligated to either pay the difference between the bond value and the bond recovery rate to the buyer in a cash settlement or buy the bond at par value in a physical delivery. The price of a credit default swap is usually measured in basis point per annum and is called the CDS spread. One feature that increases the attractiveness of the CDS contract is that the buyer of this type of credit protection does not have to own the underlying asset.

The CDS market offers more than one feature which might have contributed to the crises. The market is highly unregulated and as such it enabled AIG to have large off-balance sheet exposure toward different kinds of credit risk, ultimately causing their decline. AIG had written CDS protection worth $441 billion of which $58 billion were directly tied to subprime mortgages (The Economist, 2008). The insurance giant would probably have defaulted if not for the bailout at the hands of the US government. Since the intervention it has provided AIG with $173 billion in government aid packages, of which $49,5 billion have been passed on to counterparties in CDS transactions (The Economist, 2009).

During the last five years the credit derivatives market has grown dramatically. According to the Bank of International Settlement (BIS 2008a) the size of the CDS market was approximately $57,3 trillion in June 2008 of which single name instruments accounted for $33,3 trillion. Three years prior in December 2005 the CDS market amounted to $13,9 trillion with $10,4 trillion being single-name instruments (BIS 2007). Five years earlier the size of the market was more or less zero.

During 2009 the market size has decreased because of technical issues regarding netting outstanding contracts in a process called compression resulting in a face value of $30 trillion in March (Financial Times, 2009).

Another important factor adding problems are the difficulty of valuing credit default swaps. When insuring a bond an estimation of the credit health of the bond issuer and the seller will have to be made. In addition to this the correlation of default between these parities must be estimated. Since the seller will have to pay out the contingent claim if the lender defaults the seller can make considerable losses and even default themselves in the worse case scenario. This increases the correlation of mutual defaults in the market. Adding to the complexity is that companies wrote insurance not only on regular bonds but also on collateralized debt obligations consisting of hundreds of different mortgages making them very difficult to value.

The subsequent growth of the market combined with the complicated valuation and lack of transparency led market participants to start questioning whether their counterparties could fulfill all their bond protection obligations making investors more prudent investing in new bond issues freezing up necessary capital to firms. This ultimately led to a liquidity crises forcing government to step in with new liquidity to avoid the crises from worsening.

The well known American economist Joseph Stiglitz has summarised the role of credit default swaps in the crises:

> "With this complicated intertwining of bets of great magnitude, no one could be sure of the financial position of anyone else-or even of one's own position. Not surprisingly, the credit markets froze." (Stiglitz, 2009)

1.1 Problem discussion

The research of default probabilities have been around for decades with Altman (1968) and Merton (1974) being two of the most prominent innovators. More elaborate research has been done but the original models have been largely unchanged. As the CDS market increase in value new models to measure the value of these contracts have surfaced. The CreditGrades model is one of these, a structural model based on the Merton framework that utilizes balance sheet data as well as equity market data for calculating theoretical CDS spreads.

The model has been endorsed by some of the largest investment banks as a way to provide free pricing and analysis of credit risk. If a market participant should use to employ this structural model it is important to know how well it functions.

A lot of research has been conducted on the connection between theoretical and empirical CDS pricing. In the beginning of this decade the market for CDS contracts were small so research focused mostly on the relationship between the theoretical credit spreads and the credit spreads of risky debt. Prominent examples are Collin-Dufresne, Goldstein and Martin (2001) who tests the determinants of the credit spreads. Since then the CDS market have increased and in 2007 Fabozzi, Chang and Chen tests which variables determines the price of credit default swaps. Others examined the relationship between theoretical determinants of structural models and market prices, examples being Ericsson, Jacobs and Oviedo (2005) and Alexander and Kaeck (2008). Das, Hanouna and Sarin (2009) extend this research by comparing structural and accounting based models for determining the price of CDS contracts. Byström (2005) is the first who test the CreditGrades model of pricing when he compares the theoretical prices of multi-name CDS spreads with market prices. But the question still remains regarding how well the CreditGrades model estimates single-name CDS spreads and whether or not the financial crises have altered the estimations.

1.2 Purpose

The aim of this paper is to compare empirical single-name CDS spreads with theoretical CDS spreads estimated by CreditGrades to evaluate the performance of the model.

1.3 Disposition

This paper will be presented in three parts. Part one will cover the theoretical background on the subject and present the model that is the basis of the thesis. In part two the methodology, the implementation and the testing of the model will be discussed. In the last part our results will be presented and analysed.

2. Theory

This chapter will first discuss credit risk in a broader perspective and later focus on credit derivatives, especially credit default swaps. After this the methodology for estimating probability of default and how this can be converted into credit default swaps is presented.

2.1 Credit risk

Credit risk is faced by most participants of a society not just banks lending money to its customers. Other examples are the risk adverse investor who buys government bonds or business's who deliver goods on credit. In return for lending money or giving credit the creditor expects a return, the individual investor expects a higher return and the creditor a profitable business. But they also face the risk that the government or the customers will default and as a result not be able to meet their end of the bargain, i.e. repay their debt. In short, credit risk can be defined as the risk that a counterparty will not be able to fulfill its financial obligations.

When lending money the lender is entitled to compensation equal to the risk free rate of return and further compensation for the risk that the borrower will default and thus be unable to repay its debt, i.e. a risk premium. This risk can be expressed as a spread, the credit spread. The credit spread can be seen as the risky component of any debt. For a bond it can be expressed as:

Bond yield = Risk free interest rate + credit spread.

The size of the risk premium is determined by the credit risk exposure faced by the creditors as a result of lending money to the debtor. Credit risk exposure can be divided into three components.

- The likelihood that the counterparty will default.
- The size of the debt to the counterparty.
- The size of the claim recovered if the counterparty defaults.

The likelihood of default can be measured by the default probability as a percentage for a specified time period usually one or five years. The size of the claim recovered is often measured in relation to the size of the original debt as a percentage i.e. the recovery rate.

2.2 Credit derivatives

Credit derivatives are financial instruments which helps creditors to manage their credit risk by transferring the risk to a third party. Many of the credit derivatives do not require that the buyer of the instrument owns the underlying asset which give actors a possibility to speculate on the financial health of others. Examples of credit derivatives are credit default swaps, total return swaps and credit options.

Credit default swaps will be discussed in the next chapter. Total return swaps do not only transfer the credit risk but all economic performance of an asset for another cash flow usually Libor plus or minus a spread. By doing so both the credit risk and the market risk is transferred. Credit options are call or put options on bonds or other related instruments which gives the buyer the right but not the obligation to buy/sell the underlying instrument at a predetermined price (J.P Morgan, 1999).

The market for credit derivatives has grown extensively the last years and is changing the way banks manages credit risk. A credit derivative isolates the credit risk and makes it easy to handle. The rise of these instruments can, according to J.P Morgan (1999), be attributed to some of their strong points:

The companies, whose risk is being transferred, do not need to be a part of the transaction nor do they have to be aware of the transaction. This makes it easy to discretionary handle risk without possible damaging customer relationships.

A credit derivative makes it possible to short sell bank loans by purchasing credit derivatives. This is a position which is very difficult with regular market instruments. This solves the asymmetry in the market and makes arbitrage positions possible.

Since credit derivatives in most cases are off-balance sheet products they offer a lot of flexibility for a participant who wants to hedge or speculate on certain risks. For example it makes it possible to reduce credit risk exposure without removing assets from the balance sheet.

2.2.1 Credit default swaps

The credit default swap originally thought as a way for bondholders to protect against a bond default can also be used for speculation on the creditworthiness of a company. One key difference between a regular insurance policy and a CDS contract is that the buyer of credit protection does not have to own the underlying instrument. Like most derivative instruments credit default swaps can be used for hedging, speculation and arbitrage.

The protection buyer usually pays the CDS spread to the seller quarterly and the seller will reimburse the buyer if the bond defaults during the insured time. Below is an example of how these contracts can be used for hedging.

If a bondholder has $10 Billion worth of bond exposure towards a company with a CDS spread of 200 BPS. The bondholder wants to remove this exposure for five years so it enters into an agreement with a CDS seller of paying $50 million every quarter for five years. In most cases the bond will not default and the company will just pay its quarterly insurance. If the bond would default during the five years the insuree will stop paying its quarterly payments and the seller will reimburse the protection buyer with the par value of the bond of $10 billion. The total cost for the seller will be decided by how much the buyer has already paid in premiums and the recovery rate of the bond.

By not owning the reference entity an investor can speculate on the credit quality of a bond by either buying CDS protection if he believes the company will default or selling protection if he believes the default risk to be smaller than what is implied by the CDS spreads.

Credit default swaps is also used in arbitrage type transactions. These transactions are based on the fact that a negative relationship should be exhibited between a company's CDS spread and its stock price. An improvement in company affairs should lead to an increase in stock price and a decrease in default probability i.e. if the company shares increase in value the CDS spread decreases. If this relationship is weak an arbitrageur can take advantage of mispricing of either of these assets, when the price converge the arbitrager makes a profit. But as Yu (2006) points out the convergence process can take time, and that capital structure arbitrage is far from a textbook example of arbitrage.

Another way for an arbitrageur to profit is to use the relationship between the credit spread of the bond and the CDS spread. The asset swap spread is the difference between the yield of the bond and a risk free rate like the Libor. This can be seen as a measure of the credit risk of a bond in the same way as the CDS spread. This relationship between the credit spread and the CDS spread is called the basis and should be zero as long as counterparty risk is ignored. By taking advantage of these differences in the basis arbitrageurs can make a nearly risk free profit. (Choudhry, 2006)

2.2.2 CDS pricing

Early on the pricing of CDS contracts were very arbitrary. Today the pricing has evolved and it is more quantitative based (Nomura 2004). A typical CDS contract can be divided in two parts, one part that represents the periodic fees from the buyer to the seller. This is referred to as the fixed leg of the cash flow streams. The other part is referred to as the contingent leg and represents the contingent claim the buyer of the CDS has towards the seller. In a future state where the reference entity has defaulted, the seller of the credit protection will have to make a payment to the buyer. If the reference entity defaults the buyer of credit protection will have to pay the premium that has occurred since the last payment. In the following statement this will be disregarded and focus will be on the valuation of the credit default spread.

Theoretically the CDS spread is calculated by setting the present value of the fixed leg equal to the present value of the contingent leg. Duffie (1999) proves that given a no arbitrage argument the CDS spread is the spread over the risk free rate on the underlying asset.

The value of the premium should be equal to the present value of the default loss payment from the seller if the reference entity defaults. The present value is determined upon how much of the value that can be recovered if the reference entity defaults and the probability of that occurring. But consideration must also be taken to the probability that the seller of the CDS contract will default, and to the correlation between the default of the reference entity and the seller.

Structural models provide a methodology to calculate the probability of default and thereby the value of the CDS spread.

2.2 Models for estimating default probability and credit spreads.

Several types of models have been proposed for estimating the default probability and the related credit risk of a company. The three main models are the accounting based model, the structural model and the reduced form model.

The accounting based models first developed in the late 1960's by the likes of Beaver (1966) and Altman (1968). These models rely purely on accounting data in estimating the default probability. The advantages of these models are that they can take several factors into account at the same time and that they are very easy to use. The drawbacks are that the accounting data is at most updated every quarter and therefore might not take recent changes in the market into account. Another disadvantage is that the importance of certain coefficients might change over time making the model inefficient. This demands that the accounting based models be updated on a regular basis.

Structural models are based on the option pricing theories developed by Black and Scholes (1973) and Merton (1974). These use market data in their estimations. They are based on the fact that the shareholders of a company can be seen as having a call option of the firm’s assets with the exercise price equal to the firm’s value of debt. Should the assets be valued below the debt the shareholders will not exercise the option and the firm will default on its loans. An array of different evolved structural models have surfaced with Moody's KMV and CreditGrades as two of the more well known.

Reduced form models assume that default is unexpected. These models are less grounded in economic theory than the structural models. In these models credit prices are used to calculate the credit risk. The credit risk is specified by the occurrence of default and the recovery rate. The first is estimated by a stochastic process and the latter is usually constant. These models are flexible but it can be hard to interpret the performance because of the lack of economic grounding. One of the most well known reduced form model was developed by Hull and White (2000).

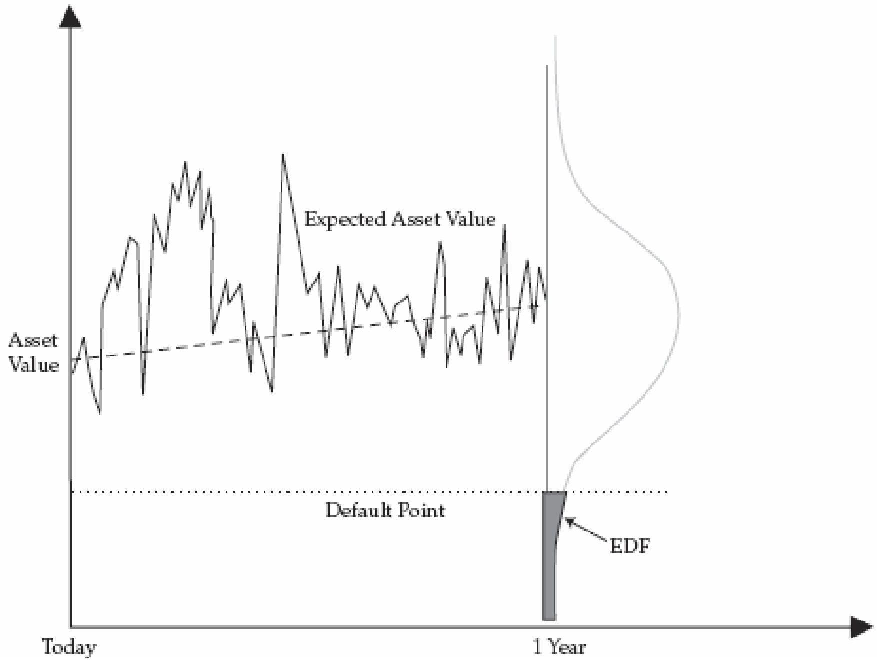
2.3 The Merton model

The Merton model is an option based structural model for estimating a company’s default probability. In his paper from 1974 Merton proves that corporate liabilities can be valued using option pricing theory. In the model the change of firm value can be described with a diffusion type stochastic process with the differential equation (1).

$$dV = (\alpha V - C)dt + \sigma V dz \tag{1}$$

Where:
V is the value of the firm, α is expected return, C is the payments to a shareholder or liability holder, σ is the standard deviation of the firm value and dz is a standard Gauss-Wiener process.

