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The Equilibrium Relationship and the Price Discovery Process of European Corporate CDS and Bond Spreads: Evidence from 2007 – 2013

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ABSTRACT

This thesis studies the dynamics of European corporate credit risk pricing over the period of 2007 – 2013. Firstly, the theoretical long-run equilibrium relationship between the two credit risk markets, the credit default swap market and the bond market, is tested. Johansen cointegration tests are used to confirm the existence of the equilibrium relationship, while entities for which the theory holds are analysed with a vector error correction model (VECM) to determine which markets contribute to the price discovery process. To further determine the leader of the price discovery process the Gonzalo-Granger measure is used analyse the speed-of-adjustment coefficients of the vector error correction models.

The study analyses the CDS premiums and credit spreads of 41 European corporate entities over the two main sub periods of 15th September 2008 to 28th June 2010 and 29th June 2010 – 9th April 2013 to determine the possible effect the crisis period has had on the dynamics of credit risk pricing. Moreover, the major movements in the CDS and bond spreads as well as their difference the CDS basis are analysed to reveal possible differences between industries. The average CDS basis is found to be negative on most entities during the crisis period, which is a result of the high increase in credit spread values after the collapse of Lehman Brothers in 2008. The post-crisis average CDS basis values, on the other hand, are positive, partly resembling the two markets' return to their normal states.

The empirical analysis reveals that the long-run equilibrium mainly exists during the crisis period, as the number of equilibrium relationships detected drops to half in the post-crisis period. Moreover, the CDS market leads the price discovery process during both of the sub periods. However, the bond markets' role in the price discovery process is detected to be larger and more significant in the crisis period than after the crisis as its share in the price discovery process drops from 35 % to 17 % as measured by the Gonzalo-Granger-measure. Thus, it seems that the bond market loses its significance as a market for credit risk trading during more stable market conditions. This is further confirmed by the Granger causality tests which imply that a causality from the CDS market to the bond market is most general among the sample entities during both analysis periods.

KEYWORDS: Credit default swap, credit spread, CDS basis, VECM

1. INTRODUCTION

The derivatives market has developed greatly during the last decade and one of the most important developments has been the growth of credit derivatives. The credit derivatives market has grown significantly from 2004 to 2007 as the total notional principal for outstanding credit derivatives contracts increased by over $51 trillion in this time period. Even though the market has grown substantially, data shows steady decrease from 2007 to 2012 resulting in outstanding notional principal of $25.1 trillion at the end of 2012. (ISDA 2013.)

Credit derivatives enable the trading of credit risk of financial instruments such as bonds. Credit derivatives can be categorized as single-name or multi-name of which single-name refers to credit derivatives that are tied to a single bond whereas multi-name refers to credit derivatives that are tied to an underlying portfolio of bonds (Hull 2012: 547). This thesis focuses on the most popular single-name credit derivative, credit default swap (CDS) and its relation to the bond market. These two markets should be theoretically linked to each other as they price the same credit risk. However, short-term deviations from this equilibrium relation have been discovered on various entities. Similarly the relation has experienced changes during the last decade as the CDS market has developed to a highly liquid and popular market for trading credit risk. Thereby, the still relatively short-lived relation has developed in a fast manner and interestingly; times of financial turmoil have emerged during this period at the end of the decade. Thus, leaving their mark on the short development path of the credit derivatives market.

The crisis period started from the U.S. subprime crisis in late 2007 and has then been followed by its spill over to Europe and the Euro-area debt crisis. Thus, the credit market has been under pressure from 2007 onwards and especially after the collapse of Lehman Brothers in 2008, as it was followed by revaluation of default risk in corporate and developed sovereign credit markets. As a result of this, credit default swap and bond spreads have experienced substantially high variation and reached high values during the crisis period. (Fontana & Scheicher 2010: 6; Coudert & Gex 2011: 5.)

1.1. Purpose of the Thesis

The purpose of the thesis is to study the two credit risk-pricing markets, the CDS and bond markets, and determine whether the theoretical long-term equivalence of credit default swap prices and bond spreads holds in practice. More precisely, the theory suggests that the difference between CDS premiums and the bond spreads, the CDS basis, should be close to zero and hold in the long run. Moreover, in case short-term deviations in the long-term equilibrium relation are detected, analysis of the lead-lag relation shows which market leads the price discovery and which adjusts to the price levels determined by the former. This thesis will analyse the two relations on European corporate entities from 2007 through 2013 and thus, extends the analysis of the two interrelated markets to European firms. In addition, it will capture the effects of the euro area debt crisis (2008 – 2010) as well as the post crisis period from mid-2010 through 2013, which previous studies have shown to affect the price discovery process of certain sovereign entities.

The previous studies on the equilibrium and lead-lag relations of the CDS and bond markets have mainly covered U.S. corporate entities as well as European and emerging market sovereign entities, while analysis of European corporate entities is scarce. First studies from early 2000's focus on U.S. corporate and emerging market sovereign entities, whereas later studies have shifted the focus towards European countries. This thesis contributes to the previous literature by studying European corporate entities and extending the analysis period to cover the global financial crisis, the European debt crisis as well as the period after the crisis.

This thesis follows the empirical methodology of studies from Blanco et al. (2005) and Zhu (2006) who were among the first to study the equilibrium relationship between the CDS and bond markets. First, the first difference stationarity of the CDS and credit spreads is tested with Augmented Dickey-Fuller test (ADF). Secondly, spread pairs that pass the ADF test are further tested for cointegration with Johansen cointegration test to confirm the existence of the long-term equilibrium. Thirdly, cointegrated spread pairs are further analysed with Vector error correction model tests (VECM) to determine how the short run dynamics of the two markets are composed, i.e. which markets contribute to the short-term price discovery process. Moreover, spread pairs that do not have a long-term equilibrium relationship are analysed with a Granger causality test to gather more information on the dynamics between the two markets. The main hypotheses of the study are the following:

H_1: A long-run equilibrium relationship between the CDS and bond markets exists.

In a case where a long-run equilibrium exists between the CDS spreads and credit spreads:

H_2: CDS premiums contribute to the price discovery process of European corporate entities.

H_3: Credit spreads contribute to the price discovery process of European corporate entities.

In a case where a long-run equilibrium does not exist between the CDS spreads and credit spreads:

H_4: CDS spreads Granger cause the credit spreads

H_5: The credit spreads Granger cause the CDS spreads

Furthermore, the aforementioned hypotheses are tested in three different time periods. First, during the crisis period (15th September 2008 to 28th June 2010), second the post-crisis period (29th June 2010 – 9th April 2013) and finally the longer sample, which differentiates between entities starting 14th December 2007 at the earliest and ending 9th April 2013 at the latest.

Following the findings of the earlier studies the long-run equilibrium is expected to be more evident during the crisis period than during stable market conditions, i.e. hypothesis 1 is accepted in more cases during the crisis than after it. Majority of earlier studies show that the CDS market leads the price discovery process on average, thus the same outcome is expected for the thesis' European corporate sample. Furthermore, the bond market has been shown to have a larger contribution to the price discovery process during turbulent market conditions and thus should contribute more to the price discovery during the crisis period than it does after it. Similarly, the Granger causality from the CDS market to the bond market is expected to be the most common finding during and after the crisis.

From now on chapter two introduces the theoretical aspects of the credit default swaps and their relation to bonds. The chapter presents the basics of the credit default swaps, their contractual properties and an overview of CDS pricing models. Moreover, the chapter mainly focuses on introducing the CDS basis and reviews the determinants of the basis in depth. Lastly, the chapter gives an overview of the CDS market and presents studies regarding its anatomy. Chapter three provides a summary of earlier studies on the subject, while chapter four introduces the econometrical framework for the thesis and chapter five presents the data. Chapter six presents the results of the empirical analysis, while chapter seven concludes.

2. THE CREDIT DEFAULT SWAPS

The market for credit derivatives started to grow following several large debt crises as well as company defaults including the Latin American debt crisis and the junk bond crisis in the 1980s, the Asian financial crisis and the Russian debt crisis in late 1990s as well as the Argentinean crisis and the bankruptcy of Enron, one of the world's largest energy companies, in 2001. Following such large scale crises the demand for transferral of credit risk had risen, and gave a rapid kick-start to the credit derivatives, which allow investors to hedge credit risk in their investments or speculate on the credit risk to either protect their existing positions or to gain return. As such credit derivatives are mainly used to hedge default risk or credit deterioration risk included for example in long bond positions. However, the credit derivative market also allows investors to assume credit risk with the objective of gaining profit. (Meissner 2005: 1- 6.)

Credit derivatives include various different instruments including futures, single and multi-name credit default swaps (CDS) as well as numerous synthetic structures such as credit linked notes (CLN), collateralized bond obligations (CBO) and collateralized debt obligations. Overall, the most popular instrument has been the credit default swap, to which this thesis focuses on, as for example in 2007 they amounted to 88 percent of the whole credit derivatives market value (ISDA 2007).

As mentioned earlier the credit default swaps itself can be divided to two groups: single-name and multi-name contracts. The single-name CDSs are issued on a single entity whereas multi-name CDSs are written on several entities and include instrument types such as *credit indices* or CDS baskets. *Credit indices* are formed by pooling single-name CDS contracts into an index. More precisely, the index takes the average rate of the single-name contracts and can consist of several different entity categories, e.g. sorted by credit rating or market sector. Another important credit instrument is a *tranche*, which is a synthetic instrument that consists of a portfolio debt instruments, e.g. bonds and mortgages. Take a CDO for example, which can either be linked to cash assets (cash CDO), such as loans, or to other credit derivatives (synthetic CDO) like a credit default swap. Typically, a CDO divides the credit risk of the portfolio of assets into several risk levels (tranches), which it then sells to other investors. (Neftci 2008: 480, Fincad 2014.)

2.1. Basics of the Credit Default Swap

A credit default swap is essentially an over-the-counter contract used for insurance or protection against a default of a company or a sovereign entity. A CDS contract enables two counterparties to trade the default risk related to a bond of a bond issuer (reference entity) so that the buyer of the CDS contract has the right to sell the underlying bonds (reference obligations/assets) to the seller for their face value (notional principal) if the reference entity defaults before the maturity of the contract. Thus, the seller assumes the default risk, but receives a constant periodic payment, i.e. CDS premium or spread, from the buyer until a default by the reference entity occurs or the contract reaches its maturity.

The CDS premium is defined as a percentage share of the notional principal, e.g. 90 basis points. In a contract where the premium is defined as 90 basis points the buyer pays annually 0.9 per cent of the notional principal to the seller. In a simplistic example, if a default occurs before the maturity of the contract, the periodic payments stop and the seller has to buy the reference obligations from the protection buyer for their face value. The cash flows between the two counterparties are presented in figure 1. (Hull 2012: 547 – 548; Meissner 2005: 15 – 16.)

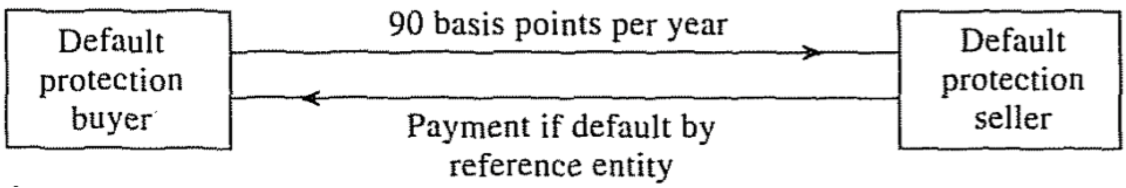

Figure 1. Structure of a credit default swap (Hull 2012: 549).

An important part of constructing a CDS contract is to determine which events count as a default and thus give the buyer the option to sell the underlying bonds to the protection seller. The counterparties can specify which credit events are included in the contract and thereby the contracts for the same reference obligations can differ from each other in terms of the premium payment as well as the credit events. However, the International Swaps and Derivatives Association (ISDA) determines all possible credit events so that the range of credit events is restricted to the six of them listed below. (Meissner 2005: 18 – 19.)

- Failure to pay
- Bankruptcy
- Obligation acceleration

- Obligation default
- Repudiation or moratorium (for sovereign entities)
- Restructuring

In case of a credit event, the credit default swap contract can be settled by either a physical or cash settlement. Credit default swaps are typically settled physically, which means that when a credit event occurs, the buyer trades the underlying bonds or any other qualifying debt instruments to the seller for a cash payment amounting to the notional principal. At the same time the periodic premium payments stop and the seller will not usually receive a separate accrued interest on the coupon payment of the bond from the protection buyer, as it is included in the bonds received. Equation 1 shows the calculation of a physical settlement. (Kakodkar, Galiani, Jónsson & Gallo 2006: 11 – 12; Meissner 2005: 19 – 20.)

(1) Physical payment = N x Reference price

where N is the notional amount of the CDS and the reference price is presented as a percentage (usually 100%).

If the settlement were to be made by cash the seller would pay the buyer a cash payment amounting to the market value of the reference obligation after the credit event, which includes the final price (recovery rate) of the bond and the accrued interest on the coupon payment. This approach can, however, be problematic, as the possibly fluctuating final price of the reference obligation has to be specified by auctions after the credit event. Equation 2 presents the calculation of the cash settlement. (Kakodkar et al. 2006: 11 – 12; Meissner 2005: 19 – 20.)

(2) Cash settlement = N x [Reference price – (Recovery rate + Accrued Interest)]

where N is the notional amount of the CDS, the reference price is presented as a percentage (usually 100%), the recovery rate of the bond at the time of the default (as a percentage) and the accrued interest is the accrued interest part of the coupon, which the protection buyer is assumed to receive from the bond. (Meissner 2005: 19 – 20.)

2.1.1. The CDS pricing models

The CDS pricing models of can be divided into three categories. First, to simple models which rely on the no-arbitrage argument between the CDS and bond markets, secondly to structural models that take fundamental variables of a company into account in the pricing process and thirdly to reduced-form models that model the price of credit risk without fundamental variables relying on market information. (Hull 2012: 550 – 551; Meissner 2005: 97, 118, 128.)

The no-arbitrage model is based on the assumption that the credit default swap and bond markets price the same credit risk so that there should not be a mispricing of credit risk between the two markets. Thus, if this equilibrium relation between the markets does not exist, arbitrage opportunities emerge. This can be explained in the following way: an investor can eliminate the credit risk of a T-year bond by buying a credit default swap on the bond issued by the reference entity. Therefore, the return of this portfolio is the yield to maturity of the bond minus the credit default swap spread, which should equal to T-year risk-free interest rate. If the difference between the yield to maturity and CDS spread differs from the T-year risk-free interest rate, there are arbitrage opportunities in the market. For example if the difference is higher than the risk-free interest rate, buying a T-year bond, a credit default swap, and shorting the risk-free interest rate would be profitable. Thus, the credit default swap spread should be equivalent to the excess of a bond yield over the risk-free rate when no arbitrage opportunities exist. Equation 3 presents the no-arbitrage argument. (Hull & White 2000: 14 – 15; Hull 2012: 550 – 551.)

(3) CDS spread = Credit risky bond yield – Risk-free interest rate

Structural models are based on the model introduced by Merton (1974), which modified the Black-Scholes option-pricing model so that the probability of firms default can be derived from firm’s equity, asset and debt values. A default therefore occurs when the debt value exceeds the asset value of the firm at the maturity of the firm’s debt, as the firm is assumed to have issued only one bond that does not pay coupons. Other models have extended this framework, so that the default can occur before the maturity of the debt at a pre-defined boundary of default.

Unlike the structural models, reduced form models price the default risk without firm’s structural variables and rely on debt prices to determine the probability of a default. A model by Jarrow and Turnbull (1995) treats the default probability as a statistical factor, so that it is a product of two independent processes, i.e. interest-rate and bankruptcy processes. Other models, such as Jarrow-Lando-Turnbull model (1997), consider historical default probabilities of differently credit rated entities, whereas Hull et al. (2000) introduce a model that takes into account the accrued interest while pricing the CDSs with models used for valuating swaps. (Meissner 2005: 118 – 152.)

Consider the Hull and White (2000) model, which calculates the CDS premium as a combination of the payoff in a case of default and the payments made by the protection buyer. They price the payoff of the CDS contract in a default as 1 – R – A(t)R where R is the expected recovery rate of the reference asset and A(t) is the accrued interest as a percentage of the bond's face value at time t. Since the payoff will trigger only in a case of a credit event the expected value of the payoff is calculated as follows:

(4) $$\int_0^T (1 - R - A(t)R)q(t)v(t)$$

Here *q(t)* is the risk-neutral default probability at time t and *v(t)* is the present value of $1 at time t. Essentially, the equation results in the expected present value of payoff when the payoff amount is discounted to t = 0. The CDS payments made by the protection buyer are calculated as the summation of the integral of all payments made until a default occurs and all payments made when there is no default. Once again *q(t)* is the risk-neutral default probability at time t, *w* is the yearly payments made by the protection buyer, *u(t)* is the present value of all payments made until time t, *e(t)* depicts the present value of accrued payments of the CDS premium at time t, π is the risk-neutral probability of the credit event not occurring during the lifetime of the CDS contract. The expected present value of the payments is:

(5) $$w\int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T)$$

The difference between equations 4 and 5 represents the value of the CDS contract to the protection buyer. Derived from this difference the CDS spread, *s*, can be calculated by setting it to zero and solving for *s* which expresses the value of annual total CDS payments as a percent of notional principal.

(6) $$s = \frac{\int_0^T (1-R-A(t)R)q(t)v(t)}{\int_0^T q(t)[u(t)+e(t)]dt+\pi u(T)}$$

2.2. CDS basis

The CDS basis is the difference between the CDS spread and the bond yield over the risk-free rate and depicts the mispricing between the derivatives and cash markets. Determination of the basis relies on the no-arbitrage argument so that the basis is defined as follows:

(7) CDS basis = CDS spread – Excess of bond yield over the risk-free rate (Asset swap spread)

Usually, an asset swap spread is used to proxy the difference between the bond yield and the risk-free rate as it directly depicts this difference (Hull 2012: 525 – 526, 550 – 551). Most commonly the CDS basis is of positive value, so that CDS spreads are valued higher than the bond yield over the risk-free rate. Similarly, a negative basis is a result of bond spreads trading higher than the CDS spreads (Choudhry 2006: 63).

From a trader's perspective both the CDS basis offers different trading possibilities depending on its value, i.e. both positive and negative basis offer possibilities for arbitrage. First, consider a negative basis trade, where the investor takes a long position on a bond, while at the same time takes a short position on the bond issuer by buying a CDS on the said reference entity. Thus, negative basis trade is used to gain return without the exposure to credit risk by exploiting the pricing differences between the bond and CDS markets, i.e. exploiting the difference between a low CDS premium and a high bond spread. In a similar way the investor can gain risk-free return also when the CDS basis is positive. A positive basis trade is established with a long position in the CDS and a short position in the bond and thus tries to gain return from the difference between a high CDS premium and a low bond spread. (Choudry 2006: 116 – 117.)

2.2.1. Drivers of the CDS basis

As described above, the value of the CDS basis has an important role in different trading strategies. Thus it is important to note that there are numerous factors that are found to drive the CDS basis towards either positive (wider) or negative value (tighter) in practice. These factors can be categorized as market factors and technical factors. Technical factors are factors that are related to the specific CDS contract or the reference asset and are linked to their fundamental and contractual issues. Market factors on the other hand are related to market conditions, trading and issues affiliated with them.

Technical factors that affect the movements of the CDS basis are the following as per Choudry (2005).

CDS premiums are above zero. As the CDS premium is fundamentally an insurance payment, where the buyer pays for the protection against a default, it is always positive. Highly rated bonds are often associated with a low credit risk, which is represented in the market as them trading below Libor. When a bank sells a CDS contract on such bond they demand premium to cover Libor. Thus this factor drives the basis wider, i.e. towards a positive basis.

