LUND UNIVERSITY

Evaluation of Capital Structure Arbitrage in the Equity-Credit Markets

Lund University School of Economics and Management

Bachelor Thesis

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Summary

Title: Evaluation of Capital Structure Arbitrage in the Equity-Credit Markets

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Keywords: Capital Structure Arbitrage, Credit Default Swaps, CreditGrades, Value-at-Risk, Arbitrage Trading

Purpose: The purpose of this thesis is to test for the existence of Capital Structure Arbitrage opportunities in the equity-credit markets.

Methodology: The mispricing of Credit Default Swap contracts are calculated and used as input in an Equity-Credit market trading strategy. The returns are then evaluated with a modified Value-at-Risk simulation.

Theoretical perspectives: A Merton-based structural model, CreditGrades, is used for credit pricing and a mispricing-convergence trading-strategy between the credit and equity markets is implemented.

Empirical foundation: Daily quotes for the Credit Default Swap spread of 37 European firms were collected for a period of two years, as well as equity-prices for the same period and the previous two years, used for model calibration.

Conclusions: The trading shows a statistically significant total return of the Capital Structure Arbitrage trading strategy of 32,9%, compared to 10,8% with pure Credit Default Swap speculation. The equity-hedge of the strategy effectively lowers Value-at-Risk, and thus results in a higher return, which supports the argument for Capital Structure Arbitrage oppertunities. The results however, are very volatile, something that might suggest that the strategy chosen is closer to speculation than arbitrage.

Sammanfattning (Summary in Swedish)

Titel: Evaluation of Capital Structure Arbitrage in the Equity-Credit Markets

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Författare: Natalia Danilina, Daniel Ferm, Fredrik Hedberg och Daniel Zakrisson

Handledare: Göran Andersson

Fem nyckelord: Capital Structure Arbitrage, Credit Default Swaps, CreditGrades, Value-at-Risk, Arbitragehandel

Syfte: Syftet med denna uppsats är att utvärdera förekomsten av kapitalstrukturarbitrage-möjligheter mellan aktie- och kredit marknaderna.

Metod: Felprissättningen av Credit Default Swap-kontrakt beräknas och används sedan som indata till en tradingstrategi. Avkastningen utvärderas därefter med en modifierad Value-at-Risk-simulering.

Teoretiska perspektiv: En Merton-baserad strukturerad modell, CreditGrades, används för kredit-prisberäkning och en arbitrage strategi med felprisättningskonvergens mellan aktie- och kreditmarknaden implementeras.

Empiri: Dagliga data för Credit Default Swap-spreaden för 37 Europeiska företag samlades in för en period av två år, tillsammans med aktie-kurser för samma period samt de två tidigare åren för användning till modell-kalibrering.

Resultat: Den totala avkastningen av kapitalstrukturarbitrage-tradingen är 32,9% jämfört med 10,8% för enbart Credit Default Swap-trading. Kapitalstrukturarbitrage-strategins aktiehedge sänker effektivt Value-at-Risk och resulterar i en högre avkastning, vilket stöder argumentet för förekomsten av kapitalstrukturarbitrage-möjligeheter. Resultaten är dock mycket volatila, vilken kan peka på att den valda strategin är mer spekulering än arbitrage.

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Chapter 1

Introduction

In this chapter we introduce the reader to the subject of this thesis. We start with a brief background regarding the credit derivatives market and the argument for Capital Structure Arbitrage. We then continue with a discussion around the scientific problem motivating our research. Lastly, we present the formal purpose and limitations of this thesis.

1.1 Background

The credit risk market is the world's fastest growing financial market, attracting everyone from hedge funds to commercial banks and insurance companies. Credit risk appears due to uncertainty in a borrower's ability to meet their contractual obligations. It leads to credit losses and is present in almost all financial activities. Nevertheless, the research of credit risk was non-existent two decades ago, because of the general lack of understanding of credit risk.

Due to the growth in the level of bankruptcies during the 1990s and early 2000s, risk management has gained increased popularity among bankers and portfolio managers. Their ability to quantify and manage risk significantly improved during the years, as the advancement in computer technology provided essential opportunities to the development of risk modeling methods. Consequently, credit risk has evolved from being an unavoidable factor in the world of finance to an acceptable and almost predictable risk factor.

The latest product of the credit risk market, credit derivatives, is the most popular new instrument for transferring credit risk. Credit derivatives are particularly used by financial institutions with high credit exposure in order to hedge or assume credit risk. A credit derivative is an OTC bilateral contract that permits users to manage their exposure to credit risk. The credit derivatives market is one of today's most significant over-the-counter markets. The expansion of the market has exceeded all expectations, growing from a notional value of $5 trillion in 2004 to over $20 trillion in 2006 (British

Bankers Association 2006).

Such a tremendous growth in the market volume has been matched and to some extent driven by the range of new credit derivative products. In terms of volume, Credit Default Swap contracts have evolved as the most popular among them, gaining more than half of the general outstanding volume in the total credit derivatives market. Generally, a CDS is an over-the-counter arrangement which moves credit risk from one party to another. Thus, an insurance buyer pays a periodic fee to an investor in return for a protection against a credit event by a reference entity. This gives investors the opportunity to go both long and short in credit without having to hold the underlying instrument. Despite being a customized over-the-counter instrument, CDS are traded in standardized form between a wide variety of market participants.

CDS contracts are primarily used by banks and other lending institutions to insure their financial positions from the credit risk of the firm defaulting. However, other market participants, such as hedge funds and other speculators have begun showing interest in trading between the equity and credit derivatives market in pursuit of arbitrage opportunities. Huge growth in the CDS market and the possibility to go short on these debt positions have made a new form of trading strategy possible. This concept of trading between a company's different asset classes, equity and debt, is known as Capital Structure Arbitrage. It is one of the most recent hedge-fund strategies that has gained popularity among investment banks and hedge-funds since 2002, and is designed to exploit pricing imperfection that exists in the capital structure of the firm (Chatiras and Mukherjee 2004).

1.2 Problem

With the recent emergence of the credit derivatives market, academic research and industry practice is still developing. The huge growth of the CDS market has been the major factor for the development of CSA strategies. CSA has been drawing more and more attention from hedge-funds and other financial institutes. Research about CSA is very limited and there is still no consensus whether this is a profitable strategy or not. CSA has been described as a trading strategy that could become "the next big thing" (Currie and Morris 2002), but there is lack of research showing any evidence for this. Those who are engaged in this type of trading are surely willing to keep their strategies secret, consequently it is very hard to retrieve information about prevailing market strategies. These are the main problems motivating this thesis, as there is evidently no consensus about CSA profitability. Another problem in evaluating CSA opportunities, and one of the biggest issues for the market to solve, is that there is yet to evolve a common asset pricing model for the new and somewhat exotic types of credit derivatives. There are numerous CDS pricing models and they vary strongly in the underlying market assumptions and pricing model complexity.

1.3 Purpose

The purpose of this thesis is to test for the existence of Capital Structure Arbitrage opportunities in the equity-credit markets.

1.4 Limitations

Since the focus of this thesis is to evaluate CSA from an equity-credit markets perspective, we limit the study by only using the equity based structural approach when pricing Credit Default Swaps. The CSA strategies subsequently used only focus on pure equity-credit trading and we do not evaluate, nor compare, our results to other strategies.

In the equity-credit trading strategy, we are only considering equity as a hedge and do not consider call-put options. Transaction costs are not taken into consideration as these costs are hard to estimate. This of course affects the profit of the trade.

We limit the study by only analyzing 37 companies from the European market, since no other study focuses on this market. The firms studied are selected randomly from the iTraxx index, however, there are some criterias in the selection process. The companies must be listed in the euro currency in order to avoid problems with currency adjustments and currency risks, and companies without sufficient information available also has to be excluded.

Chapter 2

Theory

In this chapter we present the relevant theoretical framework used as a basis for the research conducted in this thesis. We start by introducing the reader to the concept of credit risk and credit derivatives, and continue with the relevant asset pricing models used in academia and in the financial industry. Lastly, we talk about the concept of Capital Structure Arbitrage, difficulties of forecasting asset volatility and risk calculation for Credit Default Swap trading strategies.

2.1 Credit Risk

There is always an element of risk involved with debt and credit. This is called credit risk and is generally defined as the risk of loss due to a debtor's non-payment of a debt or other form of credit. Institutions often use various methods to rank companies in order to determine how large credit risk they will face.

There are three things that are particularly important for an institution to consider when entering into a transaction that will make them face a credit risk; probability of default, credit exposure and recovery rate (R). Probability of default is, as the name suggests, the probability that the counter-party will default on its obligation, for example not manage to repay a loan in a given time-frame. Credit exposure measures how large the remaining obligation will be if default should occur and recovery rate measures how much that will be possible to recover after a default.

Credit derivatives also include credit risk. Certain types of derivatives, like swaps and forwards, are particularly difficult to rate since they have an initial market value of zero. In this case, advanced methods are used to evaluate the credit risk companies are exposed to.

2.1.1 Credit Rating

Credit rating indicates the credit worthiness of firms. The rating is determined through a process called credit analysis, which takes into account many factors about the company being rated. The main firms that perform credit analysis are Standard & Poor's, Fitch and Moody's. The companies are ranked according to a rating, usually ranging from AAA to D where AAA is the highest rating, and D is the lowest. A rating of BBB or above defines that the company's debt is rated as investment-grade while a company rated below BBB has a considerable risk of defaulting, and its bonds are referred to as junk bonds. The system of rating differs somewhat between the credit rating companies.

The credit rating process is of high importance for companies, as with a poor rating it is harder to raise debt, and the interest rate will be higher. The rating eventually also affects the equity and CDS prices since the ratings are considered valuable information for many market participants. The CDS market is particularly influenced by the credit rating, since the default of a company triggers a debt payment.

2.2 Credit Default Swap

A Credit Default Swap (CDS) is the most common form of credit derivative, which is aimed to transfer credit exposure of fixed-income products between parties. A purchaser of the credit protection agrees to pay a fixed periodic fee (spread) to the seller of the CDS. The credit protection is a contract, which guarantees a payout in case a credit event occurs. Its initial value when initiated is zero, as the expected value of the protection payment equals to the negative expected value of the fee or coupon payments.

The standard use of CDS contracts is for companies to hedge credit risks. If, for example, a bank has extended debt to a company, they can protect themselves from a potential default by buying a CDS. If the company defaults on the debt during the specified time, the company that issued the CDS will pay part of the notional amount of debt, $N(1-R)$. In this way, the protection buyer has eliminated the risk and transferred it to the protection seller, who is more willing to take it.

There has been a large increase of speculation in the CDS market over the last years. Since CDS contracts increasingly sell directly over-the-counter, they can be bought and resold at will. The buyer of protection has a short position in credit, while the seller has a long. Shorting a contract is much easier compared to bonds, which is a much more complex and costly procedure.