Figure 1. Illustration: Frequency Distribution of Asset Value at Horizon and Probability of Default



Source: Kealhofer, S. (2003), Quantifying Credit Risk I: Default Prediction, *Financial Analysts Journal*, Vol. 59, No. 1: 30-44

According to the framework provided by Merton, equity can be viewed as a call option where the underlying asset is the firm, and the strike price is the value of debt. If the company value drops below the value of the debt, the default point, the company defaults, see figure (1). The value of equity can be modelled using the Black and Scholes formula for a European call option:

$$f(V,\tau) = V\phi(X_1) - Be^{-rt}\phi(x_2) \tag{2}$$

Where:
f (V,t) is the market value of equity, B is the strike price, the value of the debt and Φ is a standard normal cumulative distribution function. X_1 and X_2 is given by equation (3) and (4).

$$x_1 \equiv \frac{\log\left(\frac{V}{B}\right) + \left(r + \frac{1}{2}\sigma^2\right)t}{\sigma\sqrt{t}} \tag{3}$$

$$x_2 \equiv x_1 - \sigma\sqrt{t} \tag{4}$$

Where:
r is the risk rate of interest and σ is the asset volatility.

This can be rewritten as a yield, see equation (5), where *R(τ)* can be seen as the risk premium of the corporate debt i.e. credit spread.

$$R(\tau) - r = \frac{-1}{\tau}\log\left\{\Phi\left(h_2\left(d,\sigma^2,\tau\right)\right) + \frac{1}{d}\Phi\left(h_1\left(d,\sigma^2,\tau\right)\right)\right\} \tag{5}$$

Where:
$h_1\left(d,\sigma^2,\tau\right)$ and $h_2\left(d,\sigma^2,\tau\right)$ is given by equations (6) and (7).

$$h_1\left(d,\sigma^2,\tau\right) \equiv -\frac{\left[\frac{1}{2}\sigma^2 t - \log(d)\right]}{\sigma\sqrt{t}} \tag{6}$$

$$h_2\left(d,\sigma^2,\tau\right) \equiv -\frac{\left[\frac{1}{2}\sigma^2 t + \log(d)\right]}{\sigma\sqrt{t}} \tag{7}$$

Where:
d is given by equation (8).

$$d \equiv \frac{Be^{-rt}}{V} \tag{8}$$

The KMV model, which probably is one of the most famous structural models for valuing default probability, is a development of the Merton model. Instead of using a standard Gauss-wiener process to model the stochastic process they use a historical distribution from earlier defaults. The CreditGrades model is a competing model, free of charge using the same stochastic process as the Merton model. CreditGrades' aim is to provide a model accessible to everyone and thereby creating an industrial standard.

2.3.1 Theoretical Determinants of CDS

The theoretical determinants for valuing CDS contracts used in structural models are, 1.) risk free interest rate, 2.) firm leverage, 3.) volatility.

When the risk free rate increases the value of the CDS spread should decrease because it will decrease the risk adjusted default probability yielding lower CDS spreads.

A higher leverage will result in a higher default probability and thus higher credit spread since the company is moving towards the default barrier. In structural models leverage is seen as amount of debt relative to the total value of the firm. Neither of these can be observed directly, firm value is seen as the sum of equity and debt. Equity value is easily measured by using the current share price, but debt is harder to observe. One should use the default barrier i.e. if firm value hits this point the firm will default. The default barrier often assumed to be the book value of debt (Ericsson, et al (2005), Collin-Dufresne, et al (2001)) but other proxies can be used.

The risk of hitting the default barrier is also influenced by the volatility of the firm, i.e. the CDS spread increases if the volatility increases. Volatility of the firm is not observable but the equity volatility can be used as a proxy. In structural models the asset volatility is estimated using the leverage of the firm and the equity volatility.

2.3.2 Structural models explanatory power according to previous studies

Ericsson, et al (2005) tests the theoretical determinants for single-name CDS spreads using OLS regression. They find all of the theoretical determines to be essential in determining the value of a credit default swap and further conclude that all of the determinants are statistically and economically significant. They find no support for any other common component influencing the value.

Alexander and Kaeck (2008) find support for all the theoretical determinants. But they differ due to the prevailing market conditions. They found the CDS spreads to be extremely sensitive to volatility in turbulent times. In ordinary markets they are more sensitive to stock return.

Byström (2005) examine the correlation between equity and the iTraxx CDS index market. He finds that the stock volatility is correlated with the iTraxx CDS indices. He also finds that the indices are autocorrelated.

Collin-Dufresne, et al (2001) examines changes in credit spreads in relationship to proxies for probability of future default and changes in recovery rate. Using a multi-factor model they find that these proxies explain one quarter of the variations in credit spreads. They also find that almost all of the remaining variation could be explained by a single unidentified factor (using principle components). They concluded that the unidentified factor probably was a result of local supply and demand shocks. This study is based on the credit spreads observed in bond yields. Fabozzi, et al (2007) finds that liquidity is significant in determining the price of a CDS as well.

A more recent study by Das, et al (2009) compare an accounting based model with market based model (Merton, 1974) for calculating CDS spreads. The models perform comparable, although models that use both sources of information outperform single-source models. The authors conclude that accounting data and market information is complementary in valuing CDS spreads.

2.4 CreditGrades

CreditGrades is a structural model based on the framework provided by Merton (1974). As Byström (2005) points out, it is a simplified version of the Merton model which model default probability as a simple function of a.) stock price volatility and b.) the leverage ratio. Simplification has been made in an effort to create a new industrial standard by creating a model that is easy to apply, transparent and yet sophisticated enough to provide good results.

> "The purpose of the credit grades is to establish a robust but simple framework linking the credit and equity markets." (RiskMetrics, 2002, p. 5)

The CreditGrades model calculates a CDS spread using the following variables; stock price, debt per share, asset volatility and the risk free rate. Other parameter needed is the company specific recovery rate, the global recovery rate and the standard deviation of the global recovery rate. In this chapter the general outline of the model and how the variables are defined will be discussed.

Firm value is defined as the sum of the equity value and the financial obligations. Similar to the Merton model the CreditGrades model assumes that the firm value evolves according to a geometrical Brownian process (1).

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt \qquad (1)$$

Where:
Wt is a standard Brownian motion, σ is the volatility of the firm value and μ is the asset drift. The drift term is assumed to be equal to zero. That is because when pricing credit it is the asset drift relative to the default boundary that is meaningful. Therefore the assumption is made that firms will try to maintain a steady leverage level, thus issue more debt or pay dividends in line with the stock drift. To avoid arbitrage the drift term is set to zero.

Default is defined as a future state when the future value of the firm is below the default barrier i.e. it will not be able to meet its financial obligations. Default barrier is defined as the amount of firm assets that remains in case the firm defaults, namely the average recovery rate given default times the debt, L*D. If a large portion of the debt can be recovered the value of the CDS premium is lower and vice versa. The global recovery rate is assumed to follow a log-normal distribution with a mean L and a standard deviation, λ. This is a way of modelling the uncertainties in observing the proper default barrier level. This is one of the prominent improvements of the CreditGrades model over the Merton model, which with its fixed default barrier, creates unrealistic short term credit spreads. These parameters, L and λ, have been calculated by J.P. Morgan (Hu and Lawrence (2000) referenced through Finger (2002), p. 13) using historical data from previous defaults. As a result the model uses fixed parameters for the global recovery rate and the standard deviation of the recovery rate. These are set to 0,5 and 0,3 respectively. Yu (2006) and Byström (2006) uses market data to calculate the implied recovery rate and the implied standard of recovery rate by minimizing the residual between theoretical and empirical CDS spreads.

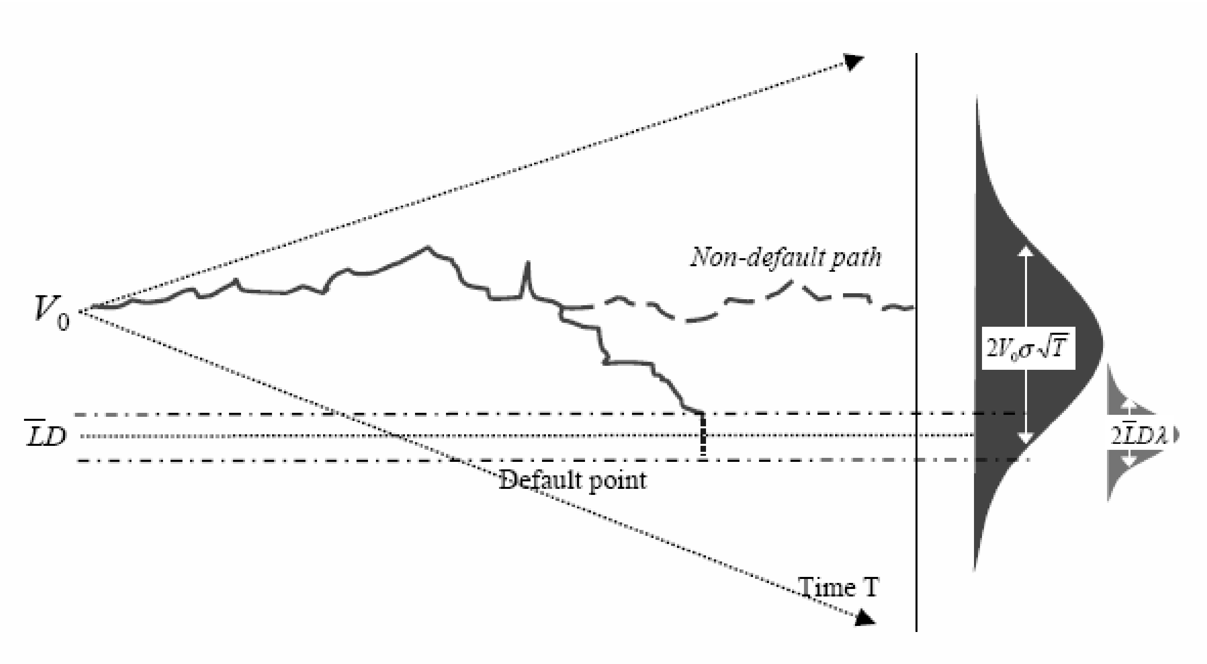


Figure 2: CreditGrades model
Source: CreditGrades technical documents (2002)

Additional variables needed to estimate the value of the credit default swap is the risk free interest rate and the firm specific recovery rate. Riskmetrics use the 5 year Libor rate as a proxy for the risk free interest rate in their empirical testing.

The model has been calibrated for use on industrial companies such as basic industry, automotive, technology, retail, consumer goods and telecommunications. Financial firms like banks are not included because their high leverage will yield theoretical credit spreads much higher than empirical credit spreads. The tighter market spreads can be explained by these firms having a lot of secured liabilities like repurchase agreements. These are included in the leverage calculation giving the firms higher leverage than their real effective ratio. Another factor is that the firms in this industry is overseen by the government and might get supported by them as opposed to a company not seen as crucial for the well being of the financial system. This implies that sovereign credit spreads should be included when looking at financial firms.

The debt per share calculations are a basic formula of taking the interest bearing long term and short term liabilities and adding the non interest bearing liabilities multiplied by 0,5. Accounts payable should not be included because they will not affect the leverage levels. This is known as the financial debt. If a company has minority interests it will be deducted from the financial debt although the deduction is limited to half of the financial debt. In the number of shares calculation the common shares and the preferred shares are included with the limitation of preferred shares to half of the common shares.

The equity volatility is a simple 1000 day historical estimation that according to RiskMetrics (2002) gives robust values for five year CDS spreads. The asset volatility is calculated from the equity volatility as a simple linear approximation of the leverage level.

Below follows a description of the calculations that are necessary for the CreditGrades model taken from the CreditGrades technical document (2002).

Probability of default can be calculated using the CreditGrades framework as specified by equation (2).

$$P(t) = \phi\left(-\frac{A_t}{2} + \frac{\log(d)}{A_t} \right) - d * \phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t} \right) \tag{2}$$

Where:

Φ is a standard brownian motion, At and d is given by equation 3 and 4.

$$A_t^2 = \left(\sigma_s^* \frac{S^*}{S^* + LD} \right)^2 t + \lambda^2 \tag{3}$$

$$d = \frac{S_0 + LD}{LD} e^{\lambda^2} \tag{4}$$

Where:
L is the global recovery rate, D is the debt per share, S_0 is the initial share price, S^* is the reference share, σ_s^* is the volatility of the reference share and λ is the standard deviation of the default barrier denoted in percentages.

When the probability of default is known the spread of the CDS can be calculated, see equation (5).

$$c^* = r(1-R)\frac{1-P(0)+H(t)}{P(0)-P(t)e^{-rt}-H(t)} \tag{5}$$

Where:
P(0) and P(t) is given by equation (2) above and H(t) is given by equation (6) below.

$$H(t) = e^{r\xi}\left(G(t+\xi)-G(\xi)\right) \tag{6}$$

Where:
r is the risk free interest rate, t is time to maturity, G(t) is given by equation (7) and ξ is given by equation (8)

$$G(t) = d^{z+1/2}\phi\left(-\frac{\log(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}\right) + d^{-z+1/2}\phi\left(-\frac{\log(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}\right) \tag{7}$$

$$\xi = \lambda^2 / \sigma^2 \tag{8}$$

$$z = \sqrt{1/4 + 2r/\sigma^2} \tag{9}$$

Where:
Φ is a standard normal cumulative distribution function, σ is the standard deviation of the firm value, λ is the standard deviation of the default barrier, d is given by equation (4) and z is given by equation (8).

2.4.1 CreditGrades explanatory power according to previous studies

Byström (2006) examines the correlation between the CreditGrades and the iTraxx CDS index market. He finds that the CDS market is lagging behind the theoretical CDS spreads obtained through CreditGrades. He also finds that the CDS spreads on the iTraxx index are significantly autocorrelated.

Yu (2006) does not test the explanatory power of the CreditGrades compared to empirical CDS spreads. Instead he uses the model to implement a capital structure arbitrage strategy. The outcome of his strategy yielded attractive results with returns in the same league as those from other fixed income arbitrage strategies. But the weak correlation between the equity and the CDS market resulted in that some trades did not converge resulting in substantial losses.