CDS contract offers greater protection. A technical default often triggers the pay out of a CDS contract, rather than a full default. Thus, the CDS contract contains additional risk, which the seller assumes and therefore requires the buyer to pay a premium to account for the risk. This results in a wider basis.

Identity of the bond and the delivery-option. The delivery option in physically settled CDS contracts allows the buyer to deliver a bond from a pool of bonds. Thus, in case of a credit event, the seller of the CDS assumes additional risk, as the buyer may deliver the cheapest available bond which fits the definition of the deliverable assets. Therefore, a large delivery basket results in a higher CDS premium which leads to a positive basis. Also when the credit rating of the reference entity drops the CDS sellers will demand a higher premium which widens the basis. Similarly an improved credit rating will drive the basis tighter.

Accrued coupon. Depending on a specific CDS contract the accrued coupon may also be required to be delivered to the buyer of the contract. In such occasions the CDS premium demanded by the seller will be higher and thus drives the CDS basis wider.

Assets trading above or below par. If the reference asset of a CDS contract is trading below its par value the seller of such contract is exposed to a risk of having to overcompensate the contract buyer in a credit event. This is due to the nature of the CDS as it is written to offer protection to the entire par value of the reference asset. If the current value of the reference asset is lower than its par value during a credit event the seller of the CDS will suffer an additional loss compared to an investor that has a long position on the reference asset. Thus, the price of a CDS whose reference asset trades below par is higher than the asset-swap price of the same reference asset and results in a wider basis. On the other hand, if the bond trades above the par value, the protection seller will suffer lower losses than an investor with a long position on the reference asset. This leads to a lower CDS basis.

Funding versus Libor. In contrast to CDS' unfunded nature, a bond is always associated with a funding cost, which is usually the repo rate of the bond. For example, if the funding cost of a bond is over the Libor rate, the CDS basis will be tightened. Similarly, a below-Libor funding cost drives the CDS basis wider.

Counterparty risk. Counterparty risk drives the basis tighter as it mainly affects the protection buyer. The buyer assumes the counterparty risk related to the protection seller for the duration of the CDS contract or until a credit event occurs. The risk presents itself if after a credit event the seller of the CDS is unable to pay out the settlement. The protection buyer can compensate the risk by favouring CDS contracts whose premium is lower than the asset-swap spread and by selecting a seller that has low default correlation to the underlying asset.

Legal risks. CDS contracts contain legal risks related to documentation. Often the risks are affiliated with the definition of credit events as broad definitions can lead to the underlying asset being viewed as it has defaulted due to a certain credit event even though a default in its true nature has not occurred. In such a case the protection seller assumes the risk.

Market factors affecting the CDS basis:

Demand. Large demand for protection drives the CDS basis higher, while a strong demand for selling protection has the opposite effect.

Liquidity premium. The CDS premiums on contracts of illiquid reference assets may include a liquidity premium demanded by the protection seller to cover risk associated with illiquid assets. For example some corporate, bonds with maturities over 10 years suffer from lack of liquidity, which results in higher premiums and consequently higher CDS basis. Furthermore, the bond may be less liquid than the CDS due to the reference credit, which drives the basis tighter. Similarly, if the CDS is the less liquid contract the CDS basis drives wider due to the larger CDS price.

Shortage of cash assets. Depending on the market, the CDS contract may be the easier or only way to get exposure on a certain reference name or asset. For example, certain corporate entities may not have issued bonds, which leaves the credit default swaps as the sole option for investors and drives the basis wider. Similarly, the difficulty of short selling certain entities' bonds increases the demand for CDS contracts as covering the short position in the repo market may be problematic. Thus the lack of options for gaining exposure on reference names results in higher CDS basis.

Structured finance market. The structured finance market drives the basis lower as for example synthetic CDOs require pools of CDS contracts to gain exposure to the credit risk of the reference names. The demand in the CDS market increases as the counterparties of the CDOs hedge the exposure of the CDO credit risk in the CDS market. This large demand in the CDS market drives the CDS basis lower.

New market issuance. The importance of the credit default swap market is evident in the case of new bond issues as the investors look to hedge the credit risk of new issuers in the CDS market rather than using government bonds or interest-rate derivatives. Particularly, in new loan issues the demand for protection in the CDS market rises and drives the basis higher. However, new bond issues can have effects towards both directions. For example, new bond issues contribute towards a broad delivery basket, which, as mentioned earlier, drives the basis wider. Similarly, the new issue also attracts investors to the cash market which respectively drives the CDS basis lower.

Some of the technical drivers of the CDS basis have been studied in a more close examination as for example the cheapest-to-deliver option and the definitions of restructuring have been found to cause mispricing between the cash on CDS markets. Moreover, the two of these combined have been found to have a larger effect on CDS spreads than the sole cheapest-to-deliver option. As explained earlier the cheapest-to-deliver options give the protection buyer a right to deliver any qualifying loans or bonds to the seller when a credit event occurs. This option should have an effect on the pricing of the CDS contract, as the seller has to assume a risk of getting a bond with a significantly lower market value than the original underlying bond (Kakodkar et al. 2006: 51).

Restructuring clauses on the other hand give a CDS contract more flexibility in terms of credit events, as restructuring can be viewed as a credit event. Restructuring may also maintain a maturity structure more complex for the reference entity's bonds, which means that bonds with different maturities remain outstanding with differences in values. Therefore the cheapest-to-deliver option has more value when it is combined with restructuring clauses, as it can be used to earn profits that are not depended on the credit quality of the reference obligation. (Packer et al. 2005: 90.)

Restructuring clauses have evolved as the credit default swap markets have grown. The clauses have been modified over the years as some misuses have occurred and therefore there are four types of restructuring clauses, which are in the order of publication: full restructuring, modified restructuring, modified-modified restructuring and no restructuring. (Packer et al. 2005: 91.)

Under the full restructuring all restructuring events qualify as a credit event and bonds with maturity up to 30 years are deliverable. Main problem with the full restructuring was that a restructuring that might not be disadvantageous to bond holders still led to a credit event. Modified restructuring clause differs from the full restructuring by limiting the deliverable bonds to those that have a maturity of 30 months or less after the CDS contract is terminated. The modified-modified restructuring clause further changes the restrictions of deliverable bonds as it states that the maturity of the deliverable restructured bonds has to be shorter than 60 months and 30 months for all other bonds. As for the no restructuring clause, it states that restructuring events are not considered as credit events. Therefore under the no restructuring clause such “soft” credit events are not possible. (Packer et al. 2005: 91.)

For example, Packer and Zhu (2005) examined contractual terms in credit default swap contracts and how they affect the CDS spreads. They found that contracts, which had cheapest-to-deliver options and other contractual terms such as restructuring clauses, had higher CDS spreads than contracts with no or fewer contractual terms. Similarly, Jankowitsch, Pullirsch and Veza (2006) show that part of the credit risk mispricing between the cash and CDS markets is due to the cheapest-to-deliver option. Therefore contractual terms need to be considered when mispricing is detected between the bond and CDS market as the terms can have significant impact in the pricing of credit default swap contracts.

More precisely, Jankowitsch, Pullirsch and Veza (2006) studied the delivery option in credit default swaps and its effect on the valuation process of credit default swaps. They found several proxies that affect the value of a cheapest-to-deliver option. The number of available bonds had the biggest influence in the valuation process. So a relatively large amount of bonds available for delivery results in a lower expected minimum price in default. Another significant factor in pricing the option was a bond pricing error, which means that there are bonds in the market whose market values differ from their theoretical prices. This affects the recovery rate of the reference obligation by lowering it if the price differences still occur after a default and therefore increases the value of a cheapest-to-deliver option and drives the CDS basis higher. (Jankowitsch, Pullirsch and Veza 2006: 19 – 22.)

Packer and Zhu (2005) study credit default swap contract pairs that are written on the same reference entity but have different restructuring clauses. Since restructuring is considered as a credit event the strictness of the clause is found to affect the CDS spreads. More precisely, they discover that CDS spreads vary with the level of restructuring as the spreads are at highest values with full restructuring, second highest with modified restructuring and lowest with no restructuring. Furthermore, they come into a conclusion that the valuation of contractual terms is not dependent on the rating of reference entities or on their sectorial or regional type even though some evidence on regional effect on the pricing is found. (Packer et al. 2005: 94–99.)

2.3. Determinants of the CDS basis

The drivers, i.e. the determinants, of credit risk pricing have been studied for a long time, first by analysing the bond spreads and later extending the studies also on the CDS spreads and the CDS basis. The studies mainly consider structural factors, e.g. firm leverage, suggested by the structural pricing models, while they also include other possible determinants, which most often can be categorized as global factors.

Collin-Dufresne, Goldstein and Martin (2001) study the determinants of bond spreads during the 1988 – 1997 period covering monthly credit spreads of 261 U.S. industrial corporate entities. They investigate the determinants in two parts. First, they run regressions to analyse the role of different factors, suggested by structural pricing models of credit risk, in determining the bond spreads and second, include other variables to explain more of the credit spread variation. They find that the variables leave most of the bond spread variation unexplained and show that factors common for all entities are more significant than firm-specific determinants. (Collin-Dufresne, Goldstein & Martin 2001: 2181, 2189 – 2191, 2204 – 2205.)

Their results imply that most of the variation in the credit spreads is a result of a unknown common component, as the their regression determines only 25 per cent of the changes. More precisely, changes in firm leverage and equity return have a significant positive and negative correlation, respectively, with the change in credit spreads, whilst both still remain economically insignificant. However, determinants, such as increase in implied volatility (VIX index), return on S&P 500 index and changes in expected probability of negative change in firm value, have a statistically and economically significant correlation with the credit spread changes. Return on S&P 500 is found to be the most significant determinant and has a negative correlation with the spread variation. (Collin-Dufresne et al. 2001: 2185 – 2191.)

Collin-Dufresne et al. (2001) add other variables in the second test to confirm the robustness of the earlier findings. The additional factors do not increase the results substantially, as only 34 per cent of the credit spread changes are determined by the coefficients and whilst most of the added variables are statistically significant, they lack economic significance. The unexplained share of the common factor still remains large and thus, Collin-Dufresne et al. (2001) suggest that the stock and bond markets are divided, so that changes in supply and demand in the two markets result into price changes rather than the firm-specific factors. (Collin-Dufresne et al 2001: 2195 – 2206.)

Campbell and Taksler (2003) conduct a study on the effects of equity volatility to the bond spreads of U.S. firms from 1995 through 1999. They find that firm specific equity volatility plays a role in determining the credit spread changes. More precisely, addition of the volatility variables increases the explanatory power of the regressions, which take into account credit ratings, accounting data and macroeconomic data, by 6 to 10 percentage points. However, these regressions still only explain 35 – 40 per cent of the spread changes. Campbell et al. (2003) find that idiosyncratic volatility is positively correlated with credit spread variations, so that increase in volatility leads to higher cost of borrowing, and that volatility and credit ratings are equally good determinants of changes in credit spreads. (Campbell and Taksler 2003: 2325 – 2327, 2344.)

Ericsson, Jacobs and Oviedo (2009) extend the studies of the determinants of credit risk to credit default swap spreads. They analyse the determinants of the changes in CDS spreads and the spread levels of U.S. corporate entities from 1999 to 2002 and find evidence of statistical significance for all of their main determinants, i.e. firm leverage, volatility and the risk-free interest rate, while their explanatory power is weak. In addition, inclusion of additional variables does not substantially increase the explanatory power of their regressions. Thereby, majority of the variation in spreads cannot be explained, even though evidence of another common component is found to be weak. (Ericsson, Jacobs & Oviedo 2009: 114 – 116, 131.)

They find that the correlations of firm-specific variables, leverage and volatility, and risk-free interest rate are significant on most entities and in more detail, positive for the first two and negative for the latter. Still, these factors determine only 23 per cent of the changes in CDS spreads for spread difference data. However, use of level data leads to higher explanatory power and thus to mixed results. To study the common component more closely, Ericsson et al. (2009) include the variables used by Collins-Dufresne et al. (2001) to their regressions and detect slight increases in the explanatory powers. Thus, they state that their regressions explain the spread changes better than the ones in the study of Collins-Dufresne et al. (2001), while still leaving a great share of variation unexplained. Contrary to the results on the low explanatory powers, their regression residual analysis suggests that the determinants suggested by theory explain most of the spread changes so that evidence on the existence of another common component detected by Collins-Dufresne et al. (2001) is rather weak. (Ericsson et al. 2009: 112, 119, 123, 131.)

Zhang, Zhou and Zhu (2009) also investigate the determinants of CDS spreads. They conduct analysis on the level data of the spreads of U.S. corporate entities and cover the 2001 – 2003 period. While equity volatility and jump risk are the main determinants studied, they also include other determinants analysed in the previous studies. They find evidence of statistical and economic significance for volatilities and jump-risks. More precisely, Zhang et al. (2009) report that volatility and jump risks increase the explanatory power of their regressions by up to 18 per cent, while other determinants, such as credit ratings, balance sheet information and macroeconomic changes, determine 50–60 per cent of CDS spread changes. Overall, volatility and jump risk measures are the most significant factors in their regressions. An increase in volatility results in an increase in CDS spreads, whereas jump risks are negatively correlated with the spread changes. (Zhang, Zhou & Zhu 2009: 5101, 5104 – 5108, 5111 – 5112, 5126.)

Longstaff, Pan, Pedersen and Singleton (2010) investigate the determinants of CDS spreads of 26 developed and emerging market sovereign entities from 2000 through 2007. They conduct a principal component analysis to determine the role of common factors in the pricing of CDS contracts and furthermore analyse the composition of the principal components. They suggest that over 50 per cent of the CDS spread changes are explained by the common factors and that global determinants have a stronger relation to the spread variation than idiosyncratic measures. (Longstaff, Pan, Pedersen & Singleton 2010: 1, 4 – 5, 21.)

Longstaff et al. (2010) detect that the changes in CDS spreads across entities can be mostly explained by five principal components as they explain 65.51 per cent of the variation. First three components account for 53.23 per cent, while the first component is detected to have the most significant role with 31.69 per cent of changes explained. This component also has a similar effect between all but 2 entities, while the effects of the other components resemble each other only for small sub-groups. Longstaff et al. (2010) identify the first component as U.S. stock market as they find that both the returns and implied volatility are highly correlated with the component, thus suggesting that the sovereign CDS spread changes are mostly driven by the U.S. stock market. (Longstaff et al. 2010: 6 – 7.)

Their regression analysis on the explanatory variables suggest that, in addition to the U.S. stock market, there are other variables that have a significant impact on the variation in

CDS spreads. More precisely, the U.S. high-yield bond spread is a significant determinant for most of the entities and has a positive correlation with the CDS spread changes. In contrast, the U.S. stock market is negatively correlated for most countries. Similarly, the impact of local stock markets is of negative sign and significant for 14 entities. Global investment-flows, equity and bond, are also detected to be significant determinants for a group of countries, supporting the dominant role of global factors in determining the spread variation. Findings on the correlation sign of the bond-flows are mixed, whereas on equity the flows are positively correlated with the spreads of 16 entities. Thus, despite the significance of the local stock markets, Longstaff et al. (2010) suggest that global factors have a greater explanatory power than local factors. (Longstaff et al. 2010: 9 – 17, 21.)

The studies on the determinants of bond and CDS spreads mainly suggest that the spread variation is due to common factors and that many firm- and country-specific factors do not have an economically significant effect on the spread changes. Still, some idiosyncratic factors are found to play a significant role as Zhang et al. (2009) show that volatility and jump risks determine a substantial amount of CDS spread variation. From the global factors, returns on S&P 500 and the VIX-index seem to be common determinants in most studies, including Collin-Dufresne et al. (2001) and Longstaff et al. (2010), for corporate and sovereign entities. The former study also suggests that U.S. high yield bond yields as well as global investment flows explain some of the sovereign CDS spread changes.

Fontana et al. (2010) investigate the determinants of CDS basis of 10 European sovereign entities covering the 2006 – 2010 period. They discover that the CDS basis substantially rose after September 2008 and conduct analysis on the factors that resulted to the mispricing between CDS and bond spreads. They discover that the change in the pricing of credit risk is a result of common factors and that during the crisis period more factors have a significant role in explaining the spread changes than during the pre-crisis period. (Fontana et al. 2010: 22 – 26.)

More precisely, the cost of shorting a bond is found to be a significant determinant for the crisis period spread changes as a rise in the shorting cost leads to a rise in CDS basis. Whereas during the first period, shorting costs had a weaker and negative effect on the basis, while still being a significant determinant. Similarly, the role of debt ratio (debt to GDB) was minor and had a negative effect in the first period, whereas the impact increased during the crisis period. The findings on the debt ratio, however, vary between cross-sections; as for the central countries the impact in spread changes was positive

(55.93), while being negative (–64.41) for the peripheral entities. In addition, idiosyncratic volatility, measured as the volatility of excess returns of stocks in the country, became a significant determinant for basis variation during the crisis, as it has a negative impact to the basis. Overall, their determinants are able to explain 95 per cent and 75 per cent of the basis variation during the pre-crisis and crisis period, respectively. In contrast, when investigating the determinants of bond and CDS spreads, Fontana et al. (2010) discover that the regressions have a lower explanatory power on both separate spreads, as only 13 and 25 per cent of the changes in CDS spreads are determined by the variables during pre-crisis and crisis periods, respectively. The same values for the bond-spread variation are greater, 57 and 16 per cent, but still substantially lower than the values for the basis changes. A notable finding on the determinant analysis is that global factors had an increasing role in explaining the two spreads after the collapse of Lehman Brothers. (Fontana et al. 2010: 17 – 18, 22 – 26.)

A study by Beirne and Fratzscher (2012) investigates the determinants of bond and CDS spreads of 31 sovereign entities from both advanced and emerging markets during the European sovereign debt crisis. They cover monthly data from 1999 to 2011 mainly analysing the role of country-specific factors. They find that country-specific economic variables explain the changes in the pricing of credit risk during the debt crisis, whereas before the crisis their role was substantially weaker. The impact of country-specific factors during the crisis is detected to be strongest for the peripheral European countries, but is also economically significant for most of the other sovereign entities. More precisely, the bond and CDS spreads of peripheral countries, Greece, Ireland, Italy, Portugal and Spain, are not affected by their country-specific economic factors before the crisis, whereas during the crisis variables such as debt-to-GDP and real GDP growth are significantly correlated with the credit spread variation. In addition, Beirne et al. (2012) find that regional spillover effects did not play a significant role in determining the spread variation and thus conclude that the increasing contribution from country-specific economic factors mainly explains the variation in credit risk pricing during the debt crisis. (Beirne & Fratzscher 2012: 1, 5, 18 – 22.)

Fontana (2011) also studied the determinants of the CDS basis of U.S. investment grade firms during the 2007 – 2009 financial crisis covering data from 2006 to 2009. He finds that the average CDS basis changes from a positive value of 3 basis points to a persistent negative basis of –36 basis points in the crisis-period. All the main determinants, that are the bond funding cost, the bond volatility and the liquidity premium, have a negative effect in the CDS basis during the crisis period. In addition, he discovers that these determinants are significant for explaining bond spreads, whereas for CDS spreads they are insignificant in most cases. More precisely, most of the variation in CDS spreads is as result of unexpected shocks in the derivatives market, while only one of the main determinants, expected bond volatility, had a statistically significant but minor economic effect to the CDS spreads. Thus, Fontana (2011) suggests that the bond funding cost had a great role in determining the CDS basis during the financial crisis. (Fontana 2011: 12 – 26, 39.)