The traded CDS volume has shown exponential growth during the last years, and by June 2006 the notional amount of outstanding CDS contracts had reached $20 trillion. The main buyers of credit default swaps are commercial banks, but hedge funds have also become a major participant in the last years. Their share of volume in both buying and selling credit protection have almost doubled since 2004. Banks have went from about 80% of the CDS market in 2000 to about 60% in 2006 while hedge funds have went from 10% to 30% in the same period (figures for buying protection). Other market participants are mutual funds and insurance companies, which constitutes around 10% of the market. (British Banker's Association 2006)

2.3 Credit Pricing Models

When pricing general credit instruments and its derivatives, the most important parameters are the firm specific probability of default and expected recovery rate. The probability of default directly impacts the firm's credit spread, the premium a firm has to pay over the risk-free interest, but also determines the CDS spread considering the nature of a CDS contract. The recovery rate also affects the CDS spread, as the protection buyer's reimbursement depends on the difference between the notional debt value and the actual recovered value.

CDS contracts are most commonly priced using simple cash-flow valuation, with the extra component of uncertainty arising from the probability of default added (Hull and White 2000). During the lifespan of a contract there are two cash-flows to take into account; the protection buyer's quarterly premiums, known as the *premium leg*, and the protection seller's insurance payment, if and when the reference entity defaults on its debt, known as the *protection leg*. The two cash-flows are in turn properly discounted, with respect to the probability of default that impacts the expected cash-flows, and defines the price of the contract as the sum of the two parts.

However, CDS contracts are by definition initiated on terms that set the price of the contract to zero, making the contract spread the determining factor. Subsequently, this lets us solve the contract spread from the discounted cash-flows by modeling what has been the focus of most credit related research in the past three decades - the probability of default.

2.3.1 Structural Models

The most important breakthrough in the field of quantitative credit assessment, dates back to when Black and Scholes (1973) and Merton (1974) introduced their famous asset pricing model, originally designed for pricing equity options. The model linked equity- and debt value to the firm's assets by considering a firm's equity and debt to be call and put options on the firm's underlying assets. Merton implied that the same option pricing model could be adapted for use in assessing credit, which led to the use of Merton's model as a base for an entire group of credit pricing models called *structural models*.

The structural models are heavily linked to the capital structure of a firm, hence the name *structural*, and defines the concept of default as the event when the value of the firm's equity falls below a certain default barrier. The structural models are very attractive as the model parameters are readily observable in the liquid and transparent equity market, as opposed to the less liquid debt market.

Merton's Model

The model Merton originally devised to assess credit is a simple one, and assumes that the firm has two classes of issued securities; equity and debt. The value of the firm's total assets is defined as the sum of the firm's equity and debt, and it is assumed to follow the same log-normal diffusion process as the firm's equity, most commonly the standard Wiener-driven Geometric Brownian Motion (GBM). The assets value can hence be described by the stochastic differential equation

$$dV_t = \mu V_t \, dt + \sigma_V V_t \, dW_t \tag{2.1}$$

where V_t is the value of the firm's total assets at time t, μ the drift (ie. the average asset return), σ_V the asset value volatility and W_t the Wiener component.

The key argument in both Black and Scholes and Merton revolves around the notion that the equity value is the residual of the firm's total assets after the debt has been re-payed, a concept first explored by Miller and Modigliani (1958). Intuitively, this originates from the seniority of debt over equity if the firm was to default, where the debtors receive their stake before any of the shareholders would. Thus, at any time t, the value of the firm's equity can be described as

$$E_t = max(V_t - D, 0) \tag{2.2}$$

where E_t and V_t is the equity and asset value respectively. This simple statement reflects the core insight of Merton and to some extent Black and Scholes, showing that the equity can be considered a call option on the firm's assets, and allows for the modeling of equity and credit using the now famous option pricing framework.

With similar model assumptions as defined by Black and Scholes, Merton specifies an option model with the equity price representing the option price, and with the firm's assets as the underlying instrument. The asset value is suitably defined by the GBM as above, fulfilling the log-normal return requirements of the Black and Scholes model. The equivalent of the option strike price in this case however, is not predetermined by an option contract, but rather by a default-barrier related to the future value of the debt the firm is obliged to repay. Applied, this defines the current equity price using the Black and Scholes model as

$$E_0 = V_0 \Phi(d_1) - Xe^{-rT} \Phi(d_2) \tag{2.3}$$

where V_0 is the initial asset value, Φ the cumulative normal distribution function, X the default-barrier (ie. the value of the firm's debt, adjusted depending on the recovery rate), T the terminal date of the firm's debt and r the risk-free interest rate. The parameters d_1 and d_2 are represented by

$$
\begin{aligned}
d_1 &= \frac{log\left(\frac{V_0}{X}\right) + \frac{1}{2}\sigma_V^2 T}{\sigma_V \sqrt{T}} \\
d_2 &= d_1 - \sigma_V \sqrt{T}
\end{aligned}
$$

where σ_V is the standard deviation of the firm's asset value. This elegantly relates not only the shareholders equity risk, but also the debtors credit risk, to the firm's capital structure. Merton continues by deriving the probability of default from the Black and Scholes model; the probability that the shareholders will not exercise their call option on the firm's assets at time T, as

$$
\mathbb{P}(E_T \leq X|V_0) = \Phi(-d_2) \tag{2.4}
$$

where d_2 is defined as above. As a result of using the plain Black and Scholes model, originally devised to value *European* equity options, equation (2.6) also reveals that Merton's model is not a so called *stopped* model; allowing the equity price to fall below the default-barrier temporarily before the time T without triggering a default.

Other Models

After Merton introduced the concept of modeling credit risk using the structural approach, several researchers has proposed modifications to the original model in order to better estimate the probability of default, resulting in an entire group of structural models. One of the more common types of modification relates to the diffusion process of the firm's equity, and thus its assets, in order to more correctly model the future of the firm in terms of volatility, jumps and other externally defined events. For example, Cox (1975) pioneered the academically successful *Constant Elasticity of Variance* (CEV) model, leading to an improved representation of the asset volatility, something further developed by Atlan and Leblanc (2005) among others.

Additionally, Black and Cox (1976) introduced the first stopped structural model (or First Passage Model), where default occurs as soon as the firm's equity drops below the specified default barrier, providing a more realistic alternative when modeling credit. Other researchers has also attempted to relate factors such as market risk, using the *Capital Asset Pricing Model* (CAPM) framework to the probability of default (Bohn 2000). For a summary of the different structural alternatives to the pure Merton model, we refer to either Berndt and Veras de Melo (2003) or Bohn (2000).

2.3.2 Reduced-Form Models

The most important alternative credit assessment method to the structural models, is a group of models called *reduced-form*. The reduced-form models was first suggested by

Duffie and Singleton (1998) and deviates from the structural models by using a time-dependent default barrier, decoupling the probability of default from the firm's capital structure. Having the probability of default exogenously defined provides more freedom in the sense that non-economic factors can be addressed, but also incurs a larger error margin when using model parameters not generally well understood (Bohn 2000).

Most commonly in reduced-form models, the probability of default is estimated using market observed credit spreads from the debt market (Hull and White 2000). This is generally considered a good approach since the observed credit spread is supposedly reflecting non-economic default affecting factors in a quantitative way. However, because of the low liquidity, high credit-spread volatility and lack of transparency in the debt market, it's not an approach entirely without its share of controversies.

2.3.3 Commercial Variants

As a result of the extreme growth seen in the credit derivatives market during the last couple of years, research related to credit pricing model has attracted increasing interest from the financial industry. As many of the credit pricing models devised in academia tend to take a very theoretical approach to solving practical problems, several commercial variants of the more successful models have emerged.

The most popular commercial credit pricing model of those publicly available is the CreditGrades model, rivaled only by Moody's KVM, and is one of the few commercial models that is published in its entirety.

The CreditGrades Model

The CreditGrades model was developed and published by a joint-venture between Goldman Sachs, J.P. Morgan and Deutsche Bank, named RiskMetrics Group, Inc. The model is a modified implementation of Merton's structural model and is widely considered to be the industry standard framework used for credit assessment (Yu 2005).

As one of the main goals of the model was to address the deflated credit spreads that resulted from Merton's model, RiskMetrics (2002) find that the deflated spreads mainly can be seen as a consequence of two factors; firstly that Merton's model allows for the equity to pass the default barrier without triggering an actual default (ie. not a stopped model) and secondly the lack of absolute realism in the pure GBM process used to model the asset development.

The CreditGrades model deviate from Merton's model by introducing an absorbing and uncertain default-barrier, and by triggering default as a stopped-model. The default-barrier is estimated by the firm's specific recovery-rate R as in most other structural models, but also assumes that it is log-normally distributed over time with a certain standard deviation λ in order to adjust for the lack of jumps and other anomalies in the GBM process.

The model uses the concept of survival probability instead of the probability of default (which are conceptual equivalents, although not mathematically), and is given by

$$\mathbb{P}(\tau \leq T|V_0) = \Phi\left(-\frac{A_t}{2} + \frac{log\,(d)}{A_t}\right) - d\Phi\left(-\frac{A_t}{2} - \frac{log(d)}{A_t}\right) \tag{2.5}$$

where τ is the time of default, T the contract lifespan and Φ the cumulative normal distribution function. The variables d and A_t are defined in the CreditGrades model as

$$\begin{aligned} d &= \frac{V_0}{RD}e^{\lambda^2} \\ A_t &= \sqrt{\sigma_V^2 t + \lambda^2} \end{aligned}$$

where V_0 is the initial asset value, σ_V the asset value volatility, D the debt-per-share, R the recovery-rate and λ the percentage standard deviation of the default-barrier. The total asset value and its standard deviation is approximated in a linear fashion from the firm's equity value and volatility (RiskMetrics 2005).

Discounting the two CDS contract cash-flows, Yu (2005) illustrates how the CDS spread can be calculated by solving the pricing integrals analytically. The spread is calculated as

$$s = r(1-R)\frac{1 - p(0) + h(T)}{p(0) - p(T)e^{-rT} - h(T)} \tag{2.6}$$

where R is the recovery rate, T the contract lifespan, $p(t)$ the survival probability and r the risk-free treasury bond interest. With $\xi = \lambda^2/\sigma^2$, $h(t)$ and $g(t)$ are helper functions defined by the CreditGrades specification as

$$\begin{aligned} h(t) &= e^{r\xi}\left[g(t+\xi) - g(\xi)\right] \\ g(t) &= d^{\left(z+\frac{1}{2}\right)}\Phi\left(-\frac{log(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}\right) + d^{\left(-z+\frac{1}{2}\right)}\Phi\left(\frac{log(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}\right) \end{aligned}$$

where d is defined as above. For a more in-depth review of the assumptions, ideas and calculations behind the CreditGrades model, we refer to either RiskMetrics (2002) or Yu (2005).

2.4 Volatility Measures

Modeling and forecasting stock market volatility has been the subject of a great research during the last decade. It is probably the most important variable in any pricing model.

Expectations about future volatility play an important role in portfolio management, hedging and asset pricing. Volatility is often used as a crude measure of the total risk of capital assets.

