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Evaluating Credit Default Swap spreads using the CreditGrades model

A study on European non-financial firms

by

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Abstract

In our paper, we analyse Credit Default Swaps (CDSs) for 67 European non-financial companies between December 2004 and December 2014, focusing on the five-year maturity corporate CDS spreads. The period of analysis is divided into three sub-periods; before the financial crisis, during the global financial crisis and the European sovereign debt crisis. The CreditGrades model is used to estimate CDS spreads where the volatility is estimated by two different methods; a Moving Average (MA) and a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The empirically observed spreads are compared with the predicted CDS spreads. Our findings suggest that the estimation of volatility with the MA approach performs better than the GARCH model. Furthermore, trading strategies are implemented seeking positive returns on the CDS market. The best performing strategies are based on the autocorrelation of the observed CDS spreads.

Keywords: credit risk,credit risk model, credit default swap (CDS), CDS spreads, structural model, CreditGrades Model, GARCH, Moving Average, trading strategies, autocorrelation, AR (1).

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1 Introduction

The unexpected financial crisis in the summer of 2007 has been the most severe shock in the financial industry since the Great Depression.The collapse of the real estate prices in the United States was the root of the financial crisis. In the United States and Europe, the lack of investor's confidence as well as availability of credit caused significant losses in financial institutions (Dieckmann and Plank, 2012). Consequently, the first phase of the financial crisis with high uncertainty and volatility extensively influenced the financial markets. Among the financial institutions the impact of the market turmoil was particularly detected in the banks that were largely exposed to asset-backed securities (ABSs) and collateralized debt obligations (CDOs). Therefore, concerns rose about the creditworthiness of the debtor (Belke and Gokus, 2011).

The most severe phase of the financial crisis was introduced with the sudden collapse of Lehman Brothers in September 2008 (Lane, 2012). In the event of this failure, there was a significant shortage of liquidity in international markets (Burkhanov, 2011). After the collapse of Lehman Brothers, there was a growing need of more accurate indicators of assessing the creditworthiness of the banking sector. Credit Default Swap (CDS) is one of the instruments used in the credit derivative markets in order to assess accurately and timely the credit risk of the entities (Belke and Gokus, 2011). During this period, the CDS spreads became more sensitive with a lot of fluctuations (Burkhanov, 2011). The special attention that CDSs have received over the last years is because the spreads express the pure credit risk of the company (Jacobs et al., 2010).

Financial institutions mainly use CDSs in order to hedge credit risk. Therefore, a pricing model that gives both exact CDS spreads and how these spreads are related to each other is desired. An industry benchmark model that was developed in order to give a standard of transparency for the pricing of CDSs in the credit market is the CreditGrades model. The model is an extension of the Black and Cox (1976) model by taking the uncertain default threshold into account. The closed-form formulas obtained by the CreditGrades model link the pricing of CDSs with the volatility and the price of stocks (Cao et al., 2011).

In our study, we will use the CreditGrades model in order to estimate the CDS spreads and then compare them with the empirically observed. Our sample period will start from December 2004 until December 2014 covering 67 European non-financial companies. Furthermore, we will apply different methods in order to estimate the volatility which is one of the main factors in the CreditGrades model. The trading strategies will be implemented on individual assets instead of the index as in previous studies. These strategies will be based on the autocorrelation found in the study of Byström (2006a).

1.1 Background

The most common risk that financial institutions face is credit risk. Generally speaking, credit risk is the risk of loss due to the counterparties' inability to meet its obligations. Thus, an accurate estimate of credit risk is essential for almost all financial activities (Byström, 2005). According to Neal (1996) "Credit risk is the probability that a borrower will default on a commitment to repay debt or bank loans". In this respect, given that the default occurs the investor will make a loss for the sake of not receiving all the agreed payments.

Credit derivatives is the most broadly used way in order to manage the risk of default (Byström, 2006a). This growth of credit derivatives results from their innovative and valuable methods that provide an efficient approach of managing credit risk to financial institutions and investors (Neal, 1996; J.P. Morgan, 1999). Credit derivatives protect the parties in interest against the inability of the borrower to meet its obligations. In other words, in case the borrower defaults, gains in credit derivatives can offset investors' losses which reduce crdit risk (Neal, 1996).

The quantitative modelling of credit risk displays some difficulties because of its properties. One of these properties is that an event of default does not happen so often; it is a rare situation. In addition, the default events happens unexpectedly causing serious losses. Last but not least, the size of the losses mentioned before is known only when the default event occurs (Schönbucher, 2003). Most of the previously applied strategies in the literature aiming to manage credit risk produced weak results. This is because there was no distinction between managing the credit risk and the underlying assets. On the other hand, credit derivatives give the option to manage the credit risk independently without affecting the risk of the underlying asset. In other words, credit derivatives such as CDSs are financial contracts

between two counterparties that transfer the credit risk to the issuer and provide protection to the buyer (J.P. Morgan, 1999).

The majority of the participants in the credit derivative markets are large investment banks with the intention of making profits by trading strategies. Investments banks use these financial instruments in order to provide their clients with tailored made solutions covering their specific needs. In the wake of these solutions, risk management processes use the most innovative methods to meet clients' expectations. Developing a sound risk management method should take many factors into consideration. Simplicity of the model is one of these factors. A simple model means that it can both be used frequently without any difficulties and provide accurate estimations (Schönbucher, 2003). As a consequence, derivatives are now used by financial institutions to create profits through arbitrage opportunities or speculative positions. One more reason that makes these markets attractive is the size and liquidity that CDSs offer (Byström, 2006a; Blanco et al., 2005). Another advantage of CDSs is that they provide efficient ways of hedging the credit risk and give an overall picture of the credit conditions in the markets (Deutsche Bank Research, 2009).

Almost all credit derivatives are over-the-counter (OTC) transactions, which are lightly regulated. This leads to a higher probability of default even though the contracts are tailored made for the specific needs of the buyer (Blanco et al., 2005). As it is already mentioned, the main tradable product in the credit derivatives market is the single-name CDS (Byström, 2006a). Despite the nature of CDSs being OTC traded, they give protection to the buyer against the risk of a credit event (Ericsson et al., 2009). The only difference between a CDS and an insurance contact is that in the former an underlying asset is not necessarily required in order to call for compensation (Blanco et al., 2005). In this contract, the one party (the buyer) pays to the other party (the seller) a premium until the end of the contact; its maturity or the default event, depending on which of these two events arises first (Yu, 2005).

1.2 Limitations and Discussion

Forecasting the prices of the CDSs is one of the main concerns of financial institutions. Since these prices are by nature fluctuating, financial institutions aim to make accurate predictions of them. Thus, they take positions based on these estimates. The positions that are taken can be long or short in the underlying securities. However, there is always a risk related to these strategies since they are based on speculations of the prices in the future which make them uncertain. Majumder (2005) states that there is a variety of credit risk models used by researchers and risk managers with the intention of determining the prices of the financial instruments.

Pricing the credit risk based on the CreditGrades model incorporates the estimation of asset volatility. This study will include two estimators of the volatility; a Moving Average and a GARCH model. However there are many ways of estimating the volatility each of them generating a different CDS value. Thus, the volatility needs to be estimated in the most appropriate way to get the best fitting model which is a general concern in the literature. CreditGrades (2002) suggests a long term Moving Average, since it yields a stable volatility. However, the volatility will not adjust to changes in the market regime. Furthermore, a GARCH model is applied to evaluate the performance of the CreditGrades model. Even though this might not be the best volatility estimate the intention is to take a faster reacting model into consideration.

To be able to calculate the returns and performance of trading strategies we follow the framework developed by Byström (2006a) where a synthetic bond is created. Thus the returns found in the trading strategies are hypothetical. Transforming the CDS spread into “cash” is a common problem for all empirical studies. Therefore, trading is also hypothetical especially the selling of CDSs, because of the regulatory capital requirements in the event of default. This means that transaction costs should be included in order trading to be more realistic. As a consequence, a specific limitation in our study is the fact that we have not taken transaction costs into account. Byström (2006a) and Avino and Nneji (2012) use the bid and ask spread to avoid this limitation. Our study is limited to mid spread since there is lack of access to these data. Hence, the returns from the trading strategies might disappear if the transaction costs would have been included.

1.3 Research Purpose

The main purpose of our study is to analyze the Credit Default Swap spreads covering non-financial firms in the Eurozone before the global financial crisis, during the financial crisis as well as during the European sovereign debt crisis. This study is focused on two main areas. The first area is to examine the effect of volatility on the predicted CDS spreads using the CreditGrades model. In addition, the performance of the models is evaluated since it is an essential part of sound risk management. The second area is centered around trading strategies where the relationship on the CDS market is investigated. Moreover, regarding the trading strategies certain criteria are selected for the formation of the portfolio.

1.4 Outline of the Thesis

This paper is organized as follows. Section 2 discusses the different approaches of measuring credit risk as well as specifically the credit risk models. This section also presents the model we use in our empirical study and reviews the existing literature in the credit risk area. Section 3 describes the methodology used to estimate the CDS spreads and shows the trading strategies implemented. Section 4 presents the findings of our empirical research and in Section 5 we conclude the study.

2 Theoretical Review

There are different approaches measuring credit risk. One of these approaches is based on the rating agencies; such as Standard & Poor's, Moody's and Fitch. Another approach is based on the traditional scoring models which use information from the balance sheet (accounting information) in order to measure credit risk. Although both approaches have been widely used, they have some disadvantages. One of the main drawbacks is the non-frequent updating of credit rankings affiliated with the rating agencies. Regarding the second approach, the traditional scoring models have also some cons. They are also not updated very often like the credit rankings and they appear to experience accounting manipulations. Furthermore, the accounting information used in the scoring models relies on historical information, which makes it difficult to assess the market in the future. In both approaches there is a difficulty in translating the values into the actual probability of default (Byström, 2006b).

Another method of assessing credit risk is the use of structural models. According to CreditGrades (2002) structural models have a number of advantages that make them attractive to investors and traders. The information used in these models are derived from a broad market that is frequently traded. Therefore, structural models show a different point of view about the credit quality of the firm. However, Elizalde (2005) criticizes the structural models by stating that the empirical tests have not been successful. This is due to the fact that estimations have shown the predicted spreads being lower than the observed ones. Another drawback is that the structural variables do not give extensive explanation for the variation in the spreads.

As an alternative way, market-based approaches are used where the information about credit risk are extracted from the market. The most widely known is the Merton (1974) model (Byström, 2006b). According to this approach, if a firm's assets are below its outstanding debt the firm defaults. In contrast to Merton's approach where the default can happen at any time, another method was introduced where the firm defaults when its asset value is below a specific threshold. This is the well-known Black and Cox (1976) model (Elizalde, 2005).

2.1 Credit Risk Models

Credit risk modelling has become an essential part of risk management practices in financial institutions. These models provide to financial institutions the measure of credit risk included in their asset portfolios (Lopez and Saidenberg, 2000). There is a variety of models in order to measure credit risk. The first model that studied credit risk is the Merton (1974) model which has a structural approach. The concept in the Merton model is that the event of default can happen only at the maturity date (Jarrow, 2009).