Fender, Hayo and Neuenkirch (2012) study the determinants of 12 emerging market sovereign CDS spreads during the 2002–2011 period. They conduct three analyses on daily CDS data. First, they investigate the impact of macroeconomic factors in the CDS spread variation. Secondly, they focus on country-specific determinants and finally analyse the effect of different factors from the U.S. financial market. They find that before the financial crisis a common factor accounts for a third of the CDS spread variation, while its explanatory power increases to almost 70 per cent during the financial crisis, meaning that during the crisis-period global factors explain more of the CDS spread changes than the country-specific factors do. More precisely, they suggest that the common factor consists of U.S. equity returns (S&P 500 index), emerging credit market returns (EMBIG index) as well as measures for risk aversion, such as option-implied volatility (VIX). The returns are detected to have a positive correlation with the spread variation, whereas the risk aversion measures are negatively correlated. (Fender, Hayo & Neuenkirch 2012: 2788 – 2790.)

Consequently, Fender et al. (2012) detect that country-specific macroeconomic factors, such as credit rating changes and debt-to-GDP ratio, are significant determinants before the crisis but become insignificant in the crisis period. However, the role of monetary policy news increases during the crisis as an increase in interest rates by the European Central Bank results in a decrease in the emerging market sovereign CDS spreads. Overall, Fender et al. (2012) state that during the crisis CDS spreads are mostly driven by international factors rather than country-specific variables, so that global market developments are displayed also in the emerging market CDS spreads. (Fender et al. 2012: 2790 – 2793.)

Eichengreen, Mody, Nedeljkovic and Sarno (2012) study the role of a common factor in determining weekly changes in CDS spreads of 45 global banks during the July 2002 – November 2008 period. They focus on the changes in the role of the common factor before and during the financial crisis and conduct a rolling principal component analysis to cover the variation. They detect that the role of the common factors significantly increased during the financial crisis, while it had previously remained stable. The first component explained approximately 40 per cent of the spread variation before the crisis, while all four common components accounted for 60 per cent of the changes. From mid-2007 onwards the contribution of common factors increased significantly. Eichengreen et al. (2012) state two dates on which the contribution of the first component had reached its new peaks, the rescue of Bear Sterns in May 2008 and the collapse of Lehman Brothers in September 2008. On these dates the first component solely explained 60 and 65 per cent of the CDS spread changes, respectively. In addition, the four factors account for a combined contribution of 60 to 80 per cent during that time. Similarly, they detect bank CDS spreads peaking at all-time high values during the same dates. (Eichengreen, Mody, Nedeljkovic & Sarno 2012: 1301 – 1306.)

In a more precise analysis Eichengreen et al. (2012) find that the high-yield spread, which is a proxy for corporate default risk, explains half of the contribution of the four common factors before the financial crisis. S&P 500 returns and implied volatility account for a 10 and 20 per cent shares respectively. Thus, they state that global economic determinants were the main factors driving bank CDS spreads before the crisis. However, during the crisis they detect that financial factors, such as bank credit risk (TED spread), influenced the CDS spread variation in a growing manner, while still remaining minor factors compared to the economic determinants. Overall, while the global economic factors explained more of the CDS spread variation before and during the crisis, Eichengreen et al. (2012) find that especially growth in the previously nearly non-existent contribution from bank credit risk resulted in the increase in the common factors' role during the crisis. (Eichengreen et al. 2012: 1310 – 1314, 1316.)

Annaert, De Ceuster, Van Roy and Vespro (2013) study the drivers of weekly CDS spread variation of 32 European banks during 2004–2010. They investigate the role of determinants categorized as credit risk, liquidity and global economic factors with standard regression analysis as well as with rolling regressions to detect changes through time, especially after the start of the financial crisis. They find that their determinants explain the spread variation better during the crisis as each of them explains at most 1 to 4 per cent of the CDS spread changes before the crisis, while the explanatory powers rise to the range from 7 to 16 per cent after the start of the crisis. Thereby all determinants combined explain 5 and 23 per cent of the spread variation before and during the crisis, respectively. Variation in the results is also detected between high and low credit rated banks, as the determinants have a higher explanatory power for highly rated banks, especially during the crisis period. (Annaert, De Ceuster, Van Roy and Vespro 2013: 1, 454 – 459.)

Annaert et al. (2013) find evidence that credit risk factors, i.e. risk-free rate and leverage, experience a substantial increase in significance during the crisis period, while they are negatively correlated with the spread changes. Similarly, liquidity, which is measured as bid-ask spread of CDS quotes, is found to become more significant, but still has weaker explanatory power than credit risk measures. In addition, global economic factors follow the same path but have the strongest impact in the bank CDS spreads during both the pre-crisis and crisis period. Overall, Annaert et al. (2013) find strong variation in the explanatory powers of the determinants trough time and more specifically a substantial increase after the start of the financial crisis. (Annaert et al. 2013: 457 – 459.)

The studies on the drivers of pricing credit risk ranging until late 2000's show that the financial turmoil has affected the determinants of CDS and bond spreads. As a generalization it can be said that that global economic factors have been the most significant ones during and before the crisis for most entities. However, the higher variations in the spreads are found to be a result of the rise of country-specific factors, as the role of the global factors has been, to some extent, stable. Still, many of the findings can only be linked to a certain sub-group, such as banks or low-risk and high-risk countries, so that variation in the whole credit risk market cannot be explained by the same determinants.

Fontana et al. (2010) show that the CDS basis variation of Euro area countries was mainly determined by the global factors. However, they state that their determinants were able to capture almost all of the variation before the crisis, whereas the explanatory power of the regression slightly decreased during the crisis period. Interestingly they were not able to explain the variation in the separate spreads as well as they could for their combination, i.e. the basis. They also highlight the peripheral euro area countries, as the findings on country-specific factors differed from the results of the whole sample. Beirne et al. (2012) detect a similar trend, as the peripheral sovereign CDS spreads have the strongest reaction to these country-specific variables, such as debt ratio.

Fender et al. (2012) show that the CDS spreads of emerging market sovereign entities react to somewhat different determinants during the crisis than their advanced economy counterparts. The discovered high explanatory power of the common factor, however, confirms that the global factors are also the most important drivers of the emerging market spreads during the crisis. The role of country-specific factors therefore decreases and the emphasis moves towards global market news to reflect the developments in the Euro area. In addition, the studies by Eichengreen et al. (2012) and Annaert et al. (2013) confirm that also the bank CDS premium has mainly been driven by global factors, while the major changes are mainly explained by bank- and country specific determinants, much like for the peripheral European nations.

2.4. The CDS Market, its anatomy and additional effects

International Swaps and Derivatives Association (ISDA), the governing body of over-the-counter derivatives contracts, reported in 2006 that the size of the credit derivatives market had reached 17.3 trillion US dollars in outstanding notional principal, following two years of rapid growth. Moreover, the credit derivatives market had grown in size by 123 percent in 2004 and by 104 percent in 2005 and had become a significant part of the whole derivatives market that totalled an outstanding notional amount of 234 trillion US dollars. The rise in outstanding notional amounts of credit derivatives continued their rapid growth in 2006 and 2007 resulting in 58.2 trillion USD in the end of 2007. Furthermore, Bank of International Settlements reported that 88 percent of the credit derivatives market consisted of positions in credit default swaps, and accounted their rapid growth to their newness. However, in the following 5 years the outstanding notional amounts declined near to the level of 2006 as shown in figure 2. (ISDA 2006; BIS 2007.)

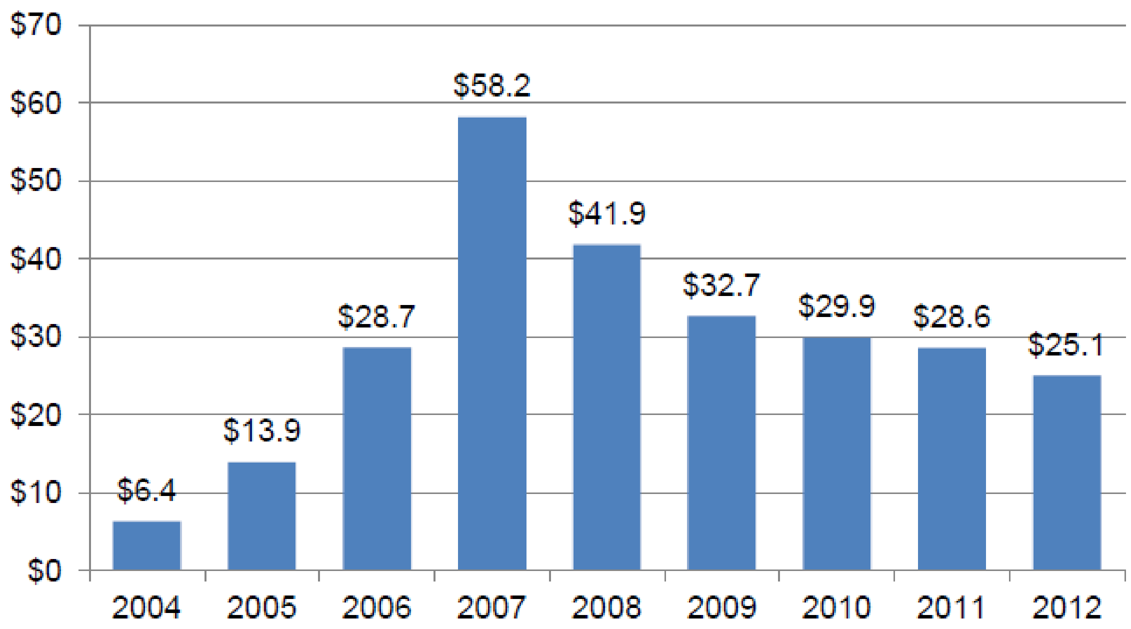

Figure 2. Annual Outstanding CDS Notional Amounts (trillion USD). (ISDA 2013.)

Even though the CDS market has decreased in terms of notional amounts from 2007 through 2012 and is likely to do so in the future one should note that the decline in outstanding notional amounts is mostly due to early termination of existing contracts, i.e. trade tear-up or portfolio compression. In such a case the two counterparties essentially replace the existing contracts with fewer new contracts that are still associated with the same risk and cash flows as the original trades but account for smaller notional amounts. The past declines in outstanding notional amount are mostly due to portfolio compression as ISDA reports that the trade tear-ups have accounted for a decrease of 85.7 trillion USD in outstanding notional amount from 2008 through 2012, while the amount in 2008 alone was 32.2 trillion USD. Therefore, the outstanding notional amount does not clearly depict the developments of the CDS market and a more proper measure as provided by Depository Trust and Clearing Corporation (DTCC) would be the trading activity of new market risk exposures (market risk transaction activity). (ISDA 2013.)

In fact, ISDA (2013) reports that the notional amount of new CDS transactions had increased in 2013 while the number of new market risk transactions had risen by 8 % and 5 % in 2012 and 2013 respectively. Interestingly, the single name CDS market had decreased over the 2011 – 2013 period by both the gross notional amount of new transactions as well as the amount of trades, while CDS indices had seen stable growth in both measures during the period. Moreover, ISDA reports that in addition to the decrease in the notional amounts, also the average notional amount of single name CDS contracts had fallen from 7.0 million USD in 2011 to 5.8 million USD in 2013. (ISDA 2013: 1- 7.)

2.4.1. The anatomy of the CDS market

In recent years several studies regarding the CDS market structure have been published to further extend the relatively limited information on the credit default swap market and its effects. For example, Ohmke & Zawadowski (2013) unfold the role of the US CDS market as a place for hedging and speculative trading, Peltonen, Scheicher & Vuillemey (2013) analyse the network structure of the CDS market and reveal the heterogeneity of the market participants across different reference entities, Saretto & Tookes (2012) show that companies whose credit risk is traded in the CDS market have longer debt maturities as well as a higher leverage ratio, and Chen et al. (2011) find that the average reference entity in the CDS market is traded only once a day, while many contracts follow a standardized custom.

Chen, Fleming, Jackson, Li and Sarkar (2011) studied CDS transaction data from 2010. They find that multi-name CDS trading is more frequent than single-name CDS trading, as the most traded CDS indices were traded over 100 times a day whilst on average a single-name CDS contract was traded once a day. However, they also note that during their sample most traded contracts were traded over 20 times a day, while the most frequently traded reference entity varied, implying that market demand is driven by economic events. Moreover, Chen et al. (2011) discover that the average size of a single-name CDS trade was €5 million, whilst the trades on indices averaged a trade value of €25 million.

Oehmke & Zawadowski (2013) analysed the composition of the US CDS market. Their study covers the October 2008 – December 2012 period, while their sample averages a gross notional amount of $ 13.02 billion and a net notional amount of $ 1.029 billion over the sample period. Overall, they find that the amount of outstanding debt has a positive relationship with the CDS net notional amounts, so that larger debt volume leads to larger CDS market for said reference entity. Likewise, other proxies for insurable interest have a similar relation with the outstanding net notional amount. For example, counterparty risk associated with buying credit enhancement from another market participant is suggested to be the main reason for the high amounts of CDS protection bought on companies providing credit enhancement services. Oehmke et al. (2013) suggest that these findings reflect the credit default swaps' role as a hedge against the investors' positions in the cash market as well as counterparty risk. In addition to hedging bond positions, the CDS market is also found to be a market for speculative trading. This is found to be most prominently represented by large net positions in the CDSs of reference entities on which the investors have conflicting views, e.g. on earnings prospects. Thus speculative trading is also suggested to increase the size of the CDS market. (Oehmke & Zawadowski 2013; 2 – 5, 13 – 15.)

Interestingly, the authors find evidence of arbitrage trades, as reference entities with a negative CDS basis have also large net notional amount of outstanding CDS. More precisely, the arbitrage trading is evident only in the case of negative CDS basis, as positive basis credit default swaps have lower net notional amounts. Oehmke et al. (2013) suggest that the asymmetric relation is due to constraints against shorting in the bond market, which makes benefiting from a positive basis trade harder for investors. On the other hand, taking a short position on the credit exposure in the CDS market is easier and thus allows arbitrageurs to benefit from the negative basis trade.

Moreover, Oehmke et al. (2013) suggest that the CDS market has standardization role, meaning that the relatively standardized CDS contracts offer more liquid as well as less costly market for trading credit risk than the bond market for reference entities with fragmented bond issues. They argue that a highly fragmented bond market on said reference entities results in large trading costs and more illiquid bond market and show that reference entities with highly fragmented bond issues have a large CDS market, i.e. outstanding net notional amount. Therefore, Oehmke et al. suggest that CDS market is an alternative market for trading credit risk, especially for the credit risk associated with fragmented bond issues. (Oehmke et al. 2013: 16 – 19.)

Peltonen, Scheicher & Vuillemey (2013) studied the structure of the CDS market and which factors affect the size of the market. They analyse transaction data of market participants from 30 December 2011 covering CDS contracts of 642 reference entities, 602 financial entities and 40 sovereigns. Their sample totals a gross notional amount of € 4.28 trillion and accounts for 32.7 percent of the single-name CDS market at that time. From their data they form an aggregate CDS network, which they find to have a net notional amount of € 349 billion, while on average market participants trade 18.7 reference entities and do business with an average of 9.6 other market participants. In addition, the average transaction is valued at a notional amount of € 7.2 million. (Peltonen, Scheicher & Vuillemey 2013: 6, 10 – 11.)

Interestingly, the average notional amounts are found to differ between sub-networks as for example the sovereign CDS contracts have an average notional amount of € 11.6 million, whereas the financial network's corresponding value is € 5.7 million. Similarly, Peltonen et al. (2013) discover that the average notional amount is larger for European reference entities than it is for non-European entities, while the more active and larger high debt volume CDS market also has higher average notional amount than the low debt volume market. Furthermore, they find that the majority of the participants trade with only a few other institutions and that this holds even though there are several different reference entities on which the participants have exposure on.

They suggest that the CDS market is dominated by small amount of traders as they find that 73 percent of the gross sales of credit default swaps are done by the ten most active market participants. Furthermore, most of the traders (72 %) buy more CDS contracts than they sell, thus leaving the role of the net protection seller to the few larger participants. In fact, Peltonen et al. (2013) discover that half of the ten institutions that dominate the CDS market in trading activity are net protection sellers, whereas the participants with lower trading activity are more often net protection buyers.

Interestingly, the share of net protection sellers on sovereign reference entities is found to be distinctly smaller than on average (10 % vs. 18%). However, the share of net protection sellers does not vary largely between other types of reference assets or their features. Still, Peltonen et al. (2013) suggest that the credit risk exposure is more concentrated in less risky market sections as for example the share of net CDS sellers is larger for high CDS spread contracts (over 300 bps) than it is for low spread contracts (18% and 13% respectively). (Peltonen et al. 2013: 11, 15.)

Furthermore, Peltonen et al. (2013) find that the level of outstanding debt (bond volume) by the reference entity affects the size and trading activity of the credit derivatives market, as high outstanding debt amount increases both the size and the activity of the market for a particular reference entity. Moreover, they imply that this relationship between outstanding bonds and market activity is a proof of CDS being used as a credit risk hedge. Bond maturities are also found to have a negative effect on the market size and activity, as for example short-term debt is associated with larger CDS market size than long-term debt.

Oehmke et al. (2013) and Peltonen et al. (2013). showed that the CDS market is essentially used to hedge the credit risk of bond issuers and at the same time acts as another market for credit risk exposure. Still, despite providing an alternative credit risk market Ashcraft and Santos (2009) find that the CDS market has not had an economically significant effect on the cost of debt financing of corporate entities. Moreover, the reference entities that were found to benefit from CDS trading were the less risky ones that were already considered as a safe investment. On contrary to the results of Ashcraft et al. (2009), Saretto and Tookes (2012) discovered that the CDS market has had an increasing effect on corporate leverage ratios and debt maturities. More precisely, the debt maturities increased by up to 1.80 years and the leverage ratios by up to 22 percent as a result of CDS trading. Moreover, the CDS market is found to affect these measures the most during times of financial distress, i.e. when the supply of credit is limited.

Another interesting implication of the introduction of the CDS market is its effect on the efficiency of the corporate and sovereign bond markets. Das, Kalimipalli and Nayak (2014) present that the corporate bond market has not improved in terms of liquidity or amount of mispricing during the 2002 – 2008 period. More precisely, they detect that the average trade size in the bond market decreases two years in succession to the beginning of CDS trading, while also the pricing errors in the market widen and the market liquidity drops. On the contrary, the sovereign bond market efficiency has improved after the start of CDS trading as is shown by Ismailescu & Phillips (2011). They suggest that especially high risk sovereign bonds have benefited from the CDS trading as the adjustment time of pricing errors has decreased, while the effects are smaller on lower risk sovereign bonds. In addition, the cost of borrowing has decreased in the case of low risk sovereigns and increased for high risk countries. Even though, the high risk sovereigns do not benefit from the higher costs, the authors suggest that the sovereign bond market as a whole does, since the credit risk pricing of such countries is hindered less by pricing errors.

3. LITERATURE REVIEW

This chapter provides a review of the main studies on the equilibrium relation and the price discovery process between the CDS and bond markets from time periods before and after the financial crisis in 2007.

3.1. The pre-crisis period

Blanco, Brennan and Marsh (2005) study the relation between bonds and credit default swaps. They cover daily data for thirty-three investment-grade companies from the United States and Europe over January 2001 – June 2002 period, while focusing on CDS contracts with maturities of 5 years. German and U.S. government bonds are used as a reference rate to proxy risk-free interest rate for European and U.S. entities respectively, while 5-year swap rates for euros and dollars are used as an alternative reference rate. First they investigate the pricing of credit risk comparing the bond spreads with CDS spreads to determine the existence of the equilibrium relation. Then, the equilibrium relation is analysed by testing for cointegration and finally, they analyse the lead-lag relation (price discovery) between the two spreads. (Blanco et al. 2005: 2260 – 2261, 2262 – 2263, 2268, 2273.)

