Trading in the Credit Derivatives market with equity-based Credit Default Swap spreads

Bachelor Thesis

Lund University School of Economics and Management

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Sammanfattning

Uppsatsens titel: Trading in the Credit Derivatives market with equity-based Credit Default Swap spreads

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Författare: Jakob Palmstierna och Martin Nilsson

Handledare: Docent Hans Byström

Fem nyckelord: Capital Structure Arbitrage, Credit Default Swap, Probability of Default, Basel II, equity-based modelling

Syfte: Vårt syfte är att testa om det går att göra Risk Arbitrage på kreditderivatmarknaden med CDS spreads baserade på aktie-priset.

Metod: Vi har skrivit rutiner för skatta parametrar samt en "rättvis" spread för ett CDS-kontrakt. Detta har sedan jämförts med aktuell spread på marknaden för att upptäcka köp/sälj-signaler. Data har erhållits från Barclays Global Investors PLC.

Teoretiska perspektiv: Vi har utgått från att en aktie följer en CEV-modell och utifrån det beräknat sannolikheten för konkurs (PD). Det finns fortfarande ingen generellt vedertagen modell för att beräkna rättvisa CDS-priser.

Empiri: Data från företag i olika investeringsklasser har använts för att skatta parametrar och uppskatta CDS-spreads.

Slutsatser: Marknaden för kreditderivat växer explosionsartat. Med detta kommer ett behov av en generell prissättningsmodell, vilket inte finns för tillfället. Vi letar således efter risk arbitrage då vi anser att CDS kontrakten kan vara felprissatta. Vår modell gör ett kompetent jobb i att förutsäga CDS spreads och således visar vår illustrativa handel med dessa kontrakt lovande resultat som visar vinst i 8 av 9 företag.

Summary

Title: Trading in the Credit Derivatives market with equity-based Credit Default Swap spreads

Seminar date: 2006-01-18

Course: Bachelor Thesis in finance, 10 swedish credits (15 ECTS)

Authors: Jakob Palmstierna and Martin Nilsson

Advisor: Associate Professor Hans Byström

Key words: Capital Structure Arbitrage, Credit Default Swap, Probability of Default, Basel II, equity-based modelling

Purpose: Our purpose is to test for Risk Arbitrage on the Credit Derivatives market with CDS spreads purely based on equity-price.

Methodology: We have written routines to estimate parametres and a "fair" spread for the CDS-contract. This spread have been compared with the actual market spread to discover buy/sell-signals. Data has been obtained from Barclays Global Investors PLC.

Theoretical perspectives: We assume the equity-price to follow a CEV-process and from this we have calculated the probability of default (PD). There is still no general model for calculation of CDS-prices.

Empirical foundation: Data from companies in different investment-grades have been used to estimate parametres and CDS-spreads.

Conclusions: The market for credit derivatives are growing enormously. With this comes a need for a general pricing model, which is not available to date. Hence we look for risk arbitrage as we suspect the CDS contracts to be mispriced. Our model does a competent job in predicting CDS spread and hence our illustrative trading results are promising – showing a profit in 8 out of 9 companies.

Abstract

This thesis gives an introduction to BASEL II and hence a motivation for the use of credit derivatives in general and Credit Default Swaps in particular. We develope (from Atlan and Leblanc (2005) and Bengtsson and Bjurhult (2006)) a model to price the CDS contracts and use this in a trading strategy – trying to find risk arbitrage.

The probability of default (PD), used in the pricing model, is derived from the stopped (i.e. the model stops as the stock price reaches 0) Constant Elasticity of Variance (CEV) model and uses only the equity price for the corresponding company as input. From the equity price, historical volatility is estimated and also used in the model. Available data is CDS spreads (for calibration) and equity price (for calibration and also prediction of CDS spreads).

A simple trading strategy is adopted. This is because we only want an indication of the qualitative properties of the model. The results from the trading are good, showing profit in 8 out of 9 companies.

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Further, we would like to thank Gustav Bengtsson and Camilla Bjurhult for writing an excellent Master's Thesis on the subject and generously sharing Matlab-code for inspiration with us.

Finally, we would like to thank Barclays Global Investors PLC for providing us with first-class CDS data.

Lund, February 2007
Martin Nilsson and Jakob Palmstierna

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Chapter 1

Introduction

1.1 Background

The credit derivative market is of explosive character. British Bankers' Association regulary makes surveys of the credit market (see Barrett and Ewan (2006)) . In 2004 they predicted the market size in 2006 to $8.2 trillion, however, in their 2006 report the actual market size is around $20 trillion. A huge number which is estimated to grow to $33 trillion in 2008.

The reason for the explosive growth is can partially be explained by the expansion of credit related products and also the introduction of new banking rules (BASEL II). The major market participant is hedge funds. Credit Default Swaps is still the most popular product among credit derivatives with a "market share" of approximately 33%. Another explanation for the massive growth is the speculative nature of CDS contracts where investors considers the market price (spread) of the CDS is relative over- or undervalued, i.e. Credit derivatives are not only used as a protection against default but also in pure speculative strategies. The combined factors for market growth makes the credit derivative market an attractive place to trade in as e.g. liquidity rises.

There are still no general pricing method for most of these credit derivative products and it is still an active topic at financial academic institutions. Credit risk has gone from being an unavoidable factor in businessmaking to an accepted, partly controllable, risk factor.

1.2 Purpose

The purpose of this thesis is to investigate trading in the credit derivatives market, looking for risk arbitrage (Capital Structure Arbitrage) opportunities using predicted credit default swap (CDS) spread based only on the underlying equity prices. Equity prices and CDS spreads are modelled with a modified CEV (Constant Elasticity of Variance) model.

1.3 Methodology

This thesis will be of a quantitative nature. However, we will first give an introduction to credit derivatives and specifically BASEL II. We utilize date acquired from Barclays Global Investors to calibrate a developed model for the prediction of CDS spreads. We also use the data to run a simple trading simulation in order to conclude the ability to predict market spreads in our developed model.

The market for credit derivatives have grown explosively but there are still no general pricing model for CDS spreads. We start from a model developed by Atlan and Leblanc (2005), which is derived from the stopped Constant Elasticity of Variance (CEV) model. Implementation of calibration and prediction routines, as well as trading routines, have been made in Matlab[1].

1.4 Limitations

We focus all our interest on the performance of the developed model. We will thus only adapt a simple trading strategy and not be concerned with e.g. hedging portfolios etc. We will not compare our model relative any other quantitative model of credit risk, e.g. CreditGrades.

1.5 Target group

The thesis is targeted to those wanting an introduction to equity-based modelling of CDS spreads and the idea of Risk Arbitrage (Capital Structure Arbitrage).

[1] Code available upon request.

1.6 Disposition

Chapter 2 discusses credit derivatives in general and CDS specifically. It gives a motivation for the use of credit derivatives and discusses Basel II.

Chapter 3 introduces the theory used in this thesis. Specifically, modelling equity, pricing CDS contracts and hedge a portfolio containing CDSs are presented.

Chapter 4 empirically use the theoretic results from Chapter 3. Simulations looking for Risk Arbitrage in the credit derivatives market are performed.

Chapter 5 discusses the results obtained in the thesis and the future of credit derivatives.

Chapter 2

Credit Derivatives

2.1 Credit Risk

Credit risk or credit worthiness is the risk loss due to counterparty defaulting on a contract, or more generally the risk loss due to some "credit event". Traditionally this applied to bonds where debt holders were concerned that the counterparty to whom they had made a loan might default on a payment. For that reason, credit risk also goes by the name default risk.

Conventional market theory describes two main risk categories: market or price risk and credit risk. Market risk refers to general risks and instabilities inherent in the market, such as inflation, interest rates, and the production of goods. To protect themselves against changes in these areas, investors mostly enter in long positions, forwards, futures and options on exchange rates or prices for assets. But while a variable rate protects the investor against market risk he still may not receive the entire return on the bond, as the bond issuer may not be able to make all its coupon payments, and therefore defaults. This is the simplest manifestation of credit risk. The derivative market is a lucrative one which aims to structure and price the market and credit risk respectively to hedge against these risks.

Dealing with over-the-counter (OTC) financial instruments bears a counterparty risk. Instead of exchanging traded futures and options, the mostly used derivative instruments in corporate treasury activities and financial institutions are interest rate swaps or currency forwards and other structured fixed income derivative. These financial instruments are traded over-the-counter and therefore entering in these contracts bears the risk of the default of the counterparty. Credit derivatives are OTC derivative financial instruments whose payoff depends on the credit quality of a certain issuer. This credit quality can be measured by credit rating of the issuer or by the credit spread of his defaultable bonds over the yield of a comparable default-free bond. They represent a diverse and heterogeneous group of transactions, which are principally concerned with the isolation of credit risk as a separately traded market-variable. The different products essentially are focused on structuring financial instruments to allow trading in this attribute in varied formats to allow hedging or risk assumption by market participants (Berndt and de Melo (2003)).

Credit derivatives are simply a mean of protection against credit risk. They come in many shapes and sizes to protect against different kind of credit risk. Essentially, a credit derivative is a security with a payoff linked to credit related event, such as default, credit rating downgrade, or structural change in a security containing credit risk. Credit derivatives can make large and important risks tradable. They form an important step toward market completion and efficient risk allocation, and can further bridge the traditional market segmentation between corporate loans and bond markets (see Berndt and de Melo (2003)).

2.2 The Bank for International Settlements

The Bank of International Settlements (BIS) is the oldest international financial organization in the World and has its headquarters in Basel, Switzerland. It was established by the G10[1] central banks to take over the collection, administration and distribution of the reparation payments imposed on Germany by the Treaty of Versailles following World War I (BIS (2006)).

Today BIS has no less than 55 member states and its main objective is to obtain and maintain monetary and financial stability. They function as a forum for discussion and cooperation amongst central banks and the financial community, and as a bank to central banks and international organizations.

[1] Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States

2.3 The Basel Committee on Banking Supervision

The BIS hosts the secretariats of several committees and organizations that focus on obtaining monetary and financial stability. The committees support central banks and authorities in charge for financial stability by providing background analysis and policy recommendations.

One of these committees is The Basel Committee on Banking Supervision (BCBS) which was established by the Governors of the G10 central banks in late 1974 as a response to the oil crisis and the following disturbances in international currency and banking markets (BCBS (2006)). The BCBS provides a forum for regular cooperation on banking supervisory matters and the initial objective for the BCBS was to close the gaps in international supervisory coverage by assuring that no foreign banking establishment escapes supervision and that the supervision is adequate. Over recent years the BCBS has developed in to a standard setting body on all aspects of banking supervision, resulting in the 1988 Basel Capital Accord (Basel I) and its Basel II revision of 2001-2006 (BCBS (2006)).

The committee does not posses any formal supervisory authority and its conclusions do not, and were never intended to, have any legal force. Rather, the BCBS formulates broad supervisory standards and guidelines and recommends statements of best practice in the expectation that individual authorities will fit them to suite their own national system. In this way, the Committee encourages convergence towards common approaches and common standards without attempting detailed harmonization of member countries' supervisory techniques (BCBS (2006)).

2.4 BASEL II

Background/main characteristics

Basel II is the second Basel Accord and represents recommendations by the Basel Committee on Banking Supervision to revise the international standards for measuring the adequacy of a bank's capital. It was created to promote greater consistency in the way banks and banking regulators approach risk management across national borders.

The Capital Basel Accord (Basel I) was set to establish a method of relating capital assets, using a simple system of risk weights and a minimum capital ratio of 8%. Whilst Basel I focus exclusively on credit risk in defining the capital to asset ratio Basel II constitute a more risk sensitive methodology to define the capital to asset ratio. It is explained by three pillars, mutually reinforcing each other:

- Minimum Capital Requirements
- Supervisory Committee
- Market Discipline

The core modification in Basel II is the factor that defines risk-weighted assets but the minimum capital to risk-weighted asset requirement of 8% remains unchanged (see WOCCU (2003)).