There are numerous methods for estimating volatility in modern credit derivatives market. Asset price volatility is usually measured in two ways; historic volatility, which involves only historic price information, and implied volatility which represents the volatility of the security underlying an option, determined by the price of the option. The standard model for volatility is the historical estimate, which involves calculating the standard deviation of returns over some historical period. The historical volatility is the input to options pricing models, although there is a growing body of evidence suggesting that the use of volatility predicted from more sophisticated time series models will lead to more accurate option valuations (Chu and Freund, 1996).

2.5 Capital Structure Arbitrage

Capital Structure Arbitrage (CSA) is an arbitrage strategy for investing in two different asset classes that reference the same entity. Investors profits by exploiting the mispricing between the two difference assets. The two asset classes are correlated and arbitrage possibilities arise from imperfections in the interaction between market and credit risk. Before the development of CDS, it was not possible to short debt in a convenient way, but with the emergence of the CDS market, arbitrage strategies like this became much more convenient. Consequently, CSA has become an increasingly popular trading strategy for banks, hedge funds and other speculative market participants. The number of funds using this strategy has shown explosive growth during recent years (Currie and Morris 2002). The three most important CSA strategies are commonly defined (Berndt and Veras de Melo 2003) as trading between; equity- and debt-markets, equity- and credit-markets and credit- and debt-markets.

The mispricing of debt is commonly analyzed with a structural model in order to evaluate if the CDS spread is under- or overpriced. When the CDS spread predicted by the structural model is lower than the market spread, an investor can take a short position in a CDS with the belief that the two markets are converging. If this is the case, the spread will go down and the investor will profit from the short CDS position.

We are only focusing on the equity-credit markets strategies in our investigation. As previous research states, it is difficult to find appropriate trading strategies that are used in the market, which is a consequence of a new emerging market, and the banks' incentives of keeping their profit strategies secret.

2.5.1 Hedging Credit Default Swaps

Hedging financial positions is used to lower the risk by avoiding exposure of different types of risks such as price movements, volatility and interest rate changes. The CDS position is hedged in order to lower the risk of change in the CDS spread. There are a number of different types of hedging alternatives that can be used to hedge CDS positions, and of the most commonly used hedging strategies is the delta hedge, which removes the risk of price movements in the underlying position, in this case the CDS spread. Delta measures the relative movement of the underlying position. A hedge is delta neutral when both positions offset each other and the profit of the long position equals the loss of the short position. The position is only delta neutral for small movements of the underlying position and the hedge must be rebalanced to sustain delta neutral when large movements occur.

A position in both stocks and stock options can be more appropriate to hedge for different types of risks, but in this thesis we will limit our strategy to only consider going short or long in stocks. This limits the hedge, especially as the equity volatility is not directly hedged. The profits from the hedging strategy is affected by the transaction costs of the instruments and a hedge with fine time intervals is less profitable because of these increasing costs.

2.5.2 Equity-Credit Markets Strategies

The equity-credit strategy is based on a position in both CDS contracts and equity referencing the same firm. The equity position is seen as a hedge, but sometimes market conditions allow for profits in both positions. With a long position in a CDS (bought protection) contract, the offsetting position is to buy equity, and vice versa if CDS is sold; equity should be sold as a hedge. The logic behind this is that taking a long position in a CDS is buying protection of default, having a negative view on that particular company and as a hedge you must take the opposite position, buying equity.

CDS spreads are viewed as an increasing function of equity volatility and leverage (Merril Lynch 2003). With increasing equity volatility the CDS spread increases, and a high volatility motivates buying protection. In a study by Zhang, Zhou and Zhu (2005), empirical results is presented that the volatility risk predicts as much as 50 percent of the CDS spread. This highlights the great importance of equity volatility regarding CDS spreads. According to the equity option volatility smile, the true volatility of equity is a decreasing function of the equity price. A high equity volatility implies a higher risk of default, when equity price increases the leverage decreases. The equity becomes less exposed to risk and a lower equity volatility is motivated. There is a long run relationship between the CDS spreads and the corresponding equity volatility skew. (Berndt and Veras de Melo 2003). In the long run, the CDS rate and equity volatility skew will revert to an equilibrium.

The price of equity is also affected by a large number of factors such as macroeconomics and industry specific issues. The different characteristics of the underlying determinants for the CDS spread and equity price implies different market behavior. This affects the trading strategy, and under certain circumstances a profit can be made in both the CDS and hedge position. In a trade with long positions in both CDS and equity, and where the spread increases at the same time as the stock price, the investor makes a profit in both positions, even though the trade should theoretically be a hedge with the equity position. The main strategy is to arbitrage on the mispricing of CDS contracts, by using the convergence argument illustrated by Fan Yu (2006). The mispricing of CDS spreads are analyzed with a structural approach to evaluate if its under- or overpriced, and used as input to a eventual trading strategy.

2.5.3 Other Strategies

As discussed by Berndt and Veras de Melo (2003), several other arbitrage strategies are commonly used other than the equity-credit one pursued in this thesis.

Equity and debt market

The most common form of trade with this strategy is to long a convertible bond and short equity, where the equity risk of the convertible bond is hedged with the position in equity. The convertible bond is a more secure instrument compared to only equity, if the stock price rise, the convertible bond behaves like equity, and if the stock price falls, the convertible bond is not as highly exposed to market risk as the equity position. This strategy is a convertible arbitrage strategy.

Credit and debt market

This trading strategy is based on the fact that the bond market regards the default risk to be much lower than in the CDS market, and this can be used to make profit on the difference of basis points between the two markets. One way is to sell CDS at a high price and buy convertible bonds at a lower spread. Another word for this kind of strategy is basis arbitrage.

2.6 Quantifying Risk

Value-at-Risk is a popular risk measure used by a large number of financial institutions. For a financial position it is defined as the maximum loss during a specified time period given a certain probability. Consequently, it represents the amount to be lost under normal market conditions. Thus, while determining Value-at-Risk, it is essential to consider the probability of loss and trading holding period, determined by the horizon(Christoffersen, 1999). Common probability values are determined by 1, 2.5 and 5 percent, whereas typical holding periods are 1, 2, 10 and 30 business days (Linsmeier and Pearson, 1996).

Value-at-Risk is mainly concerned with market risk, but can also be applied to measure two other types of financial risks, credit- and liquidity risk. Value-at-Risk has been established as the standard for risk adjustment by the most authoritative regulatory organizations. This is achieved due to the conceptual simplicity of the method and its ability to work on different levels (ECB, 2001).

Value-at-Risk can be calculated in several different ways, of which three are the most common: variance-covariance, historical simulation and Monte-Carlo simulation. Both the historical and the Monte Carlo methods are reliable for quantifying risk in the case of a more complex position. Monte Carlo approach is based on generating large amounts of random numbers based on a statistical model. Historical simulation may be inconvenient in case there is not much sufficient rate history, for instance for newly developing markets. Thus, Monte Carlo approach is considered to be more appropriate due to its flexibility in using various parameters, such as historical, market implied or user-defined characteristics (RiskMetrics, 2007).

2.6.1 Capital Requirements

The Basel Committee on Banking Supervision, hosted by the oldest global financial institution in the world, the Bank of International Settlements, has represented a capital adequacy framework, adopted as the Basel Capital Accord (Basel II). This framework intends to regulate internationally active banks' minimal risk capital requirements and is now ratified by more than 100 countries around the world (Evanoff and Wall, 2000). The framework is aimed to provide "soundness and stability" to the international banking system by demanding higher capital ratios and reducing competitive disparity among internationally active banks all over the world.

In order to provide greater stability in the international banking system, the regulation process in the Basel II is concentrated around three concepts, so-called Basel pillars: minimum capital requirements computed for three main risk components that banks face, credit, operational and market risk; supervisory review and market discipline. In our analysis we find it suitable to implement the first pillar, which proposes various ways for determining risk weights. The "standardized approach" characterizes a portfolio of bank loans by a relatively small number of risk categories, and the risk weight associated with a given category is based on an external rating institution's evaluation of counterpart risk.

The Basel Committee on Banking Supervision regulations requires financial institutions to maintain eligible capital against their market Value-at-Risk (Carling, 2002).

Chapter 3

Methodology

In this chapter we describe the methodology of the research conducted in this thesis. We start by presenting the scientific approach taken and continue with a description of the data used in our analysis. Lastly, we discuss the practical issues and decisions regarding the implementation of the pricing model, trading strategies and risk simulations described in the previous chapter.

3.1 Approach

This thesis takes a quantitative approach to test for CSA opportunities in the equity and debt markets. In order to evaluate the mispricing of CDS contracts, leading to arbitrage possibilities, we build our quantitative investigation on an implementation of the equity-credit markets strategy.

The quantitative outline of our thesis starts with the collection of data, which includes CDS and equity prices for 37 companies, as well as debt-per-share and credit rating. Afterwards, the possible mispricings of the CDS contracts spread are computed by utilizing the CreditGrades model.

In order to achieve CSA profits we apply the trading simulation, which is based on the calculated mispricing results gained from our pricing model implementation. Subsequently, after calculating either profit or loss from the CDS contracts, we simulate Value-at-Risk in order to calculate the actual return for CDS trading strategies, which is done by combining profit and Value-at-Risk.

3.2 Data

The data used in this thesis reference 37 European companies and was acquired from DataStream and Reuters. Daily CDS spreads for the common five year CDS contracts were collected from DataStream for a period of two years, and resulted in 522 observations per studied firm. The CDS data was retrieved from the iTraxx Europe index

Sector	Firm	Country	Rating	Equity	Debt	Market
Automotive	Continental	Germany	BBB+	103	46	14,941
Automotive	DaimlerChrysler	Germany	BBB+	66	152	67,342
Automotive	Peugeot	France	A-	58	234	13,608
Automotive	Renault	France	BBB+	105	167	29,904
Automotive	Volkswagen	Germany	A-	113	320	40,238
Consumer	Wolters	Holland	BBB	23	13	7,070
Consumer	Carrefour	France	A	54	53	37,994
Consumer	Lufthansa	Germany	BBB	21	34	9,786
Consumer	LVMH	France	BBB	87	35	42,634
Consumer	Metro	Germany	BBB	59	77	19,278
Consumer	Sodexho	France	BBB+	56	41	8,894
Consumer	Unilever	Holland	A+	21	16	9,786
Energy	Endesa	Spain	A	40	36	42,530
Energy	Enel	Italy	A+	8	7	52,369
Energy	Fortum	Finland	A	24	11	21,547
Energy	Iberdrola	Spain	A	42	20	48,476
Energy	Union Fenosa	Spain	A-	43	37	12,949
Finance	ABN Amro	Holland	AA-	36	538	68,502
Finance	Allianz	Germany	AA-	163	2,323	73,320
Finance	Capitalia	Italy	A	8	51	20,276
Finance	Commerzbank	Germany	A	37	903	24,293
Finance	Deutsche Bank	Germany	AA-	116	3,253	61,752
Finance	Unicredito	Italy	A+	7	77	73,610
Industrial	Akzo Nobel	Holland	A-	60	30	17,186
Industrial	Bayer	Germany	BBB+	53	54	40,151
Industrial	HeidelbergCement	Germany	BBB-	119	56	13,821
Industrial	Lafarge	France	BBB	131	90	23,089
Industrial	Linde	Germany	BBB	82	111	13,417
Industrial	Siemens	Germany	AA-	96	71	86,239
Industrial	Stora Enso	Finland	BBB-	14	55	11,304
Industrial	Upm Kymmene	Finland	BBB	19	14	10,114
Telecom	Deutsche Telecom	Germany	A-	13	19	56,882
Telecom	France Telecom	France	A-	22	27	58,597
Telecom	Nokia	Finland	A+	20	3	76,925
Telecom	Telecom Italia	Italy	BBB+	2	5	40,158
Telecom	Telefonica	Spain	BBB+	17	18	82,675
Telecom	Vivendi	France	BBB	32	18	36,521

Table 3.1: Sector, name, country, credit rating (Fitch), equity price (EUR), debt-per-share (EUR) and market capitalization (millions of EUR) for the firms analyzed.

which consists of the 125 most liquid CDS in the market.