3. Methodology

The reason CreditGrades is chosen for the study is that it has been proposed by some of the largest investment banks in the world as a new standard for measuring credit risk and very few studies have been done using this model. Yu (2006) conveys that it is the model of choice for professional arbitrageurs.

3.1 Data

The study is limited to companies in the Nordic market. Companies included are limited by the availability of data. The CDS data is collected through Datastream from CMA (Credit Market Analysis Ltd). CMA provides data for about 50 different CDS spreads in the Nordic region. All CDS spread data are mid quote data which is an average value of the bid- and ask quotes. Since we are testing a structural model the underlying asset must be traded, and for us to observe it the firm must be publicly traded. This excludes sovereign states, non-public companies and non-listed companies and limits our sample size to 35 companies.

Credit default swaps are a relatively new feature on the derivative market and therefore the study will be conducted using samples ranging from 1 January 2005 to 31 March 2009. This further limits our sample size to 30 companies. The market CDS spreads for the banks in the sample shows constant values for the first years and they are subsequently excluded from the study. The final sample consists of 22 companies from Sweden, Norway, Denmark and Finland. See Appendix 1 for details on the companies.

To test the robustness of the model a Counterparty risk index is included in the later stages of this study. Data for CDS spreads included is collected from CMA through Datastream.

The stock data is taken from the OMX homepage except for the Norwegian companies which are taken from the homepages of the companies. All debt data are taken from the quarterly reports also found on the company homepages. As a proxy for the risk free interest rate 5 year government bonds from the different countries are used and collected via Datastream.

3.2 The model

The study is based on single-name CDS spreads with five years maturity because it is the most liquid market (Ericsson, Jacobs and Oviedo, 2005). In this study the standard CreditGrades model is applied with debt levels updated every quarter. New data is incorporated the same day as it is released to the market to get an ex ante approach on the study instead of updating the data from the date when it's measured. This results in a lag of about four month before it is updated but ensures that the model is subject to no look ahead bias.

When calculating the historical volatility a 1000 day volatility window is used. The data is adjusted for stock splits and converted into yearly observations using 250 trading days per year. For the leverage calculations non-adjusted stock data is used. Because of the lag in balance sheet data, change in debt level has to be corrected when a split occurs. This is done by adjusting the debt level so that it changes at the date of split.

By dividing the time series into two subperiods a measure of how the CreditGrades model performs in a normal market setting and in a financial crises setting will be obtained. The TED-spread, often used as a measure of the general credit risk of an economy is used to decide which date to divide the time series. The original TED-spread was the difference between US Treasure bills and Eurodollar contracts represented by Libor (Brown and Smith, 2005). We calculate a Swedish TED-spread as the difference between the Swedish 3 month t-bill and the 3 month Stibor rate. This spread spiked up in August of 2007 and therefore the first of August is set to be the first date of the crises time period. The Swedish TED-spread is used because 12 out of the 22 companies in study are from Sweden.

The recent credit crises has driven up the volatility of the equity and CDS market and the performance of the model will be tested by making the model more sensitive to volatility changes. This will be done by decreasing the window of which estimates volatility to 250 days. Theoretical CDS spreads are therefore calculated using both the standard 1000 day volatility window as well as a shorter 250 day window.

The CreditGrades model do not take counterparty risk into consideration when calculating the CDS spreads and therefore no consideration will be made for this factor when testing the strength of the model in the first stage. In a later stage of the study counterparty risk will be incorporated into regressions to test for additional explanatory value.

3.2.1 Autocorrelation

Byström (2006) found the iTraxx CDS spreads to be autocorrelated. He contributed this to be a result of inefficiency in the CDS market. Since autocorrelation can be found in multi-name CDS spreads it is sensible to assume that the results would be the same for the single-name CDS spread. The observed CDS spreads are therefore tested for correlation with one day lagged CDS spreads. Correlation analysis between the dependent variable and the independent variables yield mixed results. The CG model and the CDS spreads exhibit significant correlation for 20 of the 22 companies. The number of significant results drops to 9 when the correlation between the lagged variable is tested against the dependent variable. Finally the lagged CDS returns receive a significant correlation for half of the companies. As the results show some support can be found for autocorrelation in the CDS spreads.

To validate the results above Ljung-Box's autocorrelation test is used. For results see table 3.1. To correct the regression for autocorrelation lagged variables for the empirical as well as the theoretical variable is added to the regression.

Table 3.1. Autocorrelation in empirical and theoretical CDS spread according to Ljung-Box test

	Q5 (CDS)	Q10 (CDS)	Q5 (CG)	Q10 (CG)
Assa Abloy	11.464*	14.329	15.763**	29.449***
Atlas Copco	159.21***	224.83***	0.7707	1.3697
Carlsberg	9.7770	15.595	25.567***	39.730***
Electrolux	21.895***	37.635***	3.8084	6.1989
Ericsson	4.2444	17.586	68.391***	74.238***
Fortum	7.6568	15.728	13.881**	16.438
Investor	37.736***	54.052***	6.6362	21.752*
Metso	5.0502	19.097*	5.0539	6.5157
MREAL	57.125***	58.048***	4.8949	11.412
Nokia	103.40***	105.66***	7.4424	16.470
Norske Skog	12.620*	16.797	6.5984	9.4391
SAS	3.6175	9.6204	6.5411	16.542
SCA	14.741*	22.974*	6.0030	10.174
Scania	6.1973	12.832	5.4185	15.101
Securitas	5.5710	13.383	1.8718	3.2055
Stora Enso	12.101*	24.562**	8.2350	10.825
Swedish match	2.3748	11.431	11.379*	14.843
TDC	19.303*	20.682**	183.44***	183.69***
Telenor	7.8820	13.485	3.7384	8.7262
TeliaSonera	9.7452	12.788	13.099	30.713
UPM Kymmene	19.412**	24.618**	7.8418*	11.554***
Volvo	24.268***	30.702***	14.719*	22.480*
Nr. of significant variables	12	11	8	7

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

3.3 Regression model

Regression analysis will be used to measure the power of the model. The dependent variable will be the log return series of the credit default swap spreads. The independent variables used will be the theoretical CDS spreads from the CreditGrades model as well as the one day lagged variable of the same model. The first term will measure how well the model explains market CDS spreads and the second will show if the model has any predictive ability. Since autocorrelation is present in a majority of the market CDS spreads, empirical lagged variables are included in all regressions. This might inflate the R-square value in regressions that lacks autocorrelation because variables without explanatory power are added to the regression. This effect is offset by using adjusted R-square instead of ordinary R-square values. The regression will be the following:

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta CG_t + \alpha_2 \Delta CG_{t-1} + \alpha_3 \Delta CDS_{t-1} + \varepsilon_t \qquad (1)$$

Where:
α are the regression coefficients, CDS_t is the change in the empirical CDS spreads from *t* to *t-1*, CG_t is the change in theoretical CDS spreads obtained through the CreditGrades model from *t* to *t-1*, CDS_{t-1} and CG_{t-1} are the lagged variables and ε_t is a normally distributed error.

3.4 Diagnostic testing

There are mainly four concerns regarding the consistency and efficiency regarding the regression model in use. Autocorrelation has been handled for independent variables prior to the definition of the regression model. Other than that the model will be tested for hetroskedasticity, normality and multicollinearity. The variables in use will also be tested for stationary.

The time series data is tested for heteroskedasticity using Whites test. The data exhibits significant levels of heteroskedasticity but the problem can be corrected by calculating robust standard errors. To test the regression for autocorrelation the Breusch-Godfrey test is used, which showed significant levels of autocorrelation. To compute robust standard errors in the presence of both heteroskedaticity and autocorrelation the Newey-West heteroskedasticity- and autocorrelation constant estimator (HAC) is used. This will make the statistical inference correct.

Jarque-Berra is used for testing the time-series for normality. The test shows the data is skewed and has excess kurtosis. Non-normality of the data can be a problem, but with the large number of observations it should not be a critical problem for regression analysis according to the central limit theorem.

The independent variables are tested for multicollinearity through correlation analysis. The relatively low correlation results indicate that there is no problem with multicollinearity among the variables.

Since level data, especially financial, is assumed to be non-stationary it is transformed into return series. Panel unit root test is performed on the return series reveals the data is stationary for the entire period as well as the subperiods. Augmented Dickey-Fuller, Phillip-Perron and Levin-Lin-Chu tests are used.

4. Results and analysis

In this section the results of the regressions are presented and analysed. After that a residual analysis is conducted leading up to a new regression where counterparty risk is incorporated.

A visual review of the CDS spread concludes that the CreditGrades model underestimates the CDS spread in most of the series during most of 2005-2006. During the crises period a rapid increase can be observed for CreditGrades model as well as for the observed spreads. For all of the time series spikes in the empirical CDS spreads can be observed in March 2008, the time of JP Morgan Chase’s takeover of Bear Stearns. The same pattern can be observed in September 2008 when Lehman Brothers defaulted. None of these can be seen in the theoretical CDS spreads. For graphs see appendix 2.

4.1 Regression analysis

For each company six regressions are tested. The whole period, the pre-crisis period of January 2005 to July 2007 and the crises period between August 2007 and March 2009. These three regressions are tested for both the 1000 day and the 250 day historical volatility.

As expected the model was significant for almost all companies. The exception being TDC, Nokia and Atlas Copco. The failing results with TDC can be explained with the fact that the company was target of a hostile takeover bid during the period which resulted in a CDS spread affected by input data not driven by fundamental values. That Nokia is non-significant might be explained by its extremely low leverage and subsequently low theoretical CDS spreads in the zero range for long periods. Atlas Copco's CDS spread is peculiar the first year with constant values and later on excessive jumps most likely because of error in the data. This should explain its low significance in the first period.

Table 4.1. Results from OLS regression with 1000 day volatility window

2005-2009	α 0	α 1	α 2	α 3	R2	F-stat	Prob	Ram (1)	Ram (2)
Assa Abloy	0.0019	0.1184***	0.0791***	-0.0853*	0.0280	11.321	0.0000	0.0003	0.0006
Atlas Copco	0.0022	0.0038	0.0023	-0.3396*	0.1129	46.599	0.0000	0.0000	0.0000
Carlsberg	0.0014	0.1462***	0.0982**	-0.0349	0.0399	15.862	0.0000	0.0016	0.0062
Electrolux	0.0008	0.1158**	0.0385	0.1001**	0.0334	13.380	0.0000	0.0067	0.0038
Ericsson	0.0012	0.1414***	0.0421	0.0102	0.0829	33.389	0.0000	0.0201	0.0666
Fortum	0.0009	0.0594*	0.0286	0.0006	0.0083	3.9840	0.0078	0.0042	0.0152
Investor	0.0027	0.1111***	0.0868***	-0.2018***	0.0905	36.672	0.0000	0.2318	0.0412
Metso	0.0012	0.1171***	0.0025*	0.0334	0.0510	20.255	0.0000	0.1148	0.1478
MREAL	0.0018	0.3979***	0.1536*	0.0354	0.0636	25.335	0.0000	0.0506	0.0132
Nokia	0.0018	0.0194	0.0119	-0.2711***	0.0770	30.893	0.0000	0.0011	0.0044
Norske Skog	0.0018	0.2898***	0.0480	0.0045	0.0794	31.886	0.0000	0.5026	0.4399
SAS	0.0005	0.4023***	0.0431	-0.0467	0.0940	38.157	0.0000	0.0000	0.0000
SCA	0.0011	0.1651***	0.0213	0.1033*	0.0679	27.088	0.0000	0.7972	0.4270
Scania	0.0021	0.0499*	0.0630**	-0.0636	0.0298	12.022	0.0000	0.3532	0.1690
Securitas	0.0013	0.1058***	0.0338	-0.0508	0.0190	7.9277	0.0000	0.2507	0.0143
Stora Enso	0.0022	0.1940***	0.0305	0.0631	0.0942	38.245	0.0000	0.0062	0.0023
Swedish match	0.0015	0.0302*	0.0045	-0.0555	0.0071	3.5664	0.0138	0.7050	0.8975
TDC	0.0013	-0.0150	-0.0021	0.0460	-0.0003	0.9085	0.4363	0.0825	0.0038
Telenor	0.0017	0.1216***	-0.0216	0.0219	0.0317	12.315	0.0000	0.9425	0.8927
TeliaSonera	0.0012	0.0484**	-0.0010	0.0572	0.0151	6.4819	0.0002	0.0542	0.0477
UPM Kymmene	0.0017	0.2331***	0.0312	0.0949*	0.1102	45.400	0.0000	0.0278	0.0079
Volvo	0.0019	0.1969***	0.0585*	0.0820	0.0702	28.044	0.0000	0.0004	0.0000
Nr. of significant variables		19	7	7			21	11	15
Average					5,4 %				

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is an intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spreads obtained through CreditGrades model lagged one day α 3 is the change in the observed CDS spreads lagged one day. R2 is the adjusted R-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic. Ram (1) is the result from Ramsey RESET test with 1 fitted term. Ram(2) is the result from Ramsey RESET test with 2 fitted variables.

The other two important regressors measuring predictive ability both have significant p-values for seven of the companies with an overlap for only two resulting in 12 companies with significant predictive ability for the two regressors combined. Whether this ability is strong enough to yield profits in a trading strategy is difficult to tell and extensive testing beyond the scope of this study has to be made. Byström (2006) finds significant predictive ability for the lagged CG model in all of his eight iTraxx indices as well as significance for the lagged CDS spreads in seven of the cases. We can find some support for this, but not as strong as Byström does.