The three pillars

Minimum Capital Requirements

The first pillar aims at ensuring that capital allocation is more risk sensitive. It provides improved risk sensitivity in the way that capital requirements are calculated in three of the components of risk that a bank faces: credit risk, operational risk and market risk. Other risks are not considered fully quantifiable at this stage.

Supervisory Committee

The second pillar aims at separating operational risk from credit risk, and quantifying both. It deals with the regulatory response to the first pillar, giving regulators much improved “tools” over those available to them under Basel I. It also provides a framework for dealing with all the other risks that a bank faces, such as name risk, liquidity risk and legal risk, which the accord combines under the title of residual risk management (Wikipedia (2006)).

Market discipline - Public Disclosure

The third pillar aims at attempting to align economic and regulatory capital more closely to reduce the scope for regulatory arbitrage. This is accomplished by increasing the disclosures that the bank must make. It is designed to allow the market to have a better picture of the overall risk position of the bank and to allow the counterparties of the bank price and deals appropriately.

Different approaches in Basel II

The standardized approach is similar to the 1988 Basel Capital Accord in that banks are required to slot their credit into supervisory categories based on observable characteristic of the exposures (e.g. whether the exposure is a corporate loan or a residential mortgage loan) (BCBS (2006)). The standardized approach establishes fixed risk weights corresponding to each supervisory category and makes use of external assessments to enhance risk sensitivity compared to the current Accord.

The risk weighting in the standardized approach include:

- Retail loans - 75% risk weighting
- Mortgages - 35% risk weighting (reduced from previous 50%)
- Revolving credit - 15% risk weighting
- Operational risk - 15% of average gross income

An important innovation of the standardized approach is that loans considered past due are risk weighted at 150%, unless the financial institution holding the debt has already set aside specific provisions (WOCCU (2003)).

The standardized approach recognizes a broader use of collaterals and credit risk mitigations. These financial instruments are used by banks to decrease the associated risk of an asset and have expanded to include guarantees and credit derivatives (e.g. CDS).

2.5 Credit Default Swaps

A Credit Default Swap (CDS) is a specific kind of counterparty agreement which allows the transfer of third party credit risk from one party to the other. One party in the swap is a lender that faces credit risk from a third party. The counterparty in the CDS agrees to insure this risk in exchange of an insurance premium. If the third party defaults, the party providing insurance will have to purchase the defaulted asset from the insured party.

For this, the insurer pays the insured the remaining interest on the debt, as well as the principal amount as compensation for financial loss.

CDSs can also be used to gain exposure to credit risk. Being similar to a corporate bond there are some important differences between CDSs and corporate bonds. First, a CDS does not require any initial funding, allowing leveraged position. Second, a CDS contract can be agreed over a period of time where a corporate bond isn't available. Third, taking a position as a protection buyer the CDS easily gives you a "short" position on a company. These attributes gives CDSs the potential of being a great tool for diversifying or hedging ones portfolio (Adelson (2004)).

2.5.1 How a CDS work

Since a CDS are supposed to protect you in case of a credit event it is important to define those events. The most common trigger events are *bankrupty and liquidation* (chapter 7, US), *failure to pay* and *reconstructing* (chapter 11, US). When buying a CDS you pay a premium (called spread) to the protection seller, usually on a semi-annual basis. The spread is often quoted in basis points (bps) of the notional amount. One basis point is $\frac{1}{100}\%$. Most CDS contracts have a notional (N) between \$10 and \$20 million and a maturity of five years. These numbers are not restricted and you are most of the time able to find quoted spreads for 1, 3, 5, 7 and 10 years.

In case of a credit event, either the buyer or the seller delivers a "Credit Event Notice" to its counterpart. Then the protection seller pays the protection buyer either via physical settlement or cash settlement. In a physical settlement (most common) the protection seller buys the defaulted loan or bond from the protection buyer at par. When cash settlement is used, the protection seller pays the amount $(1 - R)N$, where R is the recovery rate (see below), to the protection buyer.

Chapter 3

Theory

3.1 Measuring Credit Risk

There are, of course, a number of ways to measure credit risk. However, two of the most popular ways of quantifying risk are

Probability of Default (*PD*) The probability of default is defined as the probability that the obligor will not fulfil its obligations (e.g. default on payment) over a given time period. It is complex to estimate this parameter accurately since it not only depends on observable factors. The *PD* computed in this thesis will be derived from the *CEV* model (see 3.2.2).

Recovery Rate (*R*) In case of a credit event, the recovery rate is defined as the portion of the notional amount that is repaid (taking values between 0 and 1). Just like the *PD* this parameter is hard to estimate. In this case one often fix *R* in the models used. Loss given default (*LGD*) is simply defined as *1-R*. In this thesis we will fix *R* given the seniority of the claims.

Another important term when measuring risk is *exposure* (i.e how much credit exposure one will have at the point of default).

The most used models when quantifying credit risk are either structural models or reduced-form models. In structural models a credit-event is triggered by the movement of the companys value whereas in reduced-form models the companys value is not modelled at all. Merton's model for estimation of PD (Merton (1974)) is the basis for most structural models. It focus on the modelling of the asset value of a firm, where a firm defaults when the total assets fall below the total debts. Common reduced-form models are intensity-based models (only concerned with the default time τ) and credit migration models (that also considers migrations between credit rating classes).

We will in this thesis use a structural approach of quantifying the probability of default. In calculating PD, we will use the firm equity price (and from it extract the historical volatility) as input parameter. We define a company default time, τ, as the time when the equity price hits 0, i.e.

$$\tau = \inf\{t > 0, S_t = 0\} \tag{3.1}$$

3.2 Modelling Equity Price

3.2.1 Background

The most popular way of modelling equity price the last three decades are the Geometric Brownian Motion (GBM). Black and Scholes (1973) and Merton (1974) used this in their famous option pricing model. A GBM evolves accoding to

$$dS_t = \mu S_t dt + \sigma S_t dW_t$$

where W_t is a standard wiener process, μ is called the drift term and σ is the volatility term. However, when trying to model a CDS spread it is important that there is a possibility for the equity price to reach zero (equal to default in our assumptions). When solving the GBM, using Itô formula, we get

$$S_t = S_0 \exp\{(\mu - \frac{1}{2}\sigma^2)t + \sigma W_t\}$$

which clearly have a disability of reaching zero within finite time ($S_0 > 0$). Another assumption in the GBM is the constant volatility (i.e. the volatility is not timedependent or changing) which further add the inability of reaching zero for the stock. This is the main reasons for trying to model the equity price with another model.

3.2.2 The Constant Elasticity of Variance (CEV) model

This model was introduced by Cox (1975) and basically considers the complications with the GBM when trying to determine the CDS spread. The

CEV model has the following dynamics:

$$dS_t = \mu S_t dt + \sigma S_t^{\alpha} dW_t$$

where the extra parameter α is called the constant elasticity of variance parameter. A special case of this model is when $\alpha = 1$, it is then equal to the Black & Scholes model.

3.3 Probability of Default in the CEV Model

To be able to model the CDS spreads we need to calculate the *probability of default* (PD). Atlan and Leblanc (2005) shows how one can estimate the PD in the stopped (i.e. the model stops as the stock prices reaches 0 at time τ) CEV model.

$$\mathbb{P}(\tau \leq T|S_0) = G(\frac{1}{2(1-\alpha)}, \xi_T) \tag{3.2}$$

where G and ξ_T are defined as

$$G(x,y) = \int_{z \geq y} \frac{z^{x-1}e^{-z}}{\Gamma(x)} 1_{z>0} dz \tag{3.3}$$

$$\xi_T = \frac{rS_0^{2(1-\alpha)}}{(1-\alpha)\sigma^2(1-e^{2(1-\alpha)rT})} \tag{3.4}$$

The function $G(x,y)$ is known as the inverse (upper) gamma function which makes it more gentle to implement in i.e. Matlab (as we do in this thesis). The PD in the CEV model is illustrated in Figure 3.1.

3.4 Volatility estimation

It is a known fact that volatility is not a constant factor. However, in our model we still have the assumption of constant volatility. The most desirable way to come around this problem would be to implement a stochastic volatility model. We will no do this in this thesis because of the relative complexity of stochastic volatility models. For the interested reader on this we refer to Atlan and Leblanc (2005).

In this thesis we will instead use an Exponential Weighted Moving Average (EWMA) to estimate the volatility and thus get some variation in the

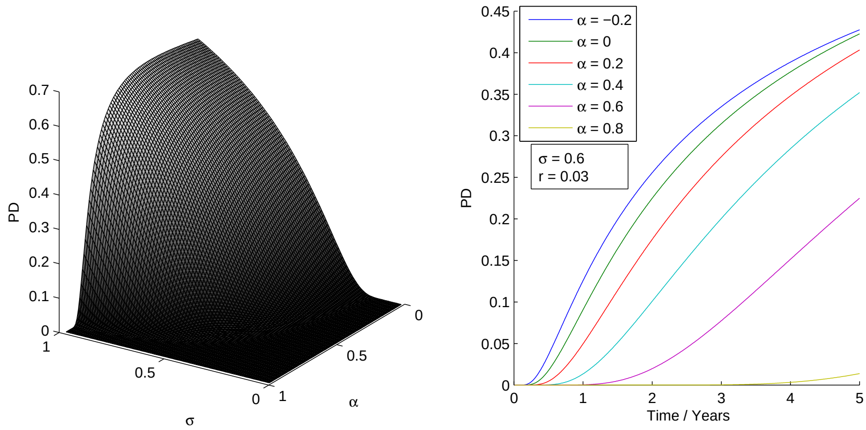

Figure 3.1: Probability of default in the CEV model. Left: PD within 5 years plotted against different values of α and σ. Right: PD as a function of time, plotted for different values of α.

volatility. The volatility is estimated from the equity prices and the EWMA is defined as

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda) u_{t-1}^2 \tag{3.5}$$

where $\lambda < 1$ is the forgetting factor, u_t is the percentage change in the market at t. To account for the CEV model, we follow Bengtsson and Bjurhult (2006) and set

$$u_t^2 = (\frac{S_t - S_{t-1}}{S_t^\alpha})^2$$

Due to the dependance on previous volatilities, the initial estimates are usually quite poor. Because of this we will discard a number of initial volatility estimates.

3.5 Modelling the CDS spreads

When trying to model a fair CDS spread entirely based on quantitative measures the most important parameters are the probability of default (PD) and recovery rate (R). We have shown above how do determine the PD in the used CEV-model. However, the recovery rate, which could be seen as a stochastic variable, are in this thesis fixed at a constant level. Basically we will adopt the model from Atlan and Leblanc (2005).

The method for pricing the CDS is to calculate the present value of the difference between expected received amount (i.e. amount received in case of credit event, seeing it from a CDS buyers point of view) and expected payed amount (i.e. premium payments until default, again seeing it from a CDS buyers point of view). These cash-flows are called the *contingent leg* and *fixed leg* respectively. The present value of the contingent leg are

$$PV_{CONTINGENT,t} = (1-R)N\mathbb{E}^Q(e^{-r(\tau-t)}1_{\tau\leq T_n}) \tag{3.6}$$

where the expectation is to be taken under the risk-neutral measure Q. τ is defined as in equation (3.1). The present value of the fixed leg, consisting of premium/spread payments are

$$PV_{FIXED,t} = -C\sum_{i=1}^{n} B(t,T_i)\mathbb{P}(\tau > T_i) \tag{3.7}$$

where C is the CDS spread. Note that $\mathbb{P}(\tau > T_i) = \mathbb{E}^Q(1_{\tau>T_i})$. Combining (3.6) and (3.7), we obtain the fair CDS price at t

$$CDS_t = PV_{FIXED} + PV_{CONTINGENT} \tag{3.8}$$

From this, assuming $CDS_0 = 0$, we can solve for the CDS spread, C, and get

$$C = \frac{(1-R)N\mathbb{E}^Q(e^{-r(\tau)}\mathbf{1}_{\tau\leq T_n})}{\sum_{i=1}^{n} B(0,T_i)\mathbb{P}(\tau > T_i)} \tag{3.9}$$

where R is the recovery rate, N the notional amount, B the risk-free zero coupon bonds (i.e the discounting factors).