Equity prices were also collected from Datastream for a total of four years, two years more than the CDS spreads. The data used was the daily close quote from each of the firm's primary listing locations. We used the additional data in order to calculate the historical equity volatility. After combining the CDS and equity data available, our final per firm data sets consisted of 522 equity price observations for the CDS spread period, and 523 observations for the volatility estimation period. We also collected debt-per-share for each company, in order to model the default barrier.

3.3 Modeling

The empirical modeling performed in this thesis was implemented using the mathematical software suite MATLAB and consists of three parts; pricing, trading and risk simulation.

3.3.1 Pricing Model

In order to calculate the fair equity-implied CDS spread, and in extension the model-market mispricing, used for speculating between the equity- and credit markets, we use an implementation of the CreditGrades model. The reasons that motivate the choice of using the CreditGrades model mainly arise from the model's status as the de-facto standard pricing model in the industry (Berndt and Veras de Melo 2003), as it is known to produce accurate and reliable credit spreads. Also, the simplicity of using a structural model, as opposed to a more complex reduced-form model, regarding the availability of required model data contributes to making it an ideal choice among the different credit pricing models. Lastly, since we subsequently use the output of the pricing model as a base for our trading model, where we trade between the equity and credit markets, using an equity-based structural model provides a good approach in order to identify mispricings between the two markets.

Model Parameters

When implementing the CreditGrades model, a number of decisions regarding the input parameters must be made. The main parameters in our implementation is the equity price S, equity volatility σ_S, debt-per-share D, recovery-rate R, standard deviation of the default-barrier λ and the risk-free interest rate r. These parameters can be divided into market observed data (S, σ_S, D, r) and firm specific model constants (R, λ).

While the original CreditGrades model uses data from a proprietary risk database (RiskMetrics 2002) in order to estimate the firm specific model constants, we must instead approximate some of the parameters based on publicly available information. Though some researchers have suggested (Yu 2005) that the recovery-rate and the standard deviation of the default-barrier can be estimated by numerically optimizing the pricing model equations using CDS market spreads, we use average recovery-rate data from information published by RiskMetrics (2002), fitting the calculated CDS spread to its market equivalent, on a per firm basis. The base parameters used are

$$\begin{aligned} R &= 0.5 \\ \lambda &= 0.3 \end{aligned}$$

where R is the recovery-rate and λ the standard deviation of the default-barrier. The method of fitting the calculated CDS spreads is a simplification of Yu's (2005) numerical optimization. Initial optimization testing resulted in extreme values for both R and λ and hence motivated developing alternative approaches. As the unmodified implementation initially produced accurate and reliable CDS spreads in the majority of the firms analyzed, but resulted in responsive but displaced spreads in a few cases, we introduce a calibration constant in order to adjust the default-barrier and thus the relative level of the spread. The calibration constant was estimated using Mean-Square-Error (MSE) minimization of the calculated spread and by using market data from a calibration period in order not to bias the trading.

Initiated Contracts

When a CDS contract first is initiated between two parties, the actual price of the contract is set to zero. The contract spread is in hand determined by the probability of default, and remains fixed over the life-span of the contract. However, if any of the parties want to get out of their commitment before the contract expires, the CDS contract will have an intristic value if the market CDS spread changed since the contract was initiated.

If, for example, the market spread has increased since the contract was first initiated, the contract will have a positive value to the protection buyer as it provides default insurance cheaper than is currently available from the market. The protection buyer will thus be able to sell the contract to another party - and make a profit. The same argument applies if the market spread has decreased, and the protection seller will be able to sell its contractual obligation for a profit.

This idea is central to the concept of speculating in the CDS market and is used to determine the price of previously initiated contracts. Due to the fact that secondary market CDS contract price data is not available, because of the OTC trading nature, we need to approximate the price of those contracts based on the difference between the agreed contract spread and current market spread. This is done in line with Yu (2005) and is essentially the equivalent of the risk-weigthed discounted spread difference, with the approximation that the time elapsed since the contract first was initiated is very small compared to T. The change in the present value of the contract, originating from the contract-market spread difference, can hence be expressed as

$$\Delta CDS(\tilde{c}, c_t) \approx (c_t - \tilde{c}) \int_0^T \frac{1}{r} e^{-rt} p(t) dt \tag{3.1}$$

where c_t is the market CDS spread at time t, $\tilde{c}$ the agreed CDS spread of the initiated contract, T the life-span of the contract, r the risk-free interest rate and $p(t)$ the survival probability as specified by the CreditGrades model. Additionally, as the price of a CDS contract at initiation is zero, the absolute value will equal the delta value of the contract, $CDS(\tilde{c}, c_t) = \Delta CDS(\tilde{c}, c_t)$, and provides the approximated secondary-market price of the initiated contract relative to its notional debt protection value.

Volatility Estimation

The volatility measure used in our pricing model in order to forecast the equity volatility is the 500-day historical standard deviation of the equity return. While some researchers (Yu et al 2007) has suggested that the option implied volatility can provide important quantitative credit information when pricing credit derivatives, we base our choice on the mean-reversion argument for volatility due to the long lifespan of five years for the CDS contracts.

Using a 500-day volatility window, and not a five year one, is a trade-off between the mean-reversion argument and the idea of using a shorter volatility measure in order to better reflect recent volatility changes that may have an impact over the entire contract lifespan.

3.3.2 Trading Algorithm

In the pursuit of CSA profits we devise a simple trading model based on the calculated mispricing resulting from our pricing model implementation. The trading model is based on a portfolio of equity and CDS contracts, both securities referencing a single firm, and use the delta-hedge CSA approach described in the previous chapter. Our implementation is an extended version of the trading model developed by Yu (2005) and is based on the argument of mispricing convergence over time.

Trading Trigger

The triggering factor in our trading model is the theoretical mispricing of the CDS contract spread. By denoting the current market spread c_t and the calculated model spread $\hat{c}_t$, we define the absolute spread mispricing as $\varepsilon_t = c_t - \hat{c}_t$. While the absolute market and model spread value is of great importance when pricing CDS contracts in the case of debt insurance, the relative mispricing and its movement over time is more important when speculating in the equity and credit markets. We define the relative spread mispricing in relation to the standard deviation of the absolute mispricing as

$$\varphi_t = \frac{\mathbb{E}(\varepsilon) - \varepsilon_t}{\sigma_\varepsilon} \tag{3.2}$$

where $\mathbb{E}(\varepsilon)$ is the expected value of ε and σ_ε its standard deviation. The relative mispricing provides a good indicator of how over- or under-priced we think the CDS contracts currently are, and is used as the algorithmic trading trigger in our model. For example, if the relative mispricing is positive, it indicates that the market CDS contracts are overpriced and that we should take a short position (vice verse if it is negative). Since a higher mispricing increase the likelihood of convergence over time, we adopt a strategy where the number of contracts held is directly proportional to the relative mispricing in order to achieve a higher gearing in the cases where the mispricing is the greatest. Number of contracts long or short ranges between 10 to -10.

When the relative mispricing later reaches zero, the position is closed by either selling or buying back the portfolio components, depending on whether the current position is long or short. The profit (or loss) realized from the closing trade will equal

$$\Delta P = \pm \sum_{i=1}^{|n|} CDS(\tilde{c}_i, c_t) \tag{3.3}$$

where n is the number of currently held contracts (negative if the position is a short one), $\tilde{c}_i$ the i-th held CDS contract spread and $\hat{c}_t$ the current market spread. The realized profit is added cumulative to our main profit indicator P and is like equation (3.3) expressed in relation to the notional debt protection value.

Equity Delta-Hedge

The delta-hedge strategy of hedging CDS contracts by buying or selling the reference firm's equity, as motivated by the CSA argument, provides a mean to reduce the risk and increase the profit in optimal circumstances. The size of the equity position taken is calculated in a similar way as Yu (2005), by numerically estimating the partial differential of the CDS contract value with respect to the stock price in order to derive the hedge-ratio. The hedge-ratio is given by

$$\delta(CDS, S) = \frac{\partial CDS}{\partial S} \int_0^T \frac{1}{r} e^{-rt} p(t) dt \tag{3.4}$$

where CDS is the value of a CDS contract, S the reference-entity's stock price, T the terminal date, r the risk-free interest rate and $p(t)$ the firm specific survival probability as specified in the CreditGrades model.

This hedge ratio determines how much equity should be bought or sold to get a delta-neutral position. In our trading model we use a more or less static hedge, only re-balancing it when our CDS position is changed, which means that the position will not stay delta-neutral as the underlying stock price changes. In order to optimally re-balance the hedge as the stock price and CDS contract spread changes, daily trades would incur substantial trading costs and reduce overall profitability. This however, is not explored in the thesis and may still in some cases reduce the risk enough to offset the related trading costs and increase the return.

Return Calculation

Because the main profit indicator P in our trading simulations is an absolute measure (although expressed in relation to the nominal debt protection value of the contracts traded), it does not consider the capital employed in creating the profit. This makes the profit made from our trading impossible to compare to similar trading strategies, for example those employed by hedge-funds.

The problem arise from the fact that even though one cannot practically enter a CDS contract without some sort of capital reserve, the price of the initial contract is zero, which makes it impossible to calculate the return of CDS trading in the same manner ($log\frac{p_t}{p_0}$) as with other financial instruments such as equity. However, we propose using a modified Value-at-Risk approach, in accordance to the recent Basel II regulations, in order to produce comparable returns for CDS trading strategies.

Basel II regulates financial institutions such as banks, insurance firms and various types of funds (common CDS market participants) in order to guarantee that they can fulfill their risk-dependent contractual obligations. Thus, it can be assumed that market participants would not enter a CDS contract agreement with a speculator, in case he does not meet approximately the same financial requirements.

The financial requirements specified by Basel II uses an n-day, 99% Value-at-Risk model, weighted with an asset- and firm specific risk multiplier. The Value-at-Risk horizon depends on the type of asset and the character of the holding, and the suggested horizon in the case of credit derivatives is 10 days (BIS 2004). As for the risk multiplier h, used to calculate the required capital, the suggested value varies between 1 and 4 for credit derived assets depending on the financial status of the holder (BIS 2004). Due to the fact that a speculator probably is less financially stable than any of the large financial institutions regulated by Basel II, we use a conservative value of $h = 5$ in order to not underestimate the capital requirements.

