Examining the Determinants of Credit Default Swap Spreads
A Study of European Financial Institutions

Elisabeth Karlson & Nathalie Willebrand
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Abstract

This study examines the determinants of European financial institutions’ Credit Default Swap (CDS) spreads. The purpose is to test how well theoretical determinants are able to explain CDS spreads and whether there exist other significant determinants. The theoretical determinants, suggested by Merton’s model, encompass of the leverage, volatility and risk-free rate. We collect weekly CDS spreads for 30 financial institutions, as well as firm-specific and market-wide variables, from December 2005 to November 2008. We use linear panel data regressions to find the chief determinants of the CDS spreads. Results show that the theoretical determinants are highly statistically significant and that their relationship to the CDS spreads are for the most part consistent with theory. However, the explanatory power of the theoretical variables for changes in the CDS spreads is only 11%. In our robustness analysis we manage to considerably improve the explanatory factor to 39% by using additional determinants. For further robustness, we run regressions on a tranquil market period and a financially distressed time-period. We conclude that theoretical determinants have rather limited explanatory power, and that additional determinants contain important information about the CDS spreads.

Keywords: Credit Default Swaps, CDS spreads, CDS spread determinants, structural model, Merton (1974) model, banks, European market.
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Acknowledgement

After much work and perseverance, we are proud to present this thesis and wish to thank everyone who helped us. First we want to thank our supervisor Bengt Kjellén, who provided us with guidance throughout the process. Deep appreciation is also extended to Glenn Haya and the library staff at Stockholm’s University for enabling us to use DataStream. Without their help the empirical part of the thesis could not have been completed. Finally, we warmly thank our families and friends for their support.

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Stockholm, January, 2009
1 Introduction

On Monday the 15\textsuperscript{th} of September 2008 the world could not close their eyes to the credit crunch any longer. The crisis reached an entirely new climax when giant investment bank, Lehman Brothers, filed in for the largest bankruptcy throughout American history. Dark Monday also witnessed a second powerful bank – Merrill Lynch – flee into the arms of Bank of America. As the fates of Lehman and Merrill were determined, worrying speculations arose as to who would be next to collapse in Wall Street. Perhaps it would be the world’s largest investor, AIG, who faced a liquidity crisis (Morgenson, 2008) or maybe America’s largest savings and loan bank, Washington Mutual, whose stock value had plunged 30\% (Dash et al., 2008). Concurrently the financial crisis hit Europe. As a chain reaction to the events in Wall Street, the Russian stock market collapses (Nicholson et al., 2008), the Nordic countries agree on lending $2.5 billion to Iceland who has been suffering from crippling bank failures (CNN Money), and banks become fearful of lending money even to each other. On Tuesday the 16\textsuperscript{th} of September 2008, the prices of insuring against a firm’s probability of default – so called Credit Default Swap (henceforth CDS) spreads – increased tremendously. To buy an insurance against default of Handelsbanken cost 86 bps, whereas Swedbank’s CDS spread increased from 130 bps to 174 bps. The same day, the UBS CDS spread reached 264 bps, while Goldman Sachs and Morgan Stanley’s CDS spread scored 443 bps and 728 bps respectively. On the other hand, the financial institutions hit by the crisis, Washington Mutual and AIG, recorded a CDS spread of 3886 bps and 3500 bps respectively (Joons, 2008).

1.1 Background

The stunning events mark the latest episode in the credit crisis, which has not only brought the collapse of once-proud financial institutions, but has also affected the broader economy into recession. Gradual development of the financial crisis is related to the latest advances in financial instruments called credit derivatives, and their management of credit risks.

Credit risk is one of the most important risks that financial institutions deal with. Credit risk can be defined as the probability of a financial loss if borrowers and counterparties default on repaying their debt. Traditionally, banks have been in the business of making loans and taking on the credit risk that a borrower may default. So in the last decades, banks have increasingly demanded for means of trading credit risks similar to the way they trade other market risks. This led to the emergence of the financial instruments called credit derivatives, which enable banks and other creditors to pass on loans and their credit risks to investors (Hull, 2006).

Ever since credit derivatives were first introduced into the market, in the mid 1990s, the notional amount outstanding of credit derivatives reached a value of $54.6 trillion by mid-2008 (Marshall et al., 2008). The most common type of credit derivative is the CDS. In fact, over two-thirds of all traded credit derivatives are CDS (Meissner, 2005a, p.6). These CDS contracts provide insurance against the risk of default by a particular company (Hull, 2006, p.507).
The CDS contract buyer pays for the insurance by paying periodic payments to the CDS seller. These periodic payments are called CDS spreads and are measured in basis points (bps). Therefore, CDS spreads can be interpreted as the market price and measurement of credit risk.

Traditionally, the credit risk has been measured by the credit spread. Credit spread is defined as follows:

\[
\text{Credit spread} = \text{Bond yield} - \text{Risk-free rate}
\]

Put in another way, the credit spread measures the risk of investing in the bond yield rather than the risk-free rate. Moreover, studies by Hull et al. (2004) show that the credit spread is equivalent to the CDS spread. The relationship between credit spreads and CDS spreads must hold under a no-arbitrage argument, otherwise an investor can make a risk-free profit. Blanco et al. (2005) test this theoretical equivalence and find that the parity holds as a long-run equilibrium condition.

Previous empirical studies have used either CDS spreads or bond credit spreads to measure the credit risk. Collin-Dufresne, Goldstein & Martin (2001) (henceforth CGM) investigate the credit risk by using bonds credit spreads. Ericsson, Jacobs and Oviedo (2004) (henceforth EJO), use CDS spreads in their investigations of the credit risk.

There are several advantages of using CDS spreads rather than bond credit spreads when measuring the credit risk. One advantage of using CDS spreads is that the CDS market responds more quickly and accurately to changes in the credit risk than bond credit spreads. Another advantage is that CDS spreads do not require the problematic choice of an appropriate benchmark risk-free rate, as opposed to bond credit spreads. As Hull et al. (2004) puts it, CDS spreads are already credit spreads. The third advantage of using CDS spreads is that the CDS spreads reflect more directly the pricing of credit risk. Hull et al. (2004) highlights that CDS spreads consist of bid and offer quotes from dealers. In contrast, bond data are simply indications from dealers who are not committed to trade at the specified indication. Finally, bond credit spreads have been found to reflect not only the credit risk, but also the bond’s illiquidity (Longstaff et al., 2004). Therefore, since the CDS market tends to be more liquid than the bond market, the CDS spreads are viewed as a better indicator of credit risk.

Recent advances in credit derivatives market have also launched indices to track CDS spreads. Relatively new indices of CDS spreads include the iTraxx Europe indices. However, in contrast to CDS spreads, the iTraxx indices insure the creditor against the default of a whole basket of bond issuers. Therefore, the data on iTraxx spreads is an alternative measure of credit risk. An empirical study that uses the iTraxx data is Byström’s (2005) investigation.

### 1.2 Problem discussion

In view of the current credit crisis, we learn that some large banks have defaulted and other banks face difficulties staying afloat. Bearing this in mind, it is particularly interesting and relevant to investigate the factors that affect credit risk of financial institutions. More specifically, because CDS spreads are better indicators of credit risk – as opposed to bond credit spreads – it is especially relevant to investigate the determinants of CDS spreads. In this case, CDS spreads are also preferred to CDS indices because they designate the credit risk of the individual firm, instead of a group of firms.
As we stated before, the CDS spreads of large banks have been rising. For this reason, it is also important to identify the determinants of CDS spreads. And considering that the CDS market is growing at an increasing rate, accentuates the importance of investigating the CDS spreads. Due to this significance, and since CDS spreads act as indicator of the credit risk, we will first look into the theories and models on credit risk and credit derivatives.

In the literature there are three main approaches for pricing credit derivatives: the traditional models, structural models and reduced-form models. Traditional models price credit risk based on historical data. More specifically, a risky bond price is derived by observing default rates of past losses and downgrades of bonds with comparable credit rating and seniority. However, traditional models are problematic because actual default and recovery rates depend on the business climate, and not on historical data (Meissner, 2005a). Hence, we choose not to use traditional models in our study.

Structural models derive the probability of default by analyzing the firm’s capital structure. The value of the company’s assets is compared to the value of the firm’s debt. In 1974, Robert Merton laid the groundwork for structural models. The Merton model is mathematically identical to the original Black-Scholes model, but with redefined variables (Ibid, 2005a). The difference between the reduced-form models and the structural models is that reduced-form models remain silent on the theoretical determinants of the prices of defaultable securities. In contrast, structural models imply that the theoretical determinants of credit risk are: leverage, volatility and the risk-free interest rate. These theoretical determinants are originally derived from Merton’s model.

Empirical investigations that have studied the theoretical determinants of credit spreads include the studies by CGM and EJO. CGM use the theoretical determinants in order to investigate the changes in bond credit spreads. Their results show that theoretical determinants have a rather limited explanatory power for changes in bond credit spreads. In contrast, EJO uses the theoretical determinants in order to investigate the levels and changes in CDS spreads. They find that theoretical determinants explain a significant amount of the levels and changes in CDS spreads. In our thesis, we will follow these studies in order to examine the CDS spreads of financial institutions.

Both studies by EJO and CGM employ U.S. datasets. Few empirical studies investigate the theoretical determinants for European datasets. Exceptions include studies by Boss and Scheicher (2002) (henceforth BS), Dülmann and Sosinska (2007) (henceforth DS), Byström (2005, 2006) and Carol et al. (2007). BS study bond credits spreads on the euro area and obtain similar results to CGM's study on the U.S. bond market. DS analyze the CDS spreads of three German banks. While Byström and Carol et al. study the iTraxx indices. In particular, Carol et al. suggest that CDS spreads follow a regime dependent behavior, in which different variables matter during different market circumstances.

In view of the fact that previous empirical investigations have come to different conclusions on the determinants of credit spreads, it is essential to perform further tests. As Carol et al. argues, it might be that crucial determinants vary depending on if the market is tranquil or undergoing a financial crisis. Moreover, during a credit crisis perhaps one bank’s failure might affect another bank’s existence, even though in theory it should not. Furthermore, as we have witnessed once high rating financial institutions falter, perhaps credit ratings do not affect the default probability of a bank. In addition, perhaps there are other important determinants, apart from the
theoretical determinants, that affect the credit risk of a bank. Portraying this discussion of the predicament of conflicting empirical results on the determinants of credit risk, we see that further empirical studies are needed.

1.3 Specification and research question

As we discussed in the previous section, further empirical studies are needed to test the determinants of the credit risk. In our thesis we decided to study the determinants of CDS spreads of European financial institutions.

We decided to use CDS spreads, instead of bond credit spreads, because of their advantages, described in 1.3 Background, for measuring credit risk. We also preferred CDS spreads over CDS indices because we are interested in the firm-specific credit risk rather than a group measurement. In addition, we decided to study the CDS spreads of European firms because few studies have concentrated on the European market. Exceptions include investigations by BS, DS, Byström and Carol et al.

Furthermore, we decided to study the CDS spreads of financial institutions because this sector has not received much attention in previous studies. Although, studies by BS and Carol et al. have included banks with other non-financial firms in their dataset, they do not exclusively focus on financial firms. To our knowledge, the only study which focuses narrowly on financial institutions is the study by DS. And even in their study, they only include 3 German banks. To our knowledge, a study including financial institutions of other European countries is missing. Therefore, in our thesis we will study exclusively the European financial institutions. That is, we will study their CDS spreads. Put in another way, we study their probability of default, the credit risk. Throughout the essay we use words like ‘bank’, ‘financial institution’ and ‘firm’ to refer to our sample.

From the discussion and specification of our sample data, we can formulate the following research question for our thesis:

- How well do the theoretical determinants explain the CDS spreads of European financial institutions?