3.6 The Model

We extend the model presented in 3.2.2, according to Bengtsson and Bjurhult (2006) and we get our model used for pricing CDS spreads as

$$dS_t = (r-q)S_t dt + \sigma_0\hat{\sigma}^{\beta}S_t^{\alpha}dW_t^Q \tag{3.10}$$

where q is the continuous dividend (company specific), r is the risk-free rate, $\hat{\sigma}$ is the timechaning volatility term (estimated with an EWMA). σ_0, α, β will be optimised to fit quoted CDS spreads. This model gives us the opportunity to deviate from the assumption of constant volatility by updating the different parameters at certain times.

3.7 Capital Structure Arbitrage (CSA)

Capital Structure Arbitrage is also known as debt-equity trading. It is important to point out that CSA is not a pure arbitrage (as defined in e.g. Rasmus (2006)) but rather a statistical arbitrage. CSA is one of the more popular trading strategies among hedge funds. The strategy is simple; take a position in debt security to hedge an equity position, or vice versa. However, we will in this thesis not use it as a hedge but in purly speculative purpose. The idea behind the strategy is to take advantage of how the equity and debt market reacts to new information.

In our case we will try to take advantage of the CDS spread being over or under priced (relative to our predicted spread) resulting in a short or long position respectively. For a more detailed discussion and a number of different trading strategies see Berndt and de Melo (2003). For a comprehensive study of CSA see Yu (2006) where the conclusion is more negative than other articles, who is (was) saying it is the "next big thing" (see Currie and Morris (2002)).

3.8 CDS portfolio

To test our model we will undertake a trading simulation by creating a portfolio of CDS contracts. Our portfolio will only containt CDS contracts and not attempt of hedging (e.g. delta- or vega-hedging) will be pursued. This is since our purpose only is to see if our model is abel to predict CDS spreads. We create a portfolio with price function

$$P(CDS_t, S_t, t) = \phi_t CDS_t \tag{3.11}$$

where CDS_t is the CDS price at t and ϕ_t is the number of conrtacts held at t. Since we only have CDS spread (and not price) available, (3.11) can't be applied dirctly to obtain portfolio value. Instead we look at the change in portfolio value, i.e.

$$\Delta P = \phi_t \Delta CDS_t \tag{3.12}$$

Assuming that the CDS price primarily depends on the CDS spread (i.e. other parameters negligable in comparison), we approximate

$$\Delta CDS_t \approx \frac{\partial CDS}{\partial C_t} \Delta C_t$$

and thus we can calculate the portfolio value at all times. Bengtsson and Bjurhult (2006) derives how one can calculate $\frac{\partial CDS_t}{\partial C_t}$ as

$$\frac{\partial CDS_t}{\partial C_t} \approx \sum_{i=1}^{n} e^{-r(T_i - t)} \mathbb{P}(\tau > T_i | S_t)$$

which we can calculate using our CEV assumptions. The portfolio will be used in our trading simulation which is presented in section 4.5.

Chapter 4

Empirical modelling

4.1 Description of data

Data was acquired from Barclays Global Investors. The companies chosen represent different industries and different ratings (S&P). The data contains the CDS spreads (maturity of five years) and equity prices for nine different companies. A summary of the companies can be seen in Table 4.1. Figures of the data is seen in Figure 4.1 and 4.2.

For each company there are 1050 data points where point 1 and 1050 correspond to 2002-07-01 and 2006-07-25 respectively. British Airways, EMI Group, Corus Group and Invensys are rated as crossover while the rest of the companies are investment grade.

Name	Rating (S&P)	Business
British Airways	BB+/Positive/– (2003)	Travel & Leisure
EMI Group	BB/Negative/B (2006)	Media
Corus Group	BB/Watch Dev/B (2006)	Industrial Metals
Invensys	B+/Positive/NR (2004)	Electrical Equipment
European Aero Dfnc & Space	A-/Watch Neg/A-2 (2006)	Aerospace & Defence
Gallaher Group	BBB/Watch Pos/A-2 (2001)	Tobacco
France Telecom	A-/Stable/A-2 (2005)	Telecom
ENEL	A+/Negative/A-1 (2000)	Electricity
Endesa	A/Watch Neg/A-1 (2001)	Electricity

Table 4.1: Summary of companies represented in data.

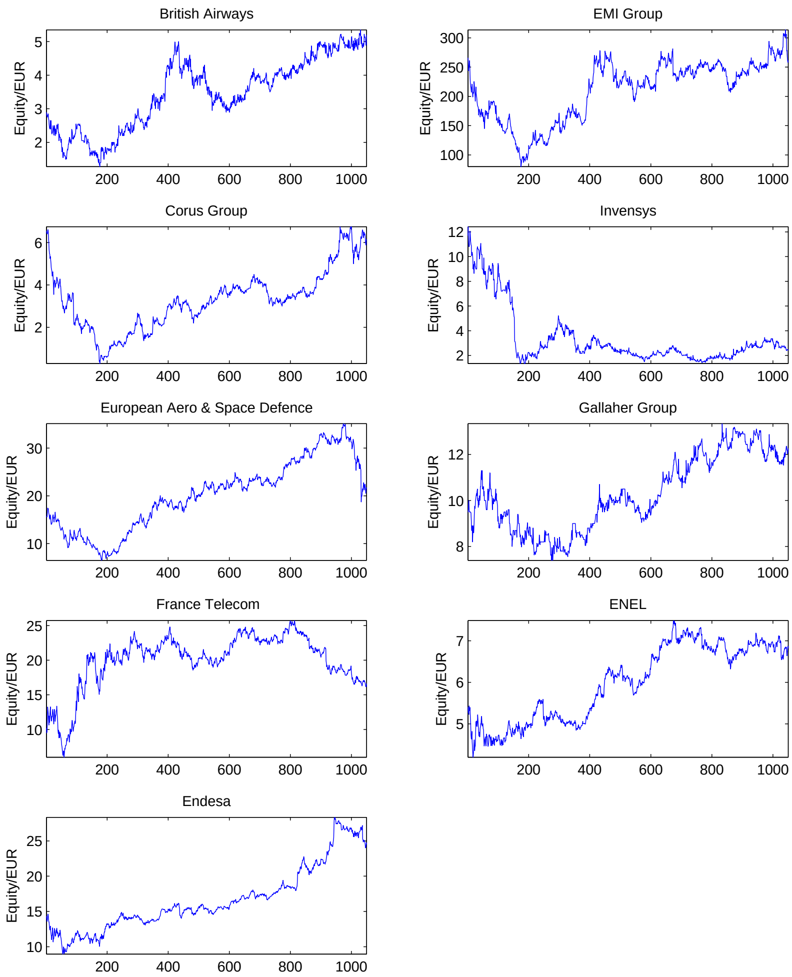

Figure 4.1: Quoted equity price for selected companies.

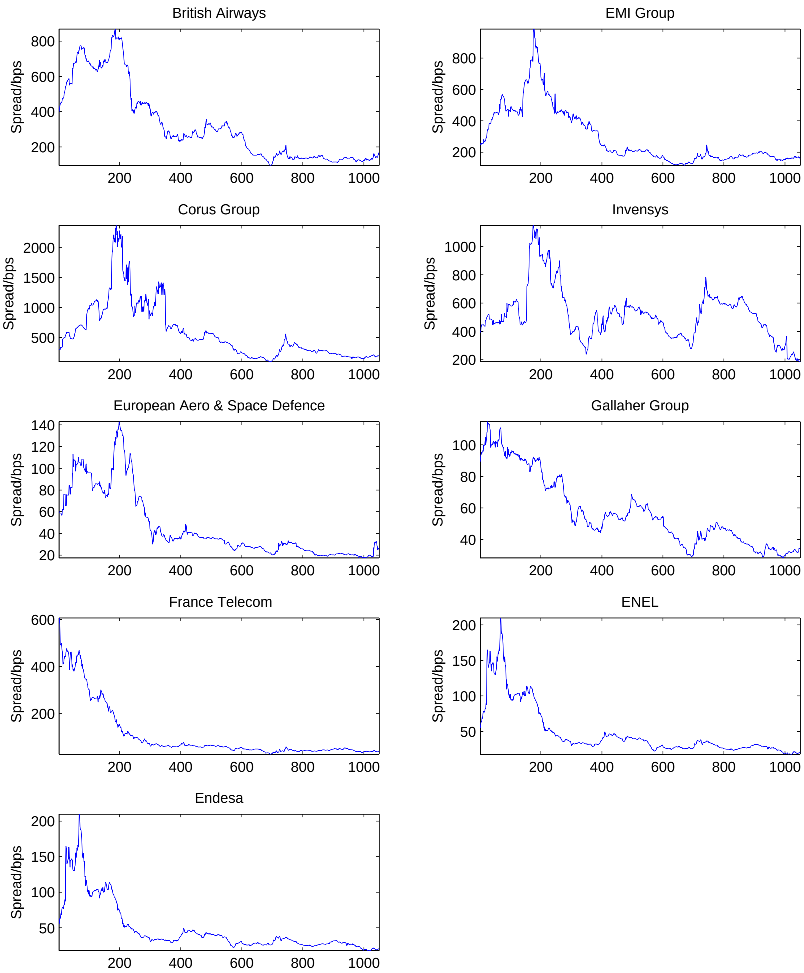

Figure 4.2: Quoted CDS spreads for selected companies.

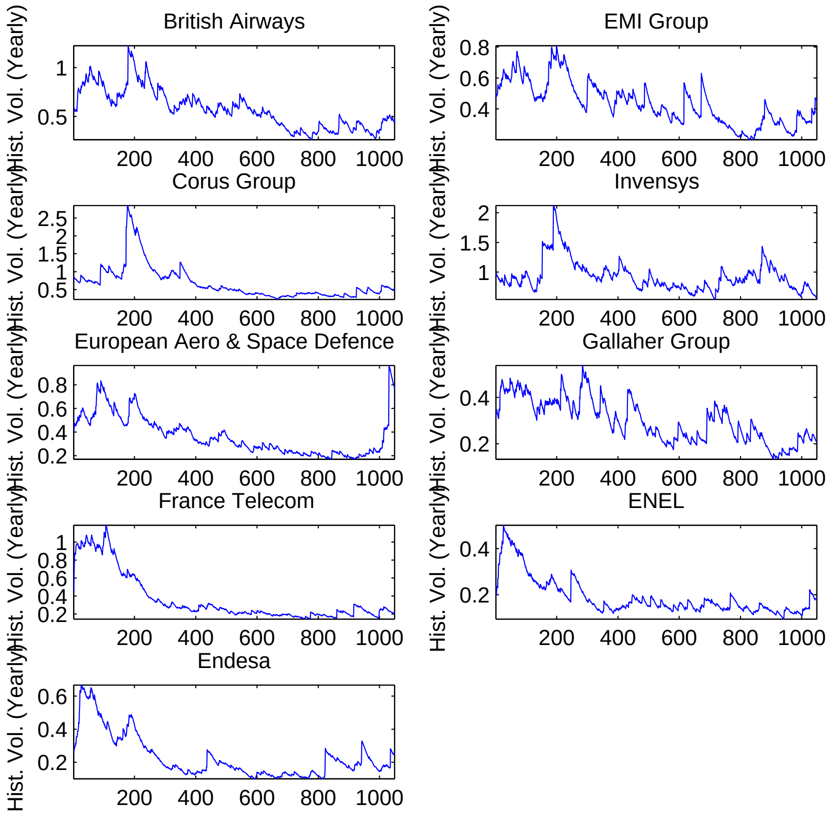

Figure 4.3: Estimated volatilities for selected companies.