As we now have a method of estimating the required capital reserve, the equivalent of the capital employed in creating the trading profit P, the return of our trading strategy can be expressed as

$$r = \frac{P}{hV} \tag{3.5}$$

where r is the relative return, P the absolute trading profit (relative the notional debt protection value), h the risk-weighted capital requirement multiplier and V the absolute portfolio Value-at-Risk (10-day, 99%, relative the notional debt protection value).

3.3.3 Value-at-Risk Simulation

In order to estimate the total portfolio Value-at-Risk, used to calculate the required capital and in extension the return of our trading strategy, we take a Monte Carlo approach to statistically estimate the trading risk. Using Monte Carlo simulations for calculating Value-at-Risk is particularly appealing when dealing with non-linear financial instruments such as options and credit derivatives (Barkhagen 2002), as it is almost impossible to solve the problem analytically using a parametric approach.

As we use an equity-based structural model in our trading strategy, we assume that equity data can successfully calculate CDS spreads using the capital structure link implied by Merton (1974). The same assumption can be applied in the Monte Carlo approach when estimating Value-at-Risk for CDS based trading, where the total portfolio risk depends on the development of both the CDS spread and the equity price, in order to approximate the CDS Value-at-Risk component based on the simulated equity development. The iterative approach taken comprise of three sequential steps; stochastic equity simulation, CSD spread calculation and portfolio loss estimation.

Equity Simulation

To simulate the equity development, we assume that the equity value follows a log-normal GBM diffusion process and we model the equity price using the discrete equivalent of the stochastic differential equation

$$dS_t = \mu S_t \, dt + \sigma_S S_t \, dW_t \tag{3.6}$$

where S_t is the firm's equity price at time t, μ the drift (ie. the average equity return), σ_S the equity price volatility and W_t the Wiener component.

The stochastic development of the equity is simulated using a large number ($i = 1000$) of n-day random paths, and by using the historical return and volatility of the firm's equity, at time t, to bias the distribution process. As mentioned earlier, we use a 10-day horizon ($n = 10$) for the Value-at-Risk estimation.

Subsequently, the CDS spreads for each of the simulated n-day equity price values are calculated, and are used as an approximation of the future CDS market spreads. Unfortunately, this undeniably results in model uncertainty, as the pricing model does not perfectly predicts the CDS spreads, which in turn may underestimate the actual portfolio Value-at-Risk. Using a Monte Carlo approach in conjunction with historical simulation, in order to calibrate the CDS spread modeling, would probably increase the reliability of our Value-at-Risk model. However, considering the limited scope of this thesis, this is left as an interesting starting-point for further research.

Portfolio Loss

Using the simulated equity price and CDS spreads, we calculate the portfolio value for each of the generated equity paths in order to estimate the potential loss and thus the Value-at-Risk. This is however where we deviate slightly from the common practice of calculating the Value-at-Risk as a percentage of the total portfolio value. The reason for this is the problem discussed above, the price of an initiated CDS contract is always zero. Instead, we estimate the Value-at-Risk in terms of the absolute loss using the total delta-value of the portfolio, similar to the approach reflected by equation (3.3). This also has the positive side effect that our Value-at-Risk measure shares the same dimension as our profit indicator P, eliminating the notional debt protection value from our trading return.

3.4 Methodology Criticism

The companies used in the analysis are large companies with a low asset volatility and high credit rating. The pricing calculations are based on the assumption that there is a certain risk of default for each company, which is derived from the credit rating. Since these companies are large and stable firms, this risk might in reality be even lower than the credit rating predicts. This may be explained by several factors, such as default protection and bailouts provided by the government. Since the investors are aware of this, and possibly act accordingly, this may alter the price in a way not predicted by the models chosen.

The accuracy of the pricing results are further complicated by the fact that we do not know the accuracy of the CreditGrades model in relation to other pricing models. Although the CreditGrades model has shown good results in predicting credit spreads, there might be other more appropriate models.

Transaction costs have not been accounted for in our modeling. There are a lot of different transaction costs for different types of transactions, which makes it hard to incorporate this in the trading models. These costs are sure to affect the total return of the trade, which means the calculated results are somewhat higher than the results that would be achieved if the trading had been done for real.

We were initially planning on incorporating volatility to a higher extent in the analysis, but were unable to due to time constraints. The results could possibly be improved by further incorporating implied volatility in the trading strategy. The hedge might also be improved with options to focus more on volatility, as it can be used to predict equity prices, and other hedging strategies, such as gamma- or vega hedging, might provide a better alternatives to lowering the risk and thus increasing the return.

Chapter 4

Analysis

In this chapter we present the empirical findings that are the result of the pricing- and trading model simulations. We illustrate the results using a variety of graphics, analyze the main results and comment on the most important findings. Lastly, we test the returns produced by our trading model for statistical significance.

4.1 Trends

By analyzing the input data used in our model, as well as the pricing output from the simulations, a couple of clear trends can be observed. Firstly, the equity markets has, during the period of the data sample, enjoyed a strong positive trend with rising equity prices and increasing corporate earnings for most of the firms in our sample. The strong equity markets has in turn lead to decreasing credit- and CDS spreads, because of the inverse relationship between equity prices and default probabilities, something further magnified by the relatively large size of the studied reference entities.

This trend has several implications for a CSA strategy such as the one pursued in this thesis. Clearly, in macro-economically good times, the probability of decreasing credit spreads is greater than in a recession when using a structural pricing framework. Thus, if macro-economic forecasting models were to be combined with a pricing model such as the one used in this thesis, a better, predicting model could be developed, providing leading indicators for the equity-credit mispricing.

Secondly, the output of our pricing simulations, illustrated in figures 4.1- 4.6, shows evidence of time-based clustering for the calculated market-model mispricing. As our simulations lack a periodic component, the most probable conclusion to draw, is that there are market parameters that are unaccounted for in our models. Since we assume that the risk-free interest rate is constant over time in our simulations, a likely lacking factor could be the term-structure of risk-free securities as well as the overall risk mood in the marketplace - but also other unknown macro-economical factors that can prove hard to quantify.

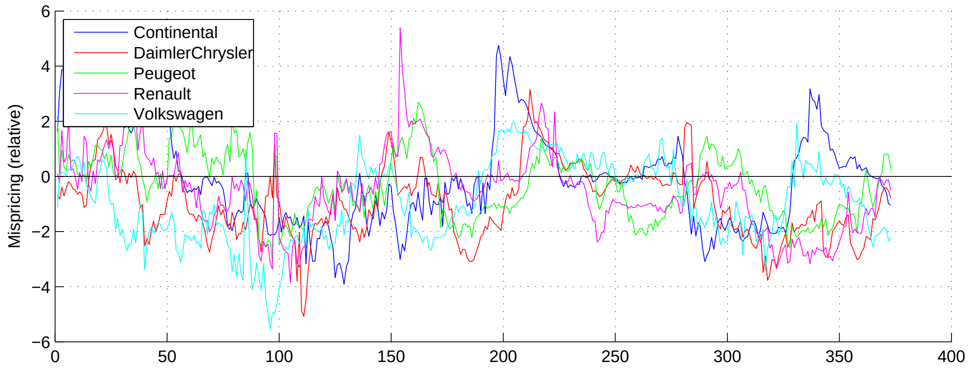

Figure 4.1: CDS spread mispricing over time for the Automotive group; Continental, Daimler Chrysler, Peugeot, Renault and Volkswagen.

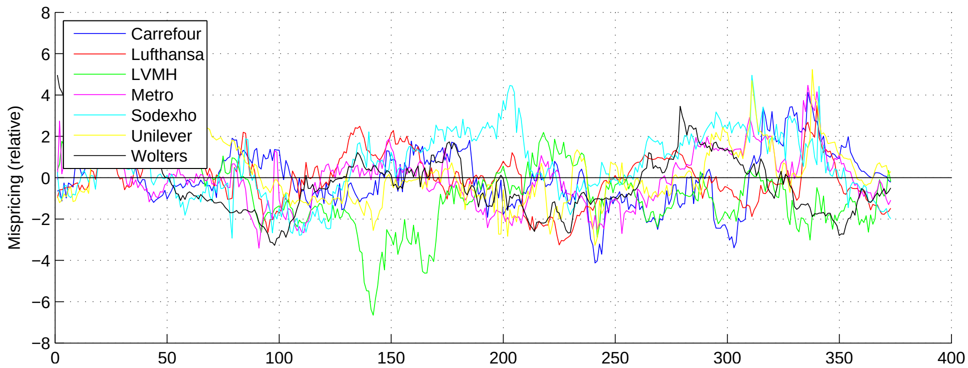

Figure 4.2: CDS spread mispricing over time for the Consumer group; Wolters, Carrefour, Lufthansa, LVMH, Metro, Sodexho and Unilever.

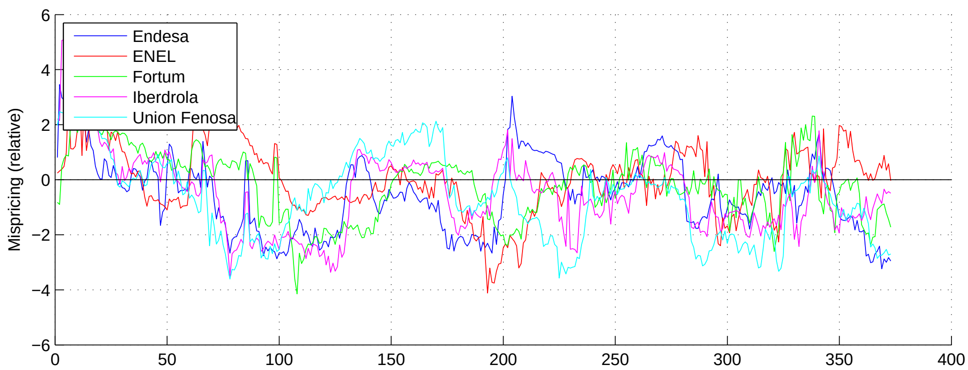

Figure 4.3: CDS spread mispricing over time for the Energy group; Endesa, Enel, Fortum, Iberdrola and Union Fenosa.

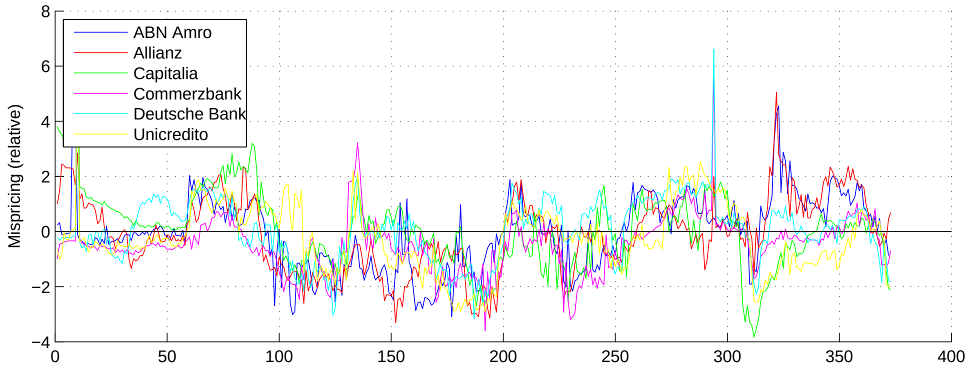

Figure 4.4: CDS spread mispricing over time for the Financial group; Allianz, Commerzbank, Deutsche Bank and Unicredito.