Their findings suggest that the theoretical equilibrium relation between CDS and bond prices holds for most sample firms. They discover that the average CDS basis is positive during the sample period and a decline in credit quality results in a rise of the average absolute basis. For example the average absolute basis (that measures the mispricing in absolute terms) of AAA – AA rated entities over swaps is 11.6 basis points (bps), rising to 13.0 bps for firms rated as A and 22.5 bps for B-rated companies. The average CDS basis for the same sub-groups is 6.9 bps, 0.5 bps and 17.9 bps. Also, U.S. firms have a lower average absolute basis than the European entities, as the average absolute basis over swaps for U.S. firms was over 6 bps lower than the one for European companies, which leads the authors to suggest that equilibrium relation is more evident for the U.S. entities. This finding is confirmed as they discover that a cointegration relation between the bond and the CDS market exists on all 16 U.S. entities, whereas evidence of cointegration for European firms was found for 10 out of 17 companies. They suggest that the European entities, on which the long-term equilibrium relation fails because of significantly positive average basis, are affected by cheapest-to-deliver options, which raise the maximum true price of credit risk and therefore CDS prices. (Blanco et al. 2005: 2265, 2268, 2278 – 2279.)

In the short-term analysis, Blanco et al. (2005) discover that on average the credit default swap market leads the bond market in price discovery on most of the 27 sample entities on which a cointegration relation was detected (including one of the rejected European companies with a shorter examination period). Evidence of the bond market contributing to price discovery is found on eight firms, whereas contribution from the CDS market is detected for 25 of the 27 firms. They also discover that on five entities on which both markets play a role in the price discovery, the credit default swap market leads the process. More precisely, on average 79 % of the price discovery happens in the derivatives market. Thus, the bond spreads adjust to the deviations in the equilibrium relation to correct the mispricing. Similarly, evidence of the CDS market Granger-causing the bond spreads is found on 6 of the European entities for which cointegration relation was not detected, whilst causality does not exist for the rest of the firms. They suggest that the credit default swap market leads the price discovery because of structural factors, such as the possibility of taking larger positions in CDS contracts than on the bond market, that make trading more convenient on the derivatives market. Different roles of the two markets are also suggested as a factor, as they argue that the bond market is used for trading bond credit risk, whereas the derivatives market is used for trading credit risk. (Blanco et al. 2005: 2271, 2274 – 2279.)

Zhu (2006) investigates the equilibrium relation over January 1999 – December 2002 period, covering 24 investment-grade corporate entities from the United States, Europe and Asia denominated in either U.S. dollars or euros. Treasury rates as well as dollar and euro swap rates are used to proxy the risk-free interest rate, while the study is restricted to credit default swap contracts with maturities of 5 years. Zhu (2006) analyses the price discrepancies between the two markets, while conducting tests on the long- and short-term relationships between the two spreads. (Zhu 2006: 211, 216 – 228.)

In line with findings from Blanco et al. (2005) Zhu discovers that the average basis spread over swap rates is positive (13.25 basis points) for the whole examination period and finds evidence on the equilibrium relation holding in the long run, as cointegration of the two spreads is detected on 14 of 24 sample entities. In addition, some evidence of cointegration is found for 9 other entities with a less restricted test, so that for most of the entities the existence of the parity relation is confirmed. Thus, the two spreads should be priced equally for most entities in the long run. (Zhu 2006: 217 – 223, 228.)

Zhu (2006) suggests that in the short run the CDS market leads the bond market in price discovery, finding 17 entities on which the CDS spreads lead the price discovery, while on 7 entities the bond spreads dominate the process. Both markets are found contributing for only 2 firms, so that the price discovery is a one-sided process for the rest of the entities. On average the CDS market leads the bond market in price discovery, contributing to 64 % of the process, whereas the role of the bond market is greater on non-U.S. entities on which bond spreads dominate the CDS spreads in price discovery (60 %). In comparison, the role of the CDS market is strongest for the U.S. firms (71 %). Zhu (2006) suggest that the leading role of the CDS market is due to fewer restrictions, i.e. short-selling and funding, in the derivatives market. (Zhu 2006: 229 – 234.)

A study by Norden and Weber (2009) covers monthly, weekly and daily time series data of 58 European, U.S. and Asian corporate entities from 2000 to 2002. Their data spans a wider range of entities, while focusing on European companies (35 of 58 sample firms). As in the studies by Blanco et al. (2005) and Zhu (2006) government bonds and swap rates for euro, dollar and pound sterling are used as a proxy for the risk-free interest rate, in addition to a synthetic Euro yield curve. Norden et al. (2009) conduct analysis on the equilibrium relation between CDS and bond spreads as well as on the lead-lag relationship between the stock, CDS and bond markets. (Norden & Weber 2009: 529 – 534.)

Norden et al. (2009) suggest that the long-term equilibrium relation holds for most of the entities, while the credit default swap market leads the price discovery on most entities. In addition the stock market leads both spreads. More precisely, they find that a cointegration relationship between the spreads exists on 15 of 20 U.S. entities, whereas 20 of 35 European entities and 1 of 3 Asian firms have a significant cointegration relationship. Credit default swap market is the only contributor in price discovery on 19 of 26 of the cointegrated entities, while contribution from both markets and solely from the bond market is detected on 8 entities in both cases. For all entities, the CDS spreads contribute to 69 % of the price discovery on average so that the bond spreads adjust to the mispricing of credit risk. More specifically, the CDS market dominates price discovery on U.S. entities (84 %), whereas both markets contribute to the price discovery on European firms. In addition, they state that role of the CDS market in price discovery has grown from 2000 to 2002 as the bond market leads the price discovery for the whole sample in the first half of the examination period, while the derivatives market has the leading role in the second half. This is, to some extent, also shown in the average basis as it was relatively close to zero during 2000 (-2 bps) and the first half of 2001 (9 bps), while during the rest of the sample period the CDS spreads were priced substantially higher than the bond spreads and thus, resulted to a high positive basis of 34 bps. (Norden et al. 2009: 534 – 538, 541 – 546, 550 – 555.)

Chan-Lau and Kim (2004) conduct a study on the equilibrium relation and price discovery between equity prices and CDS and bond spreads for 8 emerging market sovereign entities, including Brazil, Bulgaria, Colombia, Mexico, the Philippines, Russia, Turkey and Venezuela. They cover daily data from March 2001 to May 2003 for 5-year CDS contracts and use the JP Morgan Chase Emerging Market Bond Index Plus (EMBI+) index to benchmark the bond spreads. Similarly, equity values are benchmarked with the Morgan Stanley Capital Equity Price Indices (MSCI). They find evidence supporting the CDS – bond market equilibrium relation, whereas results for the price discovery are mixed. (Chan-Lau & Kim 2004: 10, 24.)

Chan-Lau et al. (2004) discover that a cointegration relation between the CDS and bond markets exists on 5 of the 8 entities, whereas evidence of cointegration between equity prices and either of the two spreads is found only for two entities. In addition, they find that both credit risk markets play a role in the price discovery as results vary between the entities. The only finding that applies for most of the entities suggests that the CDS market leads the bond market with 1-day lagged values. In addition, the equity market contributes to the price discovery for only two countries. Chan-Lau et al. (2004) suggest that the absent equilibrium relation between the equity and bond markets is due to low and volatile debt to asset values of the emerging market countries, whereas for the mixed findings on the price discovery they argue that the CDS contracts of the emerging market entities are mainly used by banks as long-period holdings to hedge their bond positions thereby resulting in a less liquid CDS market. (Chan-Lau et al. 2004: 17 – 24.)

Ammer and Cai (2011) investigate the relationship between the credit default swap and bond spreads of 9 emerging market sovereign entities during the February 2001 – March 2005 period. They concentrate on daily data of 5-year contracts denominated in U.S. dollars and benchmark the risk-free interest rate with the dollar swap rate. They detect a positive average CDS basis for all entities, with the lowest average CDS basis of 14 basis points for China and the highest average basis of 313 basis points for Venezuela forming a highly varied range of basis observations. (Ammer & Cai 2011: 375 – 378.)

In their analysis on the long-term equilibrium relation, Ammer et al. (2011) find evidence of cointegration for all but two entities that are Russia and Venezuela. In addition, they detect that bond and CDS spreads do not move in equal proportions and suggest this is partly due to cheapest-to-deliver options included in the emerging market CDS contracts. More precisely, on 6 of the 7 cointegrated entities, the bond spreads move in smaller proportions than the CDS spread. As for the lead-lag relation, they suggest that both markets contribute to the price discovery and together adjust to changes in the long-term equilibrium with a pace of 5 to 13 per cent a day. Still, the CDS market slightly leads the bond market in price discovery on average, as the contribution of the bond market is substantially higher for only 3 entities, whilst CDS spreads contribute more for the remaining 5 entities. As their findings regarding the rather small leading role of the CDS market are, at least to some extent, contrary to the ones from the corporate markets, they argue that the possible presence of CTD options lead to more illiquid emerging market CDS contracts and thereby decrease the role of the CDS market in the price discovery. (Ammer et al 2011: 378 – 383, 385 – 386.)

De Wit (2006) studies the long-term equilibrium relation on daily data of 92 firms and 11 emerging market countries from January 2004 through December 2005. The included 114 3-year, 5-year and 10-year CDS contracts are denominated in either euros or dollars, while the euro denominated contracts are a majority in the sample. In addition, euro and dollar swap rates are used as the risk-free interest rate benchmark. De Wit (2006) detects an average basis of 16.3 basis points for the whole sample, while the corresponding value for corporate entities is 9.9 basis points. In addition he also discovers that entities with high and low credit rating have a higher average basis (21.6 and 74.5 bps) than issuers with credit ratings between the two extremes (6.6 bps), while corporate entities have lower average CDS basis than the emerging market countries. Furthermore, the average CDS basis for euro denominated contracts is substantially lower than the average basis of dollar denominated credits, whereas the mispricing on 10-year contracts (35.8 bps) is greater than on 5- and 3-year contracts, 14.1 and 16.9 bps respectively. (De Wit 2006: 13 – 19.)

De Wit (2006) detects cointegration relation in 87 of the total 114 spread-pairs. Furthermore, the relation exists more frequently on the dollar denominated spreads than on the euro counterparts. Thus, De Wit (2006) suggests that the dollar denominated corporate bond market is more liquid than the euro market. However, he states that the assumed liquidity of the 5-year maturities does not lead to more evidence on the long-term equilibrium as cointegration is detected more often for contracts with 3- and 10-year maturities. Also, the equilibrium relation is more common on investment-grade entities than on speculative grade entities. Overall, De Wit finds supporting evidence on the existence of the long-term equilibrium relation between the CDS and bond spreads, even though in some cases the mispricing of credit risk seems to be ever-present. (De Wit 2006: 21 – 23.)

Aktug, Vasconcellos and Bae (2012) analyse monthly data of 30 emerging market sovereign entities over the January 2001 – November 2007 period. In contrary to the study of Chan-Lau et al. (2004), they benchmark the bond yields with the EMBIG index instead of EMBI+ index. They detect a long-term equilibrium relation on 16 of 30 countries and suggest that the efficiency of the emerging credit market has increased, as they find cointegration for 6 (instead of 5) of the 8 countries that Chan-Lau et al. (2004) analysed in their study. Aktug et al. (2012) find evidence of the bond market leading the price discovery in 10 of the 16 sovereign entities, while the CDS market contributes more in the rest of the countries, which is in contrast with the study by Ammer et al. (2011). Similarly, their results imply that the adjustment process for the cointegrated markets is faster than in the aforementioned study. (Aktug, Vasconcellos & Bae 2012.)

Li and Huang (2011) study 22 emerging market sovereign entities from January 2004 to July 2008. They find cointegration between the CDS and credit spreads for 20 entities, while Chile and South Africa are excluded from further analysis. In their short-term analysis they discover that only Egypt and Venezuela had a two-way price discovery process, while a one-way relationship is found for 8 entities leaving 10 entities for which a process of any kind does not exist. Moreover, in 5 of the 8 one-sided relationships the CDS market is found to adjust in the price changes of the bond market, whilst in 3 cases the bond market adjusts to the changes in the CDS market.

Overall, the studies show that the long-term equilibrium relation between credit default swap and bond spreads holds for most corporate and emerging market entities during the 2001 – 2007 period. Interestingly the studies on corporate entities have shown that the relation is most often detected for U.S. entities, while on some European firms the credit risk is not priced equally in the long run. Still, on average the credit risk is priced somewhat equally for the corporate sector in both markets. Similarly, the long-term relation holds for most emerging market countries, but a longer examination period and wider range of entities show that the pricing of credit risk in the bond market differs from the pricing in CDS market for almost as many countries as it is equal for.

The findings on the price discovery seem to follow the same path as the ones for the long-term equilibrium relation. The U.S. corporate CDS market dominates the bond spreads in price discovery, while findings between studies are mixed for European entities. Thus, the price discovery seems to be a two-sided process for the European firms. Similar results are also found for the emerging market sovereign entities as the price discovery is somewhat country specific and on average results to a two-sided process.

3.2. The crisis period

Fontana and Scheicher (2010) study daily and weekly data of 10 European sovereign entities during the January 2006 – June 2010 period, while the sample is delimited to contracts denominated in U.S. dollars with maturities of 10 years. Also, the 10-year dollar swap rate is used as a reference rate for the risk-free interest rate. Fontana et al. (2010) analyse two sub-periods, 1 January 2006 – 12 September 2008 (period 1) and 15 September 2008 – 28 June 2010 (period 2), as the collapse of Lehman Brothers in September 2008 divides the two periods. They discover that the findings on the equilibrium relation and price discovery differ between the two sub-periods. The average CDS basis is substantially greater after the collapse, evidence of cointegration is detected only during the latter period and the price discovery is suggested to be country-related as CDS and bond markets both play a contributing role on different entities. (Fontana et al. 2010: 10 – 14, 20 – 21.)

First, they find that on average the CDS basis was positive during both sub-periods, remained stable in the first period (20 – 30 bps), but experienced higher values (40 – 70 bps) as well as volatilities after September 2008. During the first sub-period the average CDS spreads were relatively close to zero, whereas most bond spreads were, in fact, negative as the dollar swap rate was higher than the government bond yields. During period 2, most bond spreads, with the exception of German and French spreads, rose to positive values on average. Similarly, the average CDS spreads increased significantly, which lead to a rise in average CDS basis. Fontana et al. (2010) discover two substantial peaks in the CDS bases, first in the late 2008 – early 2009 period and second in spring 2010. They suggest that during the former peak increasing liquidity risk drove bond prices down and CDS spreads up. Similarly, fiscal concerns are suggested to have an effect on the upward movements of the CDS spreads. All in all, 7 out of 10 entities had a positive CDS basis during the whole sample period, while the bond spreads of Greece, Portugal and Ireland were higher than the CDS spreads on a few occasions. (Fontana et al. 2010: 10 – 14, 33 – 35.)

Fontana et al. (2010) do not detect either cointegration or lead-lag relation between the CDS and bond spreads before the collapse of Lehman Brothers. However, during the second sub-period, the spreads of all entities are cointegrated and mixed results are found on the lead-lag relation. More precisely, on half of the entities the bond market leads price discovery, while the CDS market leads the price discovery in the rest of the cases. In all cases, one market has a clear leading role, whereas the other market does not contribute to the price discovery significantly. For example, the bond market solely leads the price discovery for France, Germany, Austria, the Netherlands and Belgium, while the credit risk is mainly priced in the CDS market for Greece, Ireland, Spain, Portugal and Italy. (Fontana et al. 2010: 20 – 21.)

A study by Delis and Mylonidis (2011) concentrates on four European sovereign entities, Greece, Italy, Portugal and Spain, and analyses the causality between their 10-year bond and CDS spreads, as the sample spans the July 2004 – May 2010 period. Also, the German government bond is used a proxy for the risk-free interest rate. Their findings are consistent with the study of Fontana et al. (2010) as Delis et al. (2011) discover that CDS spreads cause the bond spreads for all of the four entities. More precisely, CDS spreads lead the process from 2007 onwards on all entities, whereas the bond market only contributes during shorter periods. Peaks in the contribution of the bond market are found during the financial crisis (2007–2008) as well as the debt crisis (late 2009 onwards). Also, the contribution of the CDS market to the price discovery decreases during the aforementioned peaks. Therefore, Delis et al. (2011) suggest that during the crises the role of the CDS market decreases as market participants turn to the bond market, especially the German government bonds, to avoid the increasing risks. (Delis & Mylonidis 2011: 163 – 170.)

Coudert and Gex (2011) study the 5-year spreads of 35 sovereign and financial entities from January 2007 to March 2010. Their reference entities consist of 18 European and emerging market countries as well as 17 European and U.S. financial institutions. Government bond yields of Germany, the U.K. and the U.S. are used to proxy the risk-free interest rate. They find evidence of cointegration between the CDS and bond spreads, which suggests that the long-term equilibrium relation is existent. When testing for the leader in price discovery, they detect that CDS spreads lead the bond market for the financial institutions, whereas on the country subset neither spread clearly leads the other. However, in a more specific analysis they discover that bond spreads lead the CDS prices for low-risk European countries. In contrasts, the derivatives market leads price discovery for the emerging market sovereigns, while the credit risk of riskier European countries is priced in both markets. In addition, Coudert et al. (2011) find that during the financial crisis, from September 2008 onwards, the leading role of the derivatives market increases for the financial institutions. Similar effect is found also on the whole sample, even though for sovereigns no significant signs of a growing or decreasing role are discovered on either spread. (Coudert et al. 2011: 8 – 10, 12 – 17.)

Alper, Forni and Gerard (2012) investigate the relationship between credit default swap and bond spreads of 18 advanced sovereign entities. Their time series data spans from January 2008 to January 2011, thus covering the effects of the financial crisis. The data consists of 5-year CDS contracts and yields of 10-year government bonds, while the 10-year interest rate swap rates are a proxy for the risk-free interest rate. They detect cointegration in 14 of the 18 spreads analysed and evidently the strongest evidence is found for countries such as Ireland, Greece and Spain, while for France, Germany, Sweden and Portugal no cointegration was detected. Alper et al. (2012) discover that overall; the bond market adjusts to correct any deviations in the long-term equilibrium, thereby implying a leading role of the CDS spreads in price discovery. More precisely, no evidence that suggests the bond spreads solely leading the price discovery is found. In addition, they note that the adjustment process of the bond spreads is slow and thus leads to an adjustment period of 1 to 2 months. In general, Alper et al. (2012) state that during the financial crisis the equilibrium relation is strongest for the high-risk European counties, whereas for the lower risk countries they do not detect an equilibrium relation. (Alper, Forni & Gerard 2012: 5 – 6, 7 – 9, 16 – 20.)

Arce, Mayordomo and Peña (2012) analyse the effects of the Euro area crisis on 11 European sovereign entities and cover daily data of 5-year contracts from January 2004 through October 2011. They report a positive average CDS basis for most of the countries and detect rather low and stable average spreads and CDS bases from 2004 to 2008. During the rest of the examination period they find substantial growth in the average spreads and volatilities. In addition, they detect that CDS prices were persistently higher than the bond spreads after the collapse of Lehman Brothers in September 2008. (Arce, Mayordomo & Peña 2012: 8 – 9, 13, 25.)

Arce et al. (2012) detect cointegration in 64 per cent of the analysed spread-pairs and suggest that the derivatives market led the price discovery during the 2004 – 2008 period. From September 2008 onwards they discover that on average the role of the bond market increased and resulted to a rather equal contribution of both spreads during 2009–2010. In addition, they find that the bond market was the sole contributor to price discovery in late 2011. Differences in magnitudes of the role changes between different subsets were observed, as Arce et al. (2012) report that bond spreads led the price discovery for core EMU countries during 2009 – 2010, whereas for the peripheral entities the derivatives market still was the main contributor. Also, in late 2011 the bond market had a stronger role for the peripheral countries than for the core nations, while still leading the price discovery on both subsets. Overall, they suggest that the price discovery happens in different markets for each subset of countries. (Arce et al. 2012: 20 – 22, 25 – 26).