4.2 Data Analysis

4.2.1 Volatility

As discussed before, the volatility of the stockprices are not constant over time. For our chosen companies, the estimated volatility can be seen in Figure 4.3, which obviously show a timechanging behaviour.

The volatilities where estimated using an EWMA ($\lambda = 0.96$), described in section 3.4. The estimated volatilities will be used in our optimisation of the other parameters.

4.2.2 Correlation

In Figure 4.4 the autocorrelation for both equity price and CDS spread can be seen. Since our models assumes independent increments we should not be able to see any clear autocorrelation. We can, however, see some tendancies to autocorrelation in the CDS spreads for almost all companies. We will not take this in consideration since it is a relative small autocorrelation. Another way to illustrate it, again assuming that the equity price might be leading the CDS spreads (i.e. the equity market is more liquid and hence responds quicker to new information) the equity price change is plotted against the CDS spread change (and the CDS spread change lagged one day, see Figures 4.6 and 4.7). We do not find any obvious correlations in these plots and hence conclude that the CDS spreads are liquid enough.

In Figure 4.5, the CDS spreads are plotted against equity price. In most companies we see a clear negative trend. While also looking at the correlation between CDS spreads and volatility, which can be seen to be positive (see Figure 4.8), we conclude that equity price and historical volatility seems like decent input to our model.

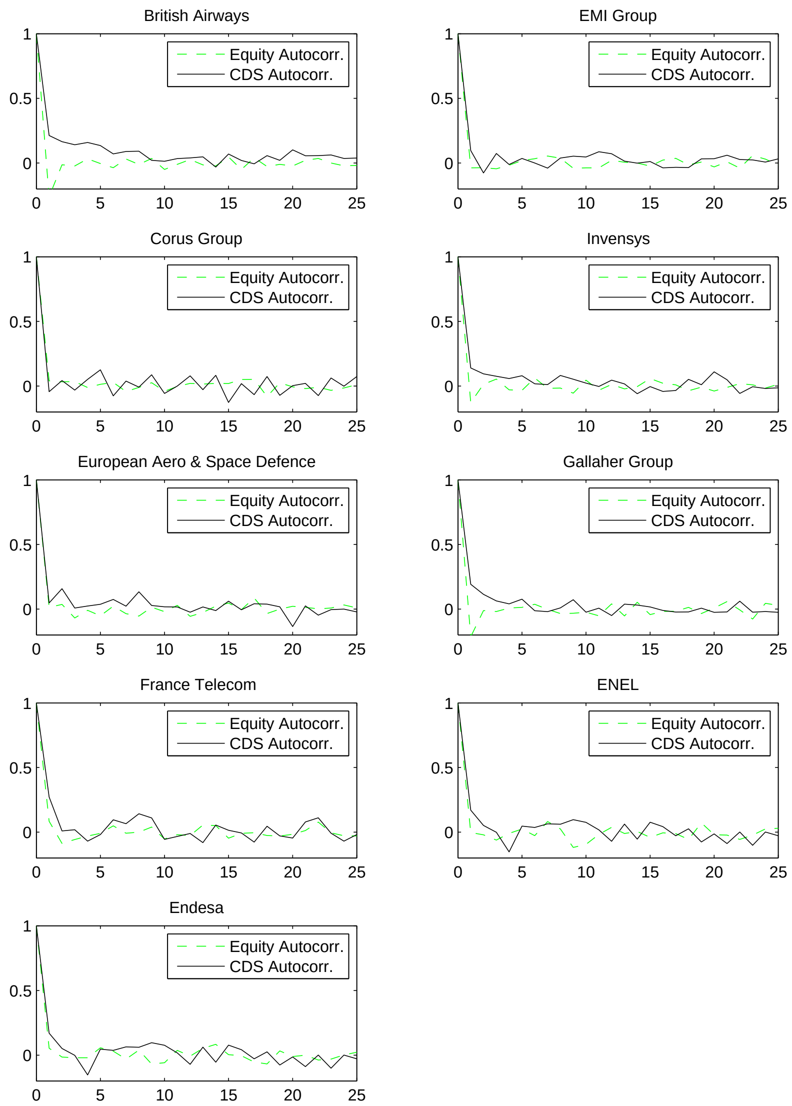

Figure 4.4: Autocorrelation plot for Equity price and CDS spread.

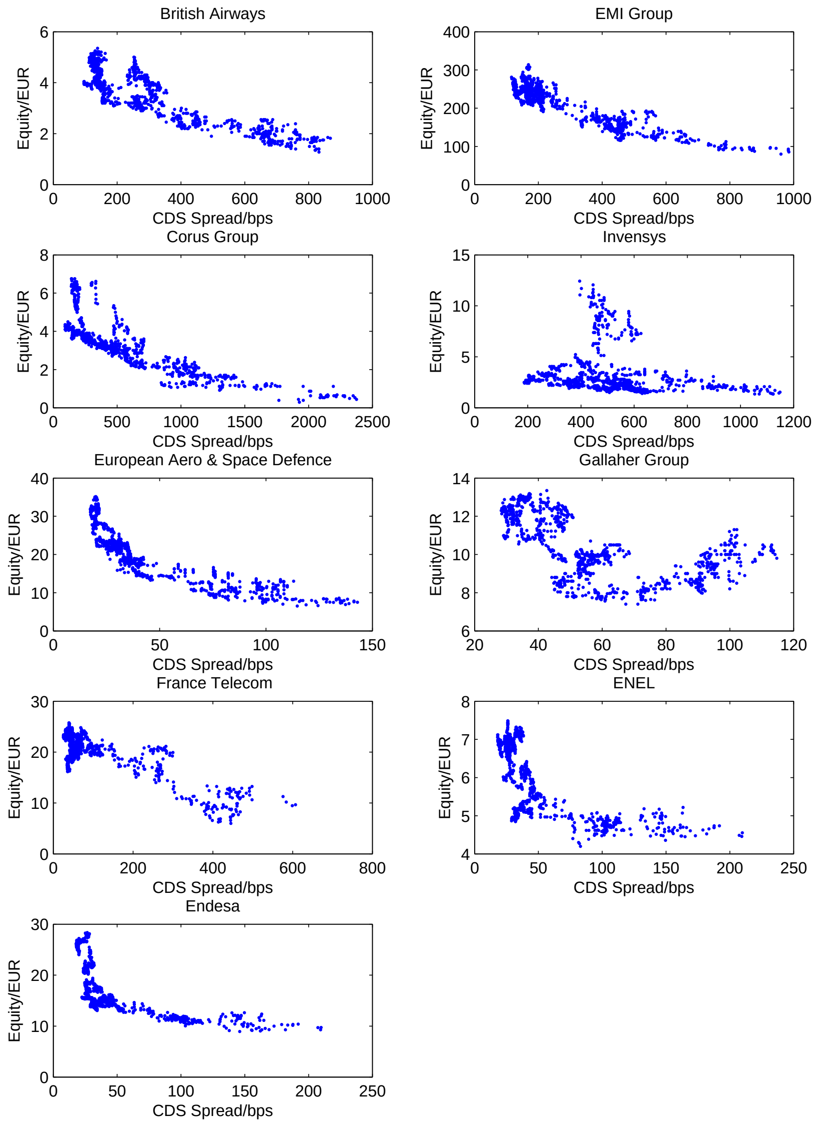

Figure 4.5: Scatter plots, Equity price vs. CDS spread.

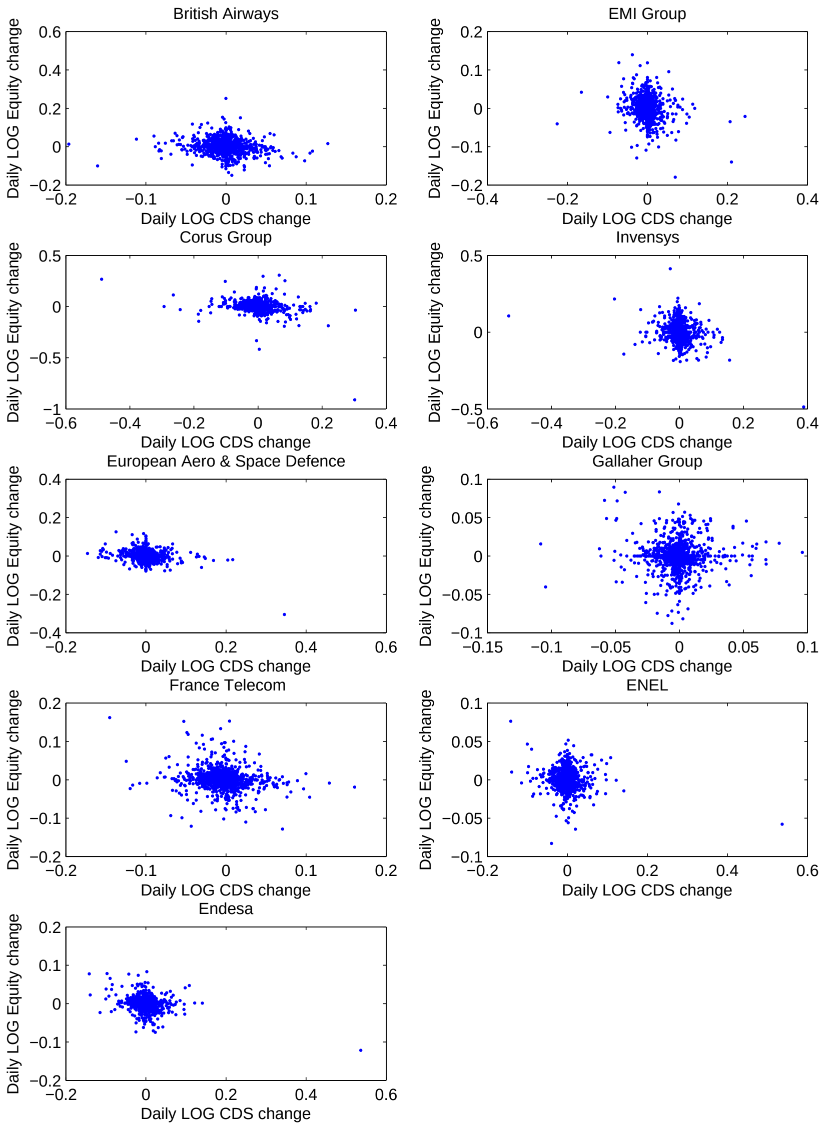

Figure 4.6: Scatter plots, log returns of Equity price vs. log returns of CDS spreads.