Despite the broad use of Merton's model (1974), it is associated with a number of disadvantages. Firstly, the model is restricted regarding the time of default since the probability of an early default is precluded (Elizalde, 2005). For that purpose the CreditGrades model came to evade it by linking the equity market with the credit market. Even though CreditGrades model and Merton model can be both used in order to estimate the probability of default, the former aims to yield predicted CDS spreads that are calculated from equity prices and information from firm's balance sheet. CreditGrades model essentially provides information about the firm's credit quality additional to the one found in the observed CDS spreads. The intention of the CreditGrades model is to give a more transparent and accurate overview for pricing credit risk (Byström, 2006a).

2.2 Credit Default Swap spreads

Credit risk and the risk of the counterparty, as an essential part of risk management, can also be used for pricing purposes (Byström, 2006b). The spread embodies the price of the protection that the seller gives to the buyer of the CDS in case of a default event. The amount of payment is calculated by multiplying the CDS spread with the notional value. Payments are normally made quarterly or semi-annually. In case the credit event occurs between two payments the seller of the CDS must receive the accumulated fee until the time of default (Schönbucher, 2003).

Previous studies assume different factors that affect the CDS spreads. For instance, Blanco et al. (2005) assume that the main factor determining the CDS spreads is credit risk. However, later studies extend the factors influencing the spreads with Jacobs et al. (2010)

positing that CDS spreads are usually affected by five variables; the implied volatility of equity markets, the industry, the risk-free rate, leverage of the underlying asset and the liquidity of CDSs. Regarding the liquidity of CDSs, their importance was specifically emphasized during the financial crisis of 2007 to 2009 where liquidity factors are said to be the reason for the severity of the crisis (Corò et al., 2013).

In the CDS market, one of the main aspects that grow very fast is the CDS indexes. These indexes unite single name CDSs into tradable and liquid indexes which are used in order to indicate the quality of the overall credit market (Byström, 2006a). The study of Alexander and Kaeck (2008) using a Markov switching model to investigate the iTraxx Europe indices finds that during regular market conditions the CDS market is sensitive to the returns on the stock market. However during turbulent periods the sensitivity moves towards the stock market volatility.

2.3 The CreditGrades Model

Our study uses the CreditGrades model, developed by RiskMetrics, JP Morgan, Goldman Sachs and Deutsche Bank in order to evaluate CDS spreads. This model belongs to the class of structural models. The main advantage of structural models is that they employ information from a wide and liquid market. The groundwork of these models is the Black and Scholes (1973) and the Merton (1974) model, which are the first proposing the relationship between equity and debt (CreditGrades, 2002).

As Byström (2006a) addresses the reason for CDSs being considerable attractive in comparison with the other financial instruments in the credit derivative market is that they provide “pure” credit risk. In this context, for investors that are interested in the credit risk, CDS contracts separate the credit risk from the interest rate risk. The CDS spread determines its price. Because the spread depends on the creditworthiness of a firm, investors seek information in the stock markets. The CreditGrades model is the most commonly used credit risk model that calculates CDS spreads based on equity prices and information derived from a firm’s balance sheet (Byström, 2006a). The aim of this model is to give a transparent standard to market participants for evaluation of credit risk. The model is considered to be precise enough as well as easy to understand by the majority of the market participants (CreditGrades, 2002). Moreover, The CreditGrades model is considered to be the most widely

used by professionals implementing capital structure arbitrage; an investment strategy exploiting the pricing between the equity and debt that a firm has (Yu, 2005). The revised Basel Accord and the outbreak of the credit derivatives market have driven the importance of modelling and measuring the credit risk extensively. Until recently, the main input in the credit risk models was the probability of default, which was estimated either from rating agencies, equity prices or macroeconomic elements. The new inputs introduced are recovery rate and correlations. The CreditGrades model is an example of these credit risk models inserting these new elements (Renault and Scaillet, 2004).

2.4 Literature Review

This section presents the research that has been conducted in the area of credit risk and the different extensions of the CreditGrades model. One of the research works that has influenced the strand of literature on assessing the credit risk as well as our study is that of CreditGrades (2002). This study provides an accurate and transparent standard to market participants in favour of managing the credit risk by linking the equity and credit markets. They apply approximations for the volatility, the asset value as well as the drift terms connecting them with market observables. Furthermore, in their study, credit is treated as an exotic equity derivative, which is expressed in a closed form formula. In addition, they measure volatility based on the Moving Average (MA) approach by using the last 1000 days of equity returns. This measure appears to be a simple and accurate estimation of the volatility implied by the CDS spreads presenting the long-term market movements.

This study is in line with Byström (2006a) who investigates the predictability of the CreditGrades model comparing the predicted with the observed CDS spreads in the iTraxx market. His study is considered to be the first using information from the CDS index market and also the first that assesses the performance of the model. Even if our study is based on that of Byström (2006a), we use two different estimates of volatility in order to get the best performing model. The different methods of estimating the volatility in our study is in line with that of Cao et al. (2011). Their study compares the option-implied volatility with the historical volatility and proves that the former can enhance the performance of the CreditGrades model. Moreover, they state that the use of option-implied volatility has more favourable effects on companies with more fluctuations on their CDS spreads, lower credit

ratings as well as more frequently traded options. In another innovative study, Byström (2014) uses an inverted version of the CreditGrades model by estimating the volatility and the stock price rather than the CDS spreads.

Some studies have dealt with the extension of the CreditGrades model. He et al. (2011) extend the model by employing jumps and assert that the performance of the model is improved. Another study using jumps in the CreditGrades model is that of Ozeki et al. (2011) in order to take the skewness of the implied volatility into account. The study of He et al. (2011) prove that the extension of the model with jumps makes it forward looking since it captures future market developments. As a result, the jumps make the model more accurate regarding the future predictions. Another extension is conducted by Escobar et al. (2012) who assume stochastic volatility correlation. This multivariate extension of the structural credit risk model incorporates that the covariance of the firm's assets follows the Wishart process and the Principal Component process. Evidence shows that the pricing problem of the equity options is solved by assuming stochastic volatility and correlation. The extension of Ozeki et al. (2011) uses a Le´vy process, referred as Le´vy CreditGrades model. According to their findings, this extension makes the model more capable than the original one.

Some other studies use structural models in order to determine bond spreads. As it is mentioned in the research of Ericsson et al. (2006), historically the structural models have underestimated the bond spreads. In their study they evaluate different structural models on both CDSs and bonds. Although their results show that the bond spreads are underestimated, for the CDS spreads the model's performance is satisfactory. Furthermore, the relationship between the stock and the CDS market is also explored. Longstaff et al. (2003) look at the lead and lag correlation between the CDS, bond and stock market showing a lagged correlation between the stock and CDS market. After this study, Norden and Weber (2009) also investigate the relationship between these markets on an individual level as well as the co-movements between them concluding that the stock market is leading the CDS market. The latest study of Avino and Lazar (2012) based on the lead-lag relationship of these two markets indicates that trading the market that is following might be better since it can be easily forecasted. As a consequence, these studies might show that the CDS market is the one that can be more easily forecasted in comparison with the stock market.

The empirical part of this study is based on the findings of Byström (2006a) where a positive autocorrelation between the actual and the predicted CDS spreads is detected. Based on this relationship between the spreads he develops a trading strategy which can be exploited and yields positive returns. Avino and Nneji (2012) also test different strategies on the CDS market and they find that the best performing one is a simple autoregressive process; AR (1) model. The findings of their research generate positive Sharpe ratios. Both these studies use the bid and ask spread to take the transaction costs into account. In the study of Byström (2006a) most of the returns disappear when these costs are taken into account.

Some studies implement capital structure arbitrage in order to take advantage of the mispricing of the stock and the CDS market. The trading implemented is usually based on the difference between the observed CDS spreads and the implied spreads obtained by the use of a credit risk model. The data for this model are obtained from the stock market. The study of Avino and Lazar (2012) finds that implementing capital structure arbitrage strategies can diversify the risk in a portfolio. This diversification gives more opportunities to investors to reduce the risk of their portfolio. Another interesting study is the one of Yu (2005) who evaluates the performance of capital structure arbitrage strategy using the CreditGrades model. His findings posit attractive Sharpe ratios which are consistent with the objectives of our study.

2.5 Comparison of the CreditGrades model with other structural models

CreditGrades (2002) posits that there are two main differences that distinguish the CreditGrades model from the other models that also belong to the class of structural models. The first difference is the objective of the model as well as the data used for it. The goal of the CreditGrades model is to estimate CDS spreads accurately and to indicate whether there are changes in a firm's credit conditions. On the other hand, other models that also belong to the category of structural models, have as a goal to produce the exact probability of default and to distinguish the healthy firms from those that are about to default. Basically, the CreditGrades model produces an outcome regarding a firm's credit quality that complements the results of the other structural models. A second difference that has been observed between them is the way the input parameters are derived in the model. The current approaches focus on the

calculation of parameters that are not observed, particularly the volatility of the firm's assets and their value. On the contrary, the CreditGrades model is related to market observations, which makes it more practical. Because of the few input parameters that the CreditGrades model is based on, it can be viewed as a simple formula.

2.6 Credit Ratings

During the financial crisis, the behaviour of credit agencies was one of the issues extensively discussed. Credit ratings provide an overall measure of the creditworthiness of an entity. Credit agencies' intention is to give relative assessment of the entities' credit conditions and making them comparable in a more simplified way. This means that the measure of credit risk presented is not precise (Micu et al., 2004). As a consequence, although the role of rating agencies is greatly important in the economy, their validity has been broadly questioned because of the drawbacks regarding the accurate and timely assessment of the credit risk of the borrower. Hence, investors became more risk averse since there was a lack of confidence in the market and they were asking for more compensation for the credit products they were interested in (Jacobs et al., 2010). Not only the CreditGrades model gives a prediction of the CDS spreads but also ranks different credits. Although the CreditGrades model serves the same purpose as rating agencies, the market data used in the model allows more frequent updates (CreditGrades, 2002).

3 Methodology

The CreditGrades model applied in our study is based on the concept of the CreditGrades (2002). In the model a default event arises when the stochastic process V, which represents the asset value, falls below the default barrier. The default barrier is defined as the value of the assets that would remain if the firm actually would default. The stochastic process V evolves according to a geometric Brownian motion with an assumption of the drift term being equal to zero in order to avoid arbitrage possibilities. Furthermore, the default barrier is expressed as the debt-per-share in the company (D) times the average recovery rate on debt (L).