Table 4.2. Results from OLS regression first subperiod with 1000 day volatility window

2005-2007	α 0	α 1	α 2	α 3	R2	F-stat	Prob	Ram (1)	Ram (2)
Assa Abloy	0.0008	0.0521	0.0442	-0.1443**	0.0197	5.3379	0.0012	0.0667	0.0218
Atlas Copco	0.0003	-0.0006	-0.0014	-0.3497**	0.1182	29.850	0.0000	0.0002	0.0001
Carlsberg	-0.0006	0.0382	0.0340	-0.1525*	0.0224	5.8849	0.0006	0.4339	0.0002
Electrolux	0.0005	0.0116	0.0298	-0.0125	-0.0011	0.7554	0.5195	0.0149	0.0511
Ericsson	0.0003	0.0436	0.0571**	-0.0174	0.0093	3.0155	0.0294	0.2221	0.3628
Fortum	0.0007	0.0148	0.0210	-0.2302**	0.0467	11.731	0.0000	0.0064	0.0153
Investor	0.0008	0.0367	0.0647*	-0.3178***	0.1053	26.334	0.0000	0.2568	0.5165
Metso	-0.000521	0.0629**	0.0267	0.0284	0.0093	3.0465	0.0282	0.3646	0.6488
MREAL	0.0024	0.4006***	0.0923	-0.0106	0.0285	7.4261	0.0000	0.7030	0.0059
Nokia	-0.0009	-0.0244	0.0220	-0.4321***	0.1831	50.072	0.0000	0.0011	0.0038
Norske Skog	0.0026	0.2786***	0.0722	-0.0128	0.0536	13.183	0.0000	0.1728	0.0186
SAS	0.0010	0.4531***	0.1191	-0.1134	0.0689	16.940	0.0000	0.6481	0.0033
SCA	0.0011	0.0677**	0.0547*	0.0030	0.0129	3.4574	0.0163	0.6437	0.6523
Scania	0.0010	0.0001	0.0549	-0.2126*	0.0604	14.652	0.0000	0.0010	0.0038
Securitas	0.0004	-0.0092	0.0358	-0.1062	0.0089	2.9007	0.0343	0.7297	0.7212
Stora Enso	0.0034*	0.1987***	0.0991*	-0.0805	0.0540	13.503	0.0000	0.6467	0.0004
Swedish match	0.0010	0.0128	0.0108	-0.1182*	0.0109	3.3830	0.0179	0.1556	0.0254
TDC	0.0026	-0.0220	0.0010	0.0603	-0.0001	0.8981	0.4416	0.1776	0.0044
Telenor	0.0014	0.0384	-0.0107	-0.1007	0.0087	2.8284	0.0378	0.1082	0.0397
TeliaSonera	0.0012	0.0246	0.0019	-0.0347	0.0015	1.3120	0.2695	0.2004	0.4243
UPM Kymmene	0.0024*	0.1156*	0.0658	0.0717	0.0300	7.7710	0.0000	0.0002	0.0008
Volvo	0.0012	0.0529*	0.0652	0.0075	0.0092	2.9630	0.0316	0.1065	0.1183
Nr. of significant variables		8	4	8			19	6	14
Average					3,9%				

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is an intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spreads obtained through CreditGrades model lagged one day α 3 is the change in the observed CDS spreads lagged one day. R2 is the adjusted R-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic. Ram (1) is the result from Ramsey RESET test with 1 fitted term. Ram(2) is the result from Ramsey RESET test with 2 fitted variables

When comparing the two subperiods a large difference between the significance of the CG model is evident. In the first time period (table 4.2) only eight of the companies yield a significant result whether the CG model can explain the changes in CDS spreads. In the second subperiod (table 4.3) the CG model explains the CDS spreads significant in 21 of the 22 cases.

Even with this discrepancy in results the predictive ability of the lagged model is the same in both periods with only four significant results. The CDS spread changes are autocorrelated in about a third of the cases for both periods. Although approximately the same numbers were significant it was not the same companies in the first subperiod as in the second.

Table 4.3. Results from OLS regression second subperiod with 1000 day volatility window

2007-2009	**α 0**	**α 1**	**α 2**	**α 3**	**R2**	**F-stat**	**Prob**	**Ram (1)**	**Ram (2)**
Assa Abloy	0.0020	0.1529***	0.0864**	0.0304	0.0647	10.863	0.0000	0.0479	0.0759
Atlas Copco	0.0015	0.1464***	0.0783**	-0.0327	0.0627	10.543	0.0000	0.2326	0.1439
Carlsberg	0.0015	0.1729***	0.1063*	0.0307	0.0654	10.935	0.0000	0.1530	0.3534
Electrolux	-0.0016	0.4978***	0.0367	0.1558***	0.1683	29.873	0.0000	0.4442	0.4888
Ericsson	0.0014	0.1876***	0.0202	0.0323	0.1493	26.039	0.0000	0.0070	0.0050
Fortum	0.0007	0.0953*	0.033	0.1292*	0.0337	5.8516	0.0006	0.0802	0.0978
Investor	0.0020	0.1534***	0.0824**	-0.0629	0.1177	20.030	0.0000	0.6635	0.6379
Metso	0.0034	0.1458***	-0.0207	0.0497	0.0958	15.731	0.0000	0.0018	0.0076
MREAL	0.0005	0.3957***	0.1711	0.1071	0.1195	19.872	0.0000	0.0779	0.1295
Nokia	0.0041	0.0295	-0.0021	-0.0442	0.0154	3.1712	0.0242	0.0013	0.0039
Norske Skog	0.0007	0.3012***	0.0273	0.0309	0.116	19.719	0.0000	0.2098	0.0025
SAS	0.0005	0.3814***	-0.0122	0.0593	0.1274	21.826	0.0000	0.0001	0.0000
SCA	-0.0004	0.2451***	-0.018	0.2072***	0.1453	25.253	0.0000	0.1103	0.0240
Scania	0.0007	0.2181***	0.0787	0.0591	0.1127	19.000	0.0000	0.0519	0.0052
Securitas	0.0016	0.2251***	0.0110	0.0269	0.0786	13.086	0.0000	0.2146	0.0051
Stora Enso	0.0012	0.1972***	-0.0048	0.1866***	0.1515	25.814	0.0000	0.0716	0.0009
Swedish match	0.0019	0.0573*	-0.0090	-0.0049	0.0116	2.6676	0.0473	0.0433	0.1299
TDC	-0.0011	0.2840*	0.1207	-0.0323	0.0078	2.1131	0.0979	0.4882	0.3691
Telenor	0.0012	0.2227***	-0.0567	0.1269*	0.1026	17.128	0.0000	0.9823	0.9603
TeliaSonera	0.0006	0.0939**	-0.0080	0.1305*	0.0474	8.0487	0.0000	0.3313	0.0038
UPM Kymmene	-0.0006	0.2942***	0.0146	0.1234*	0.1798	31.466	0.0000	0.3858	0.6415
Volvo	0.0006	0.4247***	0.0462	0.1193	0.2124	39.197	0.0000	0.0060	0.0107
Nr. of significant variables		21	4	7			21	6	11
Average					9,9%				

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is an intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spreads obtained through CreditGrades model lagged one day α 3 is the change in the observed CDS spreads lagged one day. R2 is the adjusted R-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic. Ram (1) is the result from Ramsey RESET test with 1 fitted term. Ram(2) is the result from Ramsey RESET test with 2 fitted variables

During the second time both empirical and theoretical CDS spreads were more volatile, this might indicate that the model works better in a volatile environment. This is supported by the findings of Alexander and Kaeck (2008) who finds more explanatory value for their Markow switching model in periods of high volatility.

A hypothesis is that a shorter volatility window should yield better results in the second time period incorporating data faster when the general market volatility is higher. According to the results this hypothesis turned out to be false with the shorter volatility window performing worse for practically all variables and all time periods. A reasonable explanation is that the ghost effect of a rolling window for volatility estimations gets more significant when it is reduced. For results of the regressions see appendix 3.

To measure the goodness of fit for the regressions adjusted R-square is employed which measures how well the regression line estimates the real data. The base case receives an average value of about 5,4 % while the first period performs worse and the second performs better with values of 3,9 % and 9,9 % respectively. As with the results above the shorter volatility window performs worse for all time periods.

The adjusted R-square values are ranging from 0 % to 21 % which is similar to the previous study by Byström (2006). The goodness of fit is usually higher when the determinates of CDS spreads are tested directly with additional variables beyond the structural model framework often yielding even higher R-square values. Ericsson et al (2006) finds R-Square values of about 23 % for the theoretical determinants which increases to about 30 % when four additional variables are included. Alexander and Kaeck (2008) find similar explanatory values for their models ranging from 4 % to 27 %. Determinants tested in level data instead of changes usually obtains much larger explanatory value as seen by Das et al (2009) and Ericsson et al (2006) with R-square values in the 60-70 % range.

4.1.1 Ramsey RESET test

The Ramsey RESET test indicates that many of the regressions are misspecified. This can be the result of the model being misfitted, the improper use of a lagged dependent variable or explanatory variables being omitted. The results indicate that more than half of the regressions are misspecified when either one or two fitted terms are included in the Reset test.

4.2 Residual analysis

An analysis of the residuals reveals a significant correlation between the residuals obtained from the different time series. This can also be seen when examining the covariation between the theoretical and empirical CDS spreads. Almost all the empirical CDS spreads is significantly correlated with each other, while only some of the theoretical CDS spreads are correlated. This seems to indicate that CDS spreads are not only driven by company specific information but by a systematic component shared by the different companies. See appendix 4 for correlations among the residuals.

Table 4.3. Results: Principle components analysis of the residual term obtained through OLS regression (1)

	2005-2009		2005-2007		2007-2009	
	First Component	Second Component	First Component	Second Component	First Component	Second Component
Assa Abloy	0,12	0,33	0,08	0,05	0,19	0,38
Atlas Copco	0,04	0,21	0,01	0,04	0,18	0,38
Carlsberg	0,14	0,30	0,11	0,04	0,14	0,36
Electrolux	0,25	0,05	0,26	-0,02	0,22	-0,05
Ericsson	0,21	0,00	0,23	-0,28	0,20	0,00
Fortum	0,23	0,06	0,15	0,07	0,24	-0,09
Investor	0,16	0,27	0,13	0,16	0,16	0,37
Metso	0,22	-0,21	0,17	-0,34	0,22	-0,09
MREAL	0,17	-0,41	0,17	-0,58	0,16	-0,25
Nokia	0,20	0,23	0,18	0,29	0,21	0,18
Norske Skog	0,21	-0,31	0,26	-0,07	0,20	-0,36
SAS	0,21	-0,05	0,22	0,12	0,19	-0,09
SCA	0,27	0,05	0,28	0,05	0,25	-0,06
Scania	0,24	0,11	0,21	0,12	0,25	-0,03
Securitas	0,22	0,20	0,20	0,32	0,22	0,14
Stora Enso	0,26	-0,28	0,30	-0,06	0,24	-0,21
Swedish match	0,23	0,15	0,19	-0,03	0,23	0,19
TDC	0,17	-0,32	0,21	-0,36	0,21	0,08
Telenor	0,24	0,06	0,25	0,16	0,22	-0,16
TeliaSonera	0,25	0,06	0,26	0,06	0,23	-0,09
UPM Kymmene	0,26	-0,22	0,31	0,06	0,24	-0,20
Volvo	0,25	0,07	0,24	0,19	0,24	-0,09
Explained by PC:	34,6%	5,9%	23,6%	7,0%	47,0%	6,0%

4.2.1 Principal component analysis

To further test the covariation between the residuals principle component analysis is used. For results see table 4.4. The residuals obtained through the regressions shows that one single factor accounts for around 34,6 % of the residual variation with another factor accounting for additional 5,9 %. This shows that the low R-square value is not the result of noise, instead it is a result of a systematic component which the CreditGrades model fails to account for. One variable that can be suggested is counterparty risk, especially during the second subperiod of our survey the counterparty risk has increased substantially.

4.3 Extended regression model

The result from the regressions, the Ramsey RESET test and the residual analysis acknowledge that the model has an explanatory power but it does not explain all of the variability in the CDS spreads. Theoretically the model does not take counterparty risk into account. Other factors accounted for by previous researchers include liquidity in the market, slope of the yield curve, equity returns, business climate and credit rating. Many more have been suggested by other researchers. (Collin-Dufresne et al (2001), Das et al (2009), Ericsson et al (2005).

Counterparty risk is important to acknowledge and a blunt way to do so is to use a credit default swap index of the major CDS dealers. Even though this provide a measure of default probability for the counterparty it does not take default correlation or counterparty exposure toward the underlying asset into account (Segoviano and Singh, 2008). The difficulty with counterparty risk increases when one does not know the future government policy of subsidizing or bailing out the protection sellers as done by the US government with AIG.

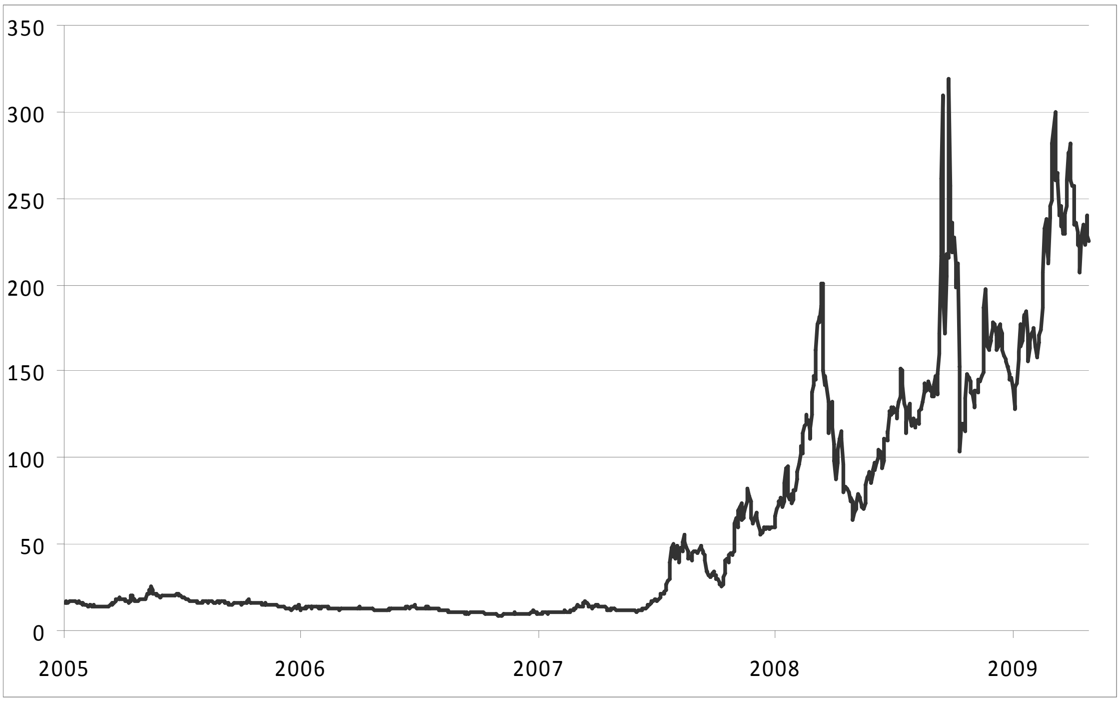


Figure 3: Counterparty risk index

To test whether the CDS spread is affected by counterparty risk, a proxy for counterparty risk is the CDR counterparty risk index (Credit Derivative Research). It was composed of the average CDS spreads for 15 of the largest CDS dealers. Since it was introduced during 2008 Lehman Brothers has been removed due to their default. We creates a similar index for the period 2005-2009, using the average of the CDS spreads for the 13 companies included in CDR's index. Royal Bank of Scotland has been excluded because of them being owned by the government. For a complete review of companies included see appendix 5. As can be seen by the graph the index increase rapidly during the two last years with spikes around the time of the Bear Stearn’s and Lehman Brother’s collapse.