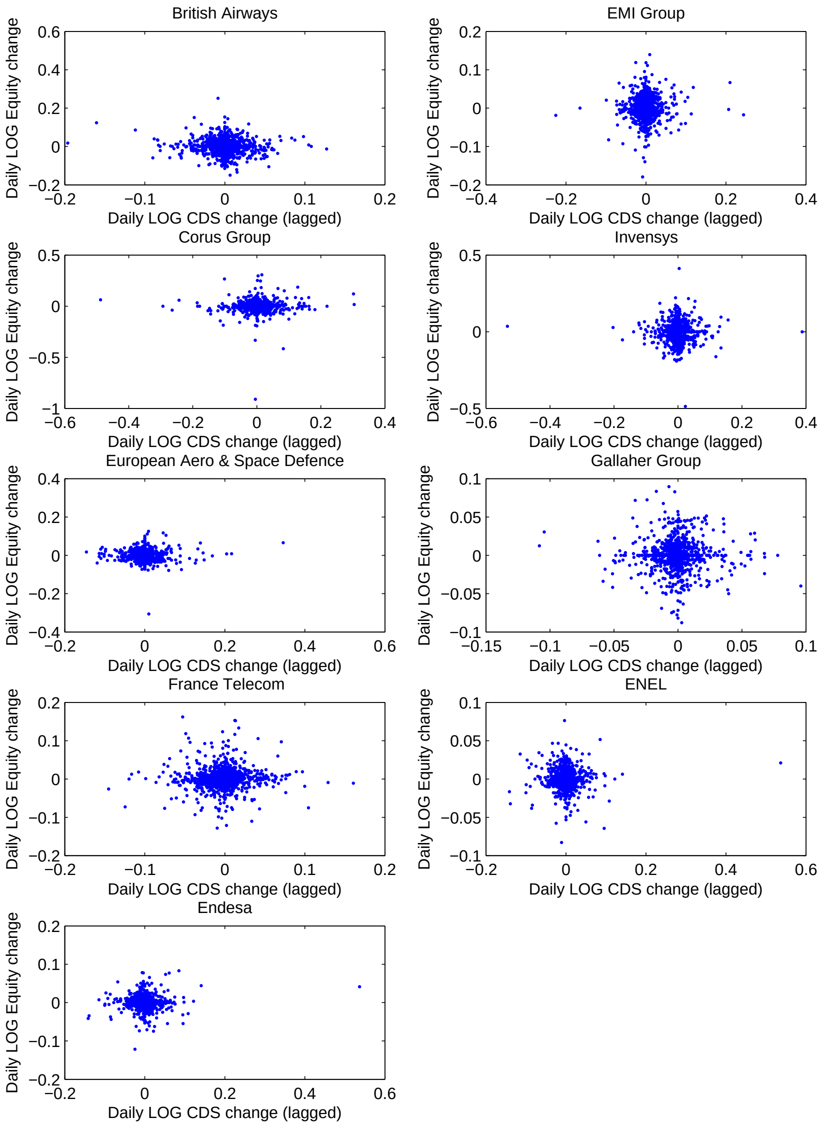

Figure 4.7: Scatter plots, log returns of Equiy price vs log returns of CDS spreads (lagged one day).

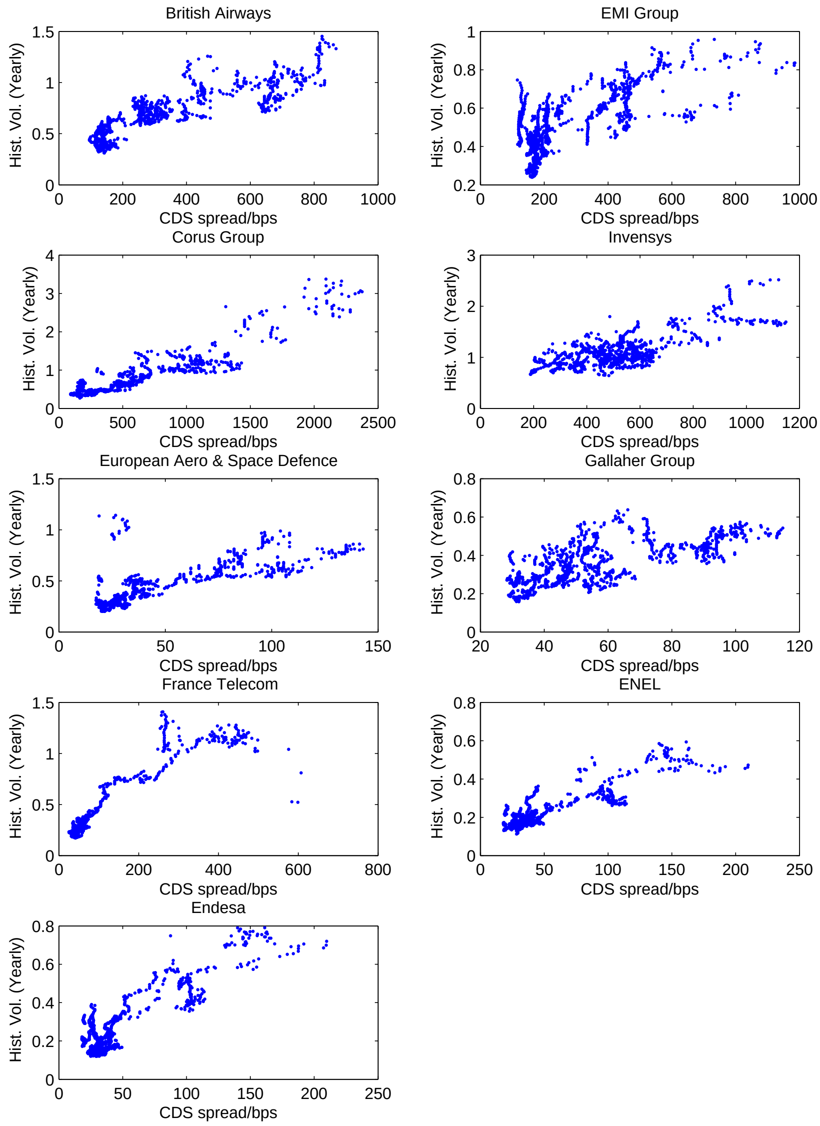

Figure 4.8: Scatter plots, CDS spreads vs. historical volatilities (EWMA estimates).

4.3 Estimation of parameters

In our model for equity price movements (eqn 3.10) we have six different parameters: $\alpha, \beta, \sigma_0, \hat{\sigma}, r$ and q. We fix the risk free rate, r, at 3%. The dividend yield, q, is a company specific value and is determined based on historical dividends for each company. $\hat{\sigma}$ is estimated as an Exponentially Weighted Moving Average (EWMA), setting the forgetting factor $\lambda = 0.96$. Because of poor estimates in the beginning of the data series we will discard l values from our original 1050. At every optimisation we use a 500 point window, moving it forward every k:th day.

To estimate the remaining parameters we will minimise the following objective function (as suggested by Bengtsson and Bjurhult (2006), with some modifications):

$$\begin{aligned} g(\alpha, \beta, \sigma_0) &= K_1 \min(0, 0.96 - \alpha)^2 + K_1 \min(0, \beta - 0.05)^2 \\ &+ K_2 \min(0, 0.99 - \alpha)^2 + K_3 \min(0, \beta - 0.011)^2 \qquad (4.1) \\ &+ \sum_{t=T-n+1}^{T} e^{tK_4} \ln(\frac{\hat{C}_t}{C_t})^2 \end{aligned}$$

Here $K_1 - K_3$ are constants, tuned for the estimation, and $\hat{C}_t$ and C_t are our estimated CDS spread (eqn 3.9) and quoted CDS spread respectively.

The reason for the penalty functions are the fact that strange modelling behaviours occur as α and β reaches one and zero respectively. When estimating spreads it becomes obvious that the penalty functions are really needed. The constant in front of the log-difference of the spread is there to give newer spreads a greater weight in the optimisation.

We use the parameters obtained from the estimation to predict the spread over a given future period. The only data used for spread prediction are the daily equity price and daily volatility estimates. Typically, we update our parameters every 10th day (i.e. $k = 10$) and use these estimates for prediction over the coming 10 days. In each optimisation, 500 data points are used, where the first 150 is discarded due to volatility estimates. This will result in 540 points that can be used for trading simulation.

How the parameters change over time (for our specific companies) can be seen in Figure 4.9. It can clearly be seen that the penalty functions are active at a large portion of the updates. This is important to get an actual probability of default estimate.

In Figure 4.10, the predicted CDS spreads are plotted with the actual quoted CDS spreads. The parameters used are updated every 10th day.

4.4 Trading method

One can assume that the equity market is more liquid than the CDS market and hence that it would be more effective (i.e. reacting faster to new information) and leading the CDS market. If this is the case, our model should do a proper job in predicting the spreads since equity is our only source for information. Since one can see some correlation between both the CDS spread vs. Equity price and CDS spread vs. Historical volatility (estimated from equity price) it is plausible that our assumptions might be right.

Since our main purpose is to see if our model is abel to predict CDS spreads we will adopt a simple trading strategy to get an indication of potential trading results. Our trading will be purely speculative. The main idea is to adjust the number of CDS contracts held in relation to the difference between quoted and estimated CDS spread. When the estimated CDS spread is higher (lower) than the quoted market spread we will buy (sell) CDS contract according to the size of the difference.

We will use the following simple trading scheme (C_t is quoted spread and $\hat{C}_t$ is our predicted spread) ;

Algorithm 1 Trading algorithm.

$$\delta = \frac{C_t - \hat{C}_t}{C_t}$$

if $0.1 < |\delta| \leq 0.2$ then hold 1 CDS contract (long if δ is negative, else short)
if $0.2 < |\delta| \leq 0.3$ then hold 2 CDS contracts
⋮
if $|\delta| > 0.5$ then hold 5 CDS contracts

i.e. we set have a maximum of 5 CDS contracts (long or short) at any time.

The trading could be further developed by e.g. using some kind of hedge. Bengtsson and Bjurhult (2006) attempts a delta-hedge to minimize the influence from the equity-based fluctuations in the CDS value. The result,

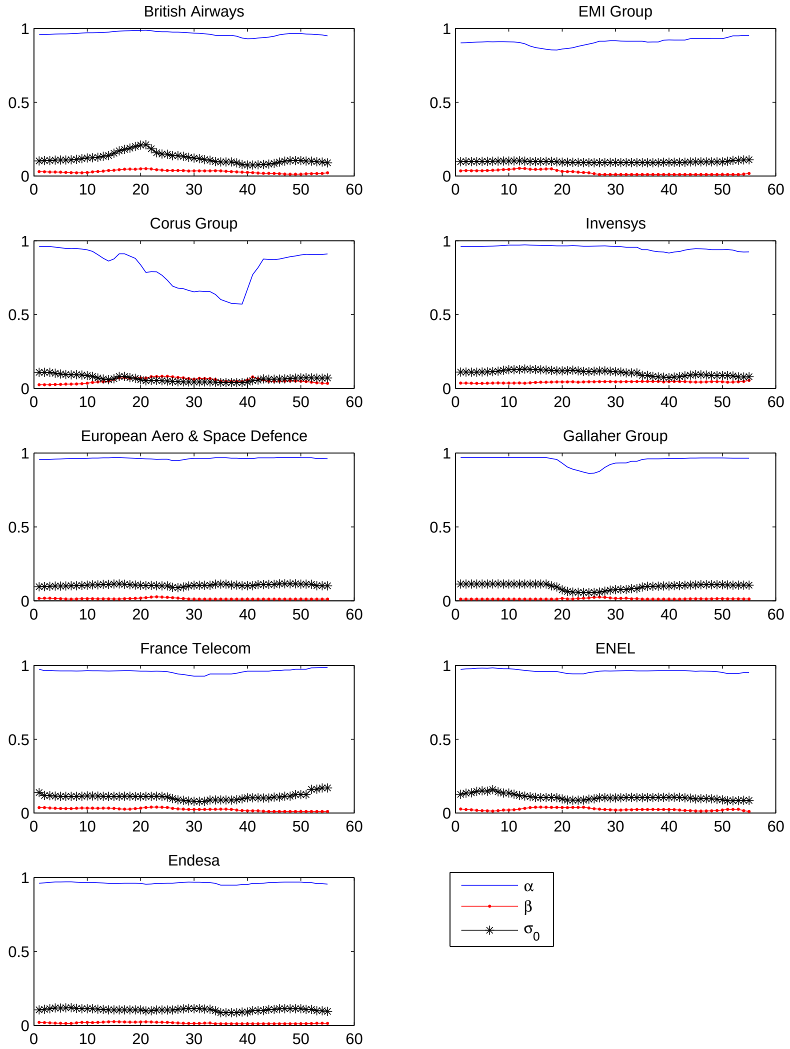

Figure 4.9: The parameters, updated every 10th day.