1.4 Purpose of the study

The purpose of our study is to test how well the theoretical determinants can explain the CDS spreads of European financial institutions. In addition, we also include a number of additional determinants in our robustness analysis in order to see if there are other important determinants. Although our study is intimately related to the studies by EJO and CGM, we will concentrate on the European market and the financial sector. To our knowledge, no previous study has specifically studied the determinants of CDS spreads of European financial institutions. Therefore, our thesis enriches the academic field in determinants of CDS spreads by focusing on the European financial institutions.
1.5 Structure of the chapters

The thesis proceeds as follows. Chapter 2 deals with methodology from a theoretical scientific aspect and the research method. In chapter 3 the basics of CDS and CDS spreads are presented with an example. The next chapter presents our theoretical framework and the theoretical determinants of credit spreads suggested by Merton’s model. In chapter 5 we describe the data we have collected. Results from regressions using the theoretical determinants are presented and discussed in chapter 6. Additional regressions are presented in our robustness analysis in chapter 7. In the last chapter, we conclude our thesis. As a final point, in case of coming across an unfamiliar term, we advise the reader to use the Glossary of Terms found at the end of the thesis, before the Appendix.
2 Methodology

This chapter begins by explaining our scientific viewpoint. Then we continue with our choice of research approach and method that is applied for our study of the determinants of CDS spreads determinants. Furthermore, we will reveal the sources used for collecting the theoretical information, as well as the sources used for collecting the data. Some words will be said about the criteria, evaluating the strength of our research's result. Lastly, we will critically examine the research's methodology and mention its limitations.

2.1 Scientific viewpoint

Before starting our research of the determinants of CDS spreads, we had to determine our scientific viewpoint. Since the purpose of our study is to examine the determinants of CDS spreads, we believe that the positivistic perspective provides better possibilities for this goal. This scientific discipline renders possibilities for simplifying reality with the intention of making things comprehensible and producing generalizations (Bryman, 2002, p. 93). Furthermore, the positivistic researcher presents facts free from subjectivity. This objectivity is valuable for our study because our intention is not to affect the results with diverse interpretations. Furthermore, as the positivistic researcher critically examines all results, we will also critically examine the results by checking their explanatory power in the regression results. Further critical examinations of our results are done in our robustness analysis as we check for other important determinants. This gives our results greater reliability and validity. Additionally, the positivistic viewpoint enables the study of a cause-effect phenomenon (Ibid, 25). In relation to our study, the dependent variable (CDS spread) is affected by explanatory variables (the determinants).

On the contrary, the hermeneutic viewpoint mainly focuses on interpretation, understanding and subjectivity. This discipline states that there is not only one single truth as positivists assert, but rather there are paradoxes (Ibid, p.24-25). However, this perspective is not very suitable for our research since we believe in objectivity when investigating statistics. In our study, we find such statistics for the CDS spreads, and their explanatory variables. A hermeneutic subjectivity would influence parts of the studied subject and not provide objectively strong results that could be tested. Therefore, the positivistic school is preferable and more appropriate than the hermeneutic standpoint.

2.2 Research approach

The differences between the quantitative and qualitative strategies are the scientific viewpoint and ontological direction. The scientific viewpoint for the quantitative method is more in line with positivism, while the appropriate viewpoint for the qualitative method is hermeneutics. The ontological direction describes how we should understand the social reality: objective existence or constructed existence (Ibid, 15). The qualitative approach corresponds to the social
construction view, and the quantitative approach corresponds to the objective existence view. For our study, the objective existence view is more appropriate because market circumstances and the economy exists out of the control of individuals.

Since the positivistic viewpoint and the objective reality view is suitable for our study, thus the quantitative method is used in our research. Furthermore, since we will examine quantitative data, the quantitative method provides better possibilities for explaining the factors affecting the CDS spreads. Besides quantifying, measuring and generalizing the impact of the determinants on the CDS spreads, the quantitative method also enables possibilities for comparative results, through replicating the method (Bryman, p.43). In contrast, the qualitative method lacks this replicating ability, as well as the measurement capacity.

Nevertheless, we do not discard the qualitative approach completely since it could be used for future studies of the determinants of CDS spreads. In fact, a study with a qualitative approach can complement our study. We are aware that financial instruments are not only affected by explanatory variables described in formulas, but are also driven through individuals working in the financial markets. The human participance behind the traded CDS contracts can play an important role in default transactions. However, the reason for not choosing the qualitative approach is because it fails to provide strong results which can be compared with other studies. And in our study we deem the effects on the CDS spreads to be independent of and outside the control of social actors. We believe this is closer to reality because of the collapse of powerful financial institutions, in which no single actor had the capacity to salvage the failing institutions.

Another reason for preferring the quantitative approach is because in our study we employ a deductive method. This implies that we focus on the ground theory and test the hypothesis of the theory (Ibid, p.22). Correspondingly, in our study we will test the theoretical determinants that are suggested by Merton’s model. The inductive method is not appropriate for our study because our aim is not generate a new theory (Ibid, p.22).

2.3 Research method

For the theoretical framework of this study, we chose to use the determinants of credit risk as identified by the Merton model. The motivation for using Merton’s model is because previous empirical studies have found the structural approach to be successful when explaining credit spreads. Furthermore, other variables that have been found to be significant in previous empirical studies will be included in our robustness test. Most of the literature on the determinants of credit spreads, the Merton model etc., were collected from different databases, such as Academic Source Premier and Business Source Premier.

More specifically, we collected data for 30 European financial institutions consisting of weekly observations sampled on Wednesdays, during the time period between the 7th of December 2005 and the 26th of November 2008. The reason for using weekly observations was in order to reduce noise, seeing as for some financial institutions the available CDS data was not liquid enough to be used on a daily basis.

All our data was obtained from the database called DataStream, and in Appendix 1 we have presented the 30 European financial institutions included in the final sample. Furthermore, the time period we study is interesting because it marks a change in the economy from a boom to a recession.
Similar to CGM and EJO we carry out regression analysis on the relationship between CDS spreads and the different determinants. The main determinants, which constitute of the explanatory variables in the regressions, consist of firm-specific and market-wide factors. We use OLS regressions as our research design. Given that our data contains both a time-series and cross-sectional dimension, we are able to perform panel data regressions. Another reason for using panel data regressions is because previous studies on the determinants of credit spreads, such as Campbell & Taksler and EJO, have employed this method. Our panel data methodology is further presented under section 5.2 Regressions. In the “Data and Regressions” chapter we will describe in details how we collected the data for the CDS spreads and explanatory variables.

2.4 Reliability, replication and validity

The criteria used to evaluate our study are reliability, replication and validity. The reliability of this study is high because we test for the stationarity of the dependent variable, as well as testing the CDS spread at two different time periods in our robustness analysis. That is, we examine how the CDS spread acts in a bust and in a boom respectively, in order to know how the CDS spread varies at different economical states.

Furthermore, by carrying out a robustness test with additional variables, we can check which variables are significant for the CDS spread. Our study can also be easily replicated, because the research procedure is well documented, with a list of the financial institutions (see Appendix 1), and the data collected from DataStream is accessible for the public, and also since we specify the studied time period. The validity of our study is also high since the method and the proxies for the dependent and explanatory variables have been used in previous empirical studies by well-known academics. Therefore, the proxies we use in our regressions accurately measure the different variables. The internal validity was also high because by performing a regression test, we investigate if the explanatory variables really do affect the CDS spreads (Bryman, p.43-45).

2.5 Critical review

Since we chose the quantitative approach our study shows statistical results. We are well aware of the fact that there could be other aspects than the theoretical determinants that can affect the CDS spreads. Therefore, we use additional variables in our robustness analysis to check if there are other important factors that can affect the CDS spread. However, as we mentioned before, it could be interesting to redo our study using a qualitative approach. Such a study could ultimately provide important contributions for explaining the CDS spreads. Another critique of our methodology is that there might be systematic factors and errors that can affect our results. Finally, we are aware that there may exist a human erroneous factor.
3 CDS and CDS spreads

In this chapter we will present the main mechanism of CDS and CDS spreads, short and technically. This is so that the reader can follow the theoretical framework.

CDS is a contract that provides insurance against the risk of default by a particular company. This is achieved through the transfer of the credit risk from one party to the other party. The buyer of the CDS will be compensated if a credit event such as a default occurs. During the term of the CDS, the CDS buyer is committed to pay a predetermined periodic payment to the CDS seller. If a specific company defaults a credit event occurs, and the CDS buyer has the right to sell the bonds for their face value. The CDS seller then agrees to buy the bonds for their face value (Hull, 2006). Put it in another way, the CDS buyer “walks away” from its debt obligations by lending back the bonds to the CDS seller (Sundaresan, 2002). But throughout the life of the CDS, or until a credit event occurs, the CDS buyer has to make the periodic payments to the CDS seller. These payments are what we call the CDS spreads, which are typically made every quarter, half year, or year. Additionally, in the event of default there are two different settlements – physical settlement and cash settlement, i.e. physical delivery of the bonds and a cash payment (Hull, 2006).

The main application of CDS is hedging against default of a bond issuer (Meissner, 2005a). To understand the mechanisms of the CDS contract, and to illustrate how a typical deal is structured, we provide an example:

Example 1

Suppose that two parties enter into a 5-year CDS on March 1, 2008. We assume that the notional principal amount is €100 million and the CDS buyer, UBS AG, agrees to pay 90 bps (= 0.9%) annually for protection against default by the bond issuer, Nordea. This is shown in Figure 1.
CDS spread: 90 bps per year

**Figure 1** Hedging with CDS

If Nordea does not default there is no credit event and UBS AG receives no payoff and pays €900 000 (0.009 * 100 000 000 = 900 000) on March 1 of each of the years 2009, 2010, 2011, 2012 and 2013. Conversely, if Nordea defaults a substantial payoff is likely. Assume that UBS AG informs the CDS seller AXA of a credit event on June 1, 2011 (a quarter of the way into the fourth year). If the contract specifies the physical settlement, UBS AG has the right to sell Nordea bonds with a face value of €100 M for €100 M. If the contract instead requires cash settlement, an independent calculation agent will poll dealers to determine the mid-market value of the cheapest deliverable bond a predesignated number of days after the credit event (Hull, 2006). Suppose this bond is worth €30 per €100 of face value, the cash payoff would then be €70 M ([(100-30)/100] * 100 000 000 = 70 000000). Naturally, the regular payments from the CDS buyer to the CDS seller stop when there is a credit event. Since the payments are made in arrears, a final accrual payment by the buyer is usually required. In our example, UBS AG would be required to pay AXA the amount of the annual payment accrued between March 1, 2011, and June 1 2011 which is approximately €225 000 (3/12 * 900 000 = 225 000) but no further payments would be required.

To summarize Figure 1, the investor UBS AG is hedging against default of the bond issuer, Nordea. In case of default and physical settlement, UBS AG takes the bond and hands it to AXA, who will pay €100 M. If it on the other hand is a cash settlement, UBS AG can sell the Nordea bonds at the final price in the market and receive €100 M – final price from AXA.
Furthermore, the CDS spread is the total amount of payments per year to buy a protection as a percent of the notional principal. Several large banks are market makers in the CDS market and when quoting on i.e. a new 5-year CDS on Nordea, a market maker might bid 200 bps and offer 210 bps. This means that the market maker is prepared to buy protection on Nordea by paying 200 bps per year (i.e. 2.0 % of the principal per year) and to sell protection on Nordea for 210 bps per year (i.e. 2.1% of the principal per year) (Hull, 2006).
4 Theoretical Framework

In this section we will present the structural approach of pricing credit derivatives and the theoretical determinants of CDS spreads as explained by the Merton model. Furthermore, we will show the connection between the Merton model and the Black-Scholes option theory. Subsequently, we will present additional determinants of CDS spreads that have been identified by previous empirical studies.

4.1 Structural approach

In 1974 Robert Merton laid the groundwork for structural models. The Merton model is mathematically identical to the original Black-Scholes model, but with redefined variables. The Black-Scholes-Merton model underlies all structural models. Structural models are comprised of firm value models and first-time passage models. They derive the probability of default by analyzing the firm’s capital structure. The value of the company’s assets is compared to the value of the firm’s debt. Furthermore, in firm value models bankruptcy occurs when the asset value of the bank is below the debt value at the debt’s maturity $T$. In first-time passage models, bankruptcy arises when the asset value drops below a pre-defined, usually exogenous barrier, which allows for bankruptcy before the maturity of the debt. Furthermore, in the empirical studies the structural approach has been more successful in explaining the determinants of credit risk as opposed to other approaches. The Merton model, which underlies all structural models, identifies three theoretical determinants: leverage, volatility and the risk-free rate. Although extensions of the Merton model have been developed, these extension models do not add any more variables to the theoretical determinants that can affect the credit risk. Since extensions of the Merton model do not provide information on further determinants, we chose to use Merton’s model with the theoretical determinants as our ground theory for our study.