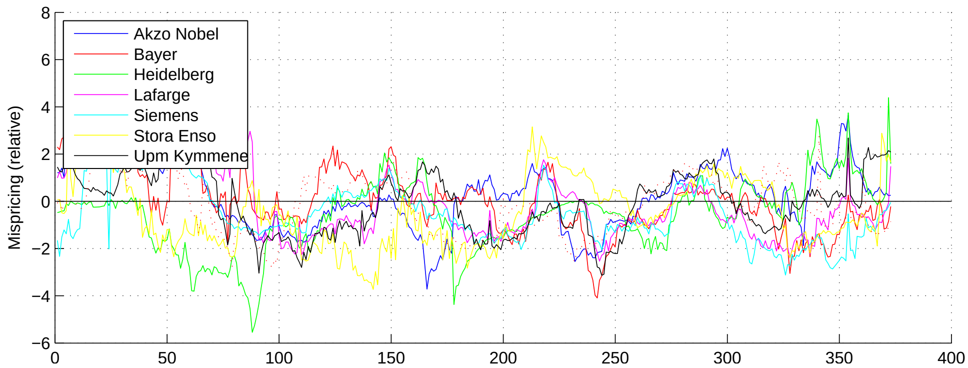

Figure 4.5: CDS spread mispricing over time for the Industrial group; Akzo Nobel, Bayer, Heidelberg, Lafarge, Linde, Siemens, Stora Enso and Upm Kymmene.

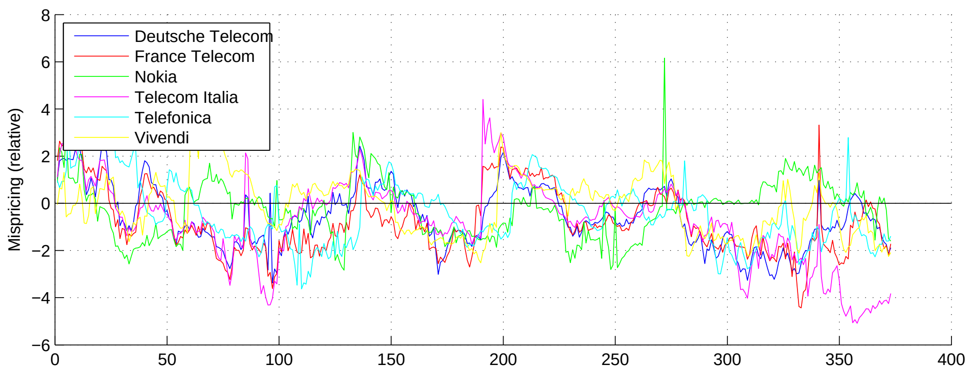

Figure 4.6: CDS spread mispricing over time for the Telecom group; Deutsche Telecom, France Telecom, Nokia, Telecom Italia, Telefonica and Vivendi.

4.2 Mispricing

Generally, our pricing implementation provided very reasonable CDS spreads when compared to market observed ones. The optimization described in the previous chapter, with regard to the level of the CDS spread and the reference entity's debt-per-share/recovery-rate, proved very successful, especially so in the case of the financial firms. Due to the nature of the industry, financial firms are heavily leveraged, and because of our choice of pricing framework, this resulted in very high CDS spreads, often an order of magnitude larger than what the market deemed fair. However, this is not very surprising as it could possibly be explained by the regulatory control imposed by governments and other non-governmental organizations world-wide, meaning that the probability of default is actually substantially smaller than suggested by the financial firms' large leverage. These results are exemplified in figures 4.7 and 4.8, and most notably in the case of ABN Amro, where the original model spread was in the hundreds.

Further, the model spreads seems to exhibit lower volatility than the market spreads for most of the firms. As the equity volatility for the reference firm is the prime non-static parameter (besides the equity price, for which the model spread is less sensitive), this suggests both that the volatility used as input generally is less volatile in it self, but also that it is lagging (as an example, see figure 4.8 and model-market mispricing) when compared to the volatility implied by the market CDS spread. This questions the choice of a 500-day historical volatility as the main volatility metric in our model, supporting other research (Yu et al 2007) that conclude that a more responsive (such as the Exponentially Weighted Moving-Average or equity-option implied volatility) metric might prove to better model the market observed CDS spreads.

4.3 Trading

Overall, our converging arbitrage strategy is profitable, both with and without the equity hedge. The size of the equity-positions taken in order to hedge the (sometimes highly risky) CDS contracts is substantial, and requires a speculator to have access to large amounts of capital in order to delta-hedge. Because of the size of the equity position, the profit (and loss) often dominates the total profit of a single close, since we do not rebalance our hedge dynamically, and overall lowers the total profit of our strategy when compared to the one where no hedge-position is taken. The total profit, return and Value-at-Risk for each of the studied firms are available in table 4.1.

For 10 out of 37 firms studied, the total profit is actually higher when compared to the trading with only CDS contracts, a hedge profit is made and could be explained by simultaneous profits from both positions. A more in-depth investigation of the occurrence of double profits or losses has not been made in this thesis, but we refer to Yu (2005) for a analytical discussion about the issue.

Most of the firms studied show negative profits for the equity hedge and for 9 of the firms it results in a negative total profit. The lower trading profit with the hedge shows that quite substantial losses are made with the equity hedge. The premisis of the hedge, to lower risk of the total position while having small effects on profits could here be disputed as the standard deviation of the profit actually increases (from 0.26 to 0.27 with the hedge) at the same time as a quite large decrease in profit is made. A more sofisticated hedging strategy, such as gamma- or vega hedging, as well as a dynamic rebalancing of the hedge could prove to more effectively mitigate the risk from the trading.

However, with the equity hedge, the modified Value-at-Risk decreases significantly (0.09 compared to 0.16 with only CDS speculation). This means that less capital has to be held, which leads to a higher mean return (54% compared to 16% without equity), even if the actual profit is lower. The equity hedge is highly effective in lowering Value-at-Risk, and thus increasing the return. There is a statistically significant (95% single-sided t-test) return of 10.8% without the hedge and 32.9% with the hedge.

Figure 4.15 and 4.16 are examples where the hedge is effective, the Value-at-Risk gets significantly lower if the hedge is included in these examples. In figure 4.17 however, the hedge isn't that effective. This varies between companies, but overall the hedge lowers the Value-at-Risk enough to produce a higher return than a strategy without a hedge.

The implemented strategy, discussed in the previous chapter, of having different numbers of contracts in proportion to the mispricing, should serve for a more accurate trading, limiting large losses as well as making it possible for larger profits when there is a large deviation between the market and model spread. When a large deviation between these two spreads occur it is likely to be a longer period of convergence and a higher number of contracts for both CDS and equity is long or short, which largely affect the profits of the trade. This is also when the largest profits or losses from the trading occurs, especially from the equity position, as a large short position in equity over a long period has a high probability of incurring a loss, since the overall trend of equity prices is increasing.

When there is a large jump in the mispricing there is a high probability of positive results from trading. This occurs when there is a large change in number of contracts bought or sold, and at the same time the hedge is changed accordingly. There are many reasons for the jumps, the firm might for example have liquidity problems, which will change their debt structure and possibly also their credit rating. There can also be other unknown firm variables, or change of market conditions. The jumps are particularly profitable because they result in a large profit in a small amount of time, leaving more time to make additional trades.

	Profit		Return		Value-at-Risk	
Firm	**CDS**	**Total**	**CDS**	**Total**	**CDS**	**Total**
Continental	0.00	-0.43	0.00	-0.48	-0.18	-0.03
DaimlerChrysler	-0.12	-0.20	-0.02	-0.02	-0.45	-0.45
Peugeot	0.20	0.44	0.17	0.79	-0.09	-0.03
Renault	0.59	0.50	0.23	1.54	-0.19	-0.03
Volkswagen	-0.03	-0.54	-0.01	0.06	-0.16	-0.15
Wolters	0.04	0.23	0.01	0.05	-0.27	-0.25
Carrefour	0.16	0.04	0.13	0.07	-0.09	-0.04
Lufthansa	0.31	0.01	0.16	1.29	-0.14	-0.02
LVMH	0.15	0.16	0.07	0.47	-0.16	-0.03
Metro	0.60	0.48	0.30	1.02	-0.15	-0.05
Sodexho	0.32	-0.06	0.15	0.21	-0.16	-0.06
Unilever	0.27	0.32	0.22	1.05	-0.09	-0.02
Endesa	0.33	-0.10	0.33	1.40	-0.07	-0.02
Enel	0.08	0.12	0.08	0.75	-0.08	-0.01
Fortum	0.18	-0.36	0.06	-0.02	-0.21	-0.13
Iberdrola	0.03	-0.27	0.03	-0.61	-0.10	-0.01
Union Fenosa	0.08	-0.30	0.06	0.42	-0.10	-0.02
ABN Amro	0.35	0.23	0.66	0.71	-0.04	-0.03
Allianz	0.09	0.19	0.05	0.23	-0.12	-0.04
Capitalia	0.67	0.33	0.34	0.49	-0.15	-0.08
Commerzbank	0.26	0.16	0.45	2.07	-0.04	-0.01
Deutsche Bank	0.83	0.64	0.64	2.81	-0.10	-0.02
Unicredito	0.06	-0.18	0.06	0.53	-0.07	-0.02
Akzo Nobel	-0.36	0.11	-0.23	-0.65	-0.11	-0.04
Bayer	0.30	0.26	0.16	1.04	-0.14	-0.03
Heidelberg	-0.15	0.35	-0.03	-0.04	-0.38	-0.28
Lafarge	0.01	0.01	0.00	-0.68	-0.15	-0.02
Linde	0.25	0.23	0.15	0.37	-0.12	-0.04
Siemens	0.17	0.43	0.17	1.63	-0.07	-0.02
Stora Enso	-0.26	-0.26	-0.03	-0.01	-0.69	-0.64
Upm Kymmene	0.17	0.02	0.13	0.07	-0.09	-0.13
Deutsche Telecom	0.38	0.07	0.26	0.13	-0.11	-0.16
France Telecom	0.32	-0.11	0.22	0.95	-0.11	-0.02
Nokia	0.16	0.09	0.11	0.41	-0.11	-0.03
Telecom Italia	0.66	0.00	0.23	0.36	-0.22	-0.13
Telefonica SA	0.48	0.12	0.19	0.38	-0.19	-0.10
Vivendi	0.53	0.13	0.27	1.11	-0.15	-0.03
Mean	0.22	0.08	0.16	0.54	-0.16	-0.09
Standard Deviation	0.26	0.27	0.18	0.75	0.12	0.13

Table 4.1: Summary of the trading simulations; profit, return and Value-at-Risk for the CDS-only and CSA trading strategies.