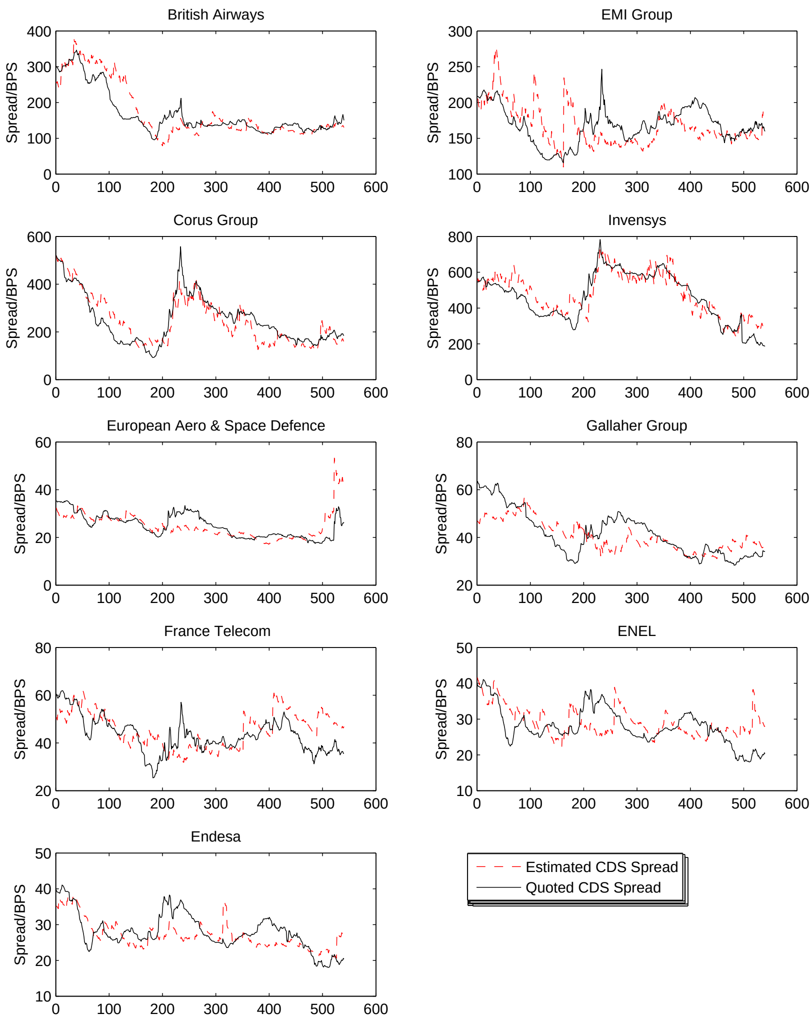

Figure 4.10: The predicted CDS spreads (using updated parameters every 10th day) plotted with the actual quoted CDS spreads.

however, is quite poor unfortunally. The choice of trading scheme is of course important if a similar strategy would actually be implemented. Our chosen trading scheme is in no way optimal but merely a indicator of how the prediction of CDS spreads work.

4.5 Result from trading

Our results are promising, showing a profit from CDS trades in 8 out of 9 companies. Trading results can be seen in Figures 4.11-4.19. In each plot the predicted and quoted spread are plotted, the number of CDS contracts helt, the profit from the holding of CDS contract and the net spread payments received. The reason for the spread payments not being included in the profit plot is the fact that these are not paid for nothing but rather as an insurance against the firrm defaulting. If included, a profitable strategy would be to short many CDS contracts until maturity (since firms defaulting is relative unusual).

One can see that the spread difference between the quoted and estimated CDS spreads most of the time converge, which is desirable.

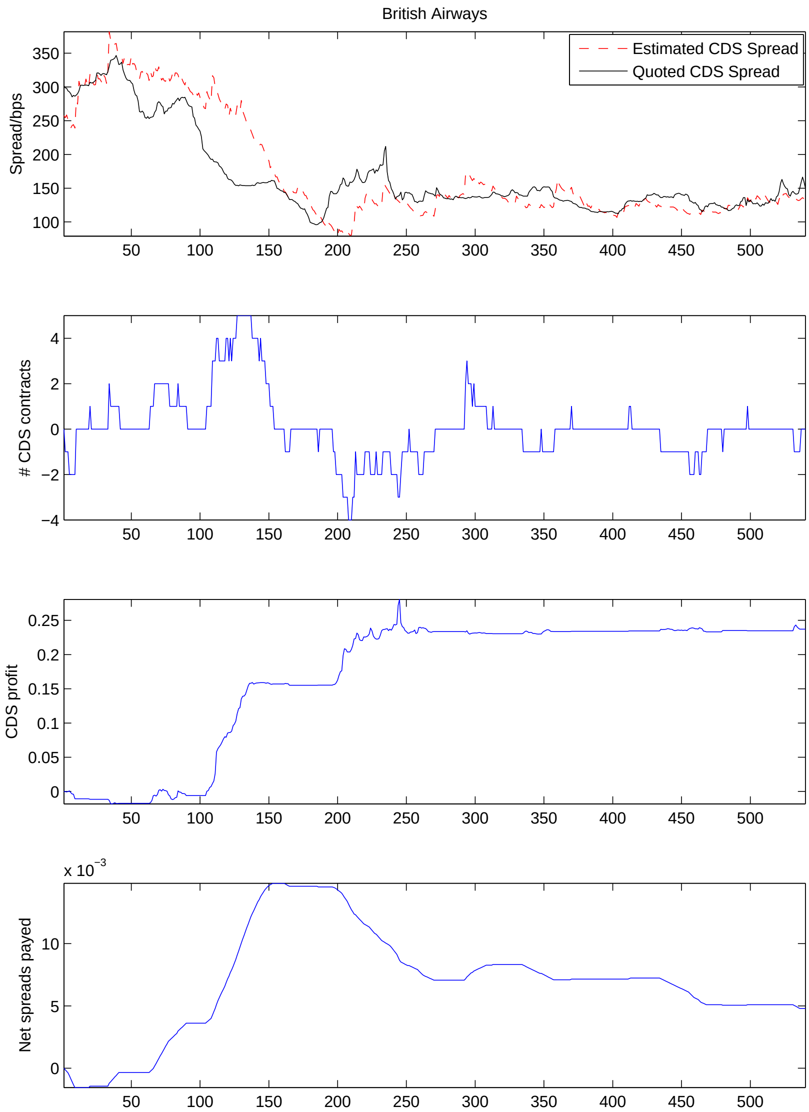

Figure 4.11: Trading result for British Airways. Notional amount of each CDS contract is 1 euro. In total, 85 trades were made.

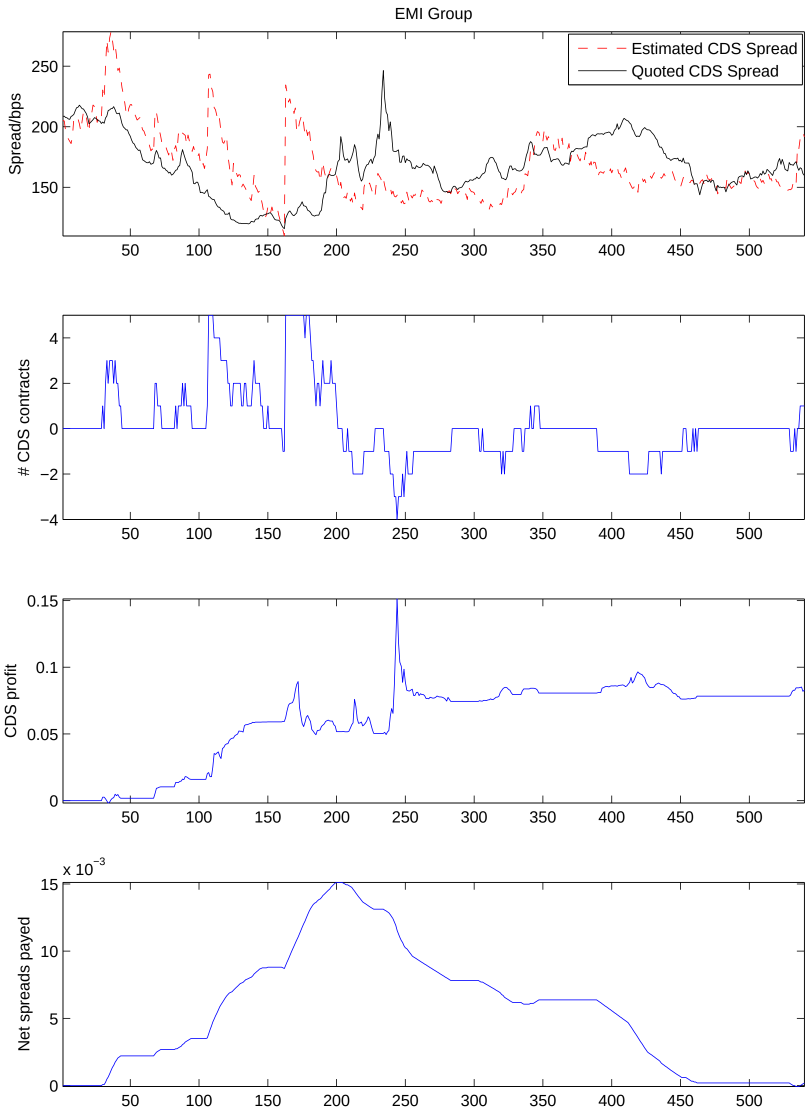

Figure 4.12: Trading result for EMI Group. Notional amount of each CDS contract is 1 euro. In total, 105 trades were made.

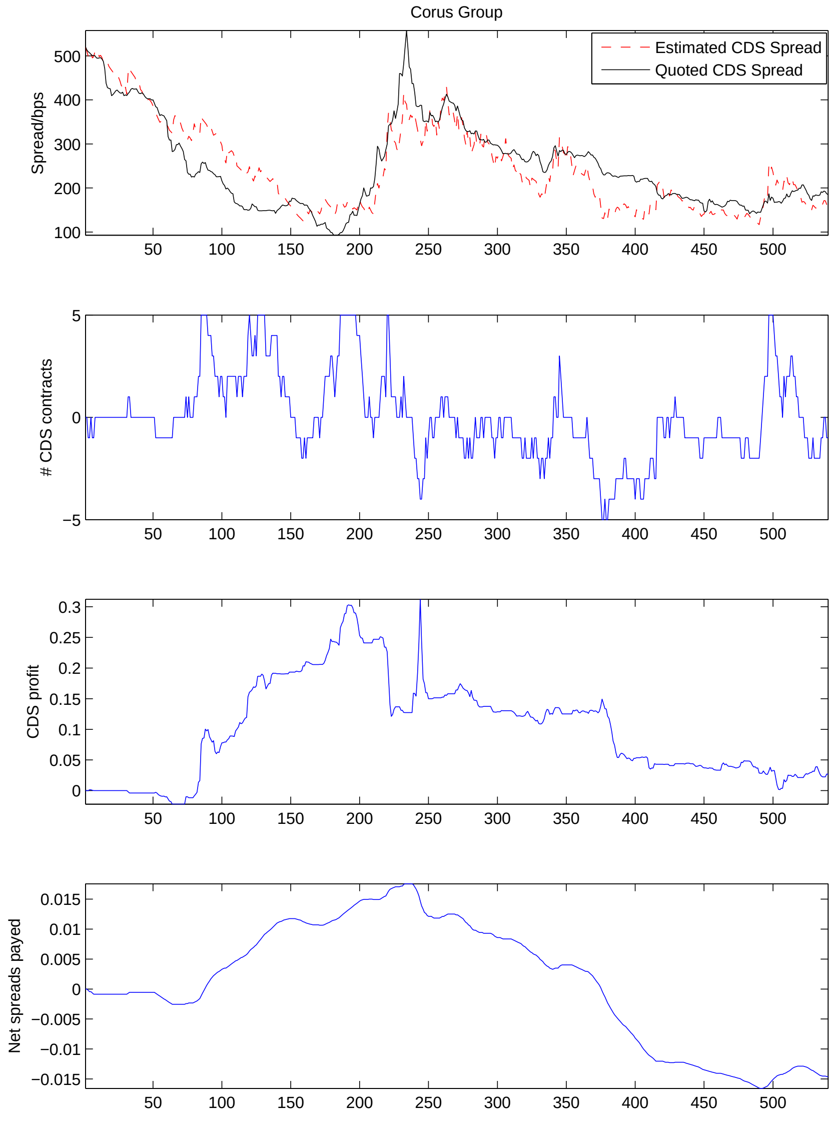

Figure 4.13: Trading result for Corus Group. Notional amount of each CDS contract is 1 euro. In total, 192 trades were made.