Below is the new regression model that includes the new index variable. For results see table 4.5.

$$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta CG_t + \alpha_2 \Delta CG_{t-1} + \alpha_3 \Delta CDS_{t-1} + \alpha_4 \Delta CRI_t + \varepsilon_t \qquad (2)$$

Where:
α are the regression coefficients, CDS_t is the change in the empirical CDS spread from *t* to *t-1*, CG_t is the change in theoretical CDS spread obtained through the CreditGrades model from *t* to *t-1*, CDS_{t-1} and CG_{t-1} are the lagged variables, CRI_t is change in the counterparty risk index and ε_t is a normally distributed error.

With the index variable included in the regressions the adjusted R-square value increases greatly. The Adjusted R-square for the whole period increases from 5,4 % to 18,6 %, see table 4.6 for results. The first period's values jump from 3,9 % to 10,1 % while the crises period values strengthen from 9,9 % to 29,0 %, see tables 4.7-8 for results. The index is highly significant for all time periods with only a couple of insignificant companies.

The Ramsey Reset test is used with the new variable and indicates mixed results. With one fitted term an improvement is evident for the first period as well as the periods as a whole. With two fitted terms more companies yields significant results. This leads us to interpret the results as inconclusive.

The results overall indicate that counterparty risk is an important factor in explaining CDS spread, but the Ramsey Reset test implies that further components that influences the CDS prices should be included.

Table 4.6. Results: OLS regression with counterparty risk

2005-2009	α 0	α 1	α 2	α 3	α 4	R2	F-stat	Prob	Ram (1)	Ram (2)
Assa Abloy	0.0013	0.0627*	0.0527*	-0.0905*	0.2655***	0.0799	24.334	0.0000	0.4545	0.1828
Atlas Copco	0.0018	0.0021	0.0015	-0.3390**	0.1555	0.1136	35.452	0.0000	0.0000	0.0000
Carlsberg	0.0006*	0.0975**	0.0989	-0.0437	0.2136***	0.0933	28.481	0.0000	0.1121	0.0287
Electrolux	-0.0002	0.0364	0.0257	0.0243	0.4854***	0.2816	104.98	0.0000	0.1858	0.0001
Ericsson	0.0004	0.0913**	0.0403	-0.0030	0.3237***	0.2098	71.573	0.0000	0.6689	0.0005
Fortum	-0.0003	0.0233	0.0262	-0.0266	0.5015***	0.2342	83.183	0.0000	0.0009	0.0001
Investor	0.0019	0.0628**	-0.1895***	0.0717**	0.2832***	0.1369	43.630	0.0000	0.0208	0.0000
Metso	0.0004	0.0642***	-0.0047	0.0106	0.3610***	0.1850	61.992	0.0000	0.1315	0.0360
MREAL	0.0014	0.2596***	0.1205	0.0169	0.2976***	0.1347	42.849	0.0000	0.0175	0.0013
Nokia	0.0009	0.0021	0.0135	-0.2830***	0.3528***	0.1948	66.016	0.0000	0.0141	0.0024
Norske Skog	0.0014	0.2008***	0.0473	-0.0186	0.2592***	0.1595	51.942	0.0000	0.2615	0.0032
SAS	0,0000	0.2787**	0.0528	-0.0645	0.2646***	0.1715	56.635	0.0000	0.0000	0.0000
SCA	0.0004	0.0968***	0.0239	0.0579	0.4033***	0.2536	91.302	0.0000	0.7107	0.0000
Scania	0.0012	0.0009	0.0470*	-0.0774	0.4097***	0.1837	60.820	0.0000	0.8926	0.0035
Securitas	0.0005	0.0443	0.0205	-0.0569	0.3293***	0.1334	41.919	0.0000	0.7169	0.0001
Stora Enso	0.0015	0.1176***	0.0290	0.0135	0.3753***	0.2620	96.434	0.0000	0.5437	0.0000
Swedish match	0.0006	0.0188	0.0053	-0.0768*	0.2992***	0.1661	53.919	0.0000	0.3660	0.0000
TDC	0.0005	-0.0197	0.0005	0.0372	0.2909***	0.0652	19.589	0.0000	0.4518	0.0077
Telenor	0.0006	0.0733**	-0.0133	-0.0371	0.4498***	0.2522	88.452	0.0000	0.9299	0.0000
TeliaSonera	0.0001	0.0200	0.0057	0.0004	0.4477***	0.2589	93.850	0.0000	0.7202	0.0000
UPM Kymmene	0.0009	0.1261***	0.0212	0.0492	0.3910***,	0.2924	112.08	0.0000	0.2669	0.0004
Volvo	0.0012	0.1012	0.0467	0.0422	0.4038***	0.2264	78.774	0.0000	0.5793	0.0000
Nr. of significant variables		12	3	5	21			22	6	21
Average						18,6%				

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is an intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spreads obtained through CreditGrades model lagged one day α 3 is the change in the observed CDS spreads lagged one day. α 4 is the change in counterparty risk index. R2 is the adjusted R-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic. Ram (1) is the result from Ramsey RESET test with 1 fitted term. Ram(2) is the result from Ramsey RESET test with 2 fitted variables

Table 4.7. Results: OLS regression with counterparty risk

2005-2007	α 0	α 1	α 2	α 3	α 4	R2	F-stat	Prob	Ram (1)	Ram (2)
Assa Abloy	0.0005	0.0506	0.0206	-0.1436**	0.1459**	0.0246	5.0655	0.0005	0.0655	0.0405
Atlas Copco	0.0008	-0.0002	0,0000	-0.3516**	-0.3201	0.1186	22.725	0.0000	0.0002	0.0002
Carlsberg	-0.0010	0.0153	0.0240**	-0.1516**	0.1578	0.0401	7.6872	0.0000	0.0302	0.0953
Electrolux	-0.0001	-0.0023	0.0242	-0.0675	0.4147***	0.1306	24.118	0.0000	0.0095	0.0079
Ericsson	-0.0011	0.0068	0.0362*	-0.0569	0.4284***	0.1410	27.135	0.0000	0.0009	0.0039
Fortum	0.0003	0.0110	0.0160	-0.2398**	0.2616**	0.0877	16.783	0.0000	0.0000	0.0000
Investor	-0.0002	0.0164	-0.3193	0.0420***	0.3399***	0.1412	27.548	0.0000	0.5435	0.0024
Metso	-0.0014	0.0400	0.0055	0.0081	0.3283***	0.0677	12.920	0.0000	0.4549	0.1741
MREAL	0.0018	0.3415**	0.0741	-0.0241	0.4382***	0.1022	19.703	0.0000	0.9323	0.2310
Nokia	-0.0015	-0.0282	0.0164	-0.4414***	0.2604**	0.2110	44.915	0.0000	0.0010	0.0024
Norske Skog	0.0021	0.2306**	0.0666	-0.0363	0.3386***	0.1077	20.468	0.0000	0.3084	0.5856
SAS	0.0007	0.4238***	0.1133	-0.1258	0.1326	0.0788	14.808	0.0000	0.0044	0.0002
SCA	0.0012	0.0514	0.0399	-0.0472	0.3579***	0.1007	18.832	0.0000	0.0355	0.1055
Scania	0.0006	-0.0151	0.0426	-0.2135*	0.2253*	0.0798	14.814	0.0000	0.1858	0.0020
Securitas	-0.0001	-0.0263	0.0148	-0.0979	0.3246***	0.0586	10.905	0.0000	0.3100	0.2236
Stora Enso	0.0028*	0.1631***	0.0865*	-0.1268**	0.3482***	0.1437	28.568	0.0000	0.0005	0.0005
Swedish match	0.0003	0.0085	0.0083	-0.1301*	0.2777***	0.0815	15.130	0.0000	0.0165	0.0162
TDC	0.0023	0.0478	0.0152	0.0437	0.1163***	0.0401	7.6973	0.0000	0.3322	0.2597
Telenor	0.0007	0.0259	-0.0335	-0.1213*	0.4135***	0.1056	19.094	0.0000	0.9126	0.8282
TeliaSonera	0.0004	0.0147	-0.0032	-0.0447	0.4684***	0.1344	25.722	0.0000	0.8583	0.7107
UPM Kymmene	0.0018	0.0782*	0.0496	0.0181	0.3669***	0.1463	29.146	0.0000	0.0000	0.0000
Volvo	0.0005	0.0169	0.0296	-0.0231	0.3845***	0.0771	14.295	0.0000	0.7484	0.8469
Nr. of significant variables		5	3	10	19			22	11	12
Average						10,1%				

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is an intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spreads obtained through CreditGrades model lagged one day α 3 is the change in the observed CDS spreads lagged one day. α 4 is the change in counterparty risk index. R2 is the adjusted R-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic. Ram (1) is the result from Ramsey RESET test with 1 fitted term. Ram(2) is the result from Ramsey RESET test with 2 fitted variables

Table 4.8. Results: OLS regression with counterparty risk

2007-2009	α 0	α 1	α 2	α 3	α 4	R2	F-stat	Prob	Ram (1)	Ram (2)
Assa Abloy	0.0018	0.0551	0.0614**	0.0138	0.3107***	0.2185	30.919	0.0000	0.6414	0.0258
Atlas Copco	0.0015	0.05522	0.0667*	-0.047720	0.2796***	0.1761	22.659	0.0000	0.7563	0.2778
Carlsberg	0.0021	0.0537*	0.0454*	0.0447	0.0551***	0.1345	17.552	0.0000	0.5644	0.0525
Electrolux	-0.0011	0.1962	0.0037	0.0904*	0.4653***	0.4036	71.732	0.0000	0.5883	0.0000
Ericsson	0.0007	0.0957**	0.0372	0.0397	0.3077***	0.263	51.311	0.0000	0.3246	0.0030
Fortum	-0.0015	0.0269	0.0339	0.0926**	0.5846***	0.3995	70.359	0.0000	0.0524	0.0001
Investor	0.0022	0.0928***	-0.0378*	0.0659	0.2589***	0.1723	23.279	0.0000	0.2890	0.0461
Metso	0.0030	0.0734*	-0.0165	0.0159	0.3675***	0.2984	45.341	0.0000	0.3544	0.1876
MREAL	0.0006	0.2396**	0.1392	0.0801	0.2449***	0.201	27.224	0.0000	0.0167	0.0092
Nokia	0.0029	0.0072	0.0029	-0.0570	0.3818***	0.2665	38.881	0.0000	0.5597	0.2225
Norske Skog	0.0005	0.1792*	0.0297	0.0049	0.2393***	0.2429	35.328	0.0000	0.2262	0.0009
SAS	0.0001	0.2034*	0.0016	0.0513	0.3269***	0.2927	45.278	0.0000	0.0641	0.0000
SCA	-0.0011	0.1385***	0.0002	0.1408	0.4006***	0.3684	62.983	0.0000	0.7709	0.0000
Scania	0.0001	0.0928**	0.0803	-0.0062	0.4435***	0.3642	62.008	0.0000	0.6768	0.0000
Securitas	0.0008	0.1249***	0.0115	-0.0010	0.3072***	0.2305	32.819	0.0000	0.9611	0.0001
Stora Enso	0.0005	0.1064***	-0.0014	0.1335*	0.3875***	0.3816	65.317	0.0000	0.7728	0.0000
Swedish match	0.0009	0.0352	-0.0021	-0.0352	0.3018***	0.2357	33.767	0.0000	0.7691	0.0000
TDC	-0.0023	0.0823	0.1609	-0.0422	0.2496***	0.193	26.352	0.0000	0.9493	0.0006
Telenor	-0.0003	0.1338***	0.0022	0.0240	0.4459***	0.3874	67.869	0.0000	0.8738	0.0000
TeliaSonera	-0.0008	0.0325	0.0226	0.0335	0.4369***	0.372	63.926	0.0000	0.6990	0.0000
UPM Kymmene	-0.0007	0.1548***	0.0058	0.0807	0.3911***	0.3874	66.919	0.0000	0.7291	0.0000
Volvo	0.0005	0.2507***	0.0712	0.0766	0.3747***	0.3981	71.270	0.0000	0.3553	0.0018
Nr. of significant variables		14	4	3	22			22	1	18
Average						29,0 %				

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is an intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spreads obtained through CreditGrades model lagged one day α 3 is the change in the observed CDS spreads lagged one day. α 4 is the change in counterparty risk index. R2 is the adjusted R-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic. Ram (1) is the result from Ramsey RESET test with 1 fitted term. Ram(2) is the result from Ramsey RESET test with 2 fitted variables

5. Conclusions

The model is found to have limited explanatory power with R-square value ranging from 0 to 21 percentages. But the CreditGrades model is significant in explaining the price of credit default swaps. We also find some support for predictive ability of the model and for autocorrelation within the CDS market. The residual analysis reveals that the model can not explain all the variability in CDS pricing and that there are other systematic factors which drives the CDS spreads. We have suggested that a counterparty risk index can be used to further strengthen the explanatory value. Using regression analysis with counterparty risk included we obtain an explanatory power of 10 to 30 % depending on which time period we look at. We conclude that the model seems to perform better in a high volatility setting and a 1000 day volatility window is more robust than a 250 day window.

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Appendix 1. Companies included in the study.