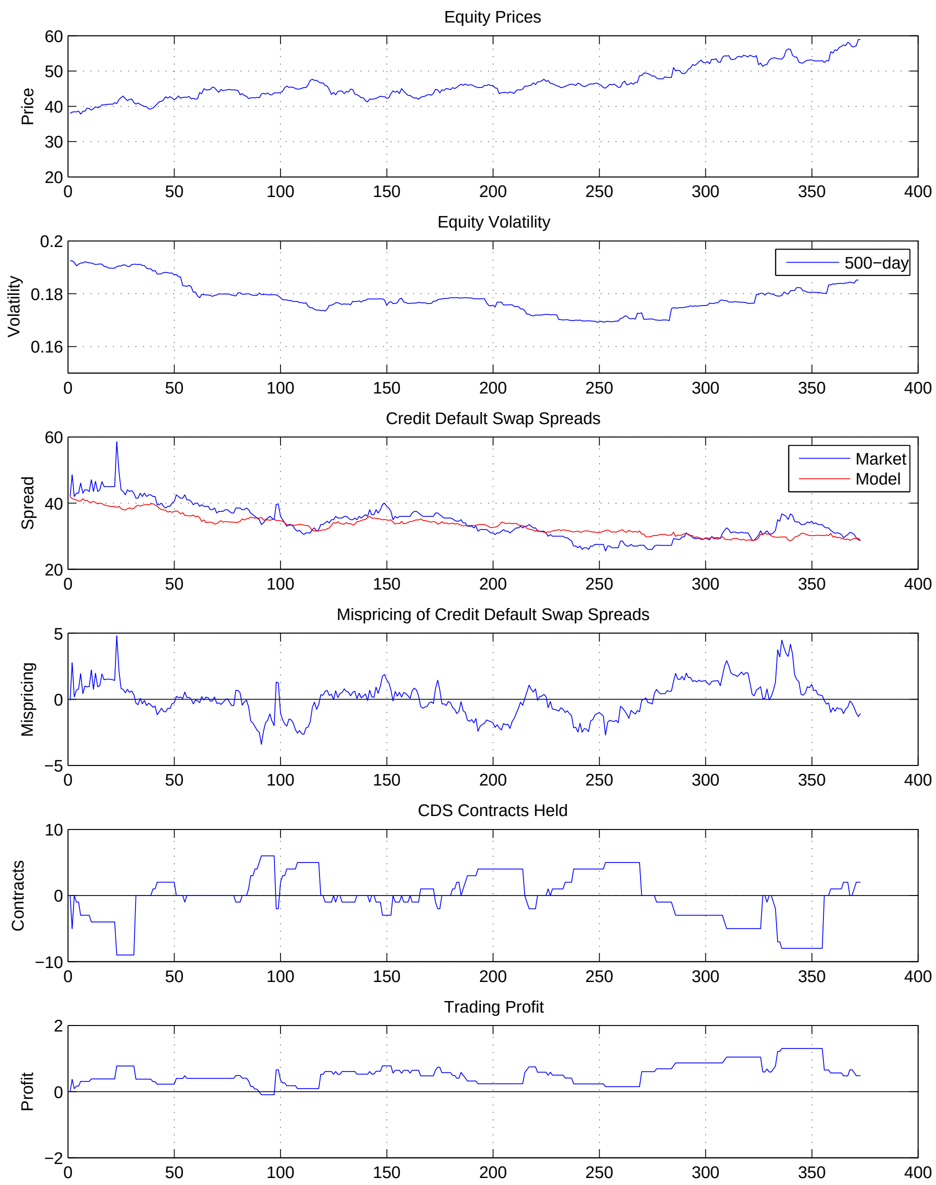

Figure 4.7: Equity price, equity volatility, market and model CDS spread, mispricing of CDS spread and trading results for Metro.

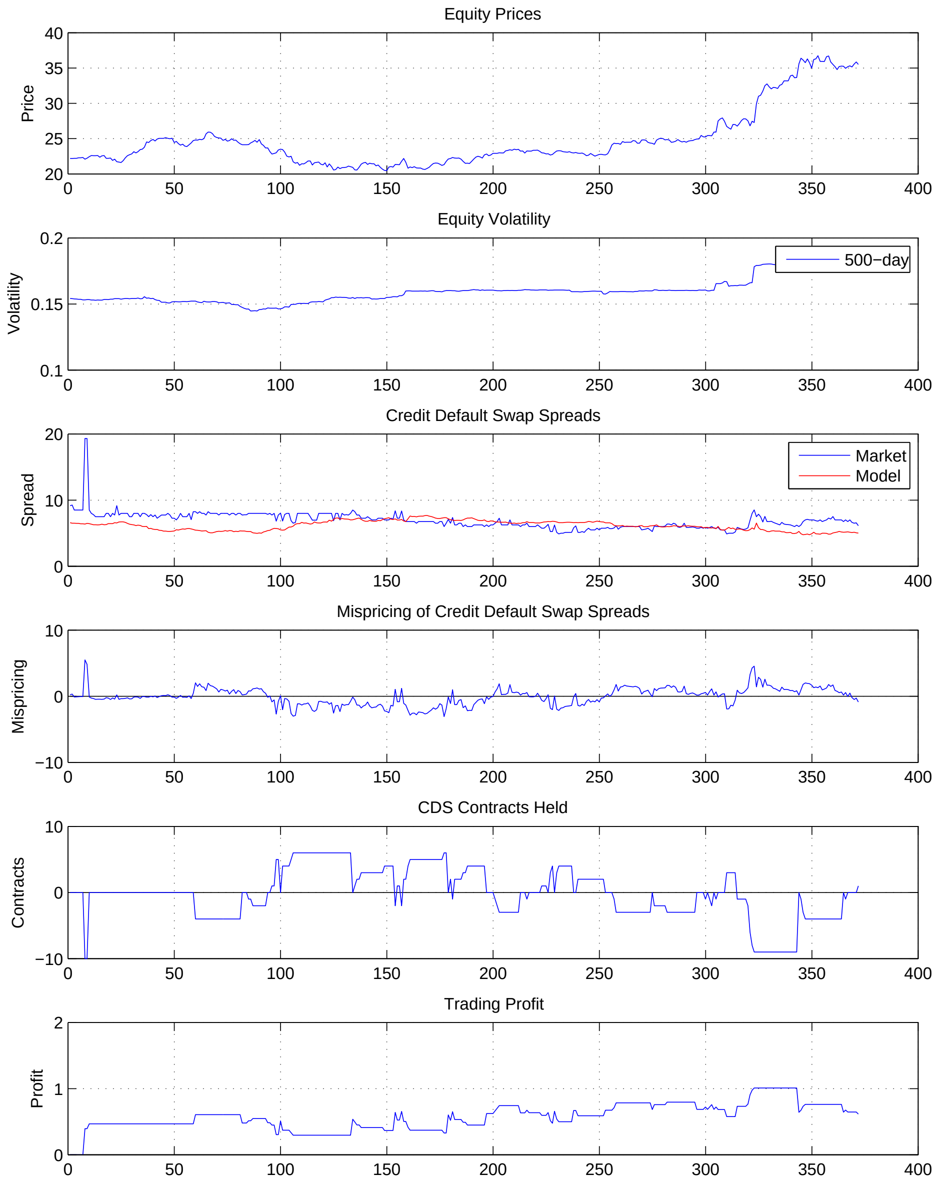

Figure 4.8: Equity price, equity volatility, market and model CDS spread, mispricing of CDS spread and trading results for ABN Amro.

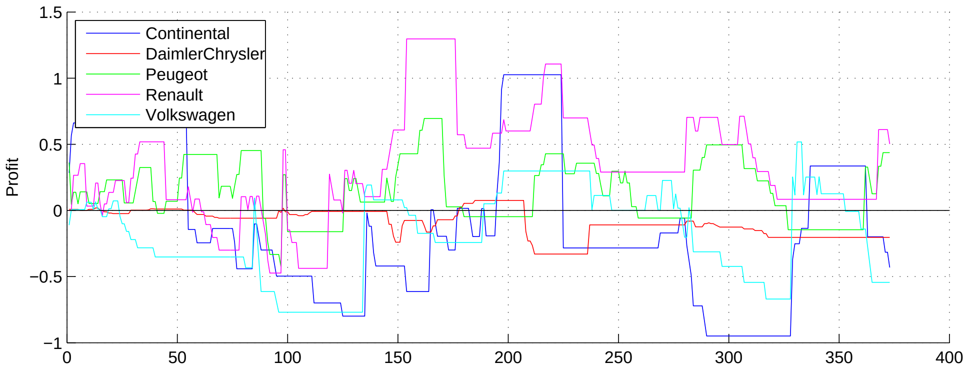

Figure 4.9: Cumulative trading profit for the Automotive group; Continental, Daimler Chrysler, Peugeot, Renault and Volkswagen.

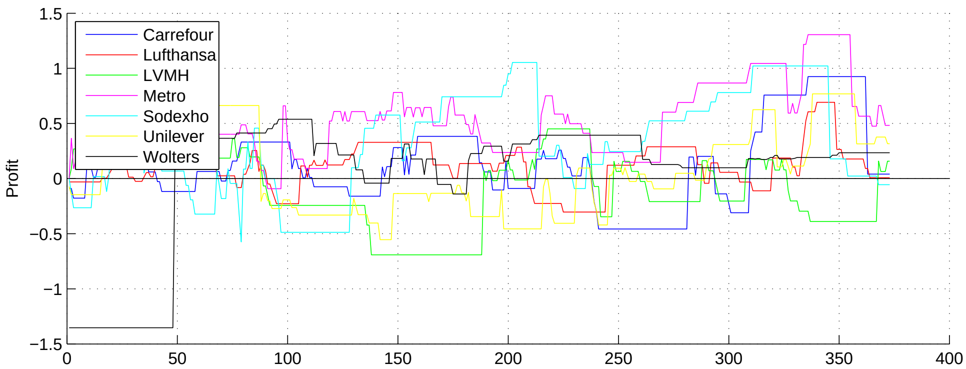

Figure 4.10: Cumulative trading profit for the Consumer group; Wolters, Carrefour, Lufthansa, LVMH, Metro, Sodexho and Unilever.

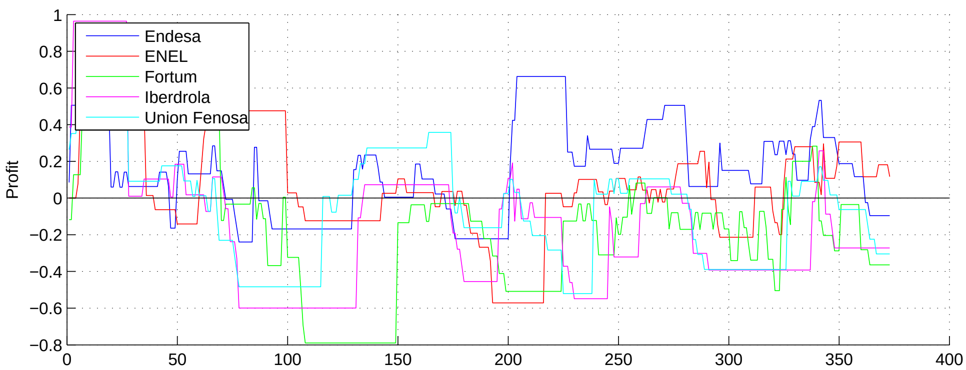

Figure 4.11: Cumulative trading profit for the Energy group; Endesa, Enel, Fortum, Iberdrola and Union Fenosa.