The financial crisis has clearly affected the relationship between CDS and bond spreads of European sovereign entities as Fontana et al. (2010) show that the equilibrium relation was non-existent before the start of the crisis in 2008 and confirm its existence during the crisis period. The studies show that the price discovery process is country specific and seems to be related to the county's credit rating and economic situation as CDS spreads are detected to mainly lead the price discovery on emerging market countries and high-risk European sovereigns, more precisely Portugal, Spain, Ireland, Italy and Greece. The credit risk of low-risk or core Euro-countries is mainly priced in the bond market. However, some deviations in the price discovery process are detected during the crisis and especially the role of the bond market has grown. This is the case mainly for the high-risk countries, as studies from Delis et al. (2011) and Arce et al. (2012) show that the role of CDS market decreases during the crisis period, as the bond market takes the leading role in late 2011. Interestingly and contrary to these studies, Coudert et al. (2011) detect that the leading role of the CDS market strengthens during the crisis for financial corporations, while neither market takes the clear leading role for the high-risk European countries.

4. METHODOLOGY

The existence of the long-term equilibrium relation is investigated by testing the two theoretically interrelated markets for cointegration so that the basis is stationary in the long run, while the two spreads are first-difference stationary (Engle & Granger 1987: 275, Blanco et al. 2006: 2267, Zhu 2005: 216). A vector error correction model is then used to determine the speed of adjustments to deviations in the long-term equilibrium for the cointegrated spreads to analyse the lead-lag relation. A measure by Gonzalo and Granger (1995) is then calculated from the adjustment coefficients to discover which market leads the price discovery process. In addition, the causality relation is also analysed for spread-pairs that are not cointegrated by testing for Granger-causality (Blanco et al. 2005: 2271).

The structure of the chapter from now on is following; first the methods for calculating the CDS basis are presented. Secondly, cointegration is defined more closely, the eligibility of time series for cointegration tests is determined and Johansen's cointegration method is introduced. Then the error correction model and its coefficients are discussed in the context of the study, which is followed by Granger causality test.

4.1. Methods for calculating the CDS basis

The analysis of the equilibrium relation between CDS spreads and bond spreads requires that the two spreads have the same maturity. This is a problem, since the CDS spreads used in the study have a constant maturity of 5 years, whereas the maturity of bond contracts is not fixed. Thus, it is required that a synthetic 5-year bond spread is formed in order to calculate the CDS basis. Two methods, suggested by Houweling et al. (2005), of creating a synthetic 5-year bond spread are used in the previous literature.

The first method uses linear interpolation to form the synthetic 5-year bond. The interpolation method requires two bonds of which one has maturity less than 5 years and the second has maturity longer than 5 years. Houweling et al. (2007: 1214) suggest that the maturities of the two bonds should be at most twice as long as the constant maturity of the CDS contract and at most twice as short as the constant CDS maturity. Thereby, the 5-year bond spread is interpolated from two bond yields that meet the requirements with equation 8, where $yield_{long,t}$ and $yield_{short,t}$ are the yields of the long and short bond contracts at time t and $M_{long,t}$ and $M_{short,t}$ are the maturities of the long and short bond contracts at time t expressed in years.

(8) $$\text{Yield}_{5-\text{year},t} = \text{yield}_{\text{long},t} * \frac{5-M_{\text{short},t}}{M_{\text{long},t}-M_{\text{short},t}} + \text{yield}_{\text{short}} * \frac{M_{\text{long},t}-5}{M_{\text{long},t}-M_{\text{short},t}}$$

The second method suggested by Houweling et al. (2007: 1214) is the matching method. The matching method uses the best available bond contract to depict the constant 5-year bond yield, so that the maturity of the proxy-bond is relatively close to the 5-year constant maturity. More precisely, Houweling et al. (2007) suggest that the maturity of the proxy should not differ by more than 10 per cent of the 5-year constant maturity. Following the studies of Blanco et al. (2005) and Zhu (2006), the interpolation method is preferred in this thesis whenever the appropriate bond contracts are available.

CDS basis is the difference between the CDS spread and the credit spread. Credit spread is the bond spread over the risk-free rate, as determined in chapter 2. In the study, the credit spread is calculated as the difference between the synthetic 5-year bond spread and the 5-year swap rate and is then used to form the basis by subtracting it from the CDS spread. This calculation is presented in equation 6.

(9) $$\text{basis}_t = \text{cds}_t - (\text{bond}_t - \text{rf}_t)$$

The choice of proxy for the risk-free rate is shown to affect the CDS basis greatly in empirical comparison of credit risk pricing. Houweling and Vorst (2005: 1214 – 1217) show that interest rate swaps and general collateral repo rates measure the risk-free interest rate more accurately than government bond yields when they compare the CDS basis values calculated with these different proxies of risk-free rate. They find that the average basis is relatively close to zero over swap and repo-rates, whereas it substantially differs from zero over government bonds and thus does not follow the no-arbitrage argument. Therefore, following the findings of Howeling et al. (2005) the swap rates are chosen to be used as the proxy for risk free rate.

As suggested by the no-arbitrage relation CDS basis should equal to zero. This relation can be further analysed by calculating the average basis (AB) and the average absolute basis (AAB) that depict the relationship between the CDS spread and the credit spread during the examination period. Moreover, the values portray the stability of the basis.

(10) $$\text{AB} = \frac{1}{N}\sum_{t=1}^{N} basis_t$$

(11) $$\text{AAB} = \frac{1}{N}\sum_{t=1}^{N} |basis_t|$$

A simple T-test is used to test whether the average basis equals zero with the following hypotheses:

H_0 : AB = 0, the average CDS basis equals zero

H_1 : AB $\neq$ 0, the average CDS basis does not equal zero

4.2. Cointegration and unit root tests

Two time-series are considered to be cointegrated, when both of the series are non-stationary and become stationary when first differenced, that is the series are I(1)-processes, and a stationary linear combination of the two time series exists. Consider first-difference stationary time series $y_t \sim I(1)$ and $x_t \sim I(1)$, for which exists a vector β so that the linear combination of y_t and x_t is stationary, i.e. $\varepsilon_t = y_t - \beta x_t \sim I(0)$, where ε_t is the deviation from long-term equilibrium. In such a case, the time series y_t and x_t are cointegrated, CI(1,1), that is they have a long-run equilibrium relation. (Gujarati 2004: 804 – 806, Enders 2009: 357 – 360, 365 – 371).

4.2.1. Augmented Dickey-Fuller test

As mentioned before, the time series have to be first-difference stationary to be eligible for cointegration analysis, that is they have a unit root. The augmented Dickey-Fuller (ADF) test is used to test the series for a unit root. It is an extension to the Dickey-Fuller (DF) test and allows testing for unit roots when the error terms are correlated. It attacks the problem of autocorrelation in the error term by introducing lagged difference terms in the regression. The augmented Dickey-Fuller test regression is presented in equation 12. (Gujarati 2004: 815 – 818.)

(12) $$\Delta y_t = \beta_0 + \beta_1 t + \delta y_{t-1} + \sum_{i=1}^{m} \alpha_t \Delta y_{t-i} + \varepsilon_t$$

where Δy_t is the first difference of series y_t, ε_t is white noise error term, i is the number of lagged first-difference terms α_t Δy_{t-i} that result in ε_t being stationary and serially uncorrelated. β_0 and $\beta_1 t$ are optional constant and linear time trend terms, respectively.

The augmented Dickey-Fuller tests the null hypothesis of the time series is non-stationary ($\delta = 0$) against the alternative hypothesis of the time series is stationary ($\delta < 0$). Thus, in a case where δ does not significantly differ from zero (the test statistic is less than the critical value in absolute terms), the null hypothesis is accepted, meaning that the time series is non-stationary. The test is then repeated for the first-differenced series for which the rejection of null hypothesis means that the first-differenced series is stationary and the original series is an I(1)-process. Alternatively, if δ is significant and less than zero for the original time series, the null hypothesis is rejected and the series is stationary, I(0). (Gujarati 2004: 815 – 818.)

H_0 : $\delta = 0$, the time series has a unit root, i.e. is non-stationary

H_1 : $\delta < 0$, the time series does not have a unit root, i.e. is stationary

4.2.2. Johansen cointegration test

Engle and Granger (1987) introduced a method to determine whether two I(1) time series are cointegrated. The method is a two-step process, which first estimates the error terms of the ordinary least squares (OLS) regression expressed in equation 13, where time series y_t is regressed on the values of time series x_t. The second part of the method tests the estimated error term series ε_t for stationarity. The error term series depicts the deviations from the equilibrium relation, and thus if the series is stationary, the two I(1)-processes are cointegrated. Equation 14 is used to test for the null hypothesis: the error term is non-stationary ($\alpha_1 = 0$). Thereby, rejection of the null hypothesis suggests that the two time series are cointegrated of order (1,1). (Enders 2009: 373–374).

(13) $$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$$

(14) $$\Delta\varepsilon_t = \alpha_1 \varepsilon_{t-1} + \varepsilon_t$$

The Engle-Granger method possesses various deficiencies. First, one of the two time-series has to be used as the regressor of the other. Thereby, there is two possible ways to test for the cointegration, by using either y_t or x_t as the dependent variable. This is a problem with small sample sizes as the two different models can imply different results. That is, one model suggests that there is cointegration between the two series, while the second one does not. Such results are spurious since cointegration should not be dependent on the choice of the dependent variable. The second problem is related to the two-step structure of the test, as the possible errors that have occurred in the first step of estimating the error terms, will also appear in the second step of testing their stationarity. Thereby, the method by Johansen is preferred, since it does not suffer from such problems. (Enders 2009: 385–386).

The Johansen cointegration (1988) method uses maximum likelihood estimators to test the relationship between the rank of a matrix and the characteristic roots. In addition, it allows multiple cointegrating vectors as well as the testing for restricted forms of the cointegrating vectors. Consider the vector autoregressive model in equation 15 and its error correction form in equation 16. (Enders 2009: 386–389, Johansen 1995: 11).

(15) $$X_t = \Pi_1 X_{t-1} + \cdots + \Pi_k X_{t-k} + \Phi D_t + \varepsilon_t$$

where X_t is a vector consisting of *n* I(1) time series variables, Π_{t-k} are parameter matrices, *k* is the lag length, D_t is a possible constant or trend term and ε_t is the error term vector that contains *n* independent and identically distributed errors , has a zero mean and variance matrix $\Sigma\varepsilon$. (Enders 2009: 390, Johansen 1995: 11).

(16) $$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Phi D_{t-i} + \varepsilon_t$$

where $\Pi_1 X_{t-1}$ is the error correction term, $\Pi = \sum_{i=1}^{k} \Pi_i - I$, $\Gamma_i = -\sum_{j=i+1}^{k} \Pi_j$ and I is an identity matrix (Johansen 1995: 45).

Johansen cointegration test determines the rank (r) of the coefficient matrix Π, i.e. the number of independent cointegrating vectors or the number of characteristic roots that are not zero. In a case where the rank differs significantly from zero the two series are cointegrated. Similarly, if the rank is zero, no cointegration exists. Thereby, the variables are cointegrated by rank r if $1 \leq r \leq k$. Two tests, the trace test and maximum eigenvalue test, can be used to determine the rank of the coefficient matrix Π:

(17) $$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

(18) $$\lambda_{max}(r, r+1) = -T(1 - \hat{\lambda}_{r+1})$$

where $\hat{\lambda}_i$ are the estimated characteristic roots of matrix Π and T is the number of observations (Enders 2009: 390 – 391.)

Trace test (eq. 17) tests the null hypothesis that there is less than or exactly *r* number of cointegrating vectors against the alternative hypothesis that the number of cointegrating vectors is *n*. The maximum eigenvalue test (eq. 18) tests the null hypothesis that there is *r* cointegrating vectors against the alternative hypothesis that the number or cointegrating vectors is r + 1. This study incorporates the trace test to test for the cointegration of the two spreads (Enders 2009: 391.)

There are three possible outcomes in the two-variable setting of this study. First, if null hypothesis of rank(Π) = 0 is rejected and the alternative hypothesis of 1 ≤ rank(Π) < 2 is accepted, a cointegration relationship exists. Secondly, there is no cointegration if null hypothesis of rank(Π) = 0 is accepted and third, if the coefficient matrix is of full rank, that is the null hypothesis that rank(Π) = 2 is accepted, the two series are stationary and there exists no cointegration relationship (Enders 2009: 390). In the context of the study the ideal case would be so that the null hypothesis is rejected with r = 0, and accepted with r = 1, so that the two spreads are cointegrated.

As mentioned earlier the Johansen method allows the inclusion of restrictions in the coefficient matrix, i.e. a constant or a trend term. To do this, the coefficient matrix has to be divided into two pieces. The coefficient matrix Π can be expressed as (n x r) matrices α and β, where r is the rank of the coefficient matrix, such that Π = αβ´. Matrix α depicts the matrix of the speed-of-adjustment parameters and β is the cointegration parameter matrix in vector-error correction model that is presented later on the thesis. Both α and β can be estimated with a maximum likelihood-estimation, where β is formed from the *r* most significant cointegrating vectors and α matrix is selected so that it satisfies the constraint of Π = αβ´. Then the effect of restrictions can be tested with a test statistic presented in equation 19. (Enders 2009: 393 –394.)

(19) $$-T\sum_{i=r+1}^{n}[\ln(1-\hat{\lambda}_i^*)-\ln(1-\hat{\lambda}_i)]$$

where $\hat{\lambda}_i \ldots \hat{\lambda}_n$ are the characteristic roots of the unrestricted model and $\hat{\lambda}_i^* \ldots \hat{\lambda}_n^*$ are the characteristic roots of the restricted model and T is the number of observations.

4.3. Vector error correction model

After the confirmation of the first-difference stationarity of the spreads and the cointegration relationship between them, a vector error correction model (VECM) is used to model the relationship. A VECM with a restricted constant β_0 is estimated for each entity, while using the co-integration rank suggested by Johansen cointegration test to estimate the long run and the speed of adjustment coefficients in the vector error correction model in equation 20. According to the theory, CDS basis should be zero and thus the constant β_0 should be zero, so that the cointegrating vector is [1,-1,0]. However, the CDS spread can deviate from the bond spread by a constant β_0 implying a cointegration vector [1,-1,β_0]. Thus, entities for which the Johansen restriction testing suggests restrictions of $\beta_0 = 1$ and $\beta_1 = 1$, are modelled in the VEC-model with the given restrictions as per the paper by Blanco et al. (2005).

(20)

$$\begin{bmatrix}\Delta CDS\\ \Delta Bond\end{bmatrix} = \begin{bmatrix}\lambda_1\\ \lambda_2\end{bmatrix}(CDS_{t-1} - \beta_0 - \beta_1 Bond_{t-1}) + \begin{bmatrix}\sum_{j=1}^{p}\gamma_{1,j}\Delta CDS_{t-j}\\ \sum_{j=1}^{p}\gamma_{2,j}\Delta CDS_{t-j}\end{bmatrix}$$

$$+ \begin{bmatrix}\sum_{j=1}^{p}\delta_{1,j}\Delta Bond_{t-j}\\ \sum_{j=1}^{p}\delta_{2,j}\Delta Bond_{t-j}\end{bmatrix} + \begin{bmatrix}\varepsilon_{1,t}\\ \varepsilon_{2,t}\end{bmatrix}$$

where CDS_t & $Bond_t$ are CDS and credit spreads at time t, λ_1 and λ_2 are adjustment coefficients that measure the two markets' adjustments for deviations in the long-term equilibrium relation and ε_1 and ε_2 are independently and identically distributed error terms.

The adjustment coefficients λ_1 and λ_2 of the VECM can be used to analyse the short run dynamics between the two spreads. More precisely, a significant and negative λ_1 (significant and positive λ_2) coefficient suggests that the bond (CDS) market leads the price discovery process and thus, the CDS market (bond market) adjusts to the deviations in the equilibrium relation. The following hypotheses are used to test the nature of the price discovery process:

H0: $\lambda_1 = 0$, Bond market does not contribute to price discovery

H1: $\lambda_1 \neq 0$ and negative, bond market contributes to the price discovery, CDS market adjusts to deviations in the long run relationship.

H0: $\lambda_2 = 0$, CDS market does not contribute to price discovery

H1: $\lambda_2 \neq 0$ and positive, CDS market contributes to the price discovery, bond market adjusts to deviations in the long run relationship.

Furthermore, the speed-of-adjustment coefficients can be used to calculate a measure that depicts each market's contribution to the price discovery process. This measure (eq. 21) by Gonzalo and Granger (1995) is the speed of adjustments ratio between the two markets under analysis.

(21)

$$\frac{\lambda_2}{(\lambda_2 - \lambda_1)}$$

The measure ranges from 0 to 1. Thus, a measure of 1 is a clear indication that the CDS market leads the price discovery process and the cash market adjusts to the deviations. Similarly, a measure of 0 implies that the bond market is the sole leader of price discovery, while a measure close to 0.5 suggests that there is contribution to the price discovery process from both markets. (Zhu 2006: 230.)

4.4. Granger causality test

Entities for which no cointegration relationship can be found with the Johansen cointegration tests can be analysed with the Granger causality test. Granger defines causality such as Y causes X, which is depicted as $Y_t \rightarrow X_t$, if the forecast of future X_t values is possible to be bettered by introducing historical values of Y_t in the function, where X_t is determined by its own lagged values (Granger 1969: 428). Thus, the historical values of Y_t can be used to predict the future values of X_t, which can be expressed as Y_t Granger causes X_t. It should be noted that the term causality in the context of the test only implies that one variable has useful information for predicting other variable (Gujarati 2004: 696).

The Granger causality test requires that the time series are stationary, thus non-stationary time series should be differenced to follow the requirement (Granger 1969: 431). However, this requirement is already fulfilled for the time series that were analysed for cointegration with the Johansen method, i.e. the series are stationary of order one but do not have a cointegration relationship with the other series. The equations for analysing the causality from both spreads to another are presented below.

(22) $$\Delta CDS_t = \sum_{j=1}^{m} \alpha_j Bond_{t-i} + \sum_{j}^{m} \beta_i CDS_i + \varepsilon_{1t}$$

(23) $$\Delta BOND_t = \sum_{j=1}^{m} \lambda_j Bond_{t-i} + \sum_{j}^{m} \delta_i CDS_i + \varepsilon_{2t}$$

where ε_{1t} and ε_{2t} are uncorrelated error terms (Granger 1969: 431).

On the two models the dependent variable is regressed on its own lagged values and the lagged values of the other spread. For example, bond market causes the CDS market if the grouped coefficients of the lagged bond values in equation 22 are significant and different from zero and the grouped coefficients of lagged CDS values are significant and equal to zero. In addition, if a causality relationship is found on both equations there exists a bilateral causality. Similarly if the sum of coefficients α_j and the sum of δ_i coefficients are insignificant there is no causality between the spreads, suggesting that the two spreads are independent. (Gujarati 2004: 697.)

Even though, the previous results may imply that there is a causality relationship between the spreads, the superiority of the aforementioned models has to be proven before the result can be confirmed. Thus, the models are compared to a restricted model that only regresses the dependent variable on its own historical values. The residual sum of squares (RSS) of both models are then tested with the F-test expressed below:

(24) $$F = [\frac{RSS_R - RSS_{UR}}{m}] / [\frac{RSS_{UR}}{n-k}]$$

where R expresses the restricted model and UR expresses the unrestricted model (Gujarati 2004: 698).