Generally speaking, standard structural models struggle with short-term credit spreads. For this reason, the average recovery rate L introduced in this model is random aiming to correct it (CreditGrades, 2002). The recovery rate is also assumed to evolve according to a lognormal distribution, which gives the following:

$$\bar{L} = E(L) \tag{1}$$

$$\lambda^2 = Var[\log(L)] \tag{2}$$

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2} \tag{3}$$

The variable Z is a standard normal random variable which is unknown until the event of default occurs. The randomness of Z takes the uncertainty into account regarding the actual debt level in the firm. As mentioned before the firm does not default as long as the asset value is above the default barrier. The survival probability in a closed form is obtained by the following formula:

$$P(t) = \phi\left(-\frac{A_t}{2} + \frac{ln(d)}{A_t}\right) - d * \phi\left(-\frac{A_t}{2} - \frac{ln(d)}{A_t}\right) \tag{4}$$

Where:

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D}$$

$$A_t^2 = \sigma^2 t + \lambda^2$$

The next step is to price a CDS using the survival probability given in the expression (4). Therefore, two additional parameters are needed in order to estimate the CDS spreads. These parameters are the risk-free interest rate and the individual recovery rate R on the underlying credit. This R is not the same as the global recovery rate $\bar{L}$. According to previous studies, different values are taken into account for the individual recovery rate. For instance, Avino and Lazar (2012) use an estimate from Moody's on the average historical rate which is equal to 0.326 while Byström (2006a) uses a fixed recovery rate for all assets equal to 0.5. This study will follow the recommended recovery rate, which is equal to 0.5 (CreditGrades, 2002). To estimate the price of the CDS, the spread is set equal to the expected loss, which gives the following expression for the CDS spread:

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

Where

$$\xi = \lambda^2/\sigma^2$$

$$G(u) = d^{z+1/2}\phi\left(-\frac{ln(d)}{\sigma\sqrt{u}} - z\sigma\sqrt{u}\right) + d^{-z+1/2}\phi\left(-\frac{ln(d)}{\sigma\sqrt{u}} + z\sigma\sqrt{u}\right)$$

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

3.1 Calibrating the model parameters

Following the CreditGrades (2002), the parameters V_0 and σ in our model represent the initial asset value and the asset volatility respectively, need to be connected to market observables. This is essential for the implementation of the survival probability formula. This is accomplished by using boundary conditions that focus on the long-term instead of the short-term probability of survival since it is mainly driven by λ. The initial asset value V_0 and asset volatility σ is expressed as:

$$V_0 = S_0 + \bar{L}D \tag{6}$$

$$\sigma = \sigma_s \frac{S}{S + \bar{L}D} \tag{7}$$

As stated in the study of CreditGrades (2002) the parameters $\bar{L}$ which is the mean of the global recovery rate and λ which is the standard deviation of the global recovery rate are set to 0.5 and 0.3 respectively. These values are based on the historical data of around 300 non-financial entities in US. Byström (2006a) minimizes the mean squared errors for the different industries. Avino and Lazar (2012) use the same value as CreditGrades (2002) for λ and for the average global recovery rate $\bar{L}$ they use a similar method as Byström (2006a) where they minimize the squared pricing errors for each firm in their sample.

In our empirical study, for reasons of simplification, we assume that the recovery rate $\bar{L}$ is equal to 0.5 as in the study of CreditGrades (2002). This parameter was originally estimated for non-financial firms in the United States. Although our study focuses on European non-financial firms we still use the same value because of difficulties in the computation of the recovery rate. The debt-per-share is estimated according to the following formula:

$$Debt\_per\_share = \frac{Debt}{No\ of\ outstanding\ shares} \tag{8}$$

3.2 Estimation of volatility

One of the main aspects of business and financial activities is forecasting the volatility of financial markets. Forecasting volatility has a direct impact on the investors' decisions which in turn affects the prices of derivatives. The often fluctuations in the financial markets especially during the financial crisis led to the need of more efficient derivatives exchanges. In derivatives, volatility represents the measure of the frequency and the size of fluctuations in the price of the underlying asset for a specific period. In other words, the uncertainty of future price movements is measured by the volatility of an asset price. The importance of forecasting volatility explains the growth of the derivatives market. In case the volatility forecasted by the investor is high, without the existence of the derivatives market the investor should choose between two options; either exiting the market or requiring higher compensation. Thus, the derivatives markets offer opportunities to investors by speculating (Maris et al., 2004).

In this study, we use a Moving Average (MA) approach suggested by CreditGrades (2002) where the last 1000 observations are used in the calculation of the standard deviation. We also include a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in our study to estimate volatility. Our aim is to take a faster reacting model into account against the sensitivity CDS market shows during turbulent times as it is suggested by Alexander and Kaeck (2008). Moreover, we want to test how our trading strategies are affected by using different volatility estimates.

In the literature, there are different attempts of estimating the asset volatility. CreditGrades (2002), for instance, suggests the use of a long-term MA of 1000-days in order to estimate the volatility. The intuition behind this method is that historically the asset volatility has been stable and by using a long-term moving average the results would give a relative stable volatility. However, in their study, one of the problems faced is that for the high quality firms the volatility is underestimated while the best estimator is achieved for low rating firms. Another study aiming to get a more responsive estimator is that of Avino and Lazar (2012). They use a 250-day MA for the equity return. CreditGrades (2002) also looks at an exponentially weighted moving average (EWMA) but the model does not give appropriate results. The exponentially weighted moving average (EWMA) is practically an extension of the historical average volatility measure. In this model, the impact of the latest observations is

stronger regarding the forecast of the volatility than the older observations have. In other words, the largest weight is incorporated in the most recent data which in turn makes the volatility to be dependent on these most recent observations (Brooks, 2008).

In 1982 Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to estimate the variance of inflation. This is a non-linear model having extensive usage in finance, since the variance of errors does not have to be constant over time as in usual linear regressions. In financial time series it is unlikely that the variance of the errors is constant. The presence of volatility clustering is also an argument for using ARCH class models. In 1986 Bollersev and Taylor independently developed the GARCH model. The conditional variance in this model is permitted to depend on the previous own lags, which means that the expression for a GARCH (1,1) model follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{9}$$

The σ_t^2 is the conditional variance that is calculated using relevant historical information. The GARCH model can be seen as an infinite order ARCH model, which decreases the risk of overfitting. Even though GARCH can be expressed as GARCH (p,q) the most common to use is the GARCH(1,1) (Brooks, 2008). According to Alberg et al. (2008) empirical evidence addresses that the dynamic behaviours of conditional variance make the ARCH models insufficient. However within the class of time series model intending to forecast the variance of returns, GARCH models appear to be the most successful (Franses and Dijk, 1996). Lamoureux and Lastrapes (1990) define the GARCH model as "a useful means for empirically capturing the momentum in conditional variance". In our study the commonly used GARCH (1,1) specification is the model used to estimate the volatility.

3.3 Data

In our empirical study we focus on the non-financial firms of the Markit iTraxx Europe CDS index. Our sample data starts from December 2004 until December 2014. The selection of the starting date is because the iTraxx Europe index was introduced in June 2004. The indices from Markit consist of the entities with the highest liquidity in the single-name CDS market. This study is implemented in the European market with the European index consisting of one hundred twenty-five investment graded entities. Among these entities a hundred are non-

financial and the rest are financial (Markit, 2013). Our selection of the non-financial entities results from the aim of our study to be consistent with the original implementation of the model by CreditGrades (2002).

Because of various reasons the number of entities included in the empirical research have decreased to sixty-seven entities. We exclude some of the entities since they are not publicly traded and their stock prices are not available. In addition, we exclude entities that their CDSs are not available for the whole sample period. Our final sample includes sixty-seven non-financial companies from the following industries: (1) Autos & Industrials (2) Consumers (3) Energy (4) Technology, Media & Telecommunications. Moreover, five-year to maturity CDS spreads is used since they are more liquid (most frequently traded) than the ones with shorter maturity. Regarding the interest rate, three month Euribor has been used in our model since Remolona and Wooldridge (2003) states that Euribor remains the key reference rate for longer-dated derivatives. Another reason for choosing Euribor is the fact that financial instruments are the most frequently traded (Ivanova and Gutiérrez, 2014).

All our empirical data have been collected from DataStream. Specifically, we collected the stock prices for the companies included in our sample as well as balance sheet data for the calculation of debt-per-share. For the stock prices our data start 1001 days before the CDS sample data (February 2003) since the stock returns are needed for the calculation of volatility with the Moving Average (MA) approach. Although the estimation of debt-per-share is based on the methodology given in the CreditGrades (2002), our data are obtained from Datastream instead of Bloomberg as in the original study which might slightly cause differences.

3.4 Descriptive Statistics

Table 1 displays the mean, the upper and lower bound for a 95% confidence interval, minimum, maximum and the standard deviation for the input variables in this study. There is a large difference between the minimum and maximum values for the stock prices and the debt per share (DPS) on an individual level. These large differences could be connected to the number of shares and the size of the company. It is likely that there is a positive correlation between a high stock price and a high debt per share. Because of this the average time series have been included. Even at the average level there are still large differences between the

mean and maximum values. The research period has been volatile with a strong booming market in the beginning of the sample followed with the financial crisis and the European sovereign debt crisis.

Table 1: Descriptive statistics

	Mean	Median	Min	Max	Std. dev
Dec 2004 - Dec 2006 (Before Financial crisis)					
CDS	37.44	53.80	2.50	578.30	33.47
Price	229.34	30.95	3.29	3529.00	451.57
DPS	17.21	20.35	0.04	202.99	32.98
Euribor	2.61	2.48	2.10	3.73	0.52
Jan 2007 - Dec 2008 (Financial crisis)					
CDS	77.53	67.80	2.90	2887.50	108.08
Price	267.60	37.04	3.61	3680.00	520.17
DPS	16.09	18.50	0.12	213.78	31.55
Euribor	4.45	4.60	2.89	5.39	0.49
Jan 2009 - Dec 2014 (European sovereign debt crisis)					
CDS	107.88	142.92	15.23	2572.50	79.08
Price	322.52	26.92	2.03	4823.50	672.78
DPS	17.78	9.84	0.28	299.84	34.66
Euribor	0.74	0.69	0.08	2.89	0.54
Dec 2004 - Dec 2014 (Whole period)					
CDS	87.35	102.90	2.50	2887.50	84.17
Price	292.42	29.24	2.03	4823.50	606.75
DPS	17.33	16.64	0.04	299.84	33.82
Euribor	1.86	1.40	0.08	5.39	1.58

The table displays the mean, median, minimum (min.), maximum (max.) as well as standard deviation (std. dev.) of CDS spreads (CDS), Stock prices (Price), debt-per-share (DPS) and 3-month Euribor (Euribor). The sample period covers four sub-periods; before the financial crisis, during the financial crisis, during the European sovereign debt crisis and the whole period.

3.5 Model Performance

Assessing whether a prediction is accurate, it should be compared with the real observations. The evaluation should be made over the whole sample period. Making the comparison incorporates the sum of the errors which will give both positive and negative values. Since these values might cancel each other out, the errors are usually taken in absolute values or squared (Brooks, 2008). In this study the Mean Absolute Percentage Error (MAPE) and the

Root Mean Squared Error (RMSE) will be used in the evaluation process. According to (Maris et al., 2004) MAPE and RMSE are the most broadly used accuracy measures. Both of these measures are used to predict the average error in a model as well as display the average difference (Willmott and Matsuura, 2005). The MAPE measures the average absolute percentage error and is given by

$$MAPE = \frac{100}{T-(T_1-1)} \sum_{t=T_1}^{T} \left| \frac{y_{t+s} - f_{t,s}}{y_{t+s}} \right| \tag{10}$$

MAPE is attractive because of the property that it shows values expressed in percentage, which makes the interpretation easier (Brooks, 2008). The RMSE shows the root of the average squared errors and is given by

$$RMSE = \sqrt{\frac{100}{T-(T_1-1)} \sum_{t=T_1}^{T} \left(y_{t+s} - f_{t,s}\right)^2} \tag{11}$$

3.6 Speculating in the CDS market

This section gives the reader an introduction to how an investor can speculate and how the profits are made on the CDS market. For simplicity, we will use annual payments in the following example, however for standard contracts the payments are done on a quarterly basis. With regards to the trading strategy, the one that sells the CDS (the protection) is usually an insurance company and the one that buys the protection is an investor. The financial institution that sells the CDS takes a long position in the underlying asset while the investor that buys the CDS is taking a short position in the underlying asset (Hull, 2011).