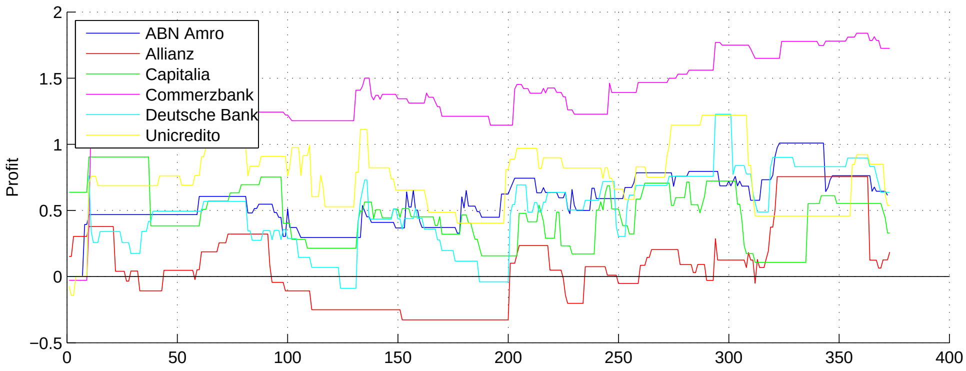

Figure 4.12: Cumulative trading profit for the Financial group; Allianz, Commerzbank, Deutsche Bank and Unicredito.

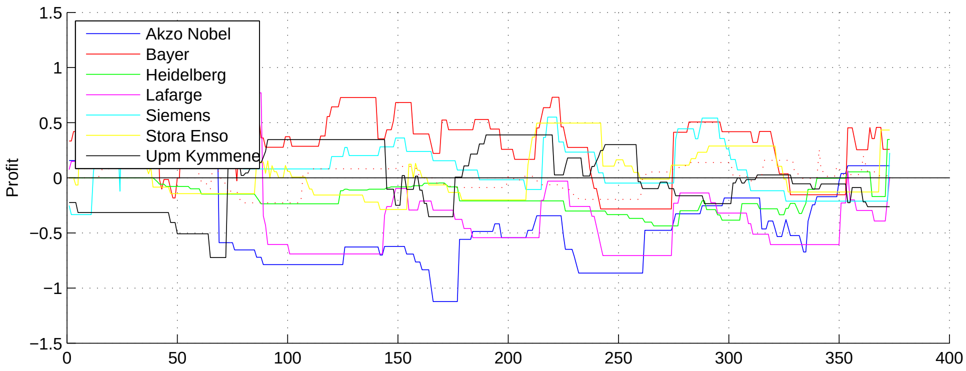

Figure 4.13: Cumulative trading profit for the Industrial group; Akzo Nobel, Bayer, Heidelberg, Lafarge, Linde, Siemens, Stora Enso and Upm Kymmene.

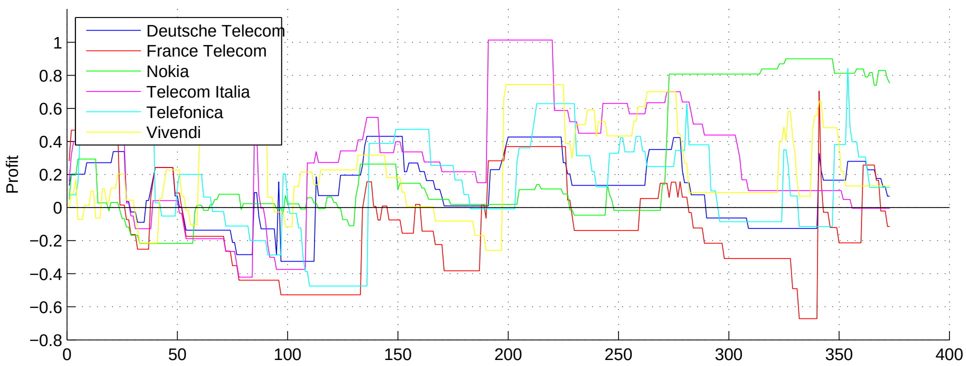

Figure 4.14: Cumulative trading profit for the Telecom group; Deutsche Telecom, France Telecom, Nokia, Telecom Italia, Telefonica and Vivendi.

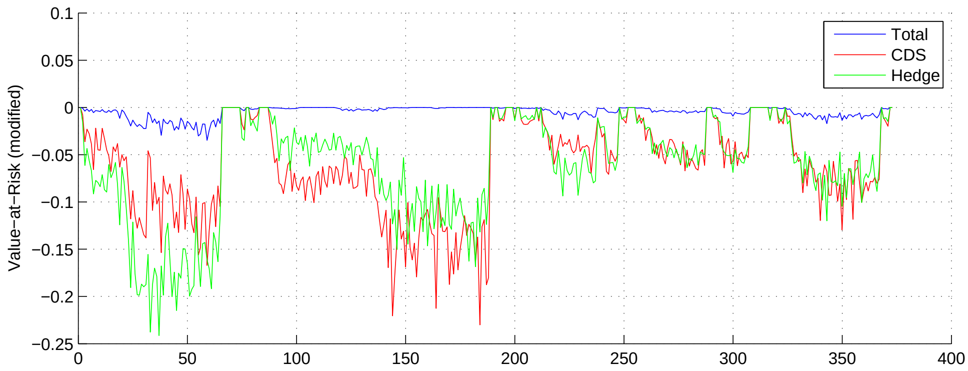

Figure 4.15: Monte Carlo simulated portfolio Value-at-Risk (99-percent, 10-day) over time for LVMH.

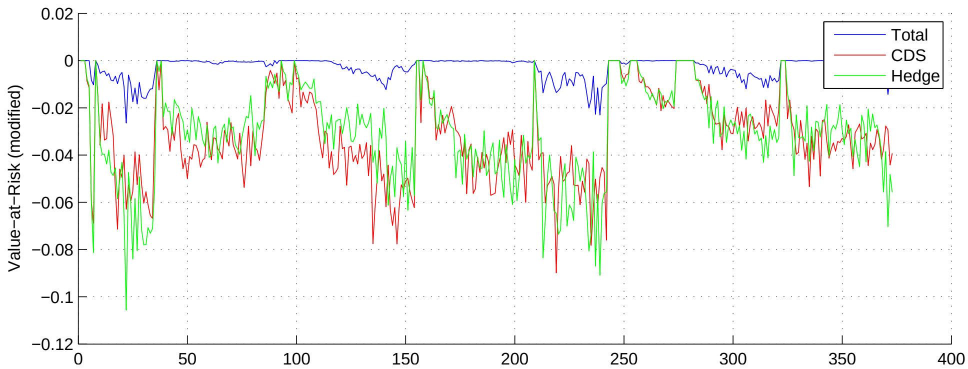

Figure 4.16: Monte Carlo simulated portfolio Value-at-Risk (99-percent, 10-day) over time for Siemens.

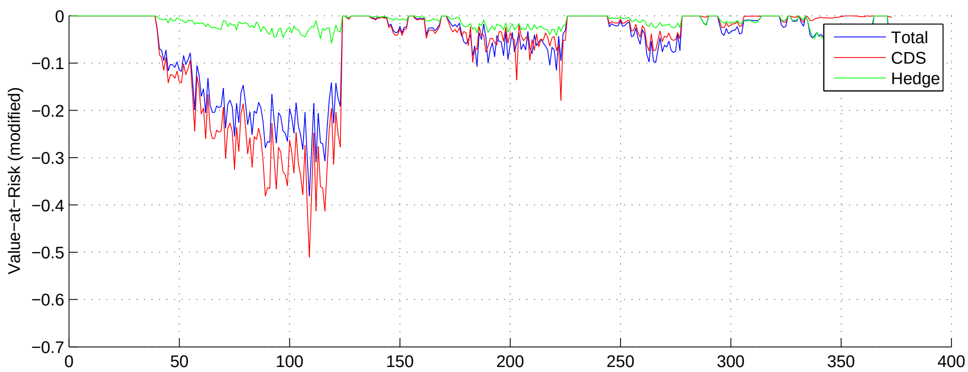

Figure 4.17: Monte Carlo simulated portfolio Value-at-Risk (99-percent, 10-day) over time for Heidelberg.

Chapter 5

Conclusions

In this brief chapter we summarize the research performed in this thesis and its findings. We discuss the main theoretical and practical implications of our work and talk about some of the shortcomings of our research. Lastly, we list some areas of research that could provide interesting starting-points for further research in the area of Capital Structure Arbitrage

5.1 Summary

Our purpose in this thesis was to test for the existence of Capital Structure Arbitrage in the equity-credit markets. In our analysis of 37 companies, we calculated a mean return of 16% with pure CDS trading and 54% with the CSA approach, with a statistically significant return of at least 10.8% and 32.9% respectively. These results support our theory of Capital Structure Arbitrage opportunities.

5.2 Discussion

It is difficult to get information about the trading strategies employed by the financial industry, as they are not publicly shared by the banks and hedge-funds using them. Our interpretation of the equity-credit markets CSA strategy could certainly be improved with more efficient trading strategies.

The trading strategy does not take macro factors into consideration. The market has had a positive trend during the whole trading period, and it would have been a profitable strategy to just short a lot of CDS contracts. Although there is no way of knowing how long current market trends will continue, there might still be some macro factors that could be worth taking into consideration to predict the trend and improve the trading strategy.

There might also be trading conditions that we are not aware of. Our thesis is theoretical in many ways, and there are usually some factors that you never think of until you experience them in practice. These unknown factors could possibly influence the trading strategy, making it less effective or even practically impossible. Another practical point worth mentioning is the problem with liquidity problems in relation to the ability to buy/sell contracts. If any financial problems arise during the trading, that might change the trading ability, and the results will thus be affected.

5.3 Further Research

The area of Capital Structure Arbitrage provides many interesting starting-points for further research as the CDS market is showing strong growth and has become more liquid with a growing number of outstanding CDS contracts and market participants. Research about CSA strategies is limited and few comprehensive studies of the market have been conducted. Even though this thesis shows some support of CSA strategies, there is still no conclusive evidence.

The market has been positive with increasing equity prices during the research period, a negative market scenario with a higher volatility and decreasing equity prices would probably produce different results. This would result in higher CDS spreads and increased volatility of mispricing, which raises the likelihood of a higher return.

There are some ways to improve the trading algorithm, as outlined in the discussion. This could also be combined with a technical analysis on the equity side to further improve the strategy. Considering risk, there are Value-at-Risk calculation methods that could possibly calculate a more exact Value-at-Risk, one option is to use Monte Carlo simulation with calibration using historical simulation.

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