4.2 Merton model

The Merton model describes the pricing of options – a model that can be applied on pricing of CDS, where the loan is the option on the company’s value. The Merton model concentrates on a firm’s equity-debt-ratio and its probability of default. Through estimating a firm’s value of debt and the firm’s default probability, a company’s value is modeled. Moreover, the valuation of credit default could be expressed as a put option on a firm’s asset (Meissner, 2005a). If an event of default occurs the equity holders of a leveraged firm have an option to “walk away” from their obligations by delivering the assets to the debt holders (Sundaresan, 2002). In order to hedge the credit risk the equity holders buy a CDS contract to protect their call option. Explicitly, this means that you buy a put option on the assets from the CDS seller. The pricing of credit derivatives the Merton model combines the Black-Scholes pricing option framework. According to Meissner (2005a), the framework could be described through this equation:

\[ V = E + D \]
where

\[ V \] – firm’s asset value, could be interpreted as the sum of the firm’s
debt

\[ D \] – debt

\[ E \] – the shareholder’s equity

More specifically, an event of default occurs when the bank’s asset value falls below the value
of the debt, and consequently fails to repay its obligations to the other party (Sundaresan, 2002).
In this case, the debt is larger than the asset value, \( D > V \), and hence the equity holders will
deliver the assets to asset holders. The calculated loss for the asset holders is:

\[ D - V \]

More technically, the valuation of credit risk and the probability of a firm going default can be
expressed as a put option on a firm’s asset. To hedge the credit risk, the equity holders should
therefore buy a CDS contract, which explicitly means that they buy a put option on the assets
from the seller of the asset holder. The price of a put option is expressed as following:

\[
P_0 = -V_0 N(-d_1) + D e^{-rT} N(-d_2)
\]

where

\[
d_1 = \frac{\ln \left( \frac{V_0}{D e^{-rT}} \right) + \left( \frac{1}{2} \sigma_v^2 T \right)}{\sigma_v \sqrt{T}}
\]

and

\[
d_2 = d_1 - \sigma_v^2 \sqrt{T}
\]

where

\( P_0 \) – the current value of the put option on the firm’s assets value, \( V_0 \)

\( V_0 \) – the firm’s assets value

\( D \) – the face value of debt to be repaid at time \( T \)

\( T \) – the option’s maturity measured in years

\( r \) – the risk-free continuously compounded interest rate

\( \sigma_v \) – the expected volatility of the asset

\( N \) – the cumulative standard normal distribution.

\( N(-d_2) \) – the probability of exercising the put option
Naturally, the equity holders therefore exercise the put when debt is larger than the asset value, which is the case of default and so is the probability of exercising the put option $N(-d_2)$.

The debt holder’s payoff at maturity, $T$, is then:

$$\min[D, V_T] = D - \max[0, D - V_T]$$

where

$V_T$ – the asset value at maturity, $T$

$T$ – debt’s maturity

$D$ – the face value of debt

Furthermore, the equity value can be explained as a call option’s value:

$$E_0 = V_0 N(d_1) - D e^{-rT} N(d_2)$$

where

$$d_1 = \frac{\ln \left( \frac{V_0}{Fe^{-rT}} \right) + \frac{1}{2} \sigma_v^2 T}{\sigma_v \sqrt{T}}$$

and

$$d_2 = d_1 - \sigma_v^2 \sqrt{T}$$

where

$E_0$ – the current value of the call option on the firm’s assets value, $V_0$

$V_0$ – firm’s assets value

$D$ – the face value of debt to be repaid at time $T$

$T$ – the option’s maturity measured in years

The equity payoff is then seen as a call option on the firm’s assets:

$$\max[0, V_T - D]$$
The probability of default, \( N (-d_2) \), is hence equivalent to the probability of not exercising the call which is the probability of exercising the put option (Meissner, 2005b).

Additionally, the CDS buyer owns the put option, which allows the firm to sell the bank (asset issuer) to the CDS seller in case of default. When the probability of default is low, this put option is often far out-of-the-money. In other words, the CDS buyer has a short position in the credit quality of asset issuer and the CDS seller has a long position. Finally, the main drawback with the Merton model is that the put option and call option prices are derived by values of \( V \) and \( D \) at time \( T \). Therefore, default before option maturity is not feasible (Meissner, 2005a).

### 4.3 Theoretical determinants of CDS spreads

In line with the studies of EJO and CGM, we will use Merton’s theoretical determinants as explanatory variables of the CDS spreads of European financial institutions. In this section we discuss Merton’s theoretical determinants: leverage, risk-free rate, and volatility.

**Leverage**

In Merton’s model, the firm’s leverage ratio is a key variable in determining the credit spread. Leverage is defined as the ratio of the firm’s debt (\( D \)) to the firm value (\( V \)). Merton’s model assumes that default occurs when the firm’s value falls below its debt value. Hence, the higher the leverage (\( D/V \)), the higher the risk of default. With respect to the put option expressed in the previous section, if \( D \) increases relatively more than \( V \), and other variables stay unchanged, then the price of the put option – and the credit spread – will increase. Put in another way, the higher the leverage, the more likely it is that the firm will default and hence the more costly the insurance against default should be (EJO, p.6). The cost of this insurance is thus reflected by a higher CDS spread. Therefore the CDS spread should increase as leverage increases.

Empirical studies confirm the positive relationship between leverage and credit spreads. CGM investigated the determinants of credit spread changes, and found that changes in leverage are statistically significant and are positively related to credit spreads, as is predicted by theory. Furthermore, EJO who investigated the determinants of CDS spreads on U.S. companies also found that leverage is consistent with theory; that is, that CDS spreads are positively related to leverage.

**Historical volatility**

The second theoretical determinant central to the Merton model is the volatility of the firm value (Ibid). The difficulty with this measurement is that a firm’s volatility is unobservable. For that reason proxies of the volatility are done by measuring historical volatility. Historical volatility is based on historical stock data. Substantiated by option theory, the price of an option should increase with the volatility of the underlying. This is because the increasing volatility of the underlying makes it more probable that the put option will be exercised. In relation to equation \( (P_{i=0}) \), the value of the put option therefore increases with volatility. Logically, increased volatility increases the probability of default. And since the probability of default increases, the cost for insuring against default – reflected by the CDS spread – should increase. Therefore the CDS spread should increase as volatility of the firm value increases.
This theoretical prediction between volatility and credit spreads is also supported by previous empirical investigations. Results from CGM show that there is a positive relationship between volatility and bond credit spread changes, as is predicted by theory. Although they find that volatility has a rather limited explanatory power, their results confirm theory and are statistically significant. EJO also obtain results that are consistent with theory; that is, CDS spreads are positively related to the volatility of the firm value. Campbell & Taksler and Cremers et al. also studied the relationship between volatility and bond credit spreads. Their results also confirm the positive relationship between volatility and credit spreads.

**Risk-free rate**

The risk-free rate is the third relevant factor for determining the credit spread. Although Merton’s model includes a risk-free rate, it assumes a constant interest rate. Nevertheless, the model does predict a negative relationship between the risk-free rate and the credit spread. There are two effects of how the risk-free rate affects the credit spread. First, with regard to the put option equation, an increase in the interest rate will decrease the present value of the expected future cash flow, which in turn decreases the probability of default. The decreased probability of default should accordingly decrease the CDS spread. The second way of affecting the credit spread is through Merton’s setup of the firm value. In Merton’s model, the expected growth rate of the firm value is equal to the risk-free rate. Thus, a higher interest rate leads to a higher expected growth rate of the firm value. A higher expected firm value will decrease the probability of default and the credit spread. Therefore, the CDS spread should decrease as the risk-free rate increases.

Previous empirical studies have also confirmed the negative relationship between the risk-free rate and credit spreads. Consistent with the empirical findings of Longstaff and Schwartz (1995), CGM also finds that an increase in the risk-free rate lowers the credit spread. Furthermore, results by EJO also conform to theoretical expectations of a negative relationship, and are statistically significant. As a result, they conclude that the risk-free rate is negatively related to the CDS spread.

**4.5 Additional determinants of CDS spreads**

Apart from Merton’s theoretical determinants, additional determinants have been found in previous empirical studies. Here we present these additional determinants. And we investigate these additional determinants in our robustness analysis.

**Equity return**

It is common to examine the relationship between credit spreads and leverage in terms of equity returns, so called firm-specific credit risk. The theoretical reasoning is as follows. Given a certain level of debt, $D$, leverage increases as the equity value decreases; thus, the less the firm is worth, the higher the credit spread should be (BS, 2002, p.187). Therefore, we expect that a higher equity return will decrease the credit spread.
**Implied volatility**

There are different volatility measures influencing the CDS spreads (Benkert, 2004). An alternative measure of volatility is the implied volatility. The implied volatility is based on the current values of stock options (Carol et al, 2007) and might be a better proxy for looking into the future volatility. Since Benkert (2004), found implied volatility to have a closer connection with CDS spreads than historical volatility, we hence expect the explanatory power to be greater. Moreover, the implied volatility is based on the trader’s expectations whilst the historical volatility is based on the past equity returns.

**Slope of the yield**

Although only the risk-free rate appears in Merton’s model the future movement of a risk-free rate could be influenced by the slope of the yield curve. According to Carol et al. (2007), the steeper the yield curve, the higher expected future interest rates are. Therefore we expect a negative relationship between the slope of the yield and the CDS spread.

**Business climate**

Business climate could be seen as a macroeconomic variable. Including this variable, default probability could depend on the stages of the business climate. Both CGM and EJO proxy the business climate of their U.S. datasets with the S&P500, and they predict that an increase in the S&P500 will decrease the credit spread. This is quite logical, since when the economy is booming firms are doing well, but when the economy is in a recessions, the credit risk is higher. Therefore, there is a negative relationship between the business climate and CDS spreads.

**Liquidity measure**

Longstaff et. al. (2005) discovered illiquidity to be characteristic for a bond’s default risk. DS who studied the CDS spreads, uses a common measurement for market liquidity – the bid-ask spread. The bid-ask spread is simply the difference between the bid and ask CDS spread. Evidently, investors demand an additional premium for liquidity risk, since the higher the bid-ask spreads are, the higher the CDS spreads are. This bid-ask spread would provide us with valuable information, in addition to raise the intensity of the explanatory factor.

**Lagged changes**

A lagged change in CDS spreads is an additional variable. This is not theoretically motivated, but according to Byström (2005, 2006) it is econometrically acceptable. Particularly, he found that iTraxx Europe indices show a significant autocorrelation in their spread changes. Therefore, we also capture lagged changes in CDS spreads as an additional explanatory factor. The only difference here is that we do not investigate CDS index spreads, instead we examine firm specific CDS spreads.
4.6 Summary of determinants

To get a clearer picture of how the theoretical determinants and additional determinants affect the CDS spreads, we present their predicted signs in the following tables. Table 1 and 2 show the predicted signs on the coefficients of the regressions described in the following chapters.

<table>
<thead>
<tr>
<th>Theoretical determinant</th>
<th>Predicted sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage</td>
<td>+</td>
</tr>
<tr>
<td>Volatility</td>
<td>+</td>
</tr>
<tr>
<td>Risk-free rate</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 1: Merton’s theoretical determinants and their predicted signs.

<table>
<thead>
<tr>
<th>Additional determinant</th>
<th>Predicted sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity return</td>
<td>-</td>
</tr>
<tr>
<td>Implied volatility</td>
<td>+</td>
</tr>
<tr>
<td>Slope of the yield</td>
<td>-</td>
</tr>
<tr>
<td>Business climate</td>
<td>-</td>
</tr>
<tr>
<td>Bid-ask spread</td>
<td>+</td>
</tr>
<tr>
<td>Lagged CDS spread</td>
<td>+</td>
</tr>
</tbody>
</table>

Table 2: Additional determinants and their predicted signs.
5 Data and Regressions

In this chapter we will present the methods we used to collect and analyze our data. First, we present the means for collecting proxies for Merton’s theoretical determinants as well as for the additional determinants. Subsequently we present the regressions and the method for how we analyzed our data. Lastly, we present the descriptive statistics of the CDS data and its determinants.