Based on Hull and White (2000), we assume the following different scenarios:

The investor, the buyer of the CDS, speculates that Company X will default soon. Therefore, the investor buys €100 of CDS protection with maturity two years from the financial institution with a CDS spread of 500 basis points annually.

- In case Company X defaults after one year the investor has to pay €5 for the CDS but because of the default the investor gets €100. In this way, the investor makes a profit of €95.
- In the opposite case, where Company X does not default and the CDS contract ends after two years which is its maturity. Meaning that the investor has to pay €10 (€5 for each year) but in comparison with the above speculation the investor does not get anything back. As a result, in the case that Company X does not default, the investor makes a loss of €10.

3.7 Applying the trading strategy

To be able to employ the trading strategy, the CDS spreads are transformed into a synthetic bond following the method used by Byström (2006a) where the CDS spread is treated as a bond spread. Hence, this spread is used in the calculation of the bond price. The calculation of the bond is presented at the formula below:

$$Bond = \frac{N}{(1 + interest\ rate + CDSspread\ )\hat{}T} \tag{12}$$

Where:

N is the nominal value, which is arbitrarily chosen. The intersest rate used is the three month Euribor and *T* is the time to maturity which is five years in our case.

The trading strategies applied in this study are based on the autocorrelation in the CDS market. The trading strategies are either based on the autocorrelation of the estimated CDS spreads using the CreditGrades model and the observed ones or on the pure autocorrelation of the observed CDS spreads represented by an AR (1) model. The autocorrelation was

originally found by Byström (2006a). This study will look at single named CDSs in comparison with Byström (2006a) and Avino and Nneji (2012) looking at a CDS index. By doing this it gives us the option of creating portfolios of individual assets instead of the whole index. Furthermore, in order to assess the possibility of finding a risk adjusted return in the CDS market, different strategies will be implemented. These strategies can be divided in two groups. The first one incorporates the autocorrelation of the CDS spreads estimated by the use of CreditGrades model with the real CDS spreads. The second group includes only the observed CDS spreads. For the strategies implementing the estimated CDS spreads either the MA or the GARCH estimated volatility can be used.

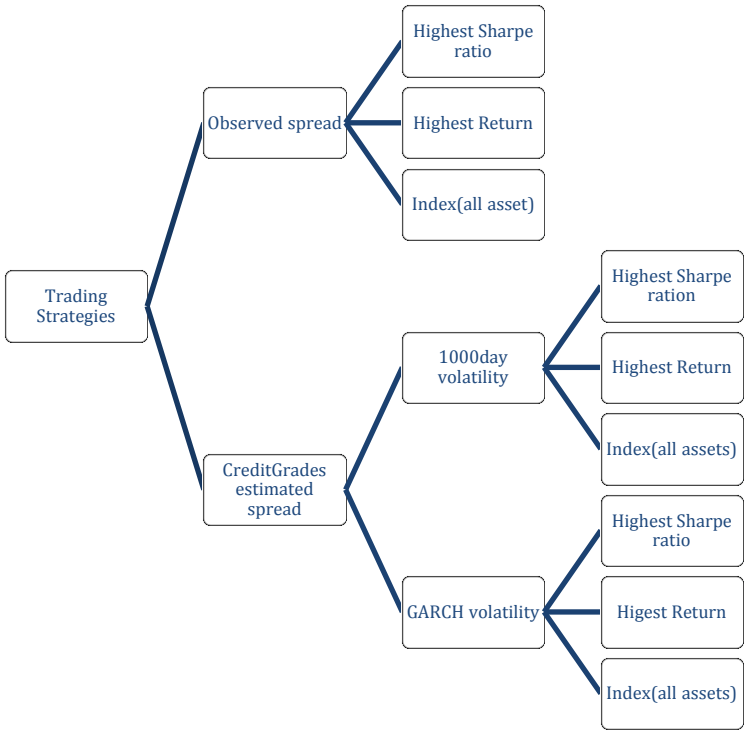
As it is mentioned the strategies built on autocorrelation, and hence the previous observations determine whether any trades should be executed. If the observations show a positive "return" the signal will be negative and the synthetic CDS bond will be sold. A positive "return" means that the spread is increased and the creditworthiness of the company has decreased. Hence a negative "return" indicates an improvement in the underlying asset and a positive signal leads to the CDS bond being bought.

Since we have the option of creating portfolios we decided to use a one-year rolling window where the assets with the best performance during the last 252 days are included into the portfolio. The one-year rolling window means that every year there will be a shift in the assets included in the trading portfolio. The selection of the assets will be based on the performance during the last year (in sample). All the returns obtained from the trading strategies are out-of-sample in copmarison with Byström (2006a) who uses only in sample. However, only the first 252 observations will be used as in sample which means that the performance of the strategies will be evaluated from November 2005 to December 2014.

The performance is measured at either the highest return or the highest Sharpe ratio. By doing this selection process we believe that we will select the best performing assets and mainly avoid the assets with not strong enough autocorrelation. To evaluate this we also include a strategy that selects all the assets incorporated in our sample which can be seen as a proxy for the non-financial iTraxx index. In our study, nine different strategies will be performed in total. In all strategies the thresholds of 0, 0.01 and 0.02 will also be included in the tests. Figure 1 displays an overview of the trading strategies employed in this study. By implementing these different strategies it is possible to assess whether the CreditGrades model adds extra information in comparison with a simple AR (1) model. The different

volatility estimates in the CreditGrades model can also evaluate whether there are any benefits using a GARCH estimated volatility in comparison with a MA as it is suggested by CreditGrades (2002). An overview of the trading strategies that will be employed in this thesis can be seen in Figure 1.

Figure 1: Overview of trading strategies

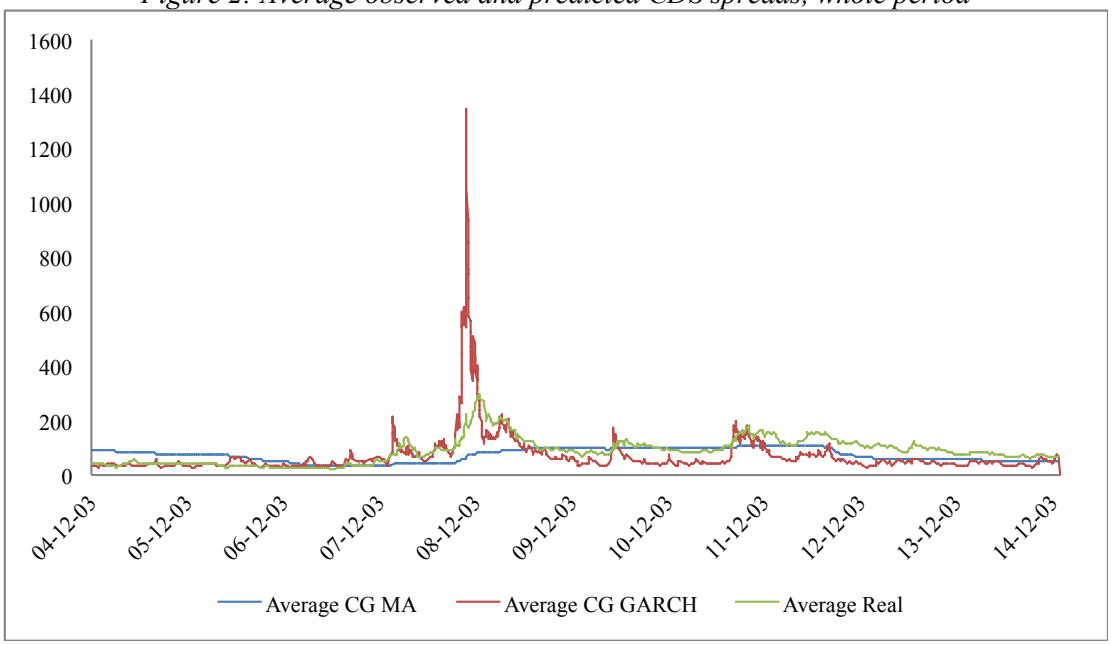


4 Empirical Analysis

One of the objectives in our study is to compare the predicted with the observed CDS spreads. This is accomplished by examining the relationship between the theoretical spreads using the CreditGrades model and the empirical spreads as it is depicted in Figure 2 and Figure 3 where they are plotted together. These two figures show the comparison between the average observed CDS spreads and the average predicted spreads. Specifically, Figure 2 presents the whole sample period of our study; from December 2004 until December 2014, while Figure 3 presents the CDS spreads after the financial crisis; from January 2009 to December 2014. Before the financial crisis, the empirically observed CDS spreads appear to be more stable than during the financial crisis of 2008 where the spreads reached new high levels. In the aftermath of the global financial crisis, the investors' uncertainty led to bigger fluctuations in the CDS market with a remaining uncertainty.

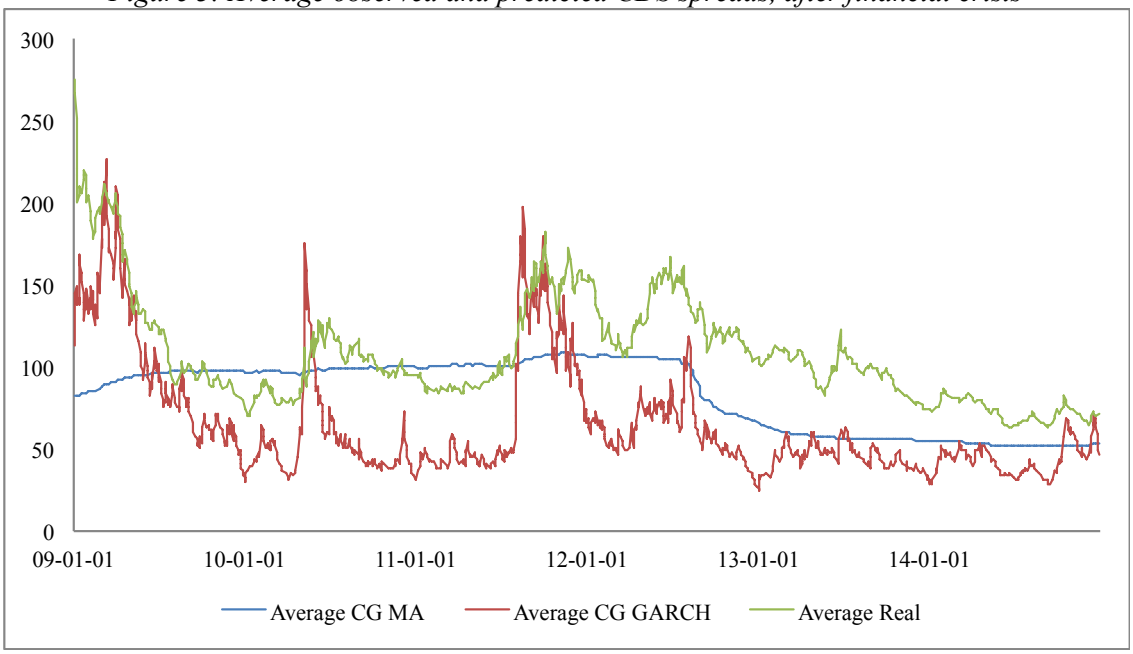
The uncertainty in the financial markets highlights the importance of the accurate estimate of credit risk (Belke and Gokus, 2011). Financial institutions use different kinds of credit risk models in order to estimate with accuracy the risk. In the credit risk model used in our study, the CreditGrades model, volatility is one of the driving factors. As a result, an accurate prediction of volatility facilitates the estimation of credit risk. In this study the estimation of volatility is conducted by the GARCH model and a Moving Average approach. Observing Figure 2 it can be noticed that during the financial crisis the CreditGrades model with GARCH estimated volatility overestimates the CDS spreads. On the other hand, the CreditGrades model with the volatility being estimated by the MA approach presents more stable CDS spreads. Figure 3 representing the period after the financial crisis has a different outlook where both models on average underestimate the real spreads. Based on the MA approach the volatility is too stable without taking the short-term trends into account in comparison with the GARCH model which takes them into consideration. Moreover, the GARCH model generates more volatile CDS spreads than the observed ones, particularly, during turbulent times.