Table 1. Companies included in the study

Company Name	Country	Industry
Atlas Copco	Sweden	Industrial Machinery
Assa Abloy	Sweden	Building Products
Carlsberg	Denmark	Brewers
Electrolux	Sweden	Household Appliances
Ericsson	Sweden	Communications Equipment
Fortum	Finland	Electric Utilities
Investor	Sweden	Multi-Sector Holdings
Metso	FInland	Industrial Machinery
MREAL	Finland	Paper Products
Nokia	Finland	Communications Equipment
Norske Skog	Norway	Paper Products
SAS	Sweden	Airlines
SCA	Sweden	Paper Products
Scania	Sweden	Construction & Farm Machinery & Heavy Trucks
Securitas	Sweden	Security & Alarm Services
Stora Enso	Finland	Paper Products
Swedish match	Sweden	Tobacco
TDC	Denmark	Integrated Telecommunication Services
Telenor	Norway	Integrated Telecommunication Services
TeliaSonera	Sweden	Integrated Telecommunication Services
UPM Kymmene	Finland	Paper Products
Volvo	Sweden	Construction & Farm Machinery & Heavy Trucks

Appendix 2: Graphs of theoretical and empirical CDS spreads

In this appendix the CDS spreads obtained from the CreditGrades models and the empirical CDS spreads observed on the market is presented. The black line in the graphs is the theoretical CDS spread while the grey line is the empirical CDS spread. CDS spreads are measure in basis points and are presented per company.