5.1 Data

In order to investigate the determinants of CDS spreads in European financial institutions, we collect data on the CDS spreads and their determinants. In this chapter we will explain how we collected all of our data, that is, CDS spreads and theoretical determinants as well as additional determinants. Subsequently, in our Results of Theoretical Determinants and our Robustness Analysis chapter, we will present the results of our regressions using theoretical determinants and additional determinants respectively. We follow the studies of EJO and CGM and use comparable proxies for the explanatory variables so that we obtain valid and accurate measures.

All our data is obtained from DataStream. The sample period consists of 156 weekly observations sampled on Wednesday, during the time period 7th of December 2005 to 26th of November 2008. We chose to use weekly observations since the available CDS data of our sample is not liquid enough to be used on a daily basis. Moreover, we chose to use weekly basis rather than monthly because it provides interesting results, and few studies have concentrated on weekly data – exceptions include DS study of three German banks.

Since we study European financial institutions, we have only included financial companies in our sample. Given that our analysis requires stock price information, only listed financial institutions were included in our sample. Our final sample consists of CDS and firm specific data on 30 European financial institutions. Appendix 1 presents a list of the financial institutions we included in our sample. In order to illustrate the features and development of the CDS spread, we have displayed in the following figure the time series graph for Deutsche Bank’s CDS spread during our sample period.
Figure 2. Deutsche Bank’s CDS spread. Figure shows time series of Deutsche Bank’s CDS spread during January 2006 to 26\textsuperscript{th} of November 2008. The figure illustrates that the first-half time-period, which was a tranquil economic period, revealed low and stable CDS spreads. The second-half time-period of our sample, starting with the sub-prime crisis in the US, depict a time-period with increasing and volatile CDS spreads. This trend represents well the overall development of the CDS spreads included in our sample. (Source: Thomson DataStream)

Our dataset of CDS spreads consist of weekly quotes on 5-year CDS contracts. The 5-year maturity is used because these CDS contracts are the most liquid (Carol et. al.; EJO, p.9). Moreover, in our sample we include only CDS contracts with senior secure priority. We collect data of so called CDS mid-quotes, which are averages of CDS bid and ask quotes. Henceforth, we denote the CDS spread of firm $i$ at time $t$ as $cds_{i,t}$.

5.1.1 Data for the theoretical determinants

Leverage

For each financial institution we calculate weekly leverage ratios by using book value of total liabilities and market value of equity. We follow CGM and define the leverage ratio ($lev_{i,t}$) as:

\[
\text{Leverage} = \frac{\text{Book Value of Total Liabilities}}{\text{Market Value of Equity} + \text{Book Value of Total Liabilities}}
\]
For most of our sample, the book value of total liabilities is available at the quarterly level. However, for some financial institutions in our sample, book value of total liabilities is only available semi-annually. In order to obtain weekly figures of total liabilities, we linearly interpolate and extrapolate the book value of total liabilities for each financial institution. In addition, we note that in DataStream, market value of equity is defined as the share price multiplied by the number of ordinary shares in issue.

**Historical Volatility**

We follow EJO and use historical volatility as a proxy for the volatility described in the Merton model. Each financial institutions’ volatility is estimated using historical data for every week. By using each firm’s equity prices and a running window of 250 days, we obtained time-series data of historical volatility \(( \text{histvol} \_t \)\) from DataStream.

**Risk-free rate**

Since EJO and CGM use a 10-year benchmark government rate as a proxy for the risk-free rate, we chose to follow them and also use a 10-year government bond. In contrast to EJO and CGM, we focus on the European market and accordingly we had to find an appropriate benchmark government rate of a European country. We decided to follow BS study of credit spreads in the euro area, and use the yield of the 10-year German government bond as the proxy for the risk-free rate. Furthermore, Koller et al. (2005) argues that the German government bonds have been found to have a higher liquidity and a lower credit risk than the bonds of other European countries. Therefore, we believed that the 10-year German government bond was a good measure for the risk-free rate \(( r_{10\text{-year}} \)\).

**5.1.2 Data for the additional determinants**

**Equity return**

For our robustness analysis we decided to go in line with CGM, and include the individual firm’s equity return \(( \text{eqret} \_t \)\). This variable is included because of CGM’s high explanatory power. CGM states that several previous studies have often used the firm’s equity return as a proxy for the firm’s health. Although equity market information is already integrated in the leverage ratio, the use of pure equity return enables a more direct test of the equity market information. Furthermore, since the correlation between equity return and the leverage ratio was not highly correlated (see Appendix 5) we found it safe to use both of the variables in our robustness regressions. Due to this weak correlation, we agree with CGM that it is possible that they provide nonredundant information. We obtain data from total return indexes on each firm’s equity. Then we calculate continuous compounded weekly returns (log-returns) from the total return indexes. The use of log-returns is motivated since it is more normally distributed and symmetrical.

**Implied Volatility**

Another measure of volatility we decided to use in our robustness analysis is implied volatility \(( \text{imvol} \_t \)\). Given that several researchers, among CGM and Cremers et al., have highlighted the importance of the implied volatility as a measure of volatility, and because the correlation between the historical volatility and implied volatility proved to be weak (see Appendix 5), we
decided to use both volatilities in our robustness regressions. The low correlation between these volatilities may imply that they measure different things. We collect time-series data of continuous implied volatility for each firm. DataStream calculates this time-series data by displaying the options volatility of the put option which is nearest to the at-the-money strike, one with a strike price above and another with strike price below the underlying price.

**Interest rate variables**

For our robustness analysis we decided to use another maturity of the German government bond to proxy the risk-free rate. We follow CGM and EJO, and use a 2-year government benchmark rate as an alternative proxy for the risk-free rate. In order to avoid multicollinearity, and since the correlation between the 10-year and 2-year yield is quite high (see Appendix 5), we decided to exclude the 10-year yield from the robustness regressions and instead use only the 2-year German government bond ($r_{t^{2-year}}$). Analogous to CGM and EJO’s studies, we also test for nonlinear effects by including the square of the 2-year yield so to account for convexity issues. According to CGM, the structural models predict that nonlinear functions of interest rates should also affect the credit spreads. Therefore, we include the square of the 2-year German government bond ($r_{t^{2-year}}^2$) in our robustness analysis.

**Slope of the yield curve**

Both the studies of CGM and EJO include the slope of the yield curve as a measure of expectations of future short rates. Similarly, we include the slope of the yield curve in our robustness regressions, and equivalent to the studies of CGM and EJO, we define the slope of the yield curve as the difference between the 10-year yield and the 2-year yield. According to CGM, the slope of the yield curve not only conveys an indication of the expectation of future interest rates, but also conveys an indication of the overall economic health. Therefore, we measured the slope of the yield curve as the difference between the 10-year and 2-year German government bond yields ($slope$).

**Business climate**

The studies of CGM and EJO use the S&P 500 returns in their regressions as a proxy for the overall state of the American economy. However, since we focus on the European market, we decided to use continuously compounded weekly returns on the FTSE 100 ($FTSE$) as a proxy for the overall business climate in Europe. As previously stated the motivation for using log-returns is that they are more normally distributed and symmetrical. The FTSE 100 is an equity index that comprises the 100 most highly capitalized companies listed on the London Stock Exchange (www.ftse.com). The motivation for using the FTSE 100 is because it is a regular quoted market index, and because of the UK’s importance for the European economy. Moreover, several of our sample firms come from the UK and therefore the FTSE 100 is an appropriate measure for the overall business climate. The market index FTSE 100 serves also as a proxy for systematic risk. Positive FTSE returns reflect expectations of better economic conditions, and are generally associated with decreasing risk premia demanded by investors. Therefore, we expect a negative relationship between FTSE returns and the CDS spreads.
**Bid-ask spread**

Similar to CGM and DS, we include a proxy for the liquidity risk in the CDS market for our robustness regressions. We follow DS and chose the bid-ask spread ($liq_{aq}$) which has become a commonly used measure of market liquidity. The motivation for this proxy of liquidity risk is that according to Fleming (2003), the bid-ask spread outperforms other proxies when measuring liquidity in the US treasury market. As investors demand an additional premium for liquidity risk, higher bid-ask spreads are associated with higher CDS spreads.

**Lagged CDS spread**

As a final point, we include the lag of the CDS spreads ($cds_{t-1}$) in order to examine if the lagged spreads can predict future movements of the CDS spreads. The study by Byström (2006) found strong autocorrelation in the iTraxx index, and that the lagged indices had a significant positive influence on the future spreads. We therefore find it interesting to include the lag of the CDS spreads in our robustness regressions.

### 5.2 Regressions

In this subsection we present our regressions and discuss the panel method by which the regressions are estimated. Our panel method is closely related to the one used by CGM and EJO. Panel data regressions are suitable for our analysis since our data contains both a cross-sectional and a time-series dimension. Some benefits of panel data is that it permits more degrees of freedom, reduces collinearity among variables, and is able to account for heterogeneity of individual cross-sections. Explaining panel data methodology is beyond the scope of this paper; therefore, for further information on panel data methodology we refer the reader to Baltalgi (2001). The analysis and regressions are estimated using econometrical program EViews 5.0.

In order to perform regression analysis on our data, the dependent variable needs to be stationary. We therefore test the stationarity of our CDS data by performing panel unit root tests on the levels of the CDS. Test results of three widely popular unit root tests show that our CDS data in levels is nonstationary (see Appendix 4). In order to make our time series stationary, we take the first differences of the CDS spreads. The test results of the three unit root tests show that our CDS data in changes is stationary (see Appendix 4). Therefore we will only use first differences of the variables in our further analysis. That is, the dataset includes changes over the past week in CDS spreads and explanatory variables. Hence, our method concurs with the method of CGM who also performs analysis on the first differences of the variables. Moreover, as CGM argues, changes in CDS spreads are determined by the changes in the explanatory variables. Therefore, the predicted signs and relationship between the CDS spreads and the explanatory variables is equivalent to the predicted signs on levels data. It should also be noted that differences in CDS spreads are harder to explain than levels. Thus, regressing on changes should therefore provide a more stringent test of the theory (EJO, 2005). According to EJO, regressions on changes are of most interest from a managerial point of view because they indicate how CDS spreads change for a particular company as the company’s leverage ratio and volatility change.
Similar to EJO, our regression analysis can be divided into two parts. First, we perform panel regressions testing the influence of the theoretical determinants; using only the change in leverage, historical volatility and the risk-free rate. Following EJO, we will first include all three variables, and then examine each variable separately. For the first part we estimate the following regressions.

\[ \Delta \text{cds}_{it} = \alpha_i + \beta_1 \Delta \text{lev}_{it} + \beta_2 \Delta \text{histvol}_{it} + \beta_3 \Delta r_t^{10\text{-year}} + \varepsilon_{it} \] (1)

\[ \Delta \text{cds}_{it} = \alpha_i + \beta_1 \Delta \text{lev}_{it} + \varepsilon_{it} \] (2)

\[ \Delta \text{cds}_{it} = \alpha_i + \beta_2 \Delta \text{histvol}_{it} + \varepsilon_{it} \] (3)

\[ \Delta \text{cds}_{it} = \alpha_i + \beta_3 \Delta r_t^{10\text{-year}} + \varepsilon_{it} \] (4)

For description of the variables see table 3. Moreover, we have denoted the subscript

- \( i \) – the specific firm
- \( t \) – the time-series dimension
- \( \alpha \) – constant to the regressions
- \( \beta \) – the coefficient for each explanatory variable

In the second part, which will be presented in our robustness analysis, similarly to EJO we include the additional determinants in our panel regressions. We include these additional determinants in order to test how well they can explain the CDS changes. We specify our robustness regression by extending our model with the additional determinants; that is, equity return, implied volatility, the square of the risk-free rate, the slope of the yield, the FTSE 100, the bid-ask spread, and the lag of the CDS spread. Including these explanatory variables leads to the following regression:

\[ \Delta \text{cds}_{it} = \alpha_i + \beta_1 \Delta \text{lev}_{it} + \beta_2 \Delta \text{histvol}_{it} + \beta_3 \Delta r_t^{10\text{-year}} + \beta_4 \Delta \text{eqret}_{it} + \beta_5 \Delta \text{implvol}_{it} + \beta_6 \left( \Delta r_t^{2\text{-year}} \right)^2 + \beta_7 \Delta \text{slope}_t + \beta_8 \Delta \text{FTSE}_t + \beta_9 \Delta \text{liq}_{it} + \beta_{10} \Delta \text{cds}_{it-1} + \varepsilon_{it} \] (5)

Note that in regression 5 we have substituted the 10-year yield for the 2-year yield, just like EJO has done in their robustness regressions. Since the 10-year and 2-year yield displayed high
correlations (see Appendix 5), we decided to follow EJO and simply use the 2-year yield in our robustness regressions.