Figure 2: Average observed and predicted CDS spreads, whole period



The figure shows the estimations of the predicted spreads in the CreditGrades (CG) model as well as the observed spreads expressed in basis points. For the predicted spreads two different methods are used to calculate the volatility; Moving Average (MA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model.The period examined is from December 2004 to December 2014 which is the whole sample period of our study.

Figure 3: Average observed and predicted CDS spreads, after financial crisis

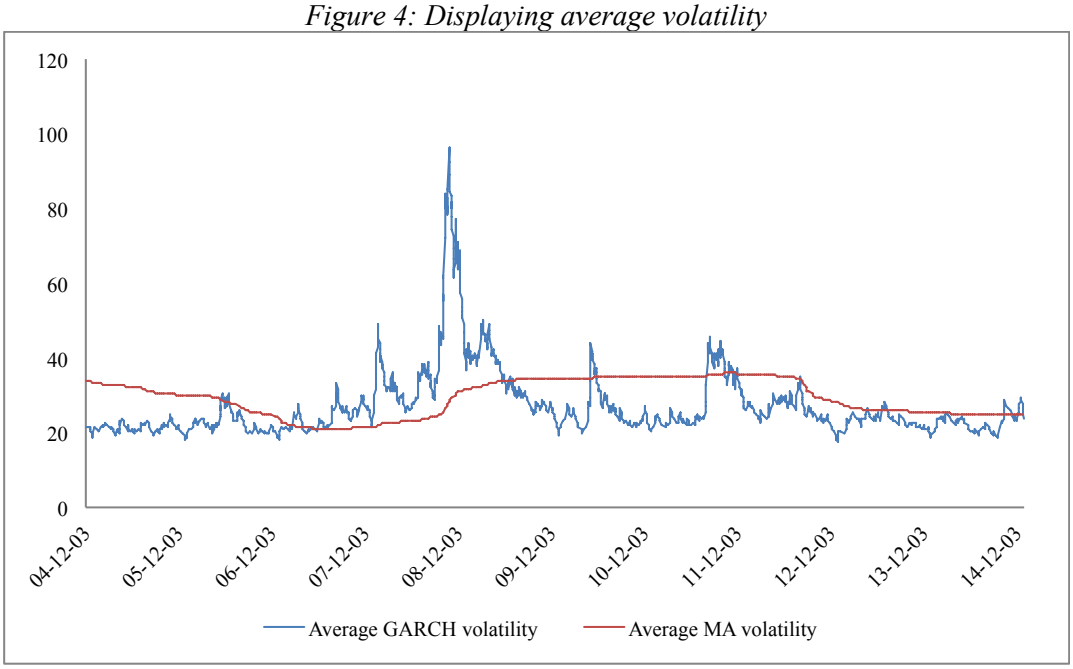


The figure shows the estimations of the predicted spreads in the CreditGrades (CG) model as well as the observed spreads expressed in basis points. For the predicted spreads two different methods are used to calculate the volatility; Moving Average (MA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The period examined is from January 2009 to December 2014 which is the period after the financial crisis.

Regarding the results previously mentioned the model specifications provided by CreditGrades (2002); the expected average recovery rate ($\bar{L}$) and λ, may not be optimal in our study which focuses on the European CDS market. Thus, the method used at either Byström (2006a) or Avino and Lazar (2012) where they optimize $\bar{L}$ and λ could have more preferable results. Figure 2 & 3 could be misleading since they show the average results. In addition, Appendix A shows the spreads for the first eight companies where the MA approach generates stable estimates while in the GARCH model fluctuations are detected especially during the financial crisis.

In order to accomplish our objective of reviewing the relationship of the predicted with the observed spreads a comparison of the two volatility methods is applied. The comparison is implemented based on the average volatility of each method which is presented in Figure 4. In addition, this approach can be an explanation for the performance of the CreditGrades model with these two volatility estimators. The MA approach generates a stable volatility as anticipated by CreditGrades (2002) and the GARCH model exhibits more fluctuations. As a consequence, the volatility estimated by the GARCH approach indicates a faster reacting model that takes the market shocks into account. Reviewing our estimations, we observe that volatility is a driver factor in the CreditGrades model since it is strongly affected by the different estimates. The high peaks of volatility generated by the GARCH estimator could be the reason for the overreactions in the estimated CDS spreads. The MA approach implemented in our study takes approximately four years of data into consideration. In the beginning of our sample can be possibly seen that the volatility is relatively high since this can be explained by the burst of the IT bubble at the turn of the millennium which could still affect our volatility estimate.

Figure 4: Displaying average volatility



The figure displays the average moving average volatility (MA) and the average GARCH estimated volatility.

An essential part of risk management is evaluating the performance of the models. Giving a more objective view, two of the most popular measures used to predict the average error in the models are the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE) (Maris et al., 2004). Table 2 & 3 display the MAPE and the RMSE respectively. Table 2 displays that for the whole period the GARCH produces a mean MAPE of 68.61 % that is slightly lower than the 75.03% given by the MA approach although the difference is not significant. Reviewing the subsamples more carefully reveals that before the financial crisis the GARCH model was a significant estimator. Nevertheless during the financial crisis the MA approach was significantly better than the GARCH model and during the European sovereign debt crisis there was no significant difference between the models. According to Table 3, the MA approach is significantly better than the GARCH model during the whole period.

Table 2: Mean absolute percentage error

	MAPE				
	Mean	Upper	Lower	Min	Max
	Before Financial crisis. Dec 2004 - Dec 2006				
MA	159.80%	191.57%	128.03%	16.92%	496.88%
GARCH	79.76%	90.90%	68.61%	23.98%	244.58%
	Financial crisis. Jan 2007- Dec 2008				
MA	67.34%	76.96%	57.72%	20.47%	322.88%
GARCH	100.11%	114.51%	85.71%	29.94%	395.21%
	European sovereign debt crisis. Jan 2009 - Dec 2014				
MA	48.26%	56.15%	40.37%	17.03%	243.91%
GARCH	54.20%	57.98%	50.43%	32.03%	93.85%
	Whole period				
MA	75.03%	83.14%	66.91%	23.99%	188.45%
GARCH	68.61%	73.04%	64.19%	40.38%	127.75%

The table presents the mean absolute percentage error (MAPE) as well as includes 95% confidence intervals. The mean, upper bound, lower bound, min and max values are calculated based on the MAPE of the individual companies. In addition, it covers the whole sample period as well as three sub-periods; before the financial crisis, during the financial crisis and during the European sovereign debt crisis.

Table 3: Root mean squared error

	RMSE				
	Mean	Upper	Lower	Min	Max
	Before Financial crisis. Dec 2004 - Dec 2006				
MA	50.41	63.11	37.71	3.57	282.13
GARCH	33.80	40.30	27.30	7.05	161.31
	Financial crisis. Jan 2007- Dec 2008				
MA	72.99	93.10	52.89	18.50	632.57
GARCH	194.06	222.34	165.78	20.73	4050.70
	European sovereign debt crisis. Jan 2009 - Dec 2014				
MA	69.47	85.36	53.57	13.26	423.06
GARCH	78.75	94.37	63.14	23.85	435.78
	Whole period				
MA	72.27	86.98	57.56	18.94	431.71
GARCH	116.32	134.01	98.63	30.41	1810.66

The table presents the root mean squared error (RMSE) as well as includes 95% confidence level. The mean, upper bound, lower bound, min and max values are calculated based on the RMSE of the individual companies. In addition, it covers the whole sample period as well as three sub-periods; before the financial crisis, during the financial crisis and during the European sovereign debt crisis.

In addition to the comparison of the volatility estimates according to MAPE and RMSE on an overall view that was previously implemented, we conduct an assessment on an individual level. This is satisfied by comparing the MAPE and RMSE for the individual companies of our study for each volatility estimator. Hence, the best performing estimates according to MAPE and RMSE respectively are depicted in Table 4 & 5. These tables can be seen as an added dimension in the process of assessing the performance. According to both tables the MA approach has the best performance except the period before the financial crisis. This can be verified by the fact that GARCH is the best performing model at that period. An explanation for the weak performance of the MA model could be the high levels of volatility in the beginning of our sample at that period. The objective comparison of MAPE and RMSE does not give a clear answer about the model that gives the best performance. Nonetheless, the MA approach seems having more satisfactory results.

Table 4: Individual evaluation of MAPE

MAPE		Times	Percentage of times
MA			
	Dec 2004 - Dec 2006 (Before Financial crisis)	25	37.31%
	Jan 2007- Dec 2008 (Financial crisis)	45	67.16%
	Jan 2009 - Dec 2014 (European sovereign debt crisis)	56	83.58%
	Dec 2004 - Dec 2014 (Whole period)	35	52.24%
GARCH			
	Dec 2004 - Dec 2006 (Before Financial crisis)	42	62.69%
	Jan 2007- Dec 2008 (Financial crisis)	22	32.84%
	Jan 2009 - Dec 2014 (European sovereign debt crisis)	11	16.42%
	Dec 2004 - Dec 2014 (Whole period)	32	47.76%

The table presents a comparison between the two different volatility measures and how they have performed on an individual level according to MAPE. In addition, it covers the whole sample period as well as three sub-periods; before the financial crisis, during the financial crisis and during the European Sovereign Debt crisis.

Table 5: Individual evaluaion of RMSE

RMSE		Times	Percentage of times
MA			
	Dec 2004 - Dec 2006 (Before Financial crisis)	30	44.78%
	Jan 2007- Dec 2008 (Financial crisis)	49	73.13%
	Jan 2009 - Dec 2014 (European sovereign debt crisis)	57	85.07%
	Dec 2004 - Dec 2014 (Whole period)	51	76.12%
GARCH			
	Dec 2004 - Dec 2006 (Before Financial crisis)	37	55.22%
	Jan 2007- Dec 2008 (Financial crisis)	18	26.87%
	Jan 2009 - Dec 2014 (European sovereign debt crisis)	10	14.93%
	Dec 2004 - Dec 2014 (Whole period)	16	23.88%

The table presents a comparison between the two different volatility measures and how they have performed on an individual level according to RMSE. In addition, it covers the whole sample period as well as three sub-periods; before the financial crisis, during the financial crisis and during the European Sovereign Debt crisis.