Figure 1: Assa Abloy

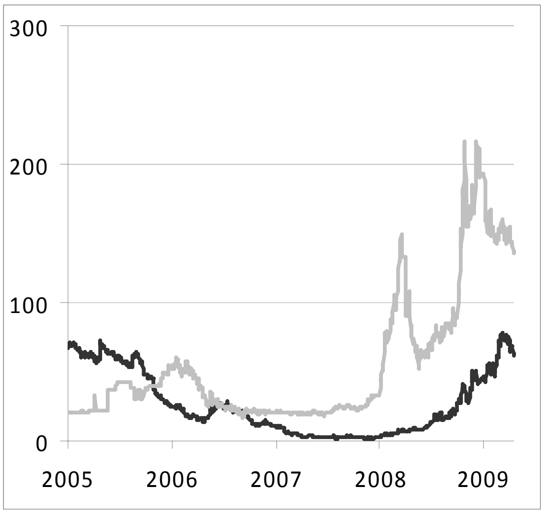


Figure 2: Atlas Copco

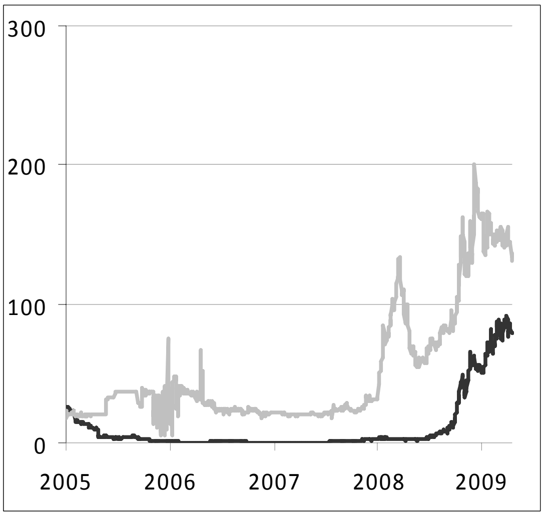


Figure 3: Carlsberg

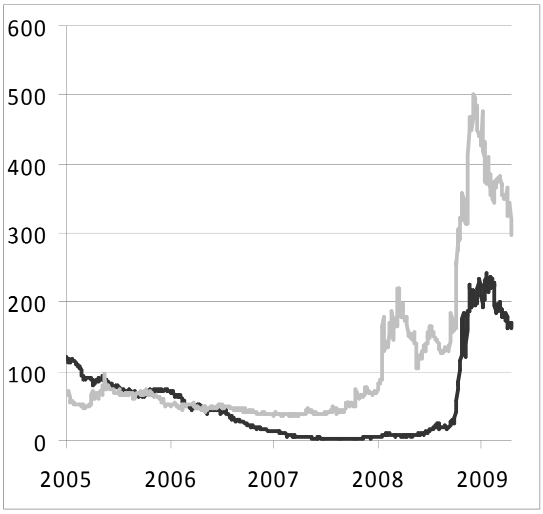


Figure 4: Electrolux

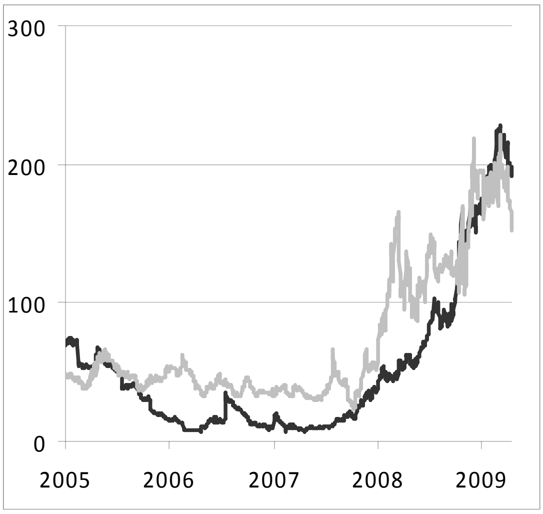


Figure 5: Ericsson

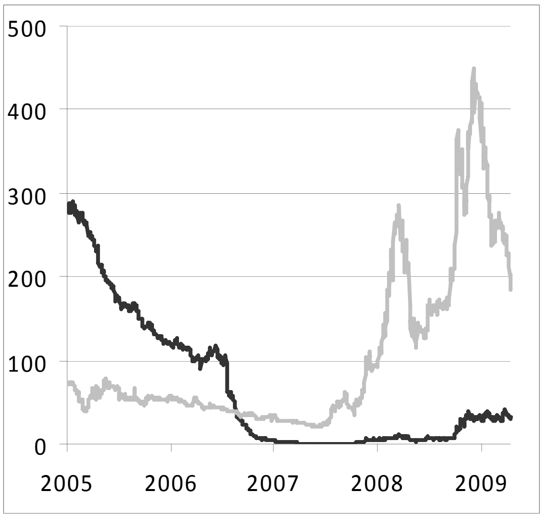


Figure 6: Fortum

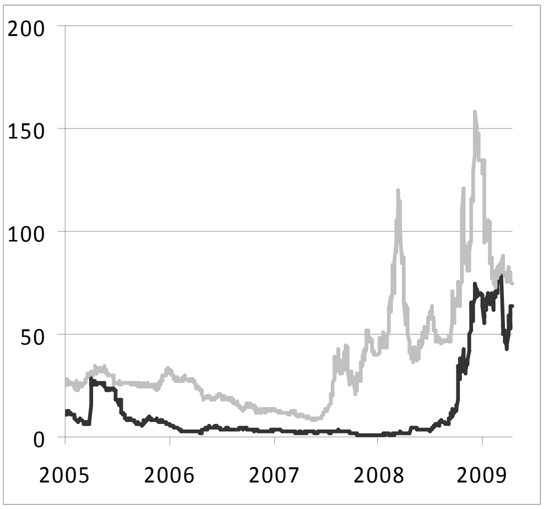


Figure 7: Investor

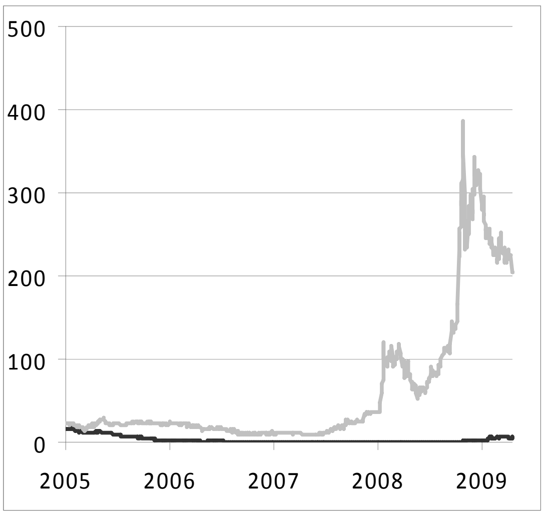


Figure 8: Metso

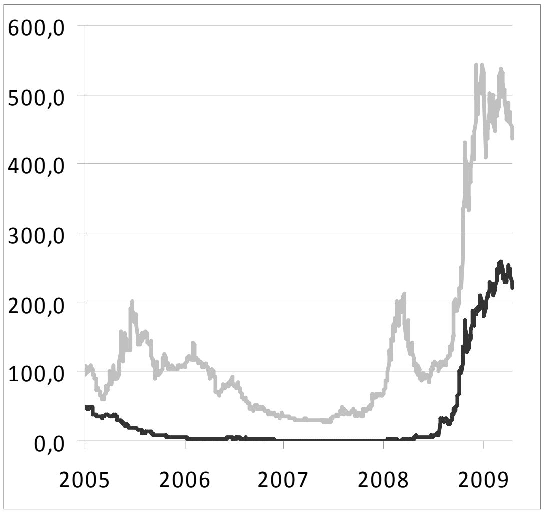


Figure 9: M-Real

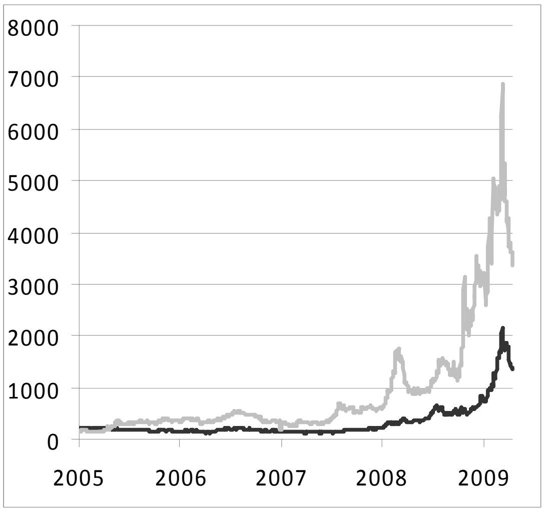


Figure 10:Nokia

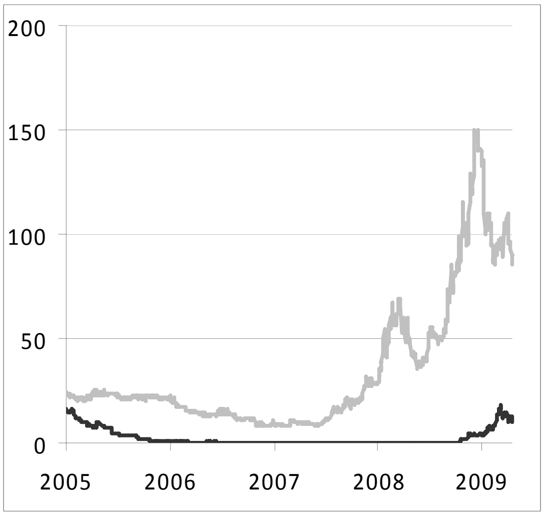


Figure 11: Norske Skog

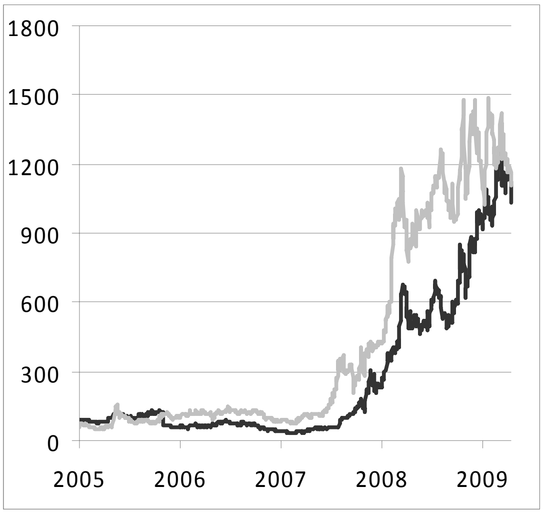


Figure 14: Scania

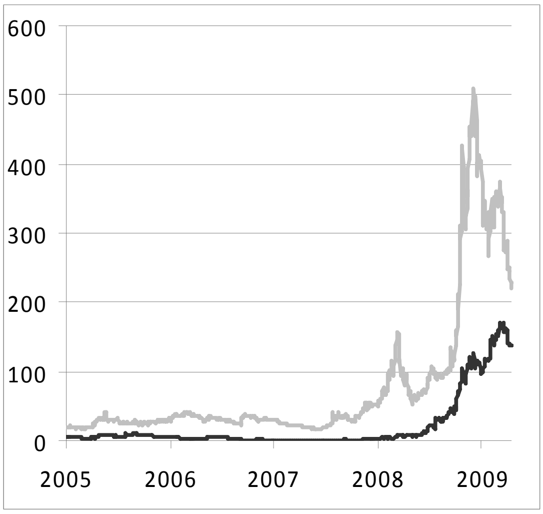


Figure 12: SAS

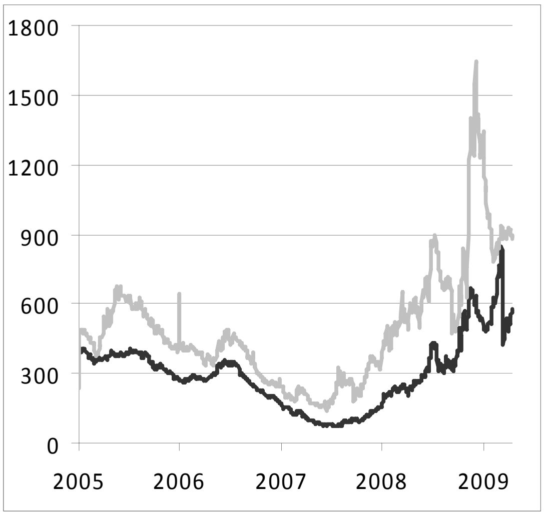


Figure 15: Securitas

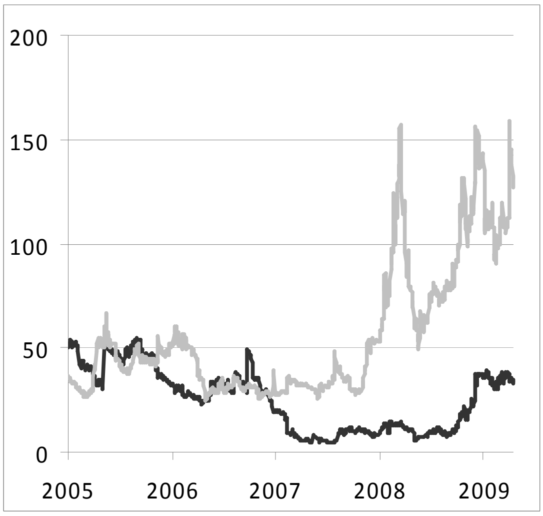


Figure 13: SCA

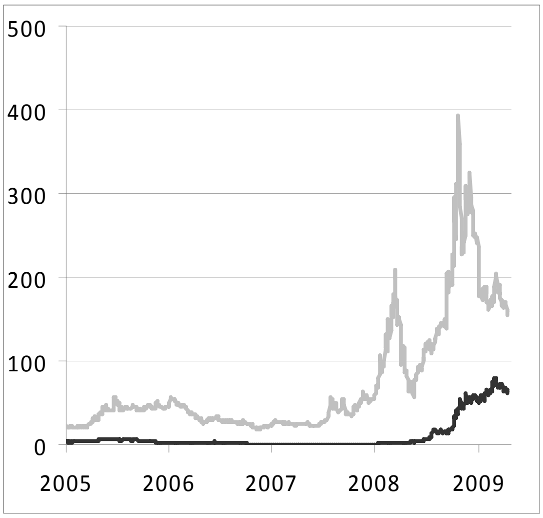


Figure 16: Stora Enso

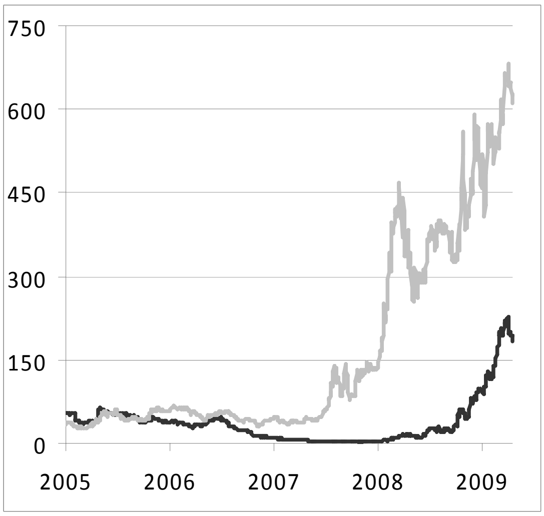


Figure 17: Swedish Match

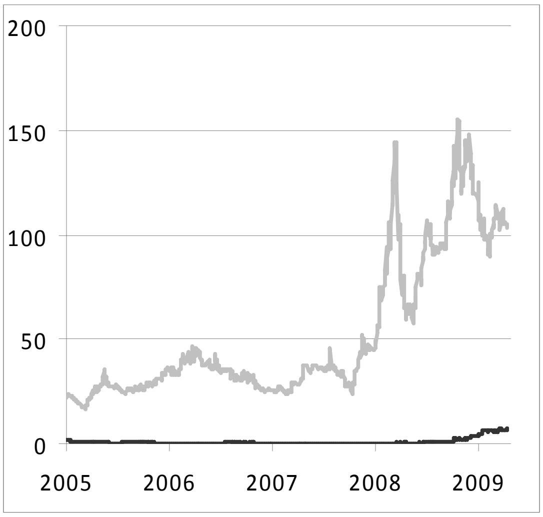


Figure 18: TDC

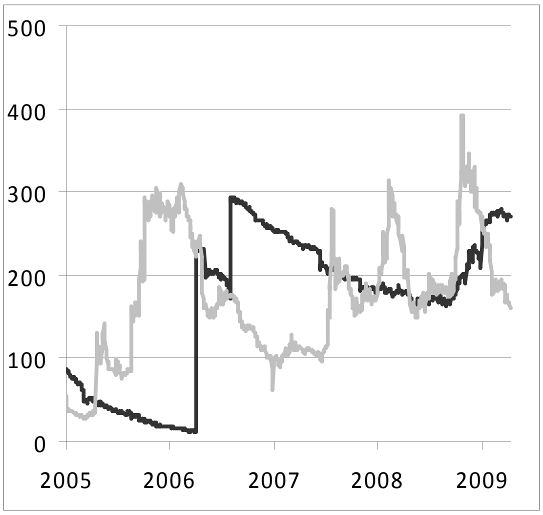


Figure 19: Telenor

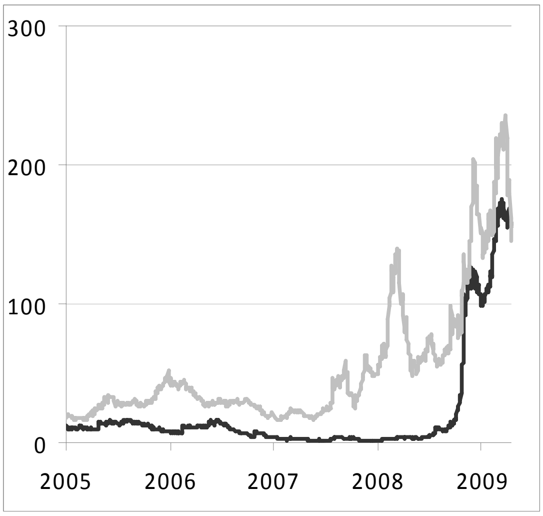


Figure 20: TeliaSonera

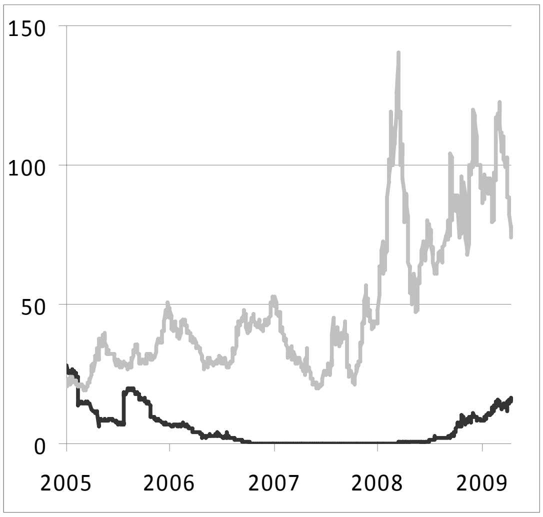


Figure 21: Volvo

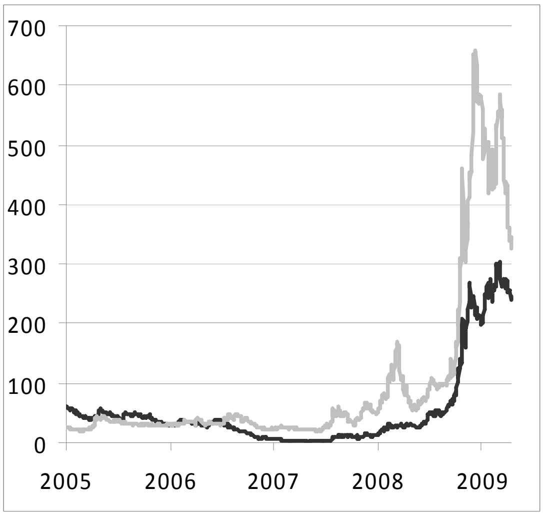
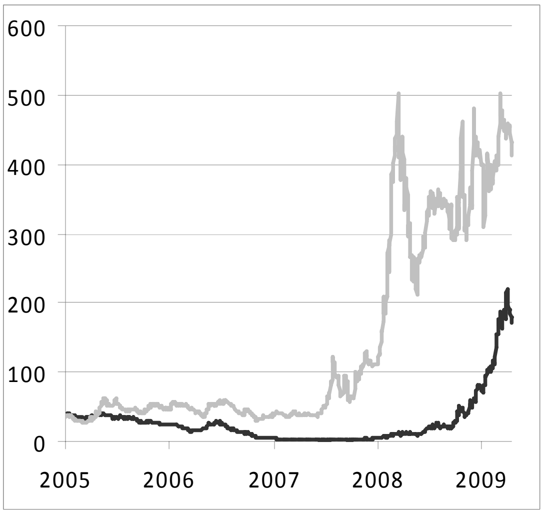


Figure 22 UPM Kymmene



Appendix 3. Results from regression with a 250 days window for volatility estimation.

Table 1. Results: OLS regression for the whole sample, using a 250 days window for volatility estimation.

2005-2009	α 0	α 1	α 2	α 3	R2	F-stat	Prob
Assa Abloy	0.0015	0.0602**	0.0227	-0.0832**	0.0151	6.4769	0.0002
Atlas Copco	0.0022	-0.0004	-0.0001	-0.3396**	0.1128	46.576	0.0000
Carlsberg	0.0011	0.0854*	0.0870*	-0.0254	0.0182	7.6229	0.0000
Elextrolux	0.0008	0.0117	0.0185	0.1090**	0.0114	5.1485	0.0015
Ericsson	0.0008	0.0212**	0.006*	0.0268	0.0144	6.2503	0.0003
Fortum	0.0010	0.0166*	0.0088	0.0030	0.0016	1.5830	0.1918
Investor	0.0019	0.0546**	0.0448**	-0.1896***	0.0557	22.149	0.0000
Metso	0.0012	0.0664***	-0.0151	0.0355	0.0243	9.9238	0.0000
MREAL	0.0022	0.2268**	0.0965*	0.0512	0.0348	13.932	0.0000
Nokia	0.0018	0.0057	0.0018	-0.2692***	0.0723	28.910	0.0000
Norske Skog	0.0016	0.2187***	0.0400	0.0087	0.0594	23.608	0.0000
SAS	0,0000	0.3827***	0.0057	-0.0335	0.0698	27.886	0.0000
SCA	0.0009	0.0838***	0.0119	0.1023*	0.0325	13.041	0.0000
Scania	0.0018	0.0469*	0.0573**	-0.0644	0.0230	9.4246	0.0000
Securitas	0.0011	0.0196	0.0244**	-0.0489	0.0045	2.6242	0.0493
Stora Enso	0.0019	0.1247***	0.0206	0.0699	0.0594	23.630	0.0000
Swedish match	0.0014	0.0113	0.0015	-0.0539	0.0022	1.7902	0.1473
TDC	0.0013	0.0019	-0.0032	0.0450	-0.0005	0.8187	0.4836
Telenor	0.0016	0.0594**	-0.0197	0.0255	0.0138	5.8364	0.0006
TeliaSonera	0.0010	0.0201**	-0.0076	0.0610	0.0094	4.3832	0.0045
UPM Kymmene	0.0015	0.1387***	-0.0005	0.1009***	0.0665	26.541	0.0000
Volvo	0.0017	0.0811**	0.0499	0.0947*	0.0311	12.501	0.0000
Nr. of significant variables		16	6	8			19
Average					3,3%		

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is a intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spread obtained through CreditGrades model lagged one day, α 3 is the change in the observed CDS spread lagged one day. R2 is the adjusted r-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic.

Table 2. Results: OLS regression for the both subperiods, using a 250 days window for volatility estimation.

2005-2007	**α 0**	**α 1**	**α 2**	**α 3**	**R2**	**F-stat**	**Prob**
Assa Abloy	0.0003	0.0365	0.0094	-0.1449**	0.0207	5.5604	0.0009
Atlas Copco	0.0003	-0.0036	-0.0035	-0.3497**	0.1182	29.863	0.0000
Carlsberg	-0.0005	-0.0012	0.0316	-0.1492*	0.0199	5.3700	0.0012
Electrolux	0.0003	-0.0086	0.0183	-0.0105	0.0005	1.1155	0.3421
Ericsson	-0.0006	0.0161*	0.0022	-0.0224	0.0080	1.7334	0.1589
Fortum	0.0007	0.0068	0.0097*	-0.2313**	0.0482	12.090	0.0000
Investor	-0.0002	0.0183	0.0243	-0.3168***	0.1005	25.055	0.0000
Metso	-0.0011	0.0255	-0.0020	0.0339	0.0017	1.3761	0.2490
MREAL	0.0022	0.1368*	0.0352	-0.0023	0.0089	2.9674	0.0314
Nokia	-0.0009	0,0000	-0.0009	-0.4305***	0.1784	48.568	0.0000
Norske Skog	0.0022	0.1754*	0.0437	-0.0138	0.0480	11.843	0.0000
SAS	0,0000	0.2871***	0.0292	-0.1071	0.0549	13.516	0.0000
SCA	0.0011	0.0395**	0.0324**	-0.0230	0.0137	3.9914	0.0078
Scania	0.0008	0.0240	0.0501*	-0.2203**	0.0605	14.877	0.0000
Securitas	0.0004	0.0031	0.0193*	-0.1049	0.0104	3.2625	0.0211
Stora Enso	0.0023	0.0840***	0.0266	-0.0652	0.03609	9.2004	0.0000
Swedish match	0.0009	0.0061	0.0026	-0.1175*	0.0096	3.0953	0.0264
TDC	0.0026	-0.0007	-0.0029	0.0607	-0.0007	0.8432	0.4705
Telenor	0.0013	0.0173	-0.0085	-0.0991	0.0070	2.4503	0.0626
TeliaSonera	0.0009	0.0137	-0.0052	-0.0336	0.0035	1.7600	0.1536
UPM Kymmene	0.0019	0.0865***	0.0117	0.0711	0.0427	10.766	0.0000
Volvo	0.0010	0.0239	0.0501	0.0031	0.0084	2.8337	0.0375
Nr. of significant variables		7	4	8			17
Average					3,6%		

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is a intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spread obtained through CreditGrades model lagged one day, α 3 is the change in the observed CDS spread lagged one day. R2 is the adjusted r-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic.

Table 3. Results: OLS regression for the both subperiods, using a 250 days window for volatility estimation.