To further investigate the robustness of the regressions, and to get additional information on the variables ability to explain the CDS spreads, we perform an additional regression analysis. In this analysis we split our sample into two equal subsamples by time period. This is particularly appropriate for our CDS data. Since the first-half time-period conveys a tranquil market with low CDS spreads, and the second-half time-period conveys an increasingly financial distressed market with high and volatile CDS spreads. We will present this regression and results in the Robustness Analysis chapter.

In the first part, regressions (1-4), we use only the basic panel regression model, which assumes that there is no unobservable heterogeneity between cross-sections. However, for our robustness regression (5) we decided to use both the basic panel regression and the panel regression with fixed effects over the cross-sections. We use the fixed effects model only on regression (5), which includes all explanatory variables. This would be sufficient in order to make the point about possible heterogeneity between firms. The fixed effects model is used to take into account possible firm-related effects, which may not be included in basic panel regressions. We followed the criterias set by Gujarati (2003) when deciding to control for fixed effects or random effects, and found that the fixed effects is more appropriate for our analysis (see Appendix 6). For more information on random and fixed effects see Baltalgi (2001) and Gujarati (2003).

All regressions are calculated using the White-diagonal method for computing coefficient covariances. This method is more appropriate if the observations in the same cross-section or time-series have different variances, and it is robust to specific heteroskedasticity in the error terms. See Baltalgi (2001) for further explanation.
5.3 Descriptive statistics

This subsection expounds the descriptive statistics of the CDS and its explanatory variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Max.</th>
<th>Min.</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δcds</td>
<td>0.802</td>
<td>208.300</td>
<td>-191.700</td>
<td>14.401</td>
<td>0.684</td>
<td>53.429</td>
<td>4650</td>
</tr>
<tr>
<td>Δlev</td>
<td>0.028</td>
<td>2.225</td>
<td>-8.369</td>
<td>0.310</td>
<td>-4.209</td>
<td>125.510</td>
<td>4650</td>
</tr>
<tr>
<td>Δhistvol</td>
<td>0.373</td>
<td>95.602</td>
<td>-2.635</td>
<td>1.756</td>
<td>35.854</td>
<td>1872.385</td>
<td>4650</td>
</tr>
<tr>
<td>Δr_{10-year, i}</td>
<td>-0.001</td>
<td>0.339</td>
<td>-0.323</td>
<td>0.102</td>
<td>-0.155</td>
<td>4.037</td>
<td>4650</td>
</tr>
<tr>
<td>Δeqret</td>
<td>-0.007</td>
<td>0.400</td>
<td>-1.510</td>
<td>0.069</td>
<td>-3.472</td>
<td>60.927</td>
<td>4650</td>
</tr>
<tr>
<td>Δimpvol</td>
<td>0.566</td>
<td>134.320</td>
<td>-95.690</td>
<td>9.621</td>
<td>1.084</td>
<td>41.843</td>
<td>3802</td>
</tr>
<tr>
<td>Δr_{2-year, i}</td>
<td>-0.003</td>
<td>0.273</td>
<td>-0.464</td>
<td>0.123</td>
<td>-0.867</td>
<td>4.792</td>
<td>4650</td>
</tr>
<tr>
<td>(Δr_{2-year, i})^2</td>
<td>0.015</td>
<td>0.215</td>
<td>1.00E-06</td>
<td>0.030</td>
<td>3.888</td>
<td>22.132</td>
<td>4650</td>
</tr>
<tr>
<td>Δslope</td>
<td>0.002</td>
<td>0.282</td>
<td>-0.250</td>
<td>0.080</td>
<td>0.911</td>
<td>5.811</td>
<td>4650</td>
</tr>
<tr>
<td>ΔFTSE</td>
<td>-0.002</td>
<td>0.121</td>
<td>-0.093</td>
<td>0.032</td>
<td>-0.312</td>
<td>4.810</td>
<td>4650</td>
</tr>
<tr>
<td>Δliq</td>
<td>0.060</td>
<td>50.000</td>
<td>-30.000</td>
<td>2.406</td>
<td>3.101</td>
<td>96.426</td>
<td>4650</td>
</tr>
<tr>
<td>Δcds_{t-1}</td>
<td>0.851</td>
<td>208.300</td>
<td>-191.700</td>
<td>14.416</td>
<td>0.681</td>
<td>53.538</td>
<td>4620</td>
</tr>
</tbody>
</table>

Table 3. Descriptive statistics. The table shows the descriptive statistics for the variables used in the changes regression. The total number of observations for implied volatility is slightly lower than other variables owing to the unavailability of implied volatility for some financial institutions.

Since levels data of the CDS has been found to be nonstationary, we will only discuss the changes data in this section, and simply refer to Appendix 2 for the descriptive statistics of levels data. Pairwise correlations between all variables are also discussed in this section.

In order to give a clear picture of the general development of the CDS spreads and their changes, we have displayed the graphs of the CDS spreads and the changes in the CDS spreads in Appendix 3. From these graphs and by looking at the average change in CDS spreads (Table 3) we see that CDS spreads have increased during the sample period with 0.802 basis points. Moreover, the changes in CDS spreads show a large standard deviation (14.401). We can also discern from Table 3 that the average firm leverage ratio in our sample has increased during this period. Due to worsening conditions in the economy, we see that the FTSE and the firm-specific equity return have decreased throughout the sample period, accompanied with a decrease in the risk-free rate (10-year and 2-year yield). Along with these worsening conditions, the volatilities have increased during the sample period. We can also distinguish an increase in the bid-ask spread, implicating that liquidity in the CDS market has decreased. For time-series graphs of the explanatory variables and their trend throughout the sample period, see Appendix 3.
When examining the distributions of the changes in CDS spreads and the explanatory variables, we find that none of the variables are normally distributed. The distribution on the CDS spreads and on the explanatory variables are found to be leptokurtic, seeing as their kurtosis coefficient is for many variables much larger than 3. Moreover the skewness coefficients for the variables show that most of the variables are not symmetrically distributed. In fact, the Jarque-Bera test, which tests the skewness and kurtosis, rejects the normal distribution for each of the variables. Due to this non-normality of the variables, it is important to keep in mind that it may lead to violation of the assumption of normally distributed residuals in further regression analysis.

In Appendix 5 we show the pairwise correlations between the individual variables. We use this correlation matrix in order to check for the existence of multicollinearity between the explanatory variables. None of the explanatory variables in our correlation matrix display high correlation coefficients, as Gujarati defines it, none of the variables display a correlation coefficient that exceeds 0.8. In fact, the highest correlation coefficient retrieved was between the 2-year and 10-year yield. Hence, we will use these in different regressions. Seeing as most of the correlations are less than 0.50, we find it safe to use all the explanatory variables in the same regression.
6 Results from Regressions

In this chapter we present and discuss the results of the regressions (1-4) using only the theoretical determinants as the explanatory variables.

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Regression 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\alpha$</td>
<td></td>
<td>0.826</td>
</tr>
<tr>
<td>(t-stat)</td>
<td></td>
<td></td>
<td>(4.559)***</td>
</tr>
<tr>
<td>Change in leverage</td>
<td>$\Delta lev_a$</td>
<td>+</td>
<td>10.254</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(5.008)***</td>
</tr>
<tr>
<td>Change in historical volatility</td>
<td>$\Delta histvol_a$</td>
<td>+</td>
<td>-0.884</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-2.188)**</td>
</tr>
<tr>
<td>Change in the risk-free rate</td>
<td>$\Delta r_{t}^{10-year}$</td>
<td>-</td>
<td>-0.264</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-7.773)***</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td>0.112</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td>4650</td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Results from regression 1. This table presents the results from OLS panel data regression using the three explanatory variables suggested by Merton, that is, the theoretical determinants. The two lowest rows show the total explanatory power and the number of observations included. The regression coefficients are reported in the last column, and their associated t-statistics are reported in parenthesis. *** indicates that the variable is significant at the 1% level, ** at the 5% level, and * at the 10% level.

6.1 Regressions with theoretical determinants

Table 4 presents the panel data regression results using the theoretical determinants described by regression (1), and Appendix 7 shows the results when the change in CDS spreads is regressed on each theoretical determinant separately, which is regression (2-4). The results from table 4 and Appendix 7 show that in regressions using only the theoretical determinants, all three variables are found to be statistically significant. However, their explanatory power is surprisingly low and even more unanticipated is that historical volatility contradicts the sign predicted by theory. Thus, the theoretical determinants seem to have a statistically significant effect on the CDS spreads of financial institutions, but with low explanatory powers.

Leverage is statistically significant and displays the correct sign for both regression (1) and (2). This is consistent with theory and the empirical findings of CGM and EJO. Results from regression (1) suggest that, other things equal, an increase of one percent in the firm’s leverage ratio should increase the CDS spread by about 10.254 bps. However, regression (2) in Appendix 7 indicates that when leverage is the only explanatory variable, its explanatory power (6%) is estimated to be lower than in regression (1). One reason for this lower explanatory power in
regression (2) may be because of an omitted variable argument, and therefore regression (1) is preferable. Moreover, in comparison to CGM and EJO, we obtain a much larger value for our leverage coefficients. We believe that the main reason for this result is because we investigate financial firms. Given that total liabilities are usually a much larger portion of total assets for financial firms in comparison to other industrial sectors, we obtain very high leverage ratios. Since the average leverage ratio for the financial firms was 93%, a one percent increase in the firm’s leverage ratio should logically drastically increase the CDS spread. We agree with DS that leverage ratios may not always provide the accurate debt value for financial firms, and may not be a good indicator for their credit risk. Furthermore, many financial institutions do not include investment banking activities and derivatives trading in their balance sheets (DS, 2007, p.271). Therefore, the information content of financial firm’s balance-sheet ratios is questionable. Due to these off-balance sheet activities and the opaqueness of large, internationally active financial firms, leverage ratio based on book values may be less informative in this sector compared to other business sectors. Nevertheless, it is interesting to consider financial institutions as reference entities since this industry sector has not received much attention in previous empirical studies. Thus, it is also of interest to regress the CDS spreads of financial firms on this theoretical determinant, in order to determine its explanatory power. The univariate regression (2) shows that leverage ratio explains little of the CDS variation, and instead this determinant should be used in conjunction with other variables.

The most surprising result from regression (1) and (3), is that changes in historical volatility is negatively related to changes in CDS spreads. Nevertheless, both regressions (1) and (3) show that the variable is statistically significant. However, the univariate regression (3) also shows the extremely low explanatory power for explaining the variations in the CDS spreads. In our view, the reason for the negative sign in the coefficient, as well as the low R² is due to the nature of the changes data in historical volatility. Although the average historical volatility has increased throughout the sample period – as is displayed in table 3 – the magnitude of the skewness coefficient as well as the extremely high kurtosis coefficient illustrate that the data is not normally distributed. In general a volatility value above 50% indicates that the firm value is very volatile. So if the historical volatility is for example 60% and it decreases a couple of percentages, it still means that the firm-value is very volatile and thus the CDS spread does not necessarily have to decrease. Moreover, since historical volatility is calculated from lagged equity prices this proxy may be less informative in comparison to the implied volatility. According to DS, implied volatility is preferred for financial firms since it is a forward looking volatility.