Apart from the models that we used in our study in order to estimate the volatility, we also implemented trading strategies aiming to give us a wider indication of volatility's accuracy. The results from the trading strategies are displayed in Table 6, where the estimates without a threshold suggest the MA being the preferred estimator of volatility. However, the model using GARCH estimated volatility is the one generating the highest returns when the thresholds are introduced. As seen in Appendix A the CreditGrades model using GARCH is more volatile and hence introduces more trading signals in comparison with the MA approach where the volatility could be too stable without giving enough signals.

Another goal of this study is to assess the possibility of finding risk adjusted returns using trading strategies on the CDS market. Appendix B reports the total performance of the examined different trading strategies which can also be seen in Table 6. The highest return is produced by the strategy based on the autocorrelation of CDS spreads and selecting the assets based on historical returns. The strategy that gives the lowest return is the one using the estimated CDS spreads with the MA approach including all assets that yield a negative return of -0.47% for the entire sample period. Examining the sub periods it can be detected that a large part of the return is obtained during the period of the European sovereign debt crisis. Before the financial crisis almost no positive returns can be observed.

Table 6: Total percentage return from the strategies

Threshold	Sharpe ratio CG MA	Return CG MA	Sharpe ratio CG GARCH	Return CG GARCH	Sharpe ratio AR(1)	Return AR(1)	All assets CG MA	All assets CG GARCH	All assets AR(1)
				Nov 2005-Dec 2006 (Before Financial crisis)					
0	-2.05%	-1.36%	-2.72%	-2.49%	-1.11%	-1.16%	-1.69%	-2.29%	-2.05%
0.01	0.04%	0.07%	-2.63%	-2.45%	-1.69%	-1.57%	-0.22%	-2.19%	-2.05%
0.02	-0.04%	-0.10%	-2.55%	-2.40%	-1.57%	-1.49%	-0.06%	-2.11%	-1.83%
				Jan 2007- Dec 2008 (Financial crisis)					
0	0.73%	4.26%	-1.60%	-2.10%	13.60%	16.58%	2.52%	-2.21%	8.97%
0.01	1.88%	2.08%	-0.49%	-1.77%	14.00%	15.75%	0.68%	-2.04%	8.80%
0.02	0.74%	0.58%	-0.86%	-1.75%	13.10%	13.77%	-0.09%	-2.05%	7.59%
				Jan 2009 - Dec 2014 (European sovereign debt crisis)					
0	22.03%	25.67%	10.49%	9.45%	57.31%	89.24%	6.14%	9.19%	30.97%
0.01	-1.39%	-0.44%	10.95%	12.26%	49.75%	76.88%	-0.91%	9.29%	26.77%
0.02	0.13%	-0.28%	9.64%	10.61%	39.91%	56.03%	-0.31%	8.90%	18.94%
				Nov 2005- Dec 2014 (Whole trading period)					
0	20.43%	29.30%	5.38%	5.64%	76.68%	118.03%	7.01%	4.39%	39.79%
0.01	0.51%	1.70%	7.53%	8.18%	67.85%	101.57%	-0.47%	4.76%	35.10%
0.02	0.82%	0.19%	4.09%	4.30%	55.78%	74.88%	-0.46%	4.46%	25.63%

The table presents the total return expressed in percentage. The period covered is before the financial crisis, during the financial crisis, during the European sovereign debt crisis as well as the whole trading period. The signals are either based on the CreditCredes (CG) estimated CDS spreads or the observed CDS spreads. The CreditGrades is estimated using two different volatility estimators; Moving Average (MA) or GARCH. Three different selection criteria are used; Sharpe ratio, return and all assets.

Obtaining returns on a risk adjusted basis can be attained by estimating the Sharpe ratio. The results of the estimations are presented below in Table 7. The highest Sharpe ratio was obtained by the same strategy that produced the highest total return. None of the strategies using GARCH estimated volatility manages to produce a positive Sharpe ratio for the whole period. On the other hand, the MA approach without threshold does produce a positive Sharpe ratio. The impact of including the thresholds on the Sharpe ratio is not always negative as can be seen during both the financial and the European crisis. For instance, the strategy using AR (1) and highest return increases the Sharpe ratio when the threshold is introduced. This indicates that the strategies' volatility drops with the introduction of a threshold, hence lowering the risk of the strategy.

The results regarding the Sharpe ratio and the total return indicate that the best performing strategies are the strategies that are based on the autocorrelation. These results are in line with Avino and Nneji (2012) finding that strategies based on autocorrelation outperforms those based on a structural model. Table 7 also displays that it is possible to find

positive Sharpe ratios using portfolios consisting of single named CDS spreads. Our results recommend using selection criteria instead of trading all assets. Both portfolio selection methods applied in this study increase the performance compared to trading all assets. This confirms our belief that it would be beneficiary to select the best performing assets into the trading portfolio.

Table 7: Sharpe ratios for the strategies

Threshold	Sharpe ratio CG MA	Return CG MA	Sharpe ratio CG GARCH	Return CG GARCH	Sharpe ratio AR(1)	Return AR(1)	All assets CG MA	All assets CG GARCH	All assets AR(1)
				Nov 2005-Dec 2006 (Before Financial crisis)					
0	-0.65	-0.38	-0.49	-0.47	-0.29	-0.34	-0.61	-0.68	-0.86
0.01	-0.43	-0.20	-0.47	-0.46	-0.40	-0.39	-1.37	-0.67	-0.94
0.02	-5.69	-2.79	-0.49	-0.48	-0.45	-0.45	-2.42	-0.68	-1.00
				Jan 2007- Dec 2008 (Financial crisis)					
0	-0.12	0.01	-0.17	-0.09	0.12	0.13	-0.02	-0.13	0.10
0.01	-0.17	-0.04	-0.16	-0.09	0.12	0.13	-0.14	-0.12	0.10
0.02	-0.49	-0.24	-0.18	-0.09	0.12	0.11	-0.38	-0.13	0.08
				Jan 2009 - Dec 2014 (European sovereign debt crisis)					
0	0.09	0.10	0.03	0.05	0.22	0.22	0.04	0.05	0.21
0.01	-0.15	-0.09	0.04	0.06	0.20	0.21	-0.22	0.06	0.20
0.02	-0.23	-0.19	0.02	0.03	0.17	0.18	-0.36	0.05	0.16
				Nov 2005- Dec 2014 (Whole trading period)					
0.00	0.01	0.06	-0.05	-0.01	0.17	0.18	-0.01	-0.02	0.14
0.01	-0.16	-0.07	-0.04	0.00	0.15	0.17	-0.18	-0.02	0.13
0.02	-0.38	-0.23	-0.06	-0.02	0.14	0.14	-0.37	-0.02	0.10

The table presents the Sharpe ratio. The period covered is before the financial crisis, during the financial crisis, during the European sovereign debt crisis as well as the whole trading period. The signals are either based on the CreditCredes (CG) estimated CDS spreads or the observed CDS spreads. The CreditGrades is estimated using two different volatility estimators; Moving Average (MA) or GARCH. Three different selection criteria are used; Sharpe ratio, return and all assets.

Byström (2006a) found significant autocorrelation in the iTraxx index, which is exploited in a trading strategy. This study confirms the autocorrelation being viable not only for the iTraxx index but also for the single name CDSs. His research was implemented in the beginning of our sample period. According to the results in our study, this was the weakest period which indicates not only the presence of autocorrelation but also a stronger relationship.

5 Conclusion

Based on the comparison between the predicted and empirically observed CDS spreads our aim was to determine the volatility estimator that fits best in the CreditGrades model. For this purpose we used the Moving Average (MA) approach and the GARCH model in order to estimate the volatility. The intention of using the GARCH model in this study was to take the market shocks into account. More specifically, since our sample period consists of large fluctuations ascending from the crash of Lehman Brothers and the fianancial difficulties experienced by many European countries our objective was to capture the market movements during this period. According to our findings, there is no clear answer about the model that actually performs best. Although the volatility estimated by the GARCH model generated time series visually similar with the observed CDS spreads, during turbulent times the model overreacted.

The Moving Average approach is the method suggested by the original study of the CreditGrades model which argues that the volatility produced should be stable and consistent with the historical asset volatility. Based on our results, the MA approach did generate more stable time series. In addition, reviewing the performance measures, the RMSE and the MAPE on an overall level did not give a definite result about the best performing volatility estimator. Yet, assessing the RMSE on an individual level the MA approach is suggested to be the preferred volatility estimator. In addition, the results obtained by the trading strategies support the MA approach being the best one. Even though the MA method is the suggested one since it seems to generate the best results we still support the GARCH model that captures the short-term movements.

Another objective of our study was to examine opportunities of positive risk-adjusted returns in the CDS market by applying trading strategies. These trading strategies that were based on the autocorrelation of the observed CDS spreads achieved the best performance. As a result the CreditGrades model is not recommended for the purpose of trading strategies. The high returns using the AR (1) also indicated that the autocorrelation that Byström (2006a) found in the iTraxx index is still present. Furthermore, the overall findings indicate the benefits of selection criteria in the trading strategies performed on the CDS market. The

strategies employed in this study rebalance the portfolio every day. However the strategy does not take positions on the assets for each day separately as the ones in the study of Byström (2006a) and Avino and Nneji (2012). This is a more realistic way of how a trading strategy should work since this strategy holds the position open and hence lowers the number of transactions. One of the limitations in this study was that the transaction costs were not taken into account. In case they were taken into consideration, the returns woulde decrease which means that the positive Sharpe ratios could disappear.

A valuable contribution of this study is that it gives guidelines to financial institutions and generally to the parties interested in measuring credit risk. This guidance involves exploiting the strong autocorrelation on the CDS market in trading strategies. The performance of these strategies can also be improved by implementing selection criteria which chooses the historically best performing assets. With regards to the CreditGrades model, the preferred volatility estimator is the MA approach which is also suggested by the original version of the model. However, the GARCH model can still be used for the purpose of a fast reacting model.