The null hypothesis of the test in equation 24 is that the lagged terms included in the unrestricted model do not cause the dependent variable ($\Sigma\alpha_j = 0$ or $\Sigma\delta_i = 0$). Thus, if the test statistic exceeds the critical value of the F-distributed test, the null hypothesis is rejected and the alternative hypothesis that there is a Granger causality relationship ($\Sigma\alpha_j \neq 0$ or $\Sigma\delta_I \neq 0$) is accepted. (Gujarati 2004: 697–698.)

H_0 : $\Sigma\alpha_j = 0$ ($\Sigma\delta_i = 0$), No Granger causality relationship exists from bonds (CDS) to CDS (bonds)

H_1 : $\Sigma\alpha_j \neq 0$ ($\Sigma\delta_i \neq 0$), Granger causality from bonds (CDS) to CDS (bonds).

The appropriate lag lengths for the previously mentioned tests are determined with the use of information criteria methods. Both Akaike Information Criterion (AIC) and Schwarz Information criterion (SIC) are used to determine the lag lengths. Essentially, these methods try to minimize the residual sum of squares of the models by introducing different lag lengths. (Gujarati 2004: 537 – 538.)

5. DATA

This chapter presents the credit default swap, bond and swap rate data, its descriptive statistics and an analysis of the CDS basis over different time periods. Overall, the data consists of 41 European corporate entities for which appropriate CDS and bond data is found from the Thomson Datastream. The examination period varies by entities, so that the whole study covers the 14th December 2007 – 9th April 2013 period, while the average length of data is 3.4 years covering 888 observations on average. Furthermore, the data is divided into two time periods to cover the effects of the global financial crisis and the European debt crisis as well as the period afterwards. Sub period 1 ranges from 15th September 2008 to 28th June 2010, whilst sub period 2 covers the 29th June 2010 – 9th April 2013 period. The crisis period is determined by following the earlier study of Fontana et al. (2010) who used the exactly same time period. Furthermore, after reviewing the time series data, 28th June 2010 is found to be a time point where most spread pairs have adjusted to stable levels following the large deviations of September 2008.

5.1. Data gathering process

Daily 5-year middle-market CDS price data is downloaded for all European corporate entities from the beginning of 2007 until the end of the second quarter of 2013. All contracts are for senior debt and are denominated in either euros or U.S. dollars. For most entities the CDS data begins on 14th December 2007, which therefore delimits the start date of the examination period.

Next, euro and dollar denominated daily senior bond price data is then downloaded for all entities for which appropriate CDS data is found. Bond data, however, is the limiting factor in the data gathering process due to two reasons. First, the lack of available bond data limits the number of entities. This is mostly due to the fact that the synthetic 5-year bond has to be constructed from numerous bonds with different maturities, while the number of total bond data available for each entity is in many cases rather small. Secondly, since the number of bond contracts for most entities is small, the life to maturity of each available bond contract limits the construction of the synthetic 5-year bond. Overall, sufficient bond data is found for 41 entities. In some cases short breaks are detected in the bond time series and such gaps are assumed to equal to the last price available. In addition, euro and dollar swap rates are downloaded to be used as the proxy for risk-free interest rate.

The synthetic 5-year bond yields are constructed with the use of linear interpolation and matching methods. The interpolation method is preferred, whenever two appropriate bonds are available. The two bonds are selected so that the maximum and minimum time left to maturity are 10 years and 2.5 years respectively, while contracts closest to 5-year maturities are prioritized. On occasions, when interpolation is not possible, matching method is used, if a bond contract with life to maturity between 5.5 and 4.5 years is available. The credit spread is then calculated as the difference of the synthetic 5-year bond yield and either euro or dollar swap rate depending on the currency denomination of the bonds that were used to construct the synthetic yield. Overall, total number of bond contracts used in the calculations is 173, while number of contracts used for the yield calculations ranges from minimum of two to maximum of six, varying among the entities. Table 16. in Appendix 1. reports the bond contracts used in in yield calculations.

5.2. Overview of the data

Table 1 presents the sample entities. Third and fourth column present the start and end dates of data for each entity. Fifth column presents the length of the examination period in years and column six reports the number of observations. The sample entities consist of 41 European corporate entities from 12 different countries with an average length of examination period of 3.4 years, i.e. 888 daily observations. RWE and TeliaSonera have the longest sample periods of 5.32 years, while the data of Daimler, Heineken and Edison spans over the shortest periods of 0.90, 1.70 and 1.77 years, respectively. Overall, there are 33 entities for which data is available, at least partly, for both of the two sub periods. More precisely, there are 3 entities that do not have enough observations during the September 2008 – June 2010 period and 5 entities that lack observations during the June 2010 – April 2013 period.

Descriptive statistics for full sample lengths are presented in table 2. Overall, the CDS basis is relatively close to zero for many entities, and in fact the average basis of all entities is 0.3 basis points. The average values of CDS spread (129.0) and credit spread (129.6) depict a similar minimal pricing difference. The average absolute basis, however, shows that on average there is 64.4 basis point difference between the two spreads. Some clear outliers are detected as the highest absolute pricing differences for Stena, Barclays Bank and Commerzbank are 184.8 bps, 171.9 bps and 170.0 bps, respectively. When all the entities with an AAB over 100 basis points are removed from the calculations, the new AAB and AB for the rest of the entities are 53.7 bps and 13.2 bps respectively. Thus, on average CDS spreads are valued higher than credit spreads during the full sample.

Table 1. Sample entities. This table reports the entities under analysis, their home countries, sector, start and end dates of the time series data, time series lenght in years as well as the number of observations.

	Country	Sector	Start	End	Lenght	Obs.
Accor	France	Services	2.3.2009	8.8.2011	2.44	636
Adecco	Switzerland	Services	14.12.2007	30.10.2009	1.88	491
BAE Systems	UK	Industrial Goods	14.12.2007	3.12.2012	4.98	1297
Barclays Bank	UK	Financial	8.10.2009	9.4.2013	3.50	914
British American Tobacco	UK	Consumer Goods	14.12.2007	19.3.2010	2.26	591
BNP Paribas	France	Financial	28.11.2008	9.4.2013	4.36	1138
Carlsberg Breweries	Denmark	Consumer Goods	13.10.2010	9.4.2013	2.49	650
Commerzbank	Germany	Financial	26.11.2009	9.4.2013	3.37	879
Daimler	Germany	Automobile	28.8.2009	23.7.2010	0.90	236
Deutsche Bank	Germany	Financial	11.5.2009	9.4.2013	3.92	1022
E.ON	Germany	Electric Utilities	14.12.2007	26.8.2011	3.70	966
Edison	Italy	Electric Utilities	3.8.2009	12.5.2011	1.77	464
Fortum	Finland	Electric Utilities	14.12.2007	21.9.2011	3.77	984
Gas Natural SDG	Spain	Oil & Gas	30.7.2009	30.7.2012	3.00	783
GDF Suez	France	Electric Utilities	20.8.2008	9.4.2013	4.64	1204
GlaxoSmithKline	UK	Healthcare	14.12.2007	17.6.2011	3.51	916
Heineken	Netherlands	Consumer Goods	30.7.2009	13.4.2011	1.70	445
Imperial Tobacco Group	UK	Consumer Goods	23.5.2008	9.4.2013	4.88	1273
Nokia	Finland	Technology	2.3.2009	8.8.2011	2.44	636
Northern Rock	UK	Financial	14.12.2007	4.2.2010	2.15	560
Novartis	Switzerland	Healthcare	5.2.2009	25.10.2012	3.72	971
Pearson	UK	Services	1.5.2008	2.12.2011	3.59	937
Pernod Ricard	France	Consumer Goods	30.7.2009	20.9.2011	2.14	559
Repsol	Spain	Oil & Gas	21.1.2008	10.10.2011	3.72	971
RWE	Germany	Electric Utilities	14.12.2007	9.4.2013	5.32	1388
Saint-Gobain	France	Industrial Goods	14.12.2007	2.12.2011	3.97	1036
Shell	Netherlands	Oil & Gas	2.3.2009	4.3.2013	4.01	1046
Siemens	Germany	Industrial Goods	2.7.2008	12.12.2011	3.45	899
Solvay	Belgium	Basic materials	11.7.2008	12.12.2012	4.42	1154
Statoil	Norway	Basic materials	24.6.2010	9.4.2013	2.79	729
Stena	Sweden	Transportation	14.12.2007	2.6.2010	2.47	644
TDC	Denmark	Telecommunications	16.6.2010	9.4.2013	2.82	735
Telenor	Norway	Telecommunications	14.12.2007	29.9.2011	3.79	990
TeliaSonera	Sweden	Telecommunications	14.12.2007	9.4.2013	5.32	1388
Tesco	UK	Services	1.10.2008	9.4.2013	4.52	1180
ThyssenKrupp	Germany	Basic materials	21.2.2008	16.12.2010	2.82	469
Vattenfall	Sweden	Electric Utilities	2.1.2009	19.3.2013	4.21	1098
Veolia Environment	France	Industrial Goods	14.12.2007	18.3.2013	5.26	1372
Vodafone	UK	Telecommunications	30.7.2009	9.4.2013	3.70	964
Volkswagen	Germany	Automobile	14.12.2007	3.8.2012	4.64	1211
Volvo	Sweden	Automobile	2.3.2009	3.6.2011	2.25	590
Average					3.4	888.2

Table 2. Descriptive statistics. This table reports the descriptive statistics for full sample lenghts, including the mean values of CDS spread, credit spread, CDS basis as well as the average absolute basis, standard deviation and minumum and maximum values of the basis.

	CDS	CS	AB	AAB	STD	MIN	MAX
Accor	149.3	183.5	-34.1	47.6	60.7	-239.6	77.1
Adecco	139.5	227.1	-87.6	88.7	67.0	-268.8	33.8
BAE Systems	116.8	152.9	-36.1	63.1	75.5	-278.7	146.3
Barclays Bank	149.1	291.4	-142.3	171.9	171.0	-534.4	91.1
British American Tobacco	79.4	155.8	-76.4	78.0	59.4	-205.6	18.8
BNP Paribas	135.0	140.1	-5.1	76.6	92.9	-463.5	225.3
Carlsberg Breweries	111.8	81.8	30.0	31.8	21.9	-27.1	74.4
Commerzbank	174.1	188.6	-14.4	156.2	170.2	-396.1	220.5
Daimler	104.1	88.7	15.4	19.7	18.5	-31.4	55.6
Deutsche Bank	126.0	83.5	42.5	61.9	63.0	-152.4	162.0
E.ON	70.1	47.1	23.0	37.7	39.3	-99.2	100.2
Edison	108.4	107.9	0.5	13.8	17.0	-54.1	59.8
Fortum	62.4	54.2	8.2	33.9	39.8	-90.9	92.3
Gas Natural SDG	205.1	219.5	-14.4	27.0	32.5	-129.3	52.7
GDF Suez	85.2	12.7	72.5	76.9	50.5	-40.2	168.6
GlaxoSmithKline	54.1	32.4	21.6	26.6	23.8	-55.8	81.2
Heineken	101.3	78.6	22.7	23.6	15.3	-12.4	68.2
Imperial Tobacco Group	142.6	126.2	16.4	65.3	73.5	-211.2	108.0
Nokia	91.0	66.2	24.8	47.4	46.2	-116.7	88.7
Northern Rock	272.9	190.9	82.0	87.4	75.1	-74.4	274.3
Novartis	41.7	19.4	22.3	28.3	22.1	-76.8	63.4
Pearson	66.8	214.9	-141.3	141.3	135.3	-536.3	5.7
Pernod Ricard	160.4	210.9	-51.2	54.6	29.4	-133.3	89.3
Repsol	153.3	145.2	8.0	29.4	40.0	-138.2	156.8
RWE	77.5	26.4	51.2	57.5	49.5	-66.4	157.9
Saint-Gobain	140.9	128.8	10.9	36.5	46.1	-188.5	128.7
Shell	65.6	6.5	59.1	59.1	29.4	-8.6	127.6
Siemens	85.2	36.0	49.3	50.8	27.3	-32.4	119.6
Solvay	104.9	82.6	22.3	39.4	43.4	-111.1	122.7
Statoil	69.9	20.1	49.8	49.8	18.7	1.4	95.8
Stena	560.5	728.8	-168.3	184.8	146.1	-515.3	355.6
TDC	103.5	105.4	-1.9	40.6	55.9	-170.7	68.1
Telenor	92.0	93.8	-1.7	46.3	57.7	-162.7	87.8
TeliaSonera	67.7	65.4	2.2	40.6	51.0	-163.9	82.0
Tesco	94.9	45.9	49.1	74.9	64.0	-190.2	127.7
ThyssenKrupp	297.0	352.6	-24.0	140.1	154.7	-317.5	266.4
Vattenfall	67.3	28.6	38.6	49.2	39.4	-79.1	102.8
Veolia Environment	131.6	93.6	38.1	58.9	65.9	-167.3	177.9
Vodafone	81.3	90.6	-9.3	76.4	96.5	-546.9	94.2
Volkswagen	135.1	74.7	60.4	63.1	38.6	-147.8	158.0
Volvo	213.8	215.0	-1.1	83.1	115.4	-405.4	113.5
Average	129.0	129.6	0.3	64.4	61.9	-186.3	119.5

A graphical comparison of the CDS bases shows that despite the differences in the average CDS basis values, the bases follow a similar trend pattern on most companies. However, the patterns of companies from the same industry resemble each other more than the patterns of companies from different industries. Similar outcome is also reached by comparing the average bases as they tend to have smaller deviations among the same sector.

Figure 3. depicts the development of the CDS bases of RWE and TeliaSonera, while the start and end dates of the European debt crisis are represented with vertical bars. Both bases seem to follow similar trends throughout the sample, even though their average bases differ by 49 basis points. For example, during the first two days of the European debt crisis (15th - 16th September 2008) both bases experience a steep rise of 51.50 and 40.79 basis points respectively. This rise is then followed by a rapid decrease of 47.90 and 40.10 basis points during the next three days. Interestingly, the period of decline following the first week of the crisis is significantly shorter for RWE, whose CDS basis reaches its lowest value of -66.44 bps in mid-October. In comparison, the basis of TeliaSonera continues its decline until mid-November where it reaches its minimum value of -163.90 bps.

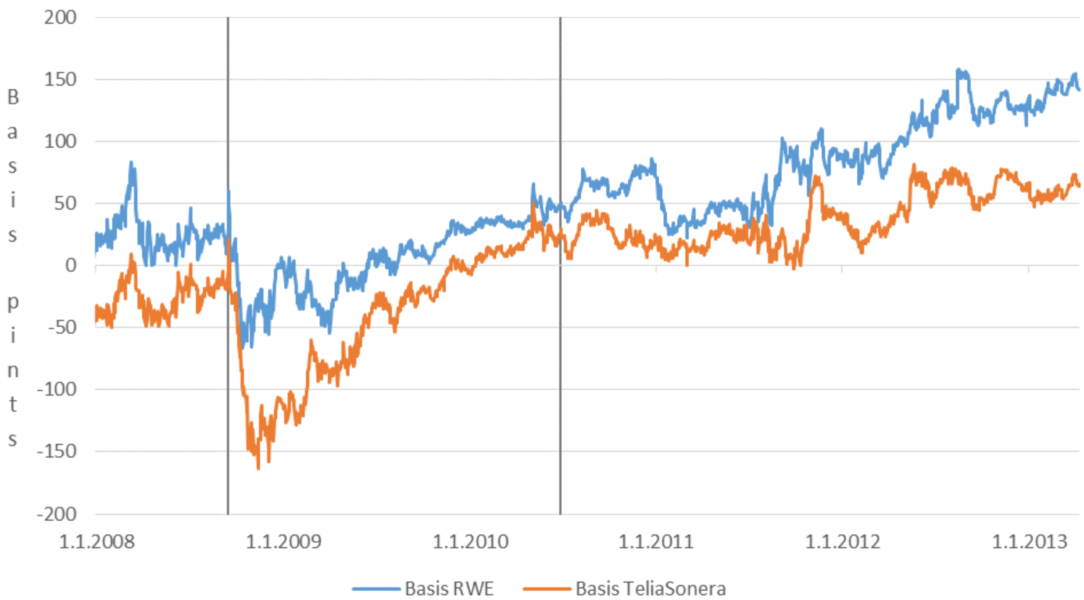

Figure 3. Comparison of the CDS bases of RWE and TeliaSonera.

A further comparison of the CDS basis of TeliaSonera along with the basis of Telenor shows that the slight differences in the movement patterns of the CDS bases could be explained by the industry sector of the companies. As shown in figure 4. the bases of the two telecommunications companies share the timing of the steep drop at the start of the

European debt crisis and reach their minimum values at nearly the same time, while their movement patterns throughout the sample are rather identical. In addition, a comparison of the CDS bases of RWE and GDF Suez, another electric utility company, depicts a similar outcome; the movement patterns are more alike among companies from the same industry than they are between companies from different sectors. Figure 5. presents the comparison between the CDS bases of RWE and GDF Suez.

The differences between the average CDS bases of companies in the same industry sector seem to be rather minimal. For example, the average basis of TeliaSonera is 2.2 basis points, while it is -1.7 basis points for Telenor. Similarly, the electric utility companies, RWE and GDF Suez, have average CDS bases of 51.20 bps and 72.50 bps, whereas healthcare companies such as Novartis and GlaxoSmithKline experience average CDS bases of 22.30 bps and 21.60 bps, respectively.

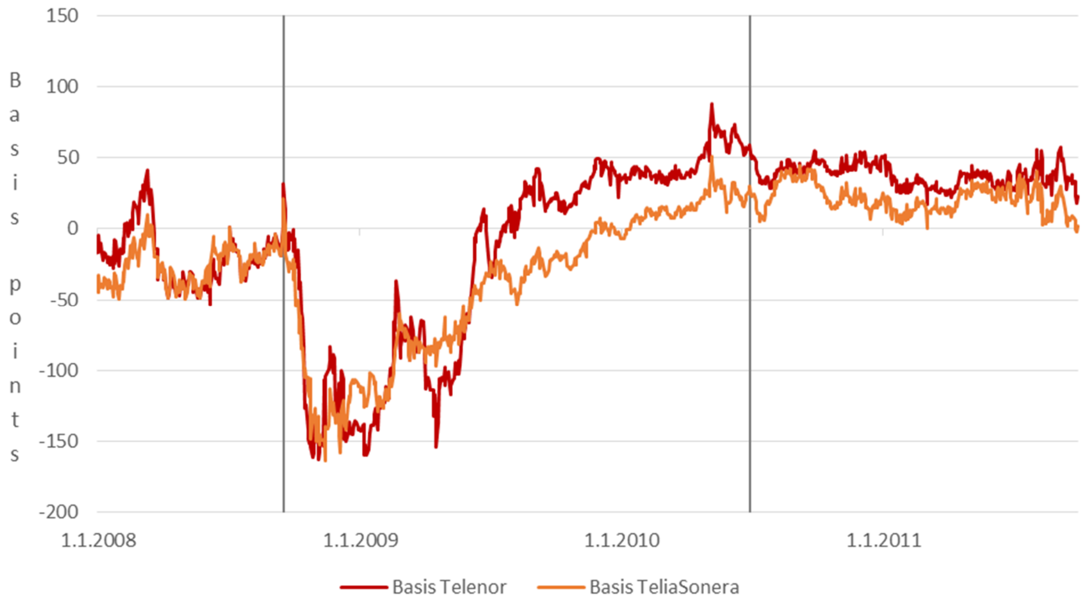

Figure 4. Comparison of the CDS bases of Telenor and TeliaSonera.

Overall, significant differences are observed in the behaviour of the basis spreads between different industry groups as well as between time periods. Since the differences between the crisis and post crisis periods are not observable from the full sample statistics a further analysis of the two sub-periods is in place. Similarly, an analysis between the industries provides information on the effect of the debt crisis on certain industries. These two aspects are analysed in the following sub-chapters.