The risk-free rate, which is proxied by the 10-year German government bond, displays the predicted sign of a negative relationship and is statistically significant in both regression (1) and (4). Results from regression (1) and (4) show that a one percent increase in the risk-free rate, all else equal, decreases the CDS spreads by about 0.264-0.347 bps. Overall the R-squares obtained from the regressions are quite low lying around 6-11%. This suggests that the theoretical determinants are not sufficient to explain all of the variation in the CDS spreads. In the regressions we have found that changes in the leverage ratio have considerably higher impacts on changes in the CDS spreads than the historical volatility and risk-free rate. Furthermore, the univariate regressions (2-4) illustrate that leverage ratio and the risk-free rate explain equally as much the variation in the CDS spreads. In addition, these variables explain the variations of the CDS spreads more than the historical volatility.
Regarding the fulfillment of the assumptions of OLS panel regressions, we find that the residuals from regression (1) are not normally distributed. Equivalent to our explanatory variables, the distributions of the residuals are highly leptokurtic. Nevertheless, since we have a large sample size, the non-normal distribution is less significant (see Gujarati for more details.).
7 Robustness Analysis

In this chapter we will test the robustness of the regression results presented in chapter 6. In these robustness regressions we include the additional determinants in order to test how well these additional variables can explain the variations in the CDS spreads. For further robustness, we have also divided our data into two time-periods and run regressions on a tranquil and turbulent economy. Finally, we discuss the results of the robustness regressions and compare our findings to previous studies.

7.1 Regressions with additional determinants

Parallel to EJO’s robustness analysis, we test the results of regression (1) by including additional determinants in our panel data regressions. The additional determinants presented initially in our chapter of Theoretical Framework are motivated by previous empirical findings by CGM, EJO, DS, Byström and Cremers et al. According to these studies, we identified the additional determinants that have been found to affect the changes in CDS spreads. These are changes in equity return, changes in implied volatility, changes in the square of the risk-free rate, changes in the slope of the yield, changes in business climate, changes in the bid-ask spread, and changes in the lagged credit spread. We include these additional determinants to our regression (1), which already comprises of the theoretical determinants. The proxies for these additional determinants have been explained in section 5.1. For the risk-free rate, we imitate EJO and use the 2-year yield rather than the 10-year yield for our robustness regression. We specify our robustness regression as follows:

\[
\Delta cds_{it} = \alpha_{i} + \beta_{1} \Delta lev_{it} + \beta_{2} \Delta histvol_{it} + \beta_{3} \Delta r_{t}^{2-year} \\
+ \beta_{4} \Delta eqret_{it} + \beta_{5} \Delta implvol_{it} + \beta_{6} \left( \Delta r_{t}^{2-year} \right)^{2} \\
+ \beta_{7} \Delta slope_{t} + \beta_{8} \Delta FTSE_{t} + \beta_{9} \Delta liq_{it} \\
+ \beta_{10} \Delta cds_{it-1} + \varepsilon_{it}
\]  

(5)

Regression (5) is estimated using both the basic panel regression model and with the cross-sectional fixed effects model. This is done in order to check if heterogeneity exists between the financial institutions. Thus, the fixed effects model is able to capture possible firm-specific information that may not be included in the explanatory variables. The difference between the basic panel model and the fixed effects model, is that the intercept is estimated for each firm in the fixed effects model, while the basic panel model assumes a common intercept for all firms.
<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Regression 5 Basic</th>
<th>Regression 5 Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (t-stat)</td>
<td>$\alpha$</td>
<td></td>
<td>1.757</td>
<td>(6.629)*****</td>
</tr>
<tr>
<td>Change in leverage</td>
<td>$\Delta lev_\alpha$</td>
<td>+</td>
<td>1.105</td>
<td>1.075</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.960)</td>
<td>(0.937)</td>
</tr>
<tr>
<td>Change in historical volatility</td>
<td>$\Delta histvol_\alpha$</td>
<td>+</td>
<td>-1.294</td>
<td>-1.298</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-4.199)*****</td>
<td>(-4.164)*****</td>
</tr>
<tr>
<td>Change in risk-free rate</td>
<td>$\Delta r_{t-\text{2-year}}$</td>
<td>-</td>
<td>-0.221</td>
<td>-0.221</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-7.444)*****</td>
<td>(-7.416)*****</td>
</tr>
<tr>
<td>Change in equity return</td>
<td>$\Delta regret_\alpha$</td>
<td>-</td>
<td>-0.414</td>
<td>-0.415</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.368)*****</td>
<td>(-3.361)*****</td>
</tr>
<tr>
<td>Change in implied volatility</td>
<td>$\Delta impvol_\alpha$</td>
<td>+</td>
<td>0.206</td>
<td>0.207</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.241)*****</td>
<td>(3.245)*****</td>
</tr>
<tr>
<td>Change in the square of the risk-free rate</td>
<td>$(\Delta r_{t-\text{2-year}})^2$</td>
<td>-</td>
<td>-0.647</td>
<td>-0.650</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.638)*****</td>
<td>(-3.626)*****</td>
</tr>
<tr>
<td>Change in slope of the yield</td>
<td>$\Delta slope_i$</td>
<td>-</td>
<td>-0.187</td>
<td>-0.187</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.797)*****</td>
<td>(-3.771)*****</td>
</tr>
<tr>
<td>Change in business climate</td>
<td>$\Delta FTSE_i$</td>
<td>-</td>
<td>0.044</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.297)</td>
<td>(0.301)</td>
</tr>
<tr>
<td>Change in bid-ask spread</td>
<td>$\Delta liq_\alpha$</td>
<td>+</td>
<td>0.026</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(8.624)*****</td>
<td>(8.593)*****</td>
</tr>
<tr>
<td>Change in lagged CDS spread</td>
<td>$\Delta cds_{t-1}$</td>
<td>+</td>
<td>-0.163</td>
<td>-0.164</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.385)*****</td>
<td>(-3.396)*****</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td>0.392</td>
<td>0.392</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td></td>
<td>3779</td>
<td>3779</td>
</tr>
</tbody>
</table>

**Table 5. Results from regression 5.** This table presents the results from OLS panel data regressions using the theoretical determinants and the additional determinants. Regression 5 Basic displays the results of the regression with the basic panel method. Regression 5 Fixed Effects illustrates the results of the regression with fixed effects over the cross-sections. The regression coefficients are reported, with their associated t-statistics reported in parenthesis. *** indicates that the variable is significant at the 1% level, ** at the 5% level, and * at the 10% level.

From table 5 we can see that the results from regression (5) estimated with the basic panel regression model is not significantly different from the results of regression (5) estimated with the fixed effects model. Therefore, we can draw the conclusion that heterogeneity does not affect the changes in CDS spreads. Seeing as the fixed effects method obtains similar results to the basic panel regression method, we find it is safe to use the basic panel regression in further analysis.
Results from regression (5) show that including additional determinants to the Merton model, increases the explanatory power substantially. Compared to regression (1) which included only the theoretical determinants and obtained an explanatory power of 11%, the regressions including the additional determinants achieve an explanatory power of 39%. Like in regression (1), historical volatility even now exhibits a negative coefficient contradicting the theoretical predicted sign. However, in contrast to results by regression (1), leverage ratio becomes insignificant as its t-statistic drops below one. Therefore, we find that additional determinants are able to explain fairly well the changes in CDS spreads.

Surprisingly, regression (5) shows that the change in leverage ratio is not a statistically significant determinant for changes in CDS spreads. While in regression (1) it was found to be statistically significant with strong economic significance. We believe that the chief reason for the insignificance is because of the way the leverage ratio is calculated. Leverage ratio is calculated using the book value of total liabilities and market value of equity. Correspondingly, changes in leverage are affected by changes in total liabilities and changes in market value of equity. Since changes in book values are only updated quarterly or semiannually, they do not provide sufficient information on the weekly changes of total liabilities. However, changes in market value of equity are reported frequently, and thus provide more accurate results of the weekly changes, as well as containing valuable information about the firm’s financial health. As market value of equity is updated every week, it adds variability on the weekly basis of leverage ratios. Owing to this variability in market value of equity, leverage ratio is able to explain changes in CDS spreads in regression (1). However, when we include the additional determinants in regression (5), equity return is able to capture the same information as market value of equity in the leverage ratio. Therefore, the leverage ratio can not explain further information on the changes in CDS spreads. In table 5 we can see that changes in equity return are statistically significant and consistent with the predicted sign. Results on equity return confirm that equity prices contain important information about the firm’s health and credit risk. This suggests that equity return is a preferable measure of financial firm’s health, instead of leverage ratio. Nevertheless, future studies should attempt to capture the changes in liabilities more realistically for more interesting results.

The same as in regression (1), results of regression (5) show that changes in historical volatility are negatively related to changes in CDS spreads. This contradicts the theoretical expectation of the predicted positive sign on the coefficient of historical volatility. As already stated, the nature of the changes data in historical volatility and since historical volatility is calculated from lagged equity prices, this proxy may not reflect the real volatility for the financial firm’s. As is argued by DS, a preferable measure of financial firm’s volatility is the forward looking implied volatility. As a matter of fact the implied volatility reported in table 5 is statistically significant and conforms with the theoretical predicted sign. Results from regression (5) suggest that, other things equal, an increase of one percent in implied volatility should increase a financial firm’s CDS spread by about 0.26 bps. However, we include both the historical and implied volatility in our regression because both volatility measures show high significance. Since both measures are statistically significant they might represent different things, and we decide therefore not to exclude either of the proxies from the regression. Moreover, the correlation matrix shows that they are weakly correlated (see Appendix 5), so we find it safe to use them in the same regression.
Similar to regression (1), results from regression (5) show that the changes in the risk-free rate is a statistically significant determinant of changes in CDS spreads. However, in contrast to regression (1), we replace the 10-year yield with the 2-year German government rate when running regression (5). We used the 10-year yield in regression (1) since it is a common proxy for the risk-free rate in empirical studies. However, in order to test whether other maturities of the German government bond yield the same prediction, we used the 2-year yield in regression (5). Both yields were found to be statistically significant and consistent with the predicted signs.

Other interest rate variables, such as the square of the 2-year yield and the slope of the yield curve were found to be statistically significant and conform with the predicted signs. These results are consistent with empirical findings by CGM and EJO.

Another interesting result is that the FTSE 100 variable is not statistically significant for the change in CDS spreads. This suggests that the state of the European economy does not affect the changes in CDS spreads significantly. Considering that the FTSE 100 is insignificant while the firm-specific equity return is highly significant may lead to the interpretation that mostly firm-specific variables affect the CDS spreads, rather than the business climate. Nevertheless, it is possible that there may exist some multicollinearity between the FTSE 100 and the equity return, which could cause the insignificance of the FTSE 100. Therefore, in a later subsection we run additional regressions in order to investigate whether the state of the economy affects the changes in CDS spreads.

Moreover, the changes in bid-ask spread are found to be statistically significant and estimated with the correct predicted sign. However, the changes in the lagged CDS spread are found to be statistically significant, but with the incorrect predicted sign. Since Byström obtained this determinant by investigating the iTraxx index spreads with results that show autocorrelation in the spreads; perhaps this finding is only specific for the iTraxx datasets and can not be applied for trend analysis in the CDS spreads. Nevertheless, the high significance of the lagged changes imply that the CDS spreads do incorporate some information about future spreads.

Overall the results of regression (5) show that the additional determinants increase the R-square by roughly 28%. Hence, the results of the robustness regression show that by adding the additional determinants to the original regressions, will lead to a substantial increase in the explanatory power. This implies that the theoretical determinants have limited explanatory power when explaining the changes in CDS spreads, and that adding additional determinants increases the explanatory power.

### 7.2 Regressions using subsamples

In this section we perform additional regression analysis in order to investigate the robustness of the regression results presented in the previous section, and so as to obtain additional information on the variables ability of explaining the CDS spreads.

For this robustness analysis we split our sample into two equal subsamples by time-period. One subsample includes all the financial firms during the time-period of 07.12.2005-05.06.2007 and another subsample of all companies during the 06.06.2007-26.11.2008. For each subsample we estimate regression (5), which includes the theoretical determinants as well as the additional determinants.
### Table 6: Results from regressions using time period subsamples.