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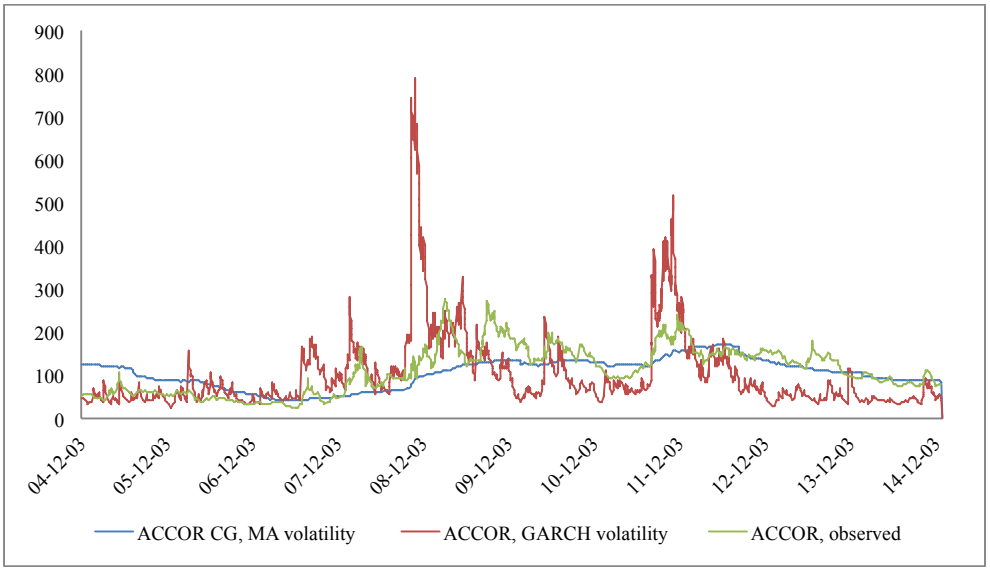
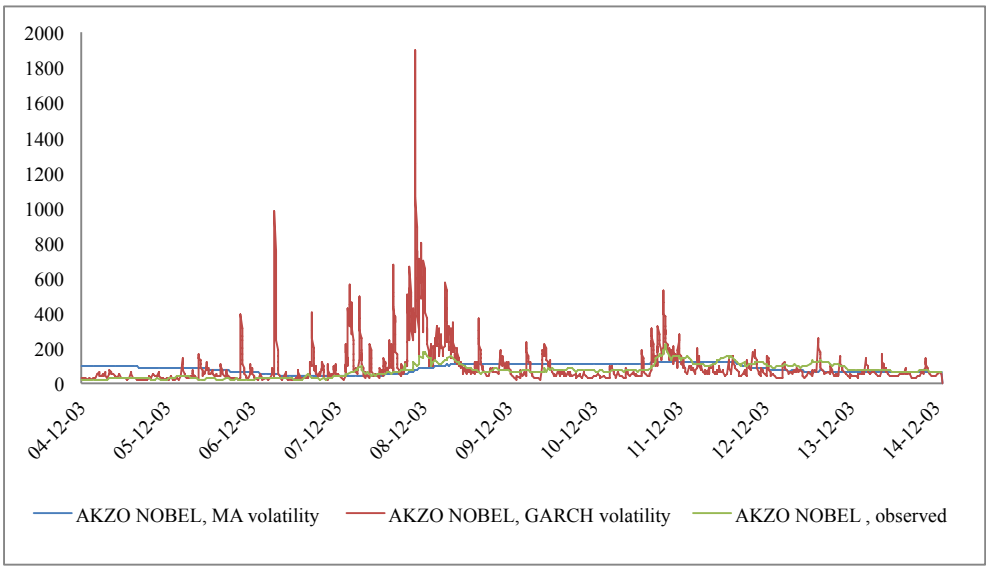
Appendix A

Appendix A 1: Observed and predicted CDS spreads for Accor



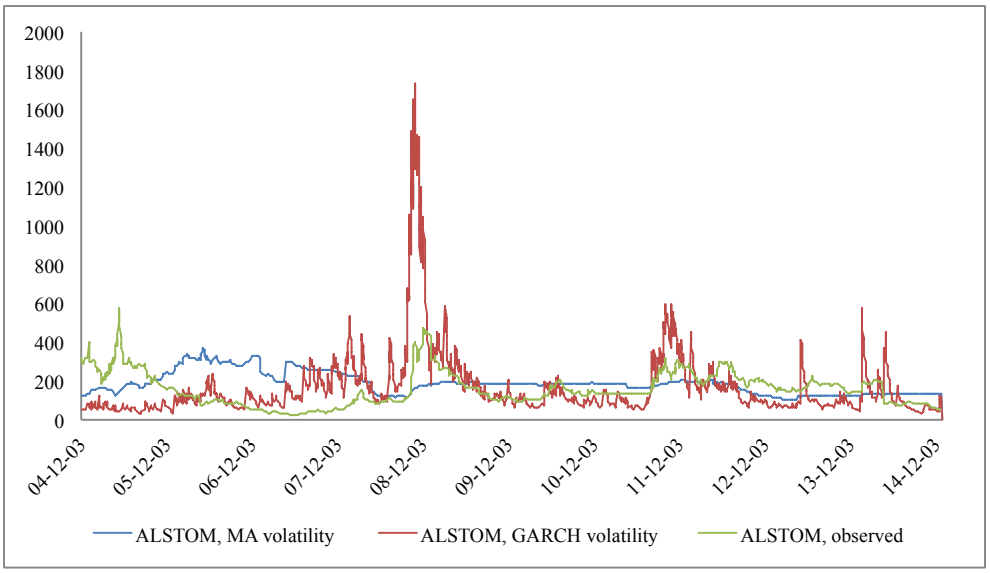
The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company ACCOR. The sample period covers December 2004 to December 2014.

Appendix A 2: Observed and predicted CDS spreads for Akzo Nobel



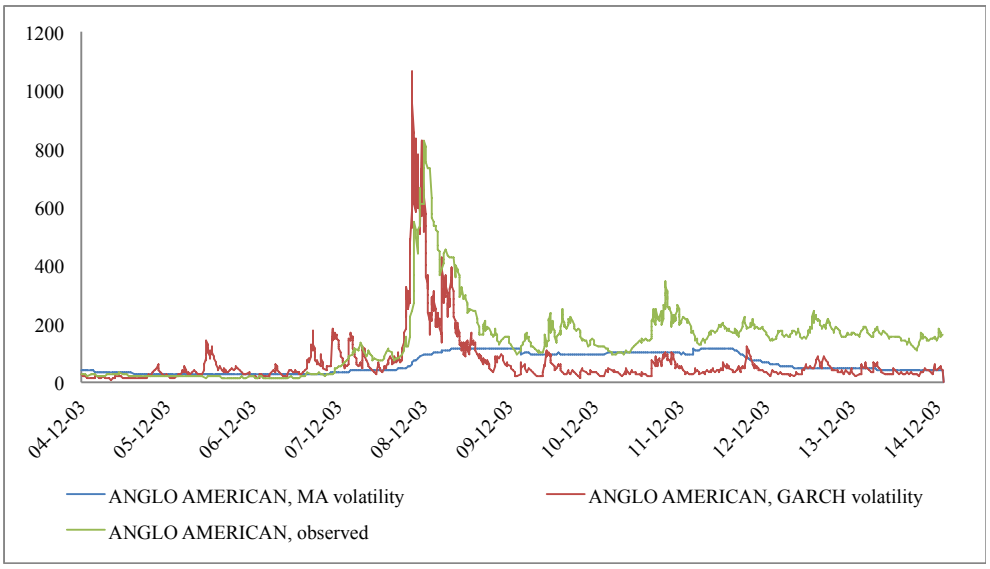
The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company AKZO NOBEL. The sample period covers December 2004 to December 2014.

Appendix A 3: Observed and predicted CDS spreads for Alstom



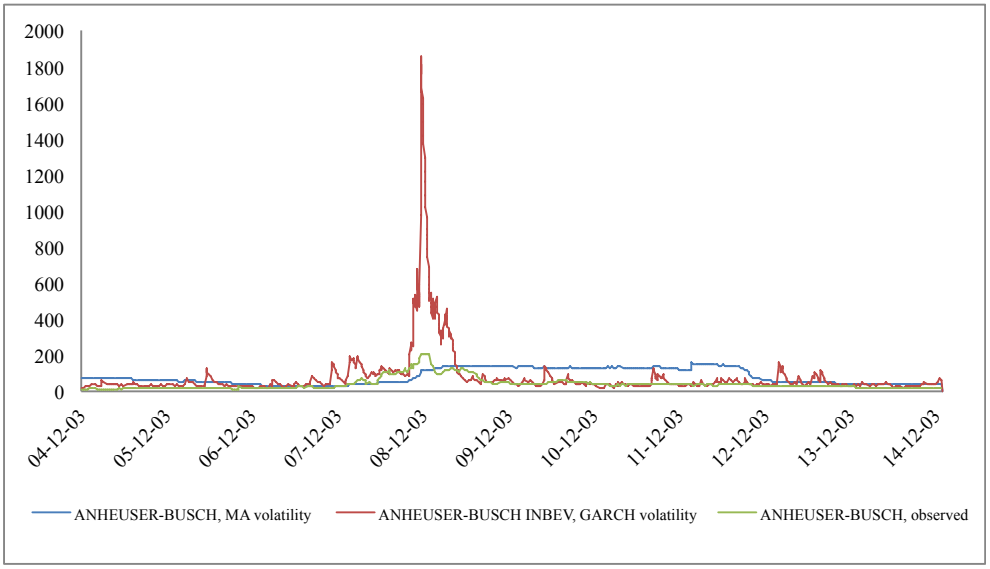
The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company ALSTOM. The sample period covers December 2004 to December 2014.

Appendix A 4: Observed and predicted CDS spreads for Anglo American



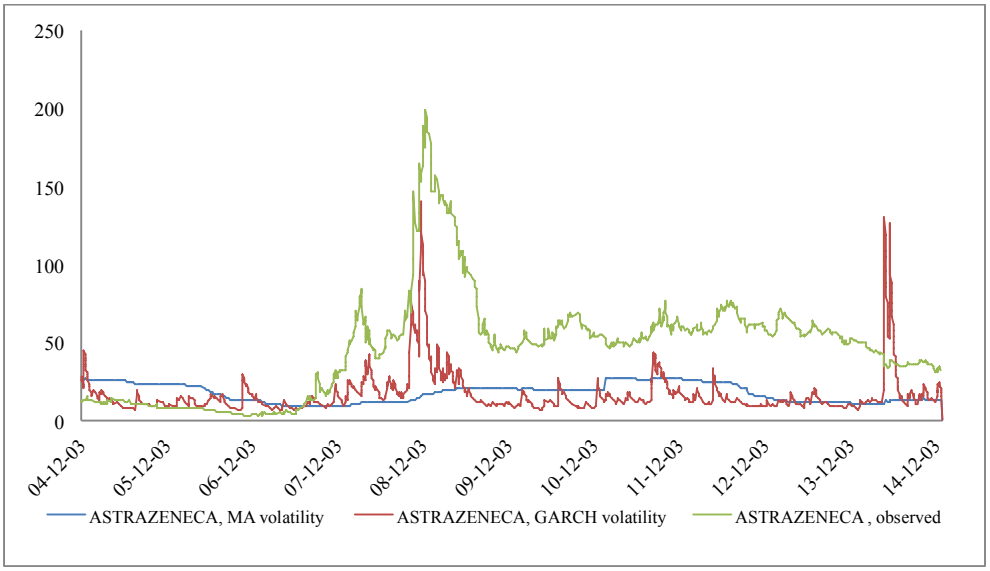
The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company ANGLO AMERICAN. The sample period covers December 2004 to December 2014.