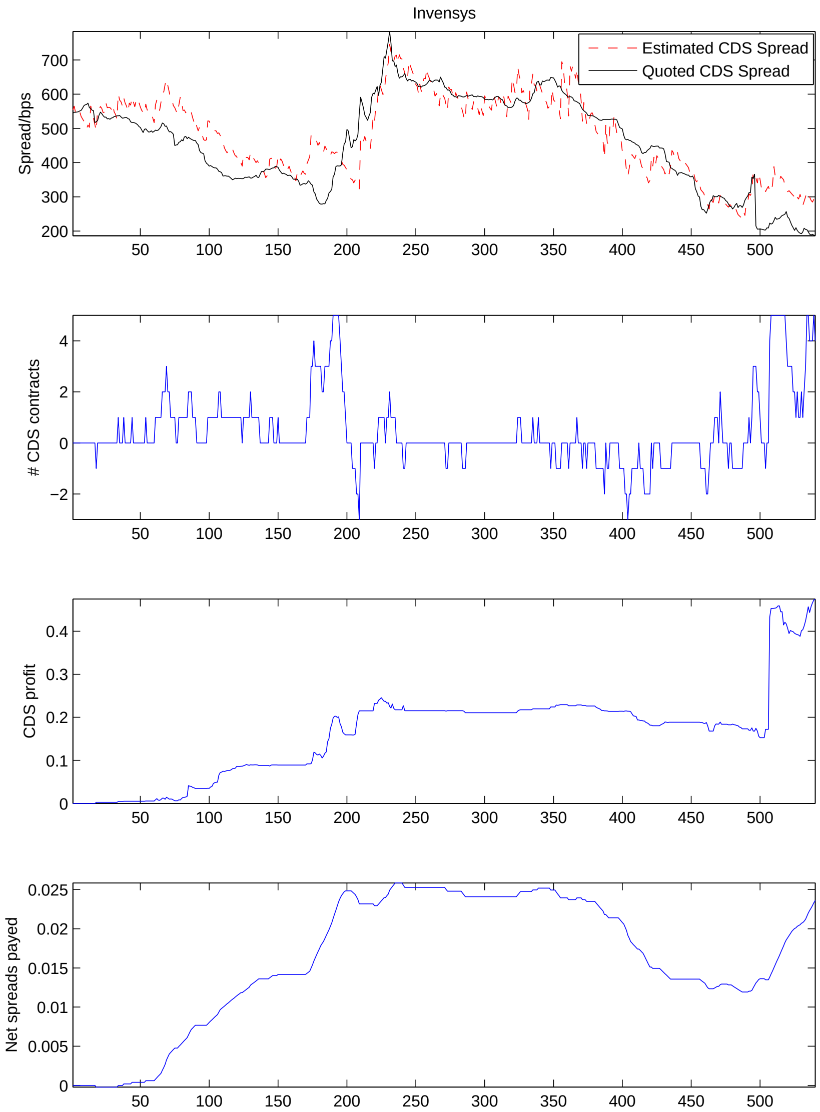

Figure 4.14: Trading result for Invensys. Notional amount of each CDS contract is 1 euro. In total, 137 trades were made.

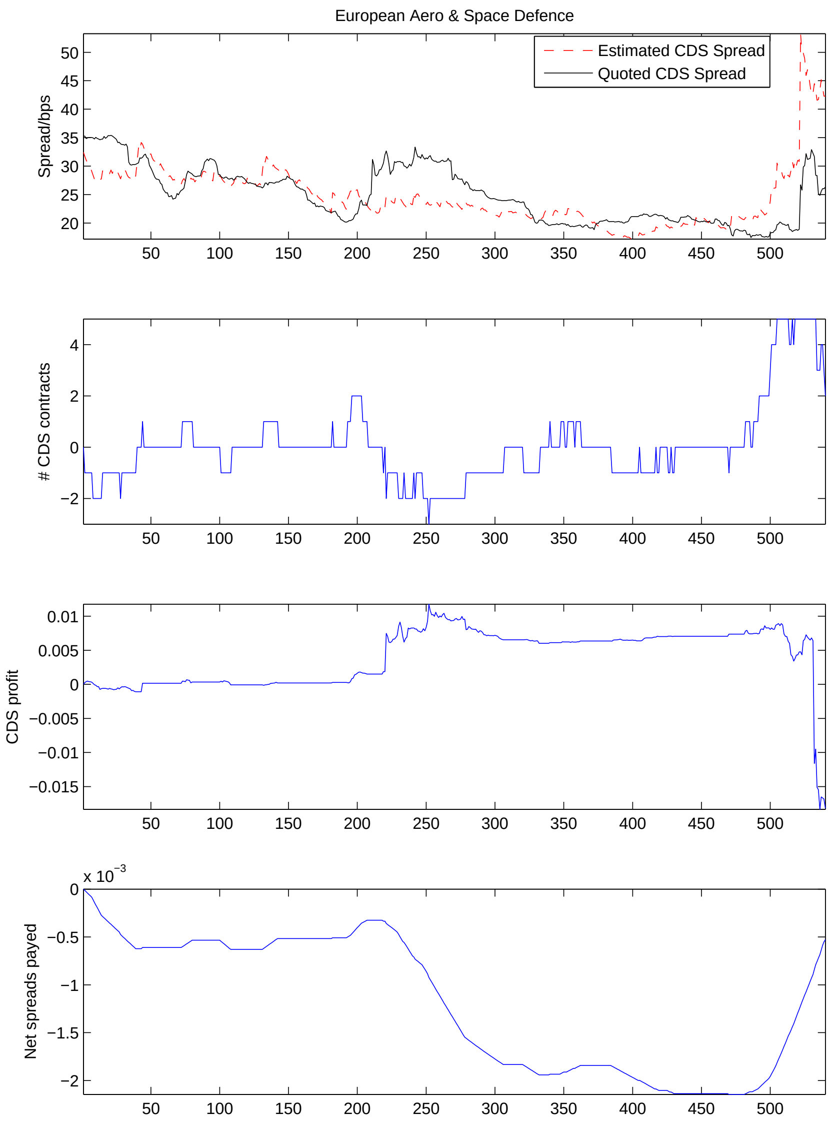

Figure 4.15: Trading result for European Aero & Space Defence. Notional amount of each CDS contract is 1 euro. In total, 72 trades were made.

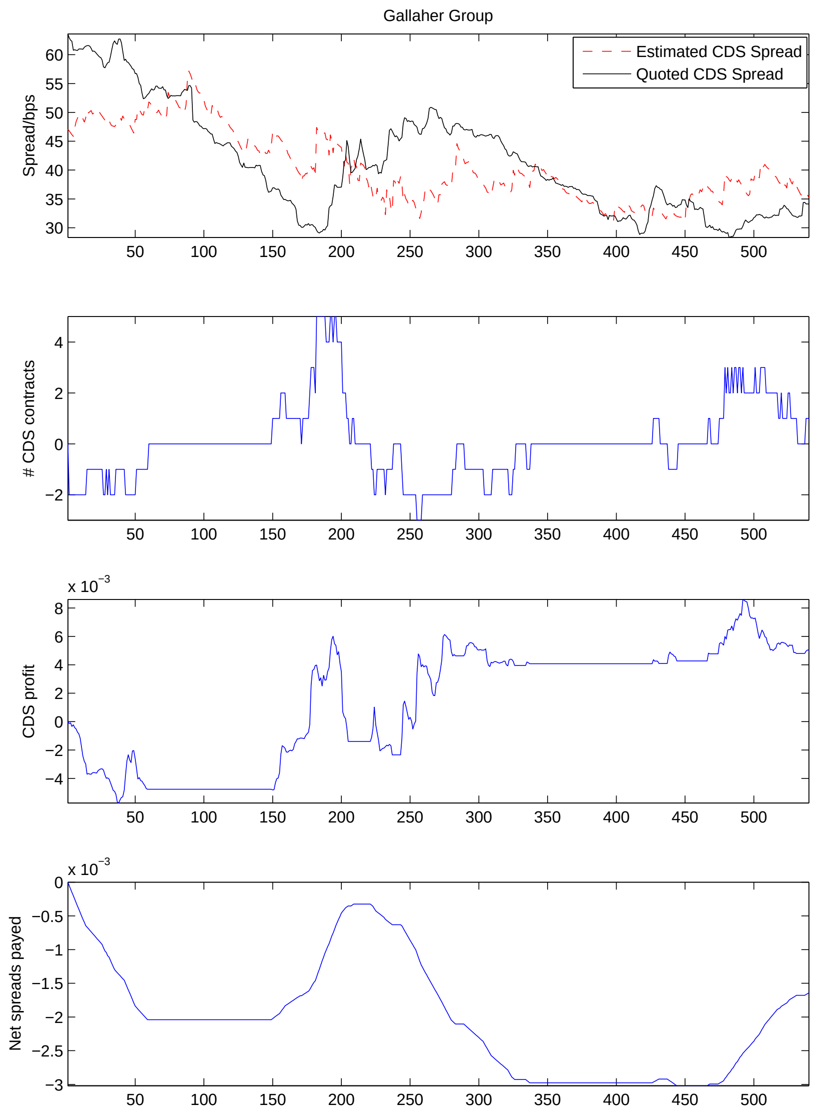

Figure 4.16: Trading result for Gallaher Group. Notional amount of each CDS contract is 1 euro. In total, 80 trades were made.

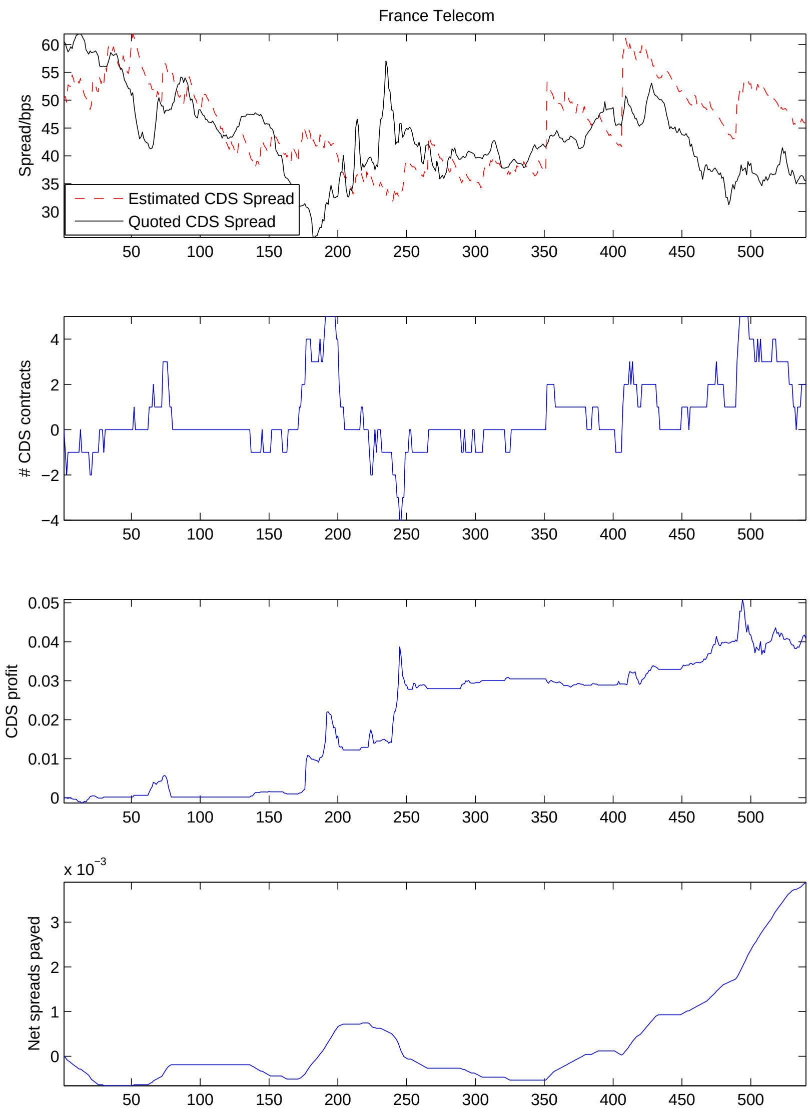

Figure 4.17: Trading result for France Telecom. Notional amount of each CDS contract is 1 euro. In total, 101 trades were made.