This table presents the results from our subsample regressions. Results from subsample period 1 are estimated using the data for changes in CDS spreads and explanatory variable during 07.12.2005 to 05.06.2007. Results from subsample period 2 are estimated using the data for changes in CDS spreads and explanatory variable during 06.06.2007 to 26.11.2008. The regression coefficients are reported, with their associated t-statistics reported in parenthesis. *** indicates that the variable is significant at the 1% level, ** at the 5% level, and * at the 10% level.

The first subsample consists of observations during the first year and a half from the full sample, while the second subsample consists of the latter year and a half. Thus our first subsample stretches approximately from the beginning of 2006 until mid-2007, and our second subsample stretches approximately from mid-2007 to late 2008. Investigating these periods is interesting because it compares different states of the economy. In general it can be said that the first time-period is characterized by tranquil and flourishing economy, while the second time-period
period can be characterized as an unstable and financially distressed economy. In the first time-period, the CDS market was stable with low bps. However, beginning in the second time-period, the CDS spreads have been increasing throughout the time-period (for figures on the trends of the CDS data see Appendix 3).

Table 6 presents the results from the subsample regressions. Results show differences between the subsamples, but also similarities between the time-periods. All three theoretical determinants, as well as equity return, are found to be statistically significant in both subsamples. This result shows that the theoretical determinants contain important information, which can affect the firm’s credit risk directly, no matter what the state of the economy is. Curiously, all three theoretical determinants display a negative relation to the change in CDS spreads during the period of financial distress, whereas in the tranquil period the signs of the coefficients are all positive.

The other additional determinants turn out to be significant in the first or the second subsample. By comparing these subsamples we see that interest rate variables such as the square of the risk-free rate and the slope of the yield turn out to be insignificant during the first period – the tranquil period. However, these interest rate variables are able to explain more variations during the second period – the volatile period. Furthermore, business climate seems to only be significant during a tranquil state of economy. Perhaps it is that once in a period of financial distress, a decrease in the stock return will not affect significantly the changes in CDS spreads, since these changes were already expected. Moreover, in contrast to our previous results of the full sample, the bid-ask spread does not affect the CDS spread in each subsample separately.

Furthermore, we can distinguish that the determinants can explain more of the variations during the financially distressed period, but can hardly explain the variations during the tranquil economy. In the turbulent period, the variables can explain about 25% of the changes in CDS spreads, which is five times higher than the explanatory power for the tranquil period. Moreover, all of the determinants except business climate and the bid-ask spread, are statistically significant in the turbulent period. In addition, the number of observations for the first period is slightly lower than the second period because some values for implied volatility were missing for some of the firms. However, since the difference between the number of observations is relatively small, it does not affect significantly our results.
8 Conclusions

The purpose of this thesis was to study the CDS spreads of European financial institutions and test their main determinants. We investigated how well the theoretical determinants could explain changes in CDS spreads, and whether there were additional determinants that could provide further explanations of CDS spreads. The theoretical determinants are: leverage, historical volatility, and the risk-free rate. And the additional determinants, which have been extracted from empirical studies, are: equity return, implied volatility, other interest rate variables, slope of the yield, business climate, liquidity and lagged CDS spreads. We formulated the following research question:

- How well do the theoretical determinants explain the CDS spreads of European financial institutions?

In order to identify the main determinants, we collected panel data on CDS spreads, and ran regressions first on the theoretical determinants and then including the additional determinants.

The results on the theoretical determinants are mainly consistent with the findings of previous studies (i.e. CGM and EJO). All three theoretical determinants are found to have a statistically significant impact on the CDS spread in the univariate regressions. Leverage ratio is also found to have economical significance in the regression including only the theoretical determinants. However, the leverage ratio is not able to explain changes in CDS spreads when adding the additional determinants to the regression. Nevertheless, the risk-free rate is significant in both the original and extended regression, along with the predicted sign by theory. Historical volatility is significant in the extended regression, but its coefficient sign is contradicting theory in almost all regressions.

When running regressions with the additional determinants, the explanatory power increases substantially. Changes in the bid-ask spread, which measures the liquidity in the CDS market, is the most significant determinant of CDS spread among additional determinants. To our surprise, this variable becomes insignificant when explaining CDS changes in our subsamples. Changes in equity return, implied volatility and the interest rate variables are in most regressions statistically significant and conform to the predicted sign by theory. Lagged CDS spread is also significant but with a different sign than predicted. However, our proxy for the change in business climate is insignificant in our extended regression. To further investigate the impact of state of the economy on the CDS spread we ran regressions using the time-period of a tranquil economy and a financially distressed economy. The results of these regressions show that the determinants explain much better the changes in CDS spreads during a financially distressed period as opposed to the tranquil period.

In conclusion, we found that the theoretical variables are statistically important determinants of changes in CDS spreads, but have limited explanatory power for changes in CDS spreads. In order to provide further explanations of the changes in CDS spreads, additional variables need to be accounted. Our results show that regressions using solely the theoretical determinants can explain around 11% of changes in CDS spreads. However, regressions including the additional determinants raise the explanatory power an explain 39% of changes in CDS spreads.
Nevertheless, the explanatory power is still quite low. This suggests that there are other factors that affect the changes in CDS spreads.

In view of the fact that little research has been done on the CDS spreads of the banking industry, there is a lot of space for further research. Concerning delimitation to the banking sector, there is a need for a better insight about the firm’s health. Thus, other key financial ratios than leverage should be investigated for a better proxy of bank’s health. Moreover, it could be interesting to test whether and how spillover effects and credit contagion can effect the CDS spreads of financial firms. In addition, since the CDS market is still a growing market, we see many possibilities in continuing investigating the CDS spread field. For example, it might be interesting to investigate the CDS spreads using more cross-sectional data. Finally, it might also be interesting to investigate the CDS spreads of a later time period when the world economy has recovered from the credit crisis.
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Glossary of Terms

*Arbitrage* – A risk-free profit, which is achieved by simultaneously buying and selling equivalent securities on different markets. In trading practice often defined as a strategy trying to exploit price differences.

*At-the-money* – An option in which the strike price equals the price of the underlying asset.

*Bankruptcy* – A party not honoring its obligations to its creditors and whose assets a trustee therefore administrates.

*Call option* – The right but not the obligation to buy an underlying asset at the strike price a certain date (European style) or during a certain period (American style).

*Cash Flow* – A revenue or expense stream that changes a cash account over a given period.

*Cash Settlement* – Type of settlement of derivatives where cash amount is paid to the profiteer.

*Counterparty* – A partner in a financial transaction.

*Credit Derivative* – A Future, Option or a Swap that transfers credit risk from one counterparty to another.

*Credit Default Swap (CDS)* – An insurance against default if the underlying asset is owned. The default swap buyer makes upfront or annual payments. The CDS seller promises to make a payment in case of default of a reference asset.

*Credit Event* – A default by the company.

*Credit Risk* – The risk of a financial loss due to a reduction in the credit quality if a debtor. It consists of two risks: credit deterioration risk and default risk.

*Credit spread* – The excess in yield of a security with credit risk over a comparable security without credit risk.

*Default* – A party not honoring its obligations to its creditors.

*Default Risk* – The risk that a debtor might be unable to make interest and notional payments.

*Face Value* – Par Value – of a bond is the principal amount that the issuer will repay at maturity if it does not default.

*Hedging* – A way of reducing risk, i.e. entering into a second trade to reduce the risk of an original trade.

*Historical Volatility* – Volatility is based on historical stock return data.

*Implied Volatility* – Volatility is implied by observed option prices when inverting the option pricing (often Black-Scholes) formula.

*iTraxx* - This is the index for credit derivatives in the European market and the price is expressed in a single number.
Long position – A trading position, which generates a profit if the underlying instrument increases in price.

Maturity – The date a transaction or a financial instrument is due to end.

Notional Principal – The total face value of the bonds that can be sold also called the calculated amount, notional amount, principal amount.

Option – Financial instrument, which can take the form of a call option or a put option.

Physical Settlement – Type of settlement of derivatives where physical delivery and payment of the underlying asset take place.

Put option – The right but not the obligation to sell an underlying asset at the strike price a certain date (European style) or during a certain period (American style).

Risk-free Rate – An interest rate that can be achieved without risk. The interest rate for securities issued by an AAA-rated government i.e. government bonds with different maturities (5 year, 10 year etc.).

Risk-neutral – An attitude toward risk that leads the investor to be indifferent between investments A with a certain expected return and investment B with the same expected return but higher uncertainty.

Short position – A trading position, which generates a profit if the underlying instrument decreases in price.

Skewness – Third moment of a distribution function. It measures the asymmetry of a distribution.

Swap – The agreement between two parties to exchange a series of cash flows.

Risk-free rate – The yield to maturity of a zero-coupon bond, usually a Treasury bond, which is used as a benchmark for other bond yields and valuations. A zero-coupon bond has no coupon payments, there is no reinvestment risk, and therefore the precise yield to maturity of the bond can be known.

Volatility – Measure the degree of movement in the relative price of security. The standard deviation of relative price movements.

Yield – The income return on an investment.

Yield Curve – Show the relationship between yields and their maturities.
## Appendix

### Appendix 1. Financial institutions used in the regressions

<table>
<thead>
<tr>
<th>Financial Institution</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Allianz SE</td>
<td>Germany</td>
</tr>
<tr>
<td>2. Aviva plc</td>
<td>UK</td>
</tr>
<tr>
<td>3. AXA</td>
<td>France</td>
</tr>
<tr>
<td>4. Banco Bilbao Vizcaya Argentaria SA</td>
<td>Spain</td>
</tr>
<tr>
<td>5. Banco Santander SA</td>
<td>Spain</td>
</tr>
<tr>
<td>6. Bank of Ireland</td>
<td>Ireland</td>
</tr>
<tr>
<td>7. Barclays plc</td>
<td>UK</td>
</tr>
<tr>
<td>8. BNP Paribas SA</td>
<td>France</td>
</tr>
<tr>
<td>9. Commerzbank AG</td>
<td>Germany</td>
</tr>
<tr>
<td>10. Crédit Agricole SA</td>
<td>France</td>
</tr>
<tr>
<td>11. Credit Suisse Group</td>
<td>Switzerland</td>
</tr>
<tr>
<td>12. Deutsche Bank AG</td>
<td>Germany</td>
</tr>
<tr>
<td>13. Deutsche Postbank AG</td>
<td>Germany</td>
</tr>
<tr>
<td>14. Dexia</td>
<td>Belgium</td>
</tr>
<tr>
<td>15. Fortis Bank SA/NV</td>
<td>Belgium</td>
</tr>
<tr>
<td>16. HBOS plc</td>
<td>UK</td>
</tr>
<tr>
<td>17. HSBC Bank plc</td>
<td>UK</td>
</tr>
<tr>
<td>18. ING Bank NV</td>
<td>Netherlands</td>
</tr>
<tr>
<td>19. Intesa Sanpaolo SpA</td>
<td>Italy</td>
</tr>
<tr>
<td>20. KBC Group NV</td>
<td>Belgium</td>
</tr>
<tr>
<td>21. Lloyds TSB Bank plc</td>
<td>UK</td>
</tr>
<tr>
<td>22. Munich Reinsurance</td>
<td>Germany</td>
</tr>
<tr>
<td>23. Natixis</td>
<td>France</td>
</tr>
<tr>
<td>24. Nordea Group</td>
<td>Sweden</td>
</tr>
<tr>
<td>25. The Royal Bank of Scotland Group plc</td>
<td>UK</td>
</tr>
<tr>
<td>26. Société Générale SA</td>
<td>France</td>
</tr>
<tr>
<td>27. Swiss Reinsurance</td>
<td>Switzerland</td>
</tr>
<tr>
<td>28. UBS AG</td>
<td>Switzerland</td>
</tr>
<tr>
<td>29. UniCredit SpA</td>
<td>Italy</td>
</tr>
<tr>
<td>30. Zurich Financial Services</td>
<td>Switzerland</td>
</tr>
</tbody>
</table>
Appendix 2. Descriptive statistics for the levels data