Appendix A 5: Observed and predicted CDS spread for Anheuser-Busch



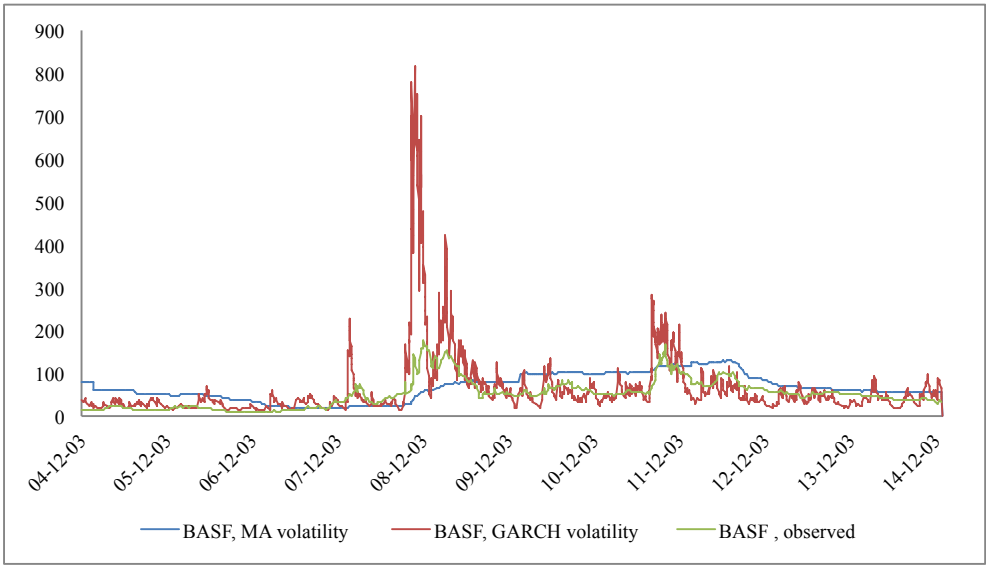
The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company ANHEUSER-BUSCH. The sample period covers December 2004 to December 2014.

Appendix A 6: Observed and predicted CDS spreads for AstraZeneca



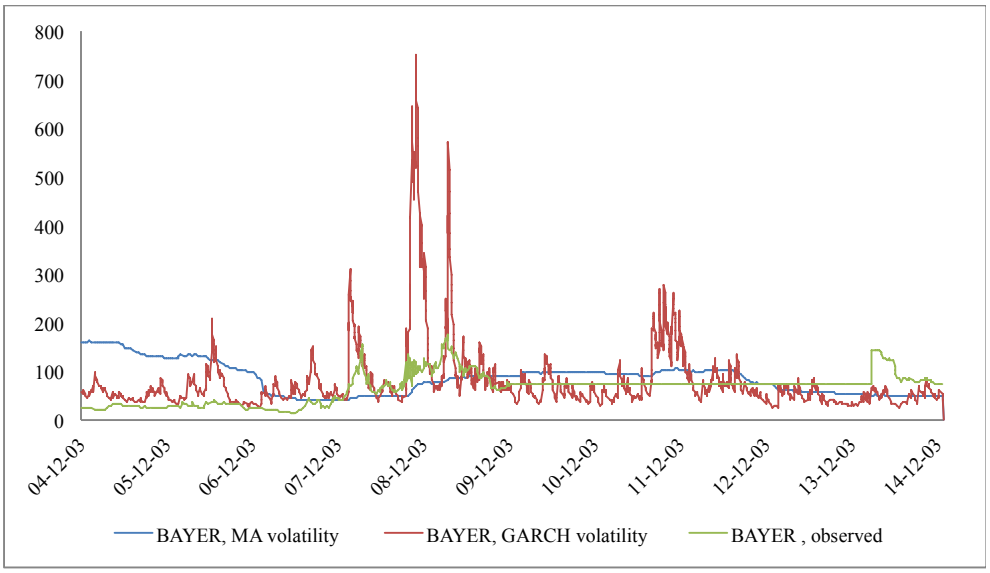
The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company ASTRAZANECA. The sample period covers December 2004 to December 2014.

Appendix A 7: Observed and predicted CDS spreads for BASF



The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company BASF. The sample period covers December 2004 to December 2014.

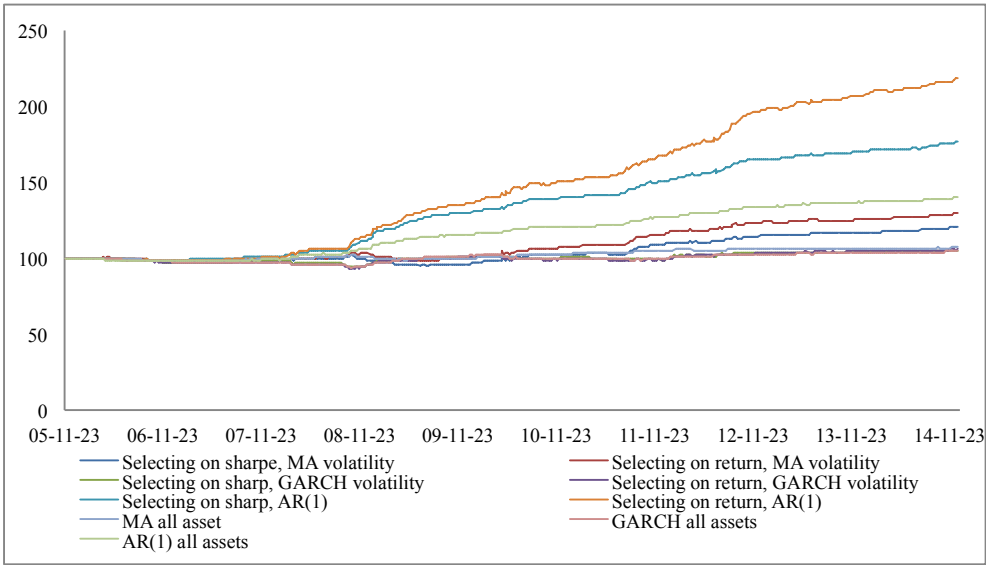
Appendix A 8: Observed and predicted CDS spreads for Bayer



The figure displays the predicted spreads obtained by using the CreditGrades (CG) model with the volatility estimated by the Moving Average (MA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) method volatility compared with the empirically observed spreads for the company BAYER. The sample period covers December 2004 to December 2014.

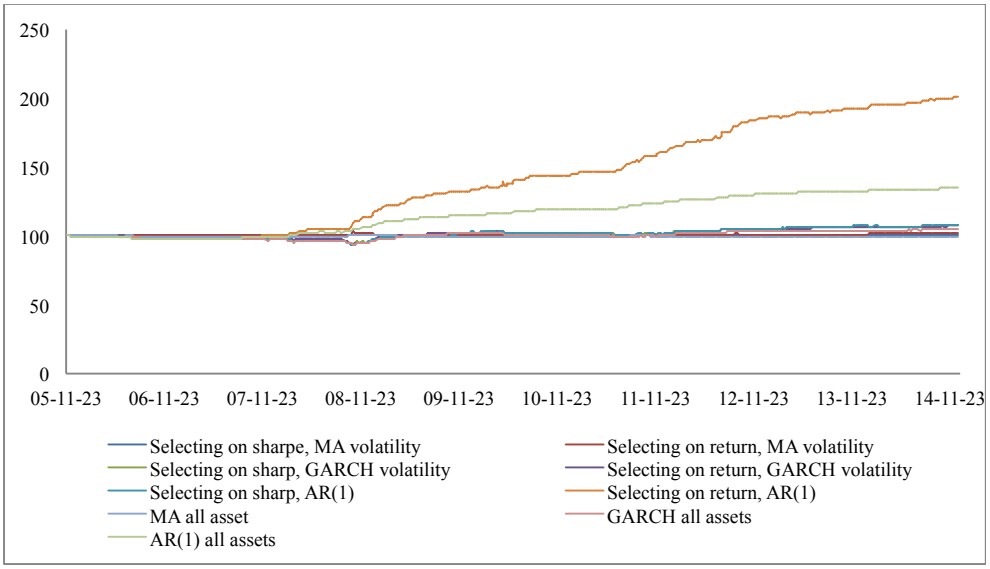
Appendix B

Appendix B 1: Total strategy performance using a threshold of 0.00



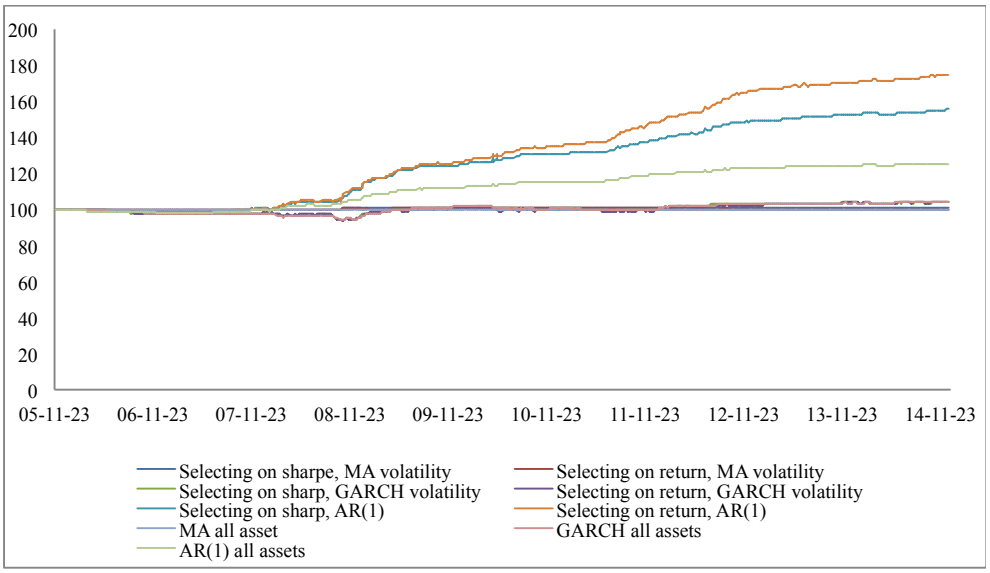
The figure presents the total performance of the trading strategies without any threshold. The strategies are using the tree different selection criteria namely; highest Sharpe ratio, highest return and trading portfolio including all assets. The three different underlying time series are; predicted spreads obtained by the CreditGrades model with the volatility estimated by the MA approach, predicted spreads obtained by the CreditGrades model with the volatility estimated by the GARCH model and the autocorrelation (AR(1)) of the observed CDS spreads. The sample period covers the whole trading period which starts from November 2005 to December 2014.

Appendix B 2: Total strategy performance using a threshold of 0.01



The figure presents the total performance of the trading strategies with a threshold of 0.01. The strategies are using the tree different selection criteria namely; highest Sharpe ratio, highest return and trading portfolio including all assets. The three different underlying time series are; predicted spreads obtained by the CreditGrades model with the volatility estimated by the MA approach, predicted spreads obtained by the CreditGrades model with the volatility estimated by the GARCH model and the autocorrelation (AR(1)) of the observed CDS spreads. The sample period covers the whole trading period which starts from November 2005 to December 2014.

Appendix B 3: Total strategy performance using a threshold of 0.02



The figure presents the total performance of the trading strategies with a threshold of 0.02. The strategies are using the tree different selection criteria namely; highest Sharpe ratio, highest return and trading portfolio including all assets. The three different underlying time series are; predicted spreads obtained by the CreditGrades model with the volatility estimated by the MA approach, predicted spreads obtained by the CreditGrades model with the volatility estimated by the GARCH model and the autocorrelation (AR(1)) of the observed CDS spreads. The sample period covers the whole trading period which starts from November 2005 to December 2014.