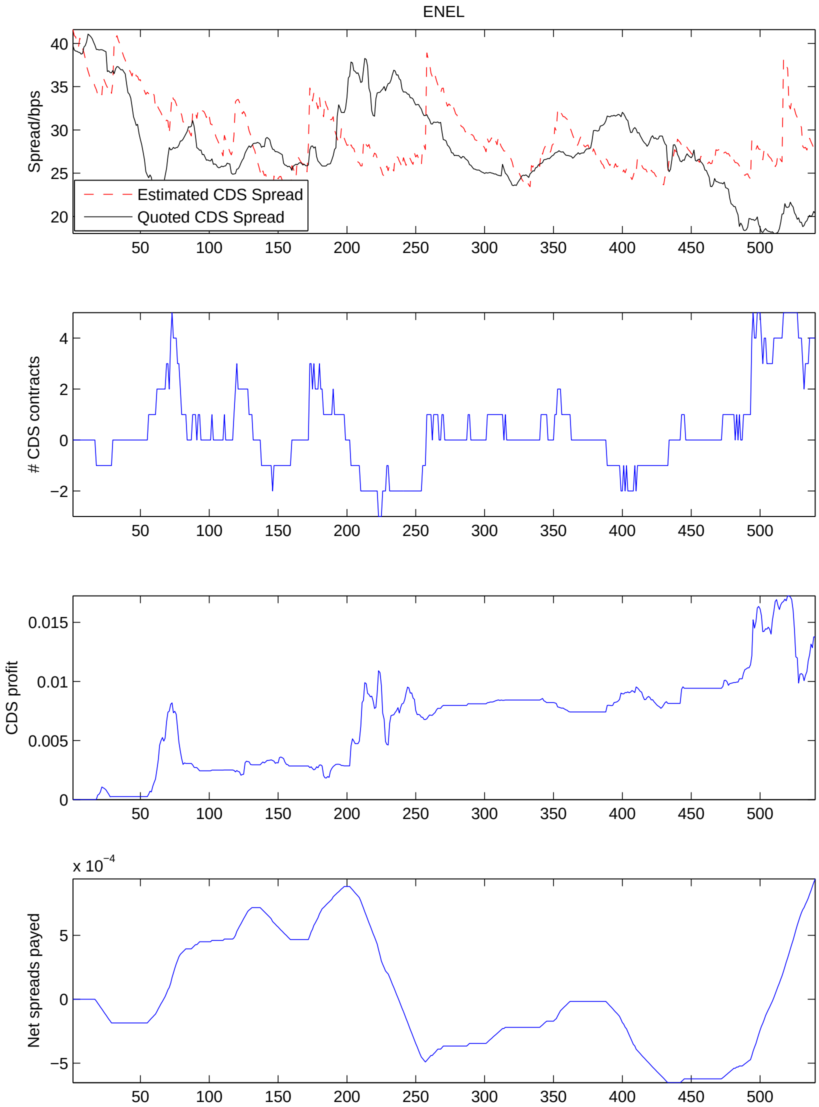

Figure 4.18: Trading result for ENEL. Notional amount of each CDS contract is 1 euro. In total, 100 trades were made.

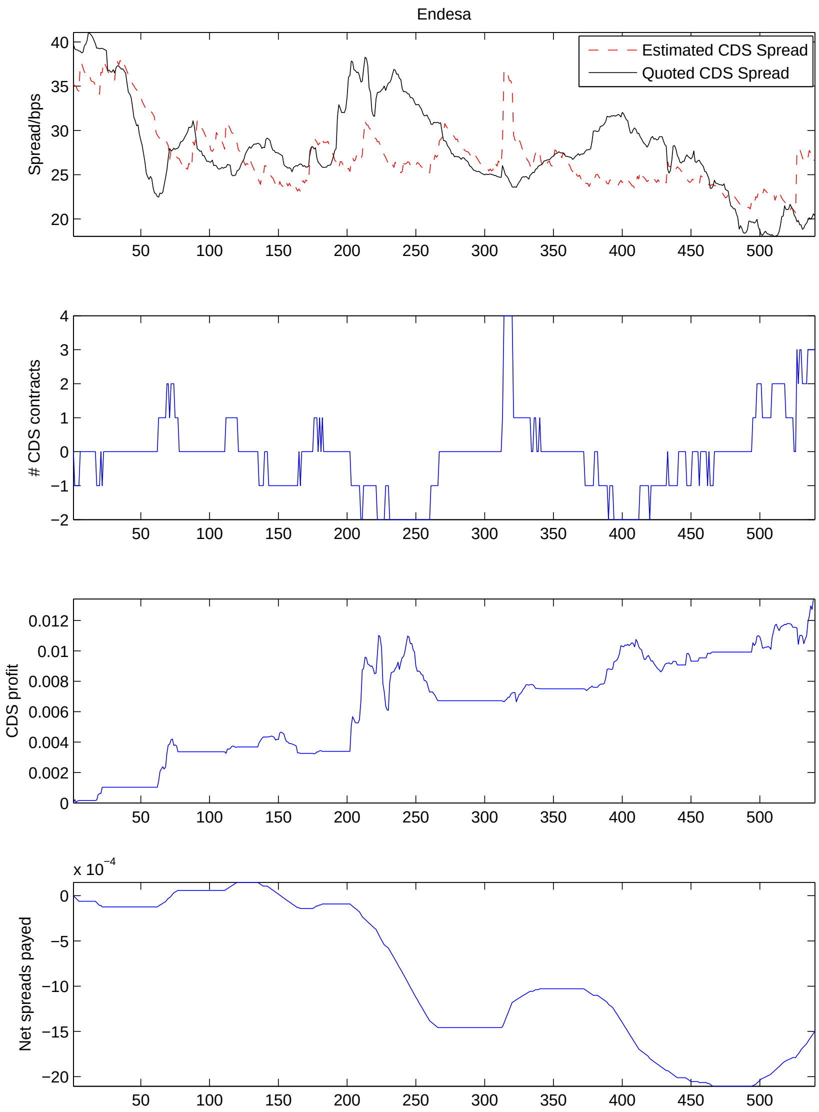

Figure 4.19: Trading result for Endesa. Notional amount of each CDS contract is 1 euro. In total, 73 trades were made.

Chapter 5

Discussion and conclusions

With the introduction of BASEL II we believe that the already huge market for credit derivatives will continue to grow. This gives investors acting on the credit derivative market good opportunities for both acquiring proper protection and also the liquidity for speculative positions. Credit Default Swaps is today the most popular credit derivative in the market but there is still no generally accepted pricing model (though models like CreditGrades, Moody's etc. are very popular).

Overall, the presented model in this thesis does a compentent job in predicting CDS spreads. An investor should of course not only depend on a model when speculating (or getting a fair-priced protection) like this but it could be useful as an input together with other company-specific variables.

Positive results can be found by using a simple trading strategy, resulting in a profit in 8 out of 9 companies. Our trading model is perhaps a bit too simple, but it is used as an indicator of possible gains and losses. When looking at the predicted spread (Figure 4.10) the model sometimes looks relative uncertain. While comparing with the historical volatilities (Figure 4.3), we see that this parameter is extremely sensitive when predicting CDS spreads. This does not come as an surprise and further investigation of the properties of CDS modelling should include some type of stochastic volatility model. However, the approach we have taken still account for the volatility to some extent. The EWMA used is a special case of a GARCH(1,1) process (General Autoregressive Conditional Heteroscedastic) which could further be investigated with parameter optimisation. Another feature of a more developed model should include jumps. Even though Atlan and Leblanc

(2005) conclude that empirically there is not any clear jumps in modelling companies defaults it could enhance the modelling results.

In terms of data quality one can also question results. Our available data is based on daily close price. However, the last trade for the CDS contract and the equity might be seperated with several hours, making it time-lagged and thus our correlation analysis might not be correct. However, we do not take this in to consideration, but merely mention it.

The result of our trading is purely theoretic, we have not yet faced the real credit market and thus we are unsure if our trading is actually plausible in a real situation. Since we in our models constantly price “new” five-year CDS contracts they might not agree when you e.g. want to sell an existing CDS contract with less time to maturity.

The notional amount of outstanding Credit Default Swap contracts on the market is huge. The growth have been explosive in the last couple of years. Since the popularity of CDS are relative new it has not yet seen a greater depression. Questions arise what would happen if companies started defaulting. There are some correlation between company defaults and a possible chain reaction could start, leading to CDS contracts triggering and thus enormous payouts for investors that are short in the contracts. One hopes that the regulation is strict enough, ensuring that the short part is able to pay in case of default. However, one scenario might be that the market have grown too fast, leaving contracts which payment cannot be secured (in case of multiple defaults). We believe that the credit derivative market in whole will continue to grow at a fast pace.

Bibliography

Adelson, M. (2004). Credit default swap (cds) primer. Technical report, Nomura Securities International, Inc.

Atlan, M. and Leblanc, B. (2005). Hybrid equity-credit modelling. *Risk*, August.

Barrett, R. and Ewan, J. (2006). Bba credit derivatives report 2006. Technical report, BBA.

BCBS (2006). Basel committee on banking supervision. www.bis.org/bcbs/history.pdf www.bis.org/bcbs/history.htm www.bis.org/bcbs/scp3ov.pdf.

Bengtsson, G. and Bjurhult, C. (2006). Equity-based modelling of credit default swaps. Master's thesis, Centre for Mathematical Sciences, Lund University.

Berndt, O. and de Melo, B. (2003). Capital structure arbitrage strategies: Models, practice and empirical evidence. Master's thesis, School of HEC at University of Lausanne.

BIS (2006). Bank of international settlements. www.bis.org/about/history.htm www.bis.org/about/index.htm www.bis.org/stability.htm.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81:637–659.

Cox, J. (1975). Notes on option pricing i: constant elasticity of variance diffusions. Technical report, Stanford University, Graduate School of Business.

Currie, A. and Morris, J. (2002). And now for capital structure arbitrage. *Euromoney*, December:38–43.

Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of finance*, 2:449–470.

Rasmus, S. (2006). *Derivative pricing.* Centre for Mathematical Sciences, Lund University.

Wikipedia (2006). Basel ii — wikipedia, the free encyclopedia. http://en.wikipedia.org/wiki/Basel_II http://en.wikipedia.org/wiki/Credit_Risk.

WOCCU (2003). World council of credit unions, inc. basel capital accord ii. http://www.woccu.org/pubs/docs/introducing_basel.doc.

Yu, F. (2006). How profitable is capital structure arbitrage? *Financial Analyst Journal.*