The table shows the descriptive statistics for all the variables using levels data. Since the levels data for our CDS sample was found to be non-stationary (see Appendix 4), we do not perform regressions on levels data. Nevertheless, to give an idea of the nature of the levels data, we include the following descriptive statistics table.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Max.</th>
<th>Min.</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>it cds</td>
<td>41.824</td>
<td>514.200</td>
<td>3.500</td>
<td>50.956</td>
<td>2.672</td>
<td>14.925</td>
<td>4680</td>
</tr>
<tr>
<td>it lev</td>
<td>93.467</td>
<td>99.865</td>
<td>80.843</td>
<td>3.217</td>
<td>-0.533</td>
<td>2.629</td>
<td>4680</td>
</tr>
<tr>
<td>it histvol</td>
<td>26.386</td>
<td>170.600</td>
<td>9.520</td>
<td>14.467</td>
<td>3.3662</td>
<td>22.562</td>
<td>4680</td>
</tr>
<tr>
<td>it r_{10-year}</td>
<td>4.010</td>
<td>4.665</td>
<td>3.246</td>
<td>0.317</td>
<td>-0.264</td>
<td>2.882</td>
<td>4680</td>
</tr>
<tr>
<td>it eqret</td>
<td>7.733</td>
<td>12.040</td>
<td>2.630</td>
<td>1.791</td>
<td>0.399</td>
<td>2.607</td>
<td>4680</td>
</tr>
<tr>
<td>it impvol</td>
<td>33.076</td>
<td>242.930</td>
<td>3.400</td>
<td>23.153</td>
<td>3.216</td>
<td>16.544</td>
<td>3828</td>
</tr>
<tr>
<td>it r_{2-year}</td>
<td>3.696</td>
<td>4.681</td>
<td>2.180</td>
<td>0.517</td>
<td>-0.559</td>
<td>3.132</td>
<td>4680</td>
</tr>
<tr>
<td>\left(r_{2-year}\right)^2</td>
<td>13.926</td>
<td>21.912</td>
<td>4.752</td>
<td>3.693</td>
<td>-0.176</td>
<td>2.674</td>
<td>4680</td>
</tr>
<tr>
<td>it slope</td>
<td>0.314</td>
<td>1.354</td>
<td>-0.091</td>
<td>0.286</td>
<td>1.228</td>
<td>4.816</td>
<td>4680</td>
</tr>
<tr>
<td>it FTSE</td>
<td>8.602</td>
<td>8.808</td>
<td>8.092</td>
<td>0.140</td>
<td>-1.213</td>
<td>5.138</td>
<td>4680</td>
</tr>
<tr>
<td>it liq</td>
<td>4.697</td>
<td>70.000</td>
<td>0.000</td>
<td>4.746</td>
<td>4.533</td>
<td>36.812</td>
<td>4680</td>
</tr>
<tr>
<td>it cds_{a-1}</td>
<td>41.207</td>
<td>502.500</td>
<td>3.500</td>
<td>50.048</td>
<td>2.625</td>
<td>14.338</td>
<td>4650</td>
</tr>
</tbody>
</table>
Appendix 3. Graphs of the CDS spreads and their determinants

Figure 3. Graph of the CDS spreads in levels data for all the 30 financial institutions during the sample period. The figure shows that CDS spreads were low before the fall of 2007, but have ever since been increasing to new and higher levels.

Figure 4. Graph of the CDS spreads in changes data for all the 30 financial institutions during the sample period. The figure shows that there have been small changes in CDS spreads before the fall of 2007, but ever since there have been considerable changes in the CDS spreads.
Figure 5. Graph of the leverage ratio in levels data for all the 30 financial institutions during the sample period. The figure shows that leverage ratios have been increasing throughout the sample period.

Figure 6. Graph of the historical volatility in levels data for all the 30 financial institutions during the sample period. The figure shows that historical volatility has been increasing throughout the sample period, but more so from the fall of 2007.
Figure 7. Graph of the 10-year and 2-year German government bond in levels data for all the 30 financial institutions during the sample period. The figure shows that the risk-free rate has been increasing until mid-2007, and then it has been mainly decreasing.

Figure 8. Graph of the slope of the yield (difference between the 10-year and 2-year German government bond) in levels data for all the 30 financial institutions during the sample period.
Figure 9. **Graph of the firm-specific equity return in levels data** for all the 30 financial institutions during the sample period. The figure shows that the equity return has been quite stable until the fall of 2007, and subsequently it has decreased.

Figure 10. **Graph of the implied volatility in levels data** for all the 30 financial institutions during the sample period. The figure shows that the firm’s implied volatility has been quite stable until the fall of 2007, but subsequently it has increased.
Figure 11. Graph of the FTSE 100 in levels data for all the 30 financial institutions during the sample period. The figure shows that the FTSE 100 has been increasing until mid-2007, and then it has been decreasing drastically.

Figure 11. Graph of the bid-ask spread in levels data for all the 30 financial institutions during the sample period. The figure shows that the bid-ask spread were low and moderately stable before the fall of 2007, but have ever since been increasing to higher levels and display large variations.
Appendix 4. Unit root tests

Panel unit root test on CDS levels: We use three unit root tests in order to test the stationary of our CDS data in levels. They test the null hypothesis that we have a unit root, meaning that the series is nonstationary. However, if the null hypothesis can be rejected the series is found to be stationary. In the following table we can see that all three of the unit root tests cannot reject the null hypothesis seeing as their probabilities is close to one. Therefore, the conclusion is that our CDS data in levels is nonstationary.

<table>
<thead>
<tr>
<th>Method</th>
<th>Statistic</th>
<th>Probability</th>
<th>Cross-sections</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Im, Pesaran and Shin W-stat</td>
<td>6.57385</td>
<td>1.0000</td>
<td>30</td>
<td>4601</td>
</tr>
<tr>
<td>ADF – Augmented Dickey-Fuller</td>
<td>22.6156</td>
<td>1.0000</td>
<td>30</td>
<td>4601</td>
</tr>
<tr>
<td>PP – Phillips Perron</td>
<td>29.7174</td>
<td>0.9996</td>
<td>30</td>
<td>4650</td>
</tr>
</tbody>
</table>

Panel unit root test on CDS changes: We perform similar unit root tests of our CDS data in changes. In the following table we can see that all three of the unit root tests reject the null hypothesis seeing as their probabilities is close to zero. Therefore, the conclusion is that our CDS data in changes is stationary.

<table>
<thead>
<tr>
<th>Method</th>
<th>Statistic</th>
<th>Probability</th>
<th>Cross-sections</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Im, Pesaran and Shin W-stat</td>
<td>-72.8756</td>
<td>0.0000</td>
<td>30</td>
<td>4577</td>
</tr>
<tr>
<td>ADF – Augmented Dickey-Fuller</td>
<td>2373.12</td>
<td>0.0000</td>
<td>30</td>
<td>4577</td>
</tr>
<tr>
<td>PP – Phillips Perron</td>
<td>2797.85</td>
<td>0.0000</td>
<td>30</td>
<td>4620</td>
</tr>
</tbody>
</table>
**Appendix 5. Correlation Matrix**

The table displays pairwise correlations between the CDS spreads, theoretical and additional determinants. The table shows correlations of changes data. The table shows that there is no high correlation between the variables, and therefore we can include all the variables in our regressions. In fact, the highest correlation found was between the 10-year and 2-year German government bond, so we decided to use each of the yields in different regressions.

<table>
<thead>
<tr>
<th></th>
<th>Δcds</th>
<th>Δlev</th>
<th>Δhistvol</th>
<th>Δr_{10-year}</th>
<th>Δeqret</th>
<th>Δimpvol</th>
<th>Δr_{2-year}</th>
<th>(Δr_{2-year})^2</th>
<th>Δslope</th>
<th>ΔFTSE</th>
<th>Δliq</th>
<th>Δcds_{t-1}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δcds</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δlev</td>
<td>0.256</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δhistvol</td>
<td>-0.085</td>
<td>0.116</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δr_{10-year}</td>
<td>-0.245</td>
<td>-0.256</td>
<td>0.014</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δeqret</td>
<td>-0.306</td>
<td>-0.662</td>
<td>-0.405</td>
<td>0.252</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δimpvol</td>
<td>0.304</td>
<td>0.372</td>
<td>0.277</td>
<td>-0.154</td>
<td>-0.648</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δr_{2-year}</td>
<td>-0.265</td>
<td>-0.335</td>
<td>-0.134</td>
<td>0.765</td>
<td>0.394</td>
<td>-0.319</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Δr_{2-year})^2</td>
<td>0.029</td>
<td>0.206</td>
<td>0.263</td>
<td>-0.249</td>
<td>-0.295</td>
<td>0.322</td>
<td>-0.465</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δslope</td>
<td>0.095</td>
<td>0.189</td>
<td>0.225</td>
<td>0.100</td>
<td>-0.286</td>
<td>0.296</td>
<td>-0.565</td>
<td>0.400</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔFTSE</td>
<td>-0.242</td>
<td>-0.582</td>
<td>-0.172</td>
<td>0.361</td>
<td>0.677</td>
<td>-0.484</td>
<td>0.478</td>
<td>-0.356</td>
<td>-0.276</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δliq</td>
<td>0.481</td>
<td>0.126</td>
<td>-0.053</td>
<td>-0.085</td>
<td>-0.136</td>
<td>0.215</td>
<td>-0.156</td>
<td>0.091</td>
<td>0.131</td>
<td>-0.106</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Δcds_{t-1}</td>
<td>-0.161</td>
<td>-0.072</td>
<td>-0.034</td>
<td>0.090</td>
<td>0.169</td>
<td>-0.035</td>
<td>0.152</td>
<td>-0.062</td>
<td>-0.120</td>
<td>0.081</td>
<td>0.013</td>
<td>1.000</td>
</tr>
</tbody>
</table>
Appendix 6. Fixed Effects vs. Random Effects Model

Consistent with Gujarati (2003), we deem which model – random or fixed effects – is more appropriate for our data analysis. Gujarati argues that the fixed effects model should be used if:

1. The number of time-series data is large and the number of cross-sectional units is small. This criteria clearly fits in to our data since the number of time-series observations in our sample is five times more than the number of cross-sectional observations.

2. It is assumed that the cross-sectional units in the sample are not random drawings from a larger sample. This criteria is also consistent with our cross-sectional dataset, since we have only selected financial firms in our sample, which are usually considered the top financial institutions in Europe.

3. The individual error component and one or more regressors are correlated. We believe that there exists omitted firm-specific components that correlate with the explanatory variables. Examples of these components are i.e. firm’s ranking, firm’s market capital, firm’s reputation as a borrower, and corporate governance.

Based on these three criterias we conclude that the fixed effects model is more appropriate for our panel data analysis.
## Appendix 7. Panel data results on individual theoretical determinant

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\alpha$</td>
<td></td>
<td>0.468</td>
</tr>
<tr>
<td>(t-stat)</td>
<td></td>
<td></td>
<td>(2.277)**</td>
</tr>
<tr>
<td>Change in leverage</td>
<td>$\Delta lev$</td>
<td>+</td>
<td>11.891</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(5.492)***</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td>0.066</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td></td>
<td>4650</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Regression 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\alpha$</td>
<td></td>
<td>1.061</td>
</tr>
<tr>
<td>(t-stat)</td>
<td></td>
<td></td>
<td>(6.207)***</td>
</tr>
<tr>
<td>Change in historical volatility</td>
<td>$\Delta histvol$</td>
<td>+</td>
<td>-0.697</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-1.964)**</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td>0.007</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td></td>
<td>4650</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Regression 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\alpha$</td>
<td></td>
<td>0.778</td>
</tr>
<tr>
<td>(t-stat)</td>
<td></td>
<td></td>
<td>(3.804)***</td>
</tr>
<tr>
<td>Change in the risk-free rate</td>
<td>$\Delta r_{10-year}$</td>
<td>-</td>
<td>-0.347</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-11.025)***</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td>0.060</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td></td>
<td>4650</td>
</tr>
</tbody>
</table>

These three tables show the results from OLS panel data regressions using the three theoretical determinants separately in each regression. Thus, we regress the changes in CDS spreads on the three individual explanatory variables. The two lowest rows show the total explanatory power and the number of observations included. The regression coefficients are reported in the last column, and their associated t-statistics are reported in parenthesis. *** indicates that the variable is significant at the 1% level, ** at the 5% level, and * at the 10% level.