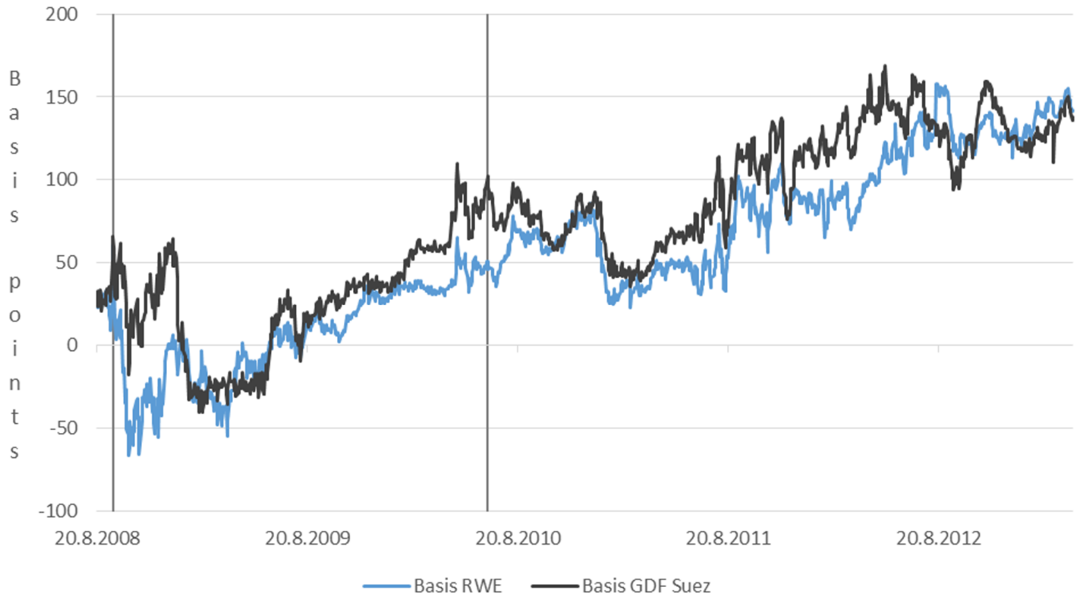

Figure 5. Comparison of the CDS bases of RWE and GDF Suez.

5.2.1. Comparison of sub periods

Tables 3. and 4. present the descriptive statistics for the two sub periods. The most notable difference between the two periods is that the average CDS basis is negative (-39.23 bps) during the crisis period, whereas during the post-crisis period the average basis is positive (26.87 bps). This shows that on average credit spreads were valued higher than CDS premiums during the debt crisis as 23 out of the 38 entities experienced a negative average basis. On average, credit spreads are more volatile with an average standard deviation of 77.91 bps and seem to be the likely cause for this difference between the sub periods, since the corresponding value during period 2 is only 40.98 bps. Moreover, the average standard deviations of CDS spreads are 46.25 bps and 28.94 bps for the two periods respectively.

During the crisis-period certain firms experience a highly negative average CDS basis, which drives the overall average basis towards a negative value. For example, the lowest average negative basis values are found for Barclays Bank (-384.43 bps), Pearson (-231.27 bps) and Stena (-211.96 bps), whereas the highest average bases only reach values of 64.68 bps, 34.79 bps and 29.39 bps for Northern Rock, Heineken and Volkswagen respectively. Overall, only 4 entities have an average basis deviating from zero by over 100 basis points, which indicates that most entities have their credit risk priced relatively equally on both markets.

Table 3. Descriptive statistics. This table reports the descriptive statistics for period 1 (15.9.2008 - 28.6.2010). Mean, maximum and minimum values as well as the standard deviation are reported for CDS spread and credit spread, respectively. In addition, the average CDS basis and number of observations are presented in the last two columns.

	CDS	MAX	MIN	STD	CS	MAX	MIN	STD	AB	AAB	OBS
Accor	172.25	274.94	119.80	36.93	231.98	506.31	130.98	85.85	-59.73	61.61	346
Adecco	155.92	211.70	123.00	19.38	274.83	455.80	165.30	78.15	-118.91	118.91	295
BAE Systems	109.37	297.50	43.00	53.14	198.23	434.06	53.93	106.32	-88.86	102.08	466
Barclays Bank	102.02	182.64	71.97	28.82	486.44	688.69	316.96	78.30	-384.43	384.43	188
British American Tobacco	83.14	183.33	52.54	29.53	173.09	359.95	41.47	92.02	-89.95	92.47	395
BNP Paribas	76.37	148.00	47.25	21.62	138.04	257.24	48.35	56.87	-61.67	72.24	412
Carlsberg Breweries	-	-	-	-	-	-	-	-	-	-	-
Commerzbank	87.94	160.90	53.35	26.58	241.39	341.33	164.60	49.33	-153.45	153.45	153
Daimler	103.00	145.00	68.97	17.12	90.48	156.34	59.82	22.89	12.52	17.23	217
Deutsche Bank	99.92	184.43	67.69	26.05	123.58	249.92	48.99	37.43	-23.66	29.95	296
E.ON	70.69	151.25	46.67	19.21	73.14	180.19	-8.37	45.27	-2.45	26.20	466
Edison	91.23	143.89	67.96	12.83	89.75	127.83	22.57	17.74	1.48	12.80	236
Fortum	66.39	160.00	42.05	24.87	82.26	177.82	2.41	51.58	-15.87	30.56	466
Gas Natural SDG	123.08	258.60	62.51	43.71	110.37	214.41	56.62	40.36	12.71	14.90	238
GDF Suez	63.58	143.75	42.07	21.51	37.87	111.78	-41.91	36.25	25.71	37.00	466
GlaxoSmithKline	59.51	105.00	38.00	20.47	36.26	135.82	-24.34	38.06	23.25	28.16	466
Heineken	111.54	150.00	85.25	20.43	82.15	114.06	44.06	13.06	29.39	29.39	238
Imperial Tobacco Group	203.61	465.00	86.21	114.87	243.32	600.75	25.66	183.25	-39.72	71.71	466
Nokia	62.62	108.33	35.66	17.89	64.66	210.05	-11.48	50.66	-2.05	39.37	346
Northern Rock	310.00	550.00	147.50	111.43	247.32	349.80	114.43	69.59	62.68	70.85	364
Novartis	44.93	75.00	25.00	13.65	37.28	144.33	-4.16	37.54	7.64	23.69	363
Pearson	68.63	187.50	35.00	29.24	299.90	658.77	84.98	156.29	-231.27	231.27	466
Pernod Ricard	184.40	275.00	129.31	40.97	225.99	325.45	156.43	39.65	-41.59	48.36	238
Repsol	180.06	516.67	73.43	105.84	173.34	395.79	74.74	92.21	6.72	33.12	466
RWE	58.10	110.83	36.37	15.25	52.06	133.33	-9.48	39.47	6.04	24.98	466
Saint-Gobain	210.63	525.00	92.63	111.09	217.48	476.75	68.59	129.67	-6.85	40.20	466
Shell	57.34	95.09	42.65	12.22	26.48	83.17	-8.26	21.09	30.86	31.13	346
Siemens	98.82	248.33	50.33	43.88	60.87	186.62	-25.16	53.77	37.95	40.95	466
Solvay	87.49	165.25	52.25	32.54	97.34	217.26	-24.30	57.32	-9.85	31.90	466
Statoil	-	-	-	-	-	-	-	-	-	-	-
Stena	645.57	1288.46	244.89	265.20	857.54	1333.09	427.67	303.55	-211.96	233.43	448
TDC	-	-	-	-	-	-	-	-	-	-	-
Telenor	114.02	234.33	59.14	47.17	136.00	331.41	-19.77	111.61	-21.98	61.61	466
TeliaSonera	67.95	121.85	40.69	21.30	109.08	264.28	10.56	69.66	-41.14	50.33	466
Tesco	99.10	185.00	61.83	25.43	102.92	333.99	6.37	93.67	-3.82	63.26	454
ThyssenKrupp	341.03	494.00	195.94	83.62	322.63	540.50	196.96	98.30	18.40	138.93	346
Vattenfall	61.99	105.00	42.61	13.61	60.63	165.38	-4.26	45.56	1.35	31.11	387
Veolia Environment	117.05	210.00	65.57	35.50	133.40	340.22	36.83	79.65	-16.36	40.64	466
Vodafone	72.70	133.03	55.22	15.67	199.79	632.29	50.80	72.32	-127.08	127.33	238
Volkswagen	166.71	416.93	65.71	75.65	131.92	355.59	17.85	84.17	34.79	42.03	466
Volvo	269.20	576.00	141.92	103.20	318.86	974.50	77.81	222.29	-49.66	94.02	346
Average	134.15	262.83	74.00	46.25	173.39	356.97	61.17	77.91	-39.23	73.20	378

In the post-crisis period only 14 % (5 of 36) of the companies have a negative average CDS basis, while during the crisis period the corresponding share was 61 %. As reported earlier, the average standard deviation of credit spreads decreased significantly from its crisis period value, which might partly cause the positive average CDS basis observed in period 2. In fact, only ThyssenKrupp and GDF Suez experienced average CDS bases that deviated from zero by over 100 basis points (-143.35 bps and 103.23 bps) during the post-crisis period.

Table 4. Descriptive statistics. This table reports the descriptive statistics for period 2 (29.6.2010 - 9.4.2013). Mean, maximum and minimum values as well as the standard deviation are reported for CDS spread and credit spread, respectively. In addition, the average CDS basis and number of observations are presented in the last two columns.

	CDS	MAX	MIN	STD	CS	MAX	MIN	STD	AB	AAB	OBS
Accor	122.00	179.16	86.30	26.00	125.59	217.21	33.78	55.73	-3.59	30.84	290
Adecco	-	-	-	-	-	-	-	-	-	-	-
BAE Systems	137.92	230.56	85.17	34.29	128.42	215.60	55.00	45.91	9.50	34.83	635
Barclays Bank	161.33	282.61	98.00	44.12	240.90	578.28	63.33	116.22	-79.57	117.17	726
British American Tobacco	-	-	-	-	-	-	-	-	-	-	-
BNP Paribas	168.24	361.16	79.16	66.84	139.14	364.96	-61.38	92.88	29.10	78.98	726
Carlsberg Breweries	111.81	153.49	85.26	16.97	81.83	164.40	30.47	31.35	29.98	31.79	650
Commerzbank	192.30	361.25	83.81	65.02	177.43	561.59	19.08	131.92	14.88	156.87	726
Daimler	-	-	-	-	-	-	-	-	-	-	-
Deutsche Bank	136.57	308.14	82.16	43.01	67.15	192.24	-16.04	44.10	69.41	74.91	726
E.ON	74.89	133.82	58.63	11.17	8.81	62.05	-17.25	12.76	66.09	66.03	304
Edison	126.25	180.26	97.27	19.04	126.69	187.60	75.10	31.04	-0.44	14.84	228
Fortum	61.20	126.78	48.37	13.83	13.41	37.37	-9.27	8.21	47.79	47.76	322
Gas Natural SDG	240.91	563.59	137.34	81.98	267.10	601.37	129.17	92.25	-26.18	32.35	545
GDF Suez	99.75	187.08	53.64	27.06	-3.48	95.49	-52.19	24.67	103.23	103.22	726
GlaxoSmithKline	55.06	66.51	46.86	6.11	21.17	46.60	-16.68	15.12	33.90	33.99	254
Heineken	89.54	104.90	73.80	9.17	74.56	92.78	58.99	7.11	14.98	16.91	207
Imperial Tobacco Group	102.55	168.61	82.26	17.37	41.97	186.12	-11.29	40.80	60.58	62.08	726
Nokia	124.97	329.70	81.19	58.12	68.04	328.86	12.77	74.22	56.93	56.96	290
Northern Rock	-	-	-	-	-	-	-	-	-	-	-
Novartis	39.78	69.93	26.33	8.22	8.74	36.07	-20.38	9.10	31.04	31.06	608
Pearson	67.77	89.93	52.31	9.11	110.51	147.96	77.33	14.93	-42.74	42.81	374
Pernod Ricard	147.86	252.69	117.68	30.21	207.05	311.25	152.07	36.81	-59.19	59.25	321
Repsol	149.98	255.14	104.71	30.04	125.03	198.03	76.32	31.73	24.95	26.98	335
RWE	97.39	162.57	59.07	23.86	10.16	79.32	-58.80	34.93	87.23	87.18	726
Saint-Gobain	137.25	259.47	95.10	42.83	100.15	200.81	35.80	36.95	37.10	38.16	374
Shell	69.64	107.80	47.63	14.86	-3.35	52.25	-43.93	23.93	72.98	72.96	700
Siemens	70.82	110.25	54.94	13.81	4.99	63.21	-32.35	17.60	65.83	65.89	380
Solvay	120.58	251.21	63.61	46.57	74.56	176.74	14.87	36.94	46.02	46.29	642
Statoil	69.90	115.68	51.37	15.61	20.17	55.05	-12.24	14.12	49.73	49.74	726
Stena	-	-	-	-	-	-	-	-	-	-	-
TDC	102.67	186.01	73.56	25.27	102.61	343.30	22.46	73.83	0.06	39.31	726
Telenor	71.37	104.52	57.56	10.59	33.56	81.69	11.66	13.65	37.81	37.87	328
TeliaSonera	65.70	94.31	47.71	11.45	27.70	89.28	-24.21	27.67	38.00	37.99	726
Tesco	92.35	127.16	69.51	14.05	10.17	44.69	-32.56	11.53	82.17	82.13	726
ThyssenKrupp	293.74	384.35	192.34	58.17	437.09	583.76	288.91	80.60	-143.35	143.29	123
Vattenfall	70.15	106.00	55.04	10.81	11.06	65.41	-38.95	23.96	59.09	59.08	711
Veolia Environment	155.82	317.37	80.21	56.42	72.83	181.83	17.21	36.46	82.99	82.95	710
Vodafone	84.06	126.36	62.88	13.31	54.78	672.29	-4.28	76.22	29.28	59.96	726
Volkswagen	116.58	202.53	67.55	33.76	34.36	90.41	-13.24	22.10	82.22	82.21	549
Volvo	135.30	210.16	100.00	32.97	67.64	154.15	34.32	27.74	67.65	67.63	244
Average	115.67	201.97	76.62	28.94	85.79	210.00	20.66	40.98	29.87	60.34	523

Similarly, like the average basis values, the absolute average basis (AAB) values depict larger price discrepancies between the two markets during the crisis than after it. More precisely, the indicative average absolute basis across the sample is 73.20 bps in period 1 and 60.34 bps during period 2. In addition, 8 companies had an AAB of over 100 bps during the crisis, while two of them experienced an average value of over 200 basis points. In comparison, only 4 entities had an AAB of over 100 bps after the crisis.

Interestingly, many companies experienced negative basis values only during the first half of the crisis period. As seen in the previous CDS basis figures a steep drop happened in the beginning of the crisis, which is a result of rapid rise in credit spreads. An example of this can be seen in figure 6, where the credit spread of Telenor rises more rapidly in September 2008 than its CDS spread does, which results in a highly negative basis of -161.37 bps by the end of October 2008. Overall, both spreads follow a similar pattern through the examination period, while the magnitude of credit spread changes is larger than its counterparts' during the beginning of the crisis.

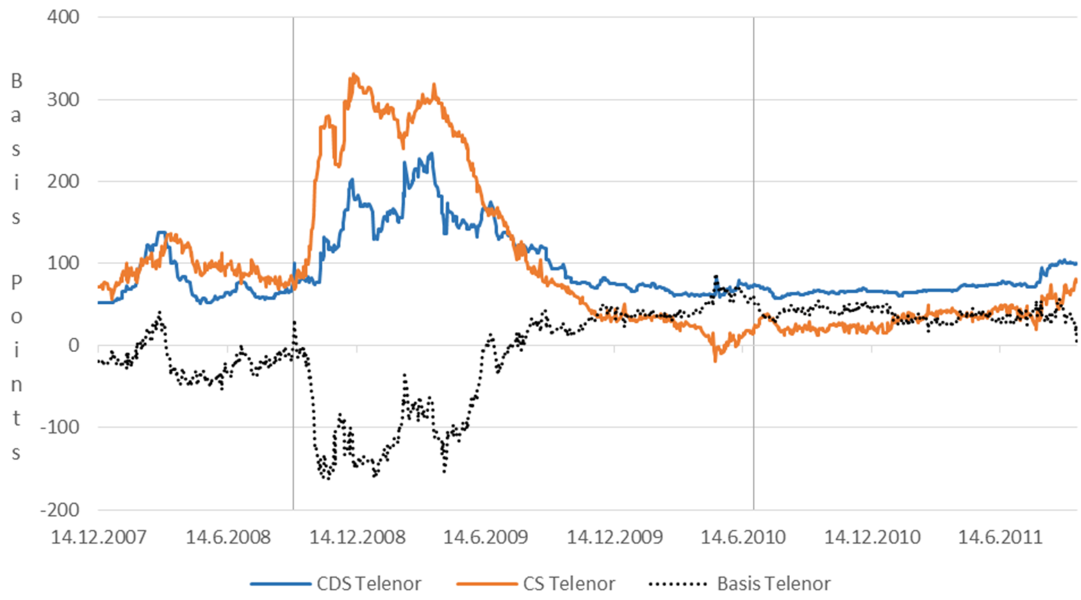

Figure 6. CDS spread, credit spread and CDS basis of Telenor.

As evidenced by figure 6. Telenor's CDS and credit spread values stop experiencing high fluctuations in August 2009 and remain at a stable level from thereon. The stability, in conjunction with the credit spreads' earlier drop near to the level of the CDS spread result in smaller pricing differences during period 2. The corresponding AAB values during period 1 and period 2 are 61.61 bps and 37.87 bps respectively. This can be used as a generalization of the behaviour of the sample firms' spreads since similar behaviour is found for most of the other companies. Still, some entities experience opposite results as for example on Volkswagen the price discrepancies are smaller during the crisis. Its AB values during period 1 and period 2 are 34.79 bps and 82.21 bps, while the corresponding AAB values are 42.03 bps and 82.21 bps respectively. The development of Volkswagen's CDS basis is depicted in figure 7.

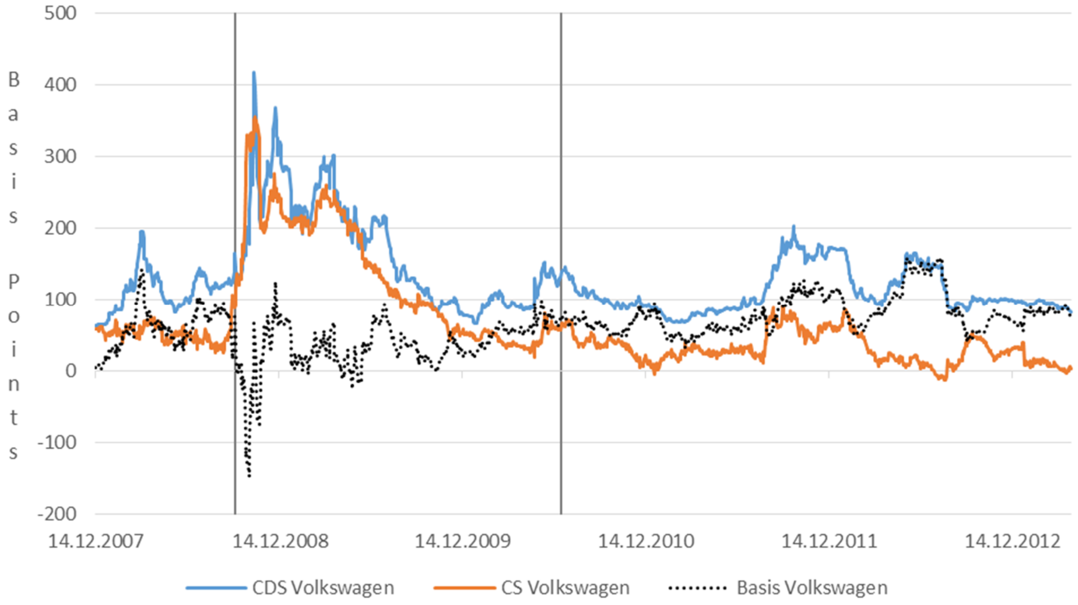

Figure 7. CDS spread, credit spread and CDS basis of Volkswagen.