2007-2009	α 0	α 1	α 2	α 3	R2	F-stat	Prob
Assa Abloy	0.0015	0.1179***	0.0569*	0.0358	0.0316	5.6626	0.0008
Atlas Copco	0.0010	0.1134**	0.0922**	-0.0274	0.0284	5.1754	0.0016
Carlsberg	0.0004	0.1695**	0.1182	0.0341	0.0437	7.4860	0.0001
Electrolux	0,0000	0.3967*	-0.0087	0.2009***	0.0876	14.702	0.0000
Ericsson	0.0022	0.0209	0.0077	0.0606	0.0181	3.5282	0.0150
Fortum	0.0003	0.0569	0.0062	0.1372*	0.0247	4.5172	0.0039
Investor	0.0008	0.1435***	0.0837*	-0.0594	0.0805	13.495	0.0000
Metso	0.0035	0.1532***	-0.0661*	0.0636	0.0832	13.619	0.0000
MREAL	-0.0005	0.4693***	0.2661**	0.1023	0.1199	19.932	0.0000
Nokia	0.0035	0.0250	-0.0004	-0.0380	0.0103	2.4465	0.0634
Norske Skog	-0.0002	0.3874*	0.0206	0.0398	0.1020	16.083	0.0000
SAS	-0.0009	0.5039***	-0.0493	0.0826	0.1072	18.130	0.0000
SCA	0.0000	0.2303***	-0.0755	0.2080***	0.0973	16.374	0.0000
Scania	0.0012	0.2751***	0.0781	0.0738	0.0799	13.396	0.0000
Securitas	0.0010*	0.1520	0.0067	0.0295	0.0315	5.6369	0.0009
Stora Enso	0.0002	0.2057***	0.0020	0.1839***	0.1192	19.805	0.0000
Swedish match	0.0018	0.0560*	-0.0148	-0.0021	0.0032	1.4576	0.2256
TDC	-0.0011	0.0428*	0.0005	-0.0312	-0.0003	0.9632	0.4100
Telenor	0.0016	0.1822***	-0.0752	0.1325*	0.0798	13.222	0.0000
TeliaSonera	0.0008	0.0769*	-0.0202	0.1346*	0.0372	6.5139	0.0003
UPM Kymmene	-0.0011	0.2651***	-0.0378	0.1246**	0.1093	18.105	0.0000
Volvo	-0.0011	0.4867***	0.1154	0.1244	0.1521	26.598	0.0000
Nr. of significant variables		18	5	7			19
Average					6,6%		

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Notes: α 0 is a intercept. α 1 is the change in theoretical CDS spreads obtained through the CreditGrades model, α 2 is the change in CDS spread obtained through CreditGrades model lagged one day, α 3 is the change in the observed CDS spread lagged one day. R2 is the adjusted r-square value for the regression. F-stat is the f-statistic of the regression model. Prob, is the p-value of the f-statistic.

Appendix 4. Cross-correlation between the residual obtained from OLS regression (1).

Table 1. Results: Cross-correlation between the residuals obtained through OLS 1.

2005-2009	AC	AA	CAR	ERIC	ELUX	FORT	INV	MET	MRE	NOK	NS	SAS	SCA	SCAN	SEC	SE	SM	TDC	TEN	TS	UPM	V
Atlas Copco (AC)	1,00																					
Assa Abloy (AA)	0,14***	1,00																				
Carlberg (CAR)	0,06*	0,14***	1,00																			
Ericsson (ERIC)	0,03	0,18***	0,17***	1,00																		
Electrulux (ELUX)	0,08*	0,24***	0,24***	0,39***	1,00																	
Fortum (FORT)	0,09**	0,22***	0,25***	0,32***	0,39***	1,00																
Investor (INV)	0,02	0,2***	0,25***	0,23***	0,24***	0,24***	1,00															
Metso (MET)	0,06	0,14***	0,17***	0,37***	0,36***	0,33***	0,23***	1,00														
M-Real (MRE)	0,03	0,11***	0,13***	0,31***	0,29***	0,26***	0,15***	0,38***	1,00													
Nokia (NOK)	0,09**	0,21***	0,22***	0,32***	0,31***	0,33***	0,29***	0,27***	0,16***	1,00												
Norska Skog (NS)	0,06	0,08***	0,17***	0,28***	0,35***	0,33***	0,14***	0,31***	0,33***	0,27***	1,00											
SAS	0,02	0,16***	0,2***	0,29***	0,37***	0,30***	0,21***	0,3***	0,22***	0,30***	0,34***	1,00										
SCA	0,08**	0,29***	0,24***	0,41***	0,52***	0,42***	0,30***	0,41***	0,29***	0,38***	0,37***	0,37***	1,00									
Scania (SCAN)	0,04	0,24***	0,24***	0,36***	0,42***	0,41***	0,28***	0,32***	0,27***	0,34***	0,33***	0,34***	0,46***	1,00								
Securitas (SEC)	0,10	0,15***	0,29***	0,32***	0,44***	0,33***	0,27***	0,32***	0,15***	0,35***	0,3***	0,32***	0,43***	0,38***	1,00							
Stora Enso (SE)	0,05	0,18***	0,2***	0,33***	0,44***	0,37***	0,28***	0,45***	0,37***	0,31***	0,46***	0,39***	0,52***	0,38***	0,37***	1,00						
Swedish Match (SM)	0,065*	0,19***	0,28***	0,37***	0,43***	0,35***	0,26***	0,35***	0,25***	0,36***	0,26***	0,32***	0,42***	0,41***	0,39***	0,35***	1,00					
TDC	0,06	0,09***	0,12***	0,25***	0,23***	0,26***	0,15***	0,28***	0,33***	0,23***	0,30***	0,26***	0,23***	0,28***	0,19***	0,36***	0,27***	1,00				
Telenor (TEN)	0,05	0,16***	0,21***	0,4***	0,41***	0,41***	0,24***	0,34***	0,24***	0,37***	0,34***	0,31***	0,48***	0,41***	0,38***	0,38***	0,35***	0,26***	1,00			
TeliaSonera (TS)	0,06	0,18***	0,24***	0,38***	0,45***	0,40***	0,24***	0,33***	0,28***	0,36***	0,33***	0,35***	0,44***	0,43***	0,40***	0,40***	0,43***	0,30***	0,55***	1,00		
UPM Kymmene (UPM)	0,05	0,22***	0,22***	0,32***	0,49***	0,43***	0,27***	0,42***	0,34***	0,32***	0,44***	0,4***	0,58***	0,38***	0,40***	0,75***	0,36***	0,34***	0,41***	0,41***	1,00	
Volvo (V)	0,07*	0,24***	0,18***	0,37***	0,46***	0,41***	0,25***	0,34***	0,24***	0,36***	0,37***	0,39***	0,48***	0,52***	0,37***	0,41***	0,36***	0,28***	0,47***	0,47***	0,43***	1,00

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Table 2. Results: Cross-correlation between the residuals obtained through OLS (1) during the first subperiod.

2005-2007	AC	AA	CAR	ERIC	ELUX	FORT	INV	MET	MRE	NOK	NS	SAS	SCA	SCAN	SEC	SM	SE	TDC	TEN	TS	UPM	V
Atlas Copco (AC)	1.00																					
Assa Abloy (AA)	0.09***	1.00																				
Carlberg (CAR)	0.03	0.02	1.00																			
Ericsson (ERIC)	-0.03	0.08	0.06	1.00																		
Electrulux (ELUX)	0.02	0.15***	0.09*	0.32***	1.00																	
Fortum (FORT)	0.05	0.03	0.18***	0.18***	0.18***	1.00																
Investor (INV)	-0.06	0.10*	0.04	0.10*	0.16***	0.13**	1.00															
Metso (MET)	-0.01	0.05	0.07	0.23***	0.15**	0.07	0.08	1.00														
M-Real (MRE)	0.00	0.06	0.06	0.38***	0.25***	0.09*	0.05	0.33***	1.00													
Nokia (NOK)	0.03	0.10*	0.02	0.12**	0.21***	0.16***	0.15***	0.10*	0.00	1.00												
Norska Skog (NS)	0.04	-0.01	0.17***	0.23***	0.25***	0.20***	0.11**	0.23***	0.25***	0.21***	1.00											
SAS	-0.03	0.05	0.13**	0.19***	0.21***	0.13**	0.10*	0.15**	0.07	0.21***	0.31***	1.00										
SCA	0.02	0.19***	0.11*	0.25***	0.37***	0.12**	0.19***	0.24***	0.20	0.21***	0.31***	0.26***	1.00									
Scania (SCAN)	-0.03	0.01	0.09*	0.20***	0.27***	0.13**	0.15**	0.08	0.10*	0.2***	0.24***	0.21***	0.26***	1.00								
Securitas (SEC)	0.05	-0.01	0.14**	0.16***	0.23***	0.10*	0.15**	0.10*	-0.03	0.23***	0.23***	0.25***	0.29***	0.21***	1.00							
Swedish Match (SM)	-0.01	0.01	0.13**	0.23***	0.26***	0.04	0.07	0.15**	0.14**	0.18***	0.17***	0.15***	0.21***	0.23***	0.19***	1.00						
Stora Enso (SE)	-0.01	0.12**	0.15***	0.27***	0.30***	0.17***	0.15**	0.31***	0.26***	0.19***	0.41***	0.32***	0.47***	0.25***	0.25***	0.18***	1.00					
TDC	0.04	0.01	0.09*	0.28***	0.22***	0.13**	0.06	0.21***	0.41***	0.08***	0.31***	0.22***	0.2***	0.2***	0.07***	0.21***	0.23***	1.00				
Telenor (TEN)	0.01	0.08	0.12**	0.26***	0.28***	0.24***	0.14**	0.13**	0.13**	0.24***	0.28***	0.2***	0.32***	0.24***	0.3***	0.19***	0.25***	0.2***	1.00			
TeliaSonera (TS)	0.00	0.09*	0.14***	0.24***	0.31***	0.18***	0.11**	0.14**	0.18***	0.19***	0.26***	0.23***	0.26***	0.26***	0.29***	0.28***	0.26***	0.31***	0.41***	1.00		
UPM Kymmene (UPM)	-0.02	0.15***	0.19***	0.23***	0.34***	0.20***	0.17***	0.21***	0.17***	0.23***	0.39***	0.34***	0.52***	0.23***	0.28***	0.20***	0.70***	0.23***	0.3***	0.31***	1.00	
Volvo (V)	0.02	0.11*	0.02	0.25***	0.26***	0.16***	0.14**	0.13**	0.04	0.23***	0.29***	0.33***	0.3***	0.29***	0.21***	0.19***	0.26***	0.22***	0.37***	0.34***	0.28***	1.00

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Table 3. Results: Cross-correlation between the residuals obtained through OLS (1) during the second subperiod.

2007-2009	AC	AA	CAR	ERIC	ELUX	FORT	INV	MET	MRE	NOK	NS	SAS	SCA	SCAN	SEC	SM	SE	TDC	TEN	TS	UPM	V
Atlas Copco (AC)	1.00																					
Assa Abloy (AA)	0.61***	1.00																				
Carlberg (CAR)	0.27***	0.31***	1.00																			
Ericsson (ERIC)	0.28***	0.34***	0.21***	1.00																		
Electrulux (ELUX)	0.34***	0.43***	0.32***	0.38***	1.00																	
Fortum (FORT)	0.40***	0.42***	0.31***	0.45***	0.50***	1.00																
Investor (INV)	0.35***	0.38***	0.36***	0.31***	0.31***	0.33***	1.00															
Metso (MET)	0.40***	0.38***	0.24***	0.41***	0.48***	0.56***	0.32***	1.00														
M-Real (MRE)	0.29***	0.27***	0.19***	0.23***	0.30***	0.40***	0.20***	0.37***	1.00													
Nokia (NOK)	0.38***	0.44***	0.35***	0.51***	0.38***	0.48***	0.42***	0.42***	0.31***	1.00												
Norska Skog (NS)	0.24***	0.27***	0.22***	0.39***	0.44***	0.52***	0.19***	0.43***	0.46***	0.39***	1.00											
SAS	0.24***	0.34***	0.25***	0.35***	0.46***	0.42***	0.29***	0.40***	0.31***	0.41***	0.39***	1.00										
SCA	0.42***	0.44***	0.33***	0.52***	0.56***	0.62***	0.39***	0.57***	0.38***	0.54***	0.49***	0.49***	1.00									
Scania (SCAN)	0.40***	0.48***	0.32***	0.49***	0.51***	0.62***	0.39***	0.51***	0.45***	0.49***	0.46***	0.46***	0.63***	1.00								
Securitas (SEC)	0.45***	0.44***	0.39***	0.46***	0.61***	0.53***	0.37***	0.50***	0.31***	0.46***	0.36***	0.37***	0.54***	0.54***	1.00							
Swedish Match (SM)	0.46***	0.48***	0.36***	0.46***	0.50***	0.56***	0.38***	0.48***	0.31***	0.52***	0.38***	0.43***	0.58***	0.54***	0.55***	1.00						
Stora Enso (SE)	0.38***	0.40***	0.26***	0.41***	0.54***	0.56***	0.38***	0.52***	0.42***	0.42***	0.56***	0.45***	0.61***	0.55***	0.49***	0.46***	1.00					
TDC	0.33***	0.45***	0.34***	0.45***	0.43***	0.49***	0.35***	0.41***	0.30***	0.47***	0.44***	0.39***	0.50***	0.57***	0.40***	0.50***	0.46***	1.00				
Telenor (TEN)	0.28***	0.31***	0.28***	0.48***	0.48***	0.54***	0.30***	0.47***	0.32***	0.47***	0.43***	0.39***	0.57**	0.55***	0.43***	0.45***	0.50***	0.43***	1.00			
TeliaSonera (TS)	0.35***	0.40***	0.30***	0.48***	0.51***	0.56***	0.33***	0.50***	0.37***	0.50***	0.44***	0.44***	0.57**	0.59***	0.47***	0.54***	0.53***	0.46***	0.67***	1.00		
UPM Kymmene (UPM)	0.42***	0.42***	0.27***	0.42***	0.59***	0.58***	0.35***	0.55***	0.45***	0.42***	0.54***	0.45***	0.66***	0.55***	0.53***	0.46***	0.78***	0.42***	0.50***	0.51***	1.00	
Volvo (V)	0.37***	0.48***	0.29***	0.44***	0.55***	0.59***	0.36***	0.52***	0.41***	0.46***	0.50***	0.44***	0.63***	0.75***	0.54***	0.47***	0.54***	0.54***	0.54***	0.58***	0.59***	1.00

*** Significance level 0,1 percent

** Significance level 1 percent

* Significance level 5 percent

Appendix 5. Companies included in the counterparty risk index.

Table 1. Counterparty risk index

No.	Company	Country
1.	ABN AMRO	Netherlands
2.	Bank of America	United States
3.	Barclays	United Kingdom
4.	BNP Paribas	France
5.	Citigroup	United States
6.	Credit Suisse	Switzerland
7.	Deutsche Bank	Germany
8.	Goldman sachs	United States
9.	HSBC Bank	United Kingdom
10.	JPMorgan Chase	United States
11.	Merrill Lynch & Co	United States
12.	UBS AG	Switzerland
13.	Wachovia	United States