5.2.2. Comparison between industries

The earlier graphical analysis revealed differences in the movement patterns of CDS bases between companies from different industry sections. Thus, this sub-chapter focuses on the analysis between the industries. Tables 17. and 18. in Appendix 2 present the descriptive statistics from tables 3 and 4 sorted by industries and also report the indicative average values for each industry section.

The highest price discrepancies during both sub-periods are found for the financial sector. The sector's average AAB is 142.19 bps during the crisis and 106.98 bps during the post-crisis period. In fact, 4 of the 5 financial firms experienced a negative average CDS basis in period 1 resulting into a sector average of -112.11 bps, while Northern Rock was the only exception with a positive CDS basis of 62.68 bps. Barclays Bank experienced the highest absolute average basis in the group (384.43 bps) during its relatively short crisis period sample, whereas after the crisis the highest price discrepancies were detected for Commerzbank (AAB of 156.87 bps). In comparison, Deutsche Bank had the lowest AAB values of 29.95 bps and 74.91 bps during both of the two sub-periods.

The only other industry group with an AAB over 100 bps was the services sector which recorded an absolute average basis of 118.76 bps. All of the four companies had an AAB of over 60 bps, while Pearson and Adecco recorded the highest pricing discrepancies in the group with 231.27 bps and 118.91 bps respectively. In addition, each services company had a negative average CDS basis resulting in a group average of -103.43 bps.

Interestingly, the credit risk of electric utility companies was priced most accurately in the two markets during the crisis, as the sector's AAB was 23.42 bps. Other industries with similar pricing discrepancies were Healthcare (25.93 bps) and Oil & Gas (26.38 bps). Overall, 9 out of the 11 entities within the three sectors had a positive average CDS basis during the crisis, i.e. their CDS premiums were valued higher than the corresponding credit spreads. In addition to these sectors also basic materials had a positive AB during the crisis.

A comparison between industries with negative and positive AB values reveals that the industries with negative average basis had larger average absolute basis values and thus larger price discrepancies during the crisis. Therefore, most of the price discrepancies are due to the large overpricing of credit spreads. In the case of industries with a negative AB the investors may have seen the respective bonds as safer investments, which could be caused by the fear of rising counterparty risk in the CDS contracts. Still, it is not clear which of the two spreads causes the other. This opens a question of whether the credit spreads overreacted to the changes in CDS premiums or the CDS premiums reacted weakly to the substantial changes in the credit spreads. This matter will be discussed more closely later in the thesis, as the empirical analysis reveals more information on the matter.

Similar conclusions cannot be drawn in period 2 as only the basic materials sector, consisting of two companies, has a negative AB and, which is largely due to the substantially large negative AB of ThyssenKrupp (-143.35 bps). ThyssenKrupp also has the second largest AAB of the whole sample of entities during period 2 and thus increases the AAB of the basic material sector to the second highest level measured post-crisis. In addition to the financial sector and basic materials, also the automobile sector has a rather high AAB of 74.92 bps, while the rest of the industries measure AAB values lower than 60 bps.

In addition to the financial companies, the telecommunications, services and consumer goods sectors were the other industry groups whose AAB values significantly decreased after the crisis. For example the telecommunications companies experienced a drop of

35.98 bps as their AAB decreased from 79.76 bps during the crisis to a post-crisis value of 43.78 bps. Similarly, the AAB of service companies decreased by 66.83 bps from 118.76 bps to 51.93 bps, while the consumer goods group's AAB dropped by 17.98 bps. In comparison, the electric utilities sector had the highest increase in AAB of 27.79 bps.

6. EMPIRICAL FINDINGS

This chapter presents the empirical findings regarding the long-term equilibrium relationship and the short-term price discovery process. The Augmented Dickey-Fuller, Johansen Cointegration, Vector Error Correction model and Granger Causality tests are all performed for three different time periods, period 1 (15^{th} September 2008 to 28^{th} June 2010), period 2 (29^{th} June 2010 – 9^{th} April 2013) and the full length sample (starting from 14^{th} December 2007).

As discussed in the data section, the average CDS basis values on the most part differed from zero during the two sub periods. These findings were further confirmed with a simple T-test testing the null hypothesis of AB = 0. These results are presented in tables 19 and– 20 in Appendix 3. Overall, in only five cases in period 1 and in three cases in period 2 the null hypothesis is accepted implying that price discrepancies between the markets were evident both during and after the crisis.

6.1. Augmented Dickey-Fuller & Johansen Cointegration tests

The Johansen Cointegration test is used to determine whether there exists a long-run cointegration relationship between the CDS premium and the credit spread of a company. However, to be able to run the Johansen cointegration tests both of these spreads have to be first difference stationary, as mentioned in chapter 4. Thus, Augmented Dickey-Fuller tests are run for all spread pairs and for the full sample length as well as the two sub-periods.

The results of the ADF-tests can be found in Tables 21 – 23 in Appendix 4, which present the t-statistics as well as the p-values for each individual ADF-test. Columns 1 through 4 present the results for level data (Y_t), while the corresponding values for first-differenced time series (ΔY_t) are found in columns 5 – 8. More importantly, the five percent MacKinnon one-sided p-value is used as a boundary for the rejection of the null hypothesis in the ADF-tests. If the null hypothesis is rejected for either of the two level time series (Y_t), the spread pair is not applicable for cointegration analysis. Furthermore, the null hypothesis must be rejected on the first-differenced data for it to be suitable for Johansen cointegration tests. Entities that do not qualify for cointegration tests are highlighted in bold in the tables.

Test results for the full sample lengths imply that four entities do not pass the ADF-tests, including Barclays, Statoil, Tesco and Volvo. Each of these companies had either one or two stationary non-differenced spreads which thus are not applicable for the Johansen Cointegration test. Interestingly, the ADF-test for sub-period 1 shows that only the spread pair of Tesco has to be delimited from further testing, while 6 entities in sub-period 2 do not pass the test. These entities include Fortum, GlaxoSmithKline, Novartis, Statoil, Tesco and Vodafone. In addition, Tesco is the only company which does not pass any of the three ADF-tests and is not analysed further in this study, while Statoil's data only spans the latter sub-period during which its credit spread is discovered to be stationary without differencing.

Following the ADF-tests the Johansen cointegration trace tests are run for first-differenced stationary spread pairs. These tests are conducted in a three-fold manner for all three periods. First, the unrestricted Johansen trace tests are run for all entities to determine cointegration between the spreads. Then, two restrictions are issued on spread pairs which are found to have one cointegrating vector. The first restriction [1,-1,c] tests whether the CDS basis equals a constant value, while the second [1,-1,0] determines if the basis is zero. Tables 5 – 7 present the results of Johansen cointegration tests for sub-period 1, sub-period 2 and the full sample lengths respectively.

The crisis period results in table 5 imply that 23 of the 38 analysed entities have a cointegration relationship between their CDS premiums and credit spreads. For 10 of these companies one cointegrating vector is found to exist at 1 % significance level and for another 10 companies at 5 % level, while for 3 firms the vector is significant at 10 % level. Furthermore, both restrictions are accepted for 10 companies at least at the 5 % level, whereas neither of the two restrictions are accepted for the remaining 13 companies.

Even though the cointegration test results for the crisis period are promising in terms of number of confirmed cointegration relationships, the post-crisis results show a significant decrease in the number of cointegrated spread pairs. More precisely, 11 of the 35 entities in the post-crisis period have a cointegrating vector, while only on 3 spread pairs the cointegrating vector is found significant at 1 % level. Furthermore, the significance of the cointegration relationship is confirmed for 4 entities at both 5 % and 10 % levels. Still, both of the restrictions are accepted for 6 spread pairs at the 5 % significance level.

Interestingly, a cross-examination of the cointegration test results shows that only 6 companies have a cointegrating vector during both of the sub-periods. These companies are Deutsche Bank, Gas Natural SDG, Imperial Tobacco Group, Repsol, Solvay and

Telenor. Thus, while the full sample cointegration results in table 7 imply that 20 entities have a cointegration relationship, they seem to be significantly affected by the high amount cointegrated spread pairs during the crisis period. Therefore, the results of the two sub-periods will be examined more closely than the full sample results as they provide more information on the differences between the two sub-periods.

Table 5. Johansen Cointegration trace test for subperiod 1 (15.9.2008 - 28.6.2010). This table reports the Johansen trace statistics as well as their p-values for each entity. Rejection of null hypothesis at 1%, 5% and 10 % levels is presented with *, ** and *** respectively. Entities for which cointegration is confirmed either at 1% or 5% levels are highlighted in bold and at 10 % level in italics. In addition, results for LR tests on the imposed restrictions are presented for all entities with one confirmed cointegrating vector. First restriction, [1,-1,c], implies that CDS basis is equal to a constant value, whereas the second restriction, [1,-1,0], implies that CDS basis is equal to zero. Restrictions follow X^2-distribution with one and two degrees of freedom respectively. Bolded p-values for restrictions imply the acceptance of the null hypothesis, i.e. [1,-1,c] = cds basis is a constant value.

	Trace test						Restrictions on vector			
	Number of cointegrating vectors									
Entity	None	p-value		At most 1	p-value		[1,-1,c]	p-value	[1,-1,0]	p-value
Accor	23.303	0.019	**	5.377	0.245		0.008	**0.931**	5.707	**0.058**
Adecco	13.997	0.083	***	0.874	0.350		11.435	0.001	11.466	0.003
BAE Systems	4.270	0.881		1.166	0.280		-	-	-	-
Barclays Bank	7.040	0.573		0.304	0.581		-	-	-	-
British American Tobacco	18.054	0.020	**	0.202	0.653		17.608	0.000	17.697	0.000
BNP Paribas	9.238	0.344		1.373	0.241		-	-	-	-
Commerzbank	17.618	0.024	**	0.011	0.917		15.630	0.000	16.968	0.000
Daimler	11.086	0.206		3.877	0.049	**	-	-	-	-
Deutsche Bank	39.705	0.000	*	1.757	0.185		0.545	**0.460**	0.636	**0.727**
E.ON	26.054	0.001	*	1.891	0.169		17.229	0.000	19.232	0.000
Edison	15.291	0.054	***	3.102	0.078	***	-	-	-	-
Fortum	29.228	0.018	**	9.331	0.161		3.254	**0.071**	3.510	**0.173**
Gas Natural SDG	20.371	0.009	*	1.668	0.197		6.949	0.008	7.550	0.023
GDF Suez	5.822	0.716		2.445	0.118		-	-	-	-
GlaxoSmithKline	16.277	0.038	**	1.126	0.289		9.277	0.002	11.005	0.004
Heineken	26.044	0.001	*	3.530	0.060	***	8.792	0.003	21.512	0.000
Imperial Tobacco Group	20.506	0.008	*	0.265	0.607		18.502	0.000	19.484	0.000
Nokia	27.266	0.033	**	8.671	0.202		0.036	**0.850**	0.123	**0.940**
Northern Rock	8.642	0.400		2.632	0.105		-	-	-	-
Novartis	10.591	0.238		4.203	0.040	**	-	-	-	-
Pearson	19.460	0.012	*	3.180	0.075	***	12.962	0.000	14.927	0.001
Pernod Ricard	6.108	0.683		1.899	0.168		-	-	-	-
Repsol	21.150	0.038	**	4.205	0.382		0.123	**0.726**	0.223	**0.895**
RWE	17.734	0.023	**	0.922	0.337		14.124	0.000	16.323	0.000
Saint-Gobain	13.338	0.103		0.229	0.633		-	-	-	-
Shell	13.489	0.098	***	0.709	0.400		1.466	**0.226**	5.777	**0.056**
Siemens	10.643	0.235		0.781	0.377		-	-	-	-
Solvay	32.311	0.007	*	9.429	0.156		2.566	**0.109**	3.549	**0.170**
Stena	17.642	0.023	**	1.483	0.223		0.249	**0.618**	3.304	**0.192**
Telenor	14.721	0.065	***	0.111	0.739		12.965	0.000	14.609	0.001
TeliaSonera	33.231	0.005	*	6.765	0.370		1.268	**0.260**	1.293	**0.524**
ThyssenKrupp	6.199	0.672		0.723	0.395		-	-	-	-
Vattenfall	10.683	0.232		1.769	0.184		-	-	-	-
Veolia Environment	19.632	0.011	**	0.884	0.347		15.375	0.000	18.672	0.000
Vodafone	61.132	0.000	*	0.091	0.763		41.229	0.000	42.062	0.000
Volkswagen	24.035	0.002	*	1.399	0.237		3.179	**0.075**	5.145	**0.076**
Volvo	17.459	0.025		6.724	0.010	***	-	-	-	-

Table 6. Johansen Cointegration trace test for subperiod 2 (29.6.2010 - 9.4.2013). This table reports the Johansen trace statistics as well as their p-values for each enty. Rejection of null hypothesis at 1%, 5% and 10 % levels is presented with *, ** and *** respectively. Entities for which cointegration is confirmed either at 1% or 5% levels are highlighted in bold and at 10 % level in italics. In addition, results for LR tests on the imposed restrictions are presented for all entities with one confirmed cointegrating vector. First restriction, [1,-1,c], implies that CDS basis is equal to a constant value, whereas the second restriction, [1,-1,0], implies that CDS basis is equal to zero. Restrictions follow X^2-distribution with one and two degrees of freedom respectively. Bolded p-values for restrictions imply the acceptance of the null hypothesis, i.e. [1,-1,c] = cds basis is a constant value.

	Trace test						Restrictions on vector			
	Number of cointegrating vectors									
Entity	None	p-value		At most 1	p-value		[1,-1,c]	p-value	[1,-1,0]	p-value
Accor	5.132	0.795		1.486	0.223		-	-	-	-
BAE Systems	22.628	0.004	**	3.042	0.081	***	1.816	**0.178**	1.953	**0.377**
Barclays Bank	11.397	0.188		3.988	0.046	**	-	-	-	-
BNP Paribas	31.569	0.009	*	2.210	0.954		11.063	0.001	27.892	0.000
Carlsberg Breweries	10.990	0.212		1.063	0.303		-	-	-	-
Commerzbank	15.783	0.045	**	4.029	0.045	**	-	-	-	-
Deutsche Bank	43.039	0.000	*	4.960	0.602		6.892	0.009	32.995	0.000
E.ON	22.247	0.004	*	9.124	0.003	*	-	-	-	-
Edison	14.771	0.064	***	1.157	0.282		9.630	0.002	10.674	0.005
Gas Natural SDG	23.375	0.003	*	0.293	0.588		5.681	0.017	6.083	0.048
GDF Suez	10.448	0.248		2.386	0.122		-	-	-	-
Heineken	5.699	0.731		0.297	0.586		-	-	-	-
Imperial Tobacco Group	24.068	0.014	**	3.019	0.577		11.658	0.001	11.690	0.003
Nokia	11.308	0.193		3.502	0.061	***	-	-	-	-
Pearson	10.306	0.258		1.671	0.196		-	-	-	-
Pernod Ricard	16.833	0.031	**	1.438	0.230		0.011	**0.918**	0.657	**0.720**
Repsol	19.771	0.058	***	5.199	0.262		3.383	**0.066**	3.904	**0.142**
RWE	6.430	0.645		0.836	0.360		-	-	-	-
Saint-Gobain	15.489	0.050	***	1.401	0.237		3.320	**0.068**	4.734	**0.094**
Shell	7.306	0.542		2.764	0.096	***	-	-	-	-
Siemens	15.939	0.043	**	4.346	0.037	**	-	-	-	-
Solvay	25.016	0.064	***	2.816	0.898		1.018	**0.313**	1.018	**0.601**
TDC	16.989	0.030	**	4.545	0.033	**	-	-	-	
Telenor	16.718	0.033	**	0.095	0.758		2.785	**0.095**	2.814	**0.245**
TeliaSonera	7.244	0.549		0.155	0.694		-	-	-	-
ThyssenKrupp	6.253	0.666		0.000	0.985		-	-	-	-
Vattenfall	6.234	0.668		1.218	0.270		-	-	-	-
Veolia Environment	6.713	0.611		2.588	0.108		-	-	-	-
Volkswagen	5.579	0.745		2.307	0.129		-	-	-	-
Volvo	11.788	0.167		3.195	0.074	***	-	-	-	-

Overall, the Johansen cointegration test results imply that the long-term equilibrium relation mainly exists during the crisis period, as the number of detected cointegration relationships drops significantly in the post-crisis period. Another notable matter is the fact that majority of the accepted restrictions, imply that CDS premiums were the sole contributors to price discovery process. This matter will be discussed more closely in the next sub-chapter.

In certain cases that are accepted at 5 % level, such as Heineken and Pearson in period 1, the results also imply the existence of 2 cointegrating vectors at 10 % level. Similarly, there is 1 such case in period 2 and 5 in the full sample. This of course is not desirable as the VECM analysis cannot be performed for such spread pairs. However, these companies are still included in the list of entities for the VECM analysis.

Table 7. Johansen Cointegration trace test for full sample lenghts. This table reports the Johansen trace statistics as well as their p-values for each entity for their full sample lenghts. Rejection of null hypothesis at 1%, 5% and 10 % levels is presented with *, ** and *** respectively. Entities for which cointegration is confirmed either at 1% or 5% levels are highlighted in bold and at 10 % in italics. In addition, results for LR tests on the imposed restrictions are presented for all entities with one confirmed cointegrating vector. First restriction, [1,-1,c], implies that CDS basis is equal to a constant value, whereas the second restriction, [1,-1,0], implies that CDS basis is equal to zero. Restrictions follow X^2 -distribu with one and two degrees of freedom respectively. Bolded p-values for restrictions imply the acceptance of the null hypothesis, i.e. [1,-1,c] = cds basis is a constant value.

	Trace test						Restrictions on vector			
	Number of cointegrating vectors									
Entity	None	p-value		At most 1	p-value		[1,-1,c]	p-value	[1,-1,0]	p-value
Accor	30.886	0.011	**	8.965	0.183		0.147	**0.702**	7.141	0.028
Adecco	17.314	0.026	**	3.449	0.063	***	9.095	0.003	13.777	0.001
BAE Systems	11.273	0.195		3.934	0.047	***	-	-	-	-
British American Tobacco	26.660	0.001	*	1.365	0.243		23.375	0.000	25.065	0.000
BNP Paribas	4.475	0.862		0.238	0.626		-	-	-	-
Commerzbank	16.485	0.035	**	3.767	0.052	***	8.051	0.005	11.951	0.003
Daimler	9.420	0.328		2.193	0.139		-	-	-	-
Deutsche Bank	39.743	0.001	*	5.252	0.561		3.486	**0.062**	4.911	**0.086**
E.ON	11.475	0.184		3.586	0.058	***	-	-	-	-
Edison	17.327	0.026	**	1.355	0.244		5.740	0.017	10.768	0.005
Fortum	12.289	0.144		1.932	0.165		-	-	-	-
Gas Natural SDG	27.549	0.001	*	0.004	0.947		12.858	0.000	25.396	0.000
GDF Suez	26.950	0.037	**	7.927	0.258		1.666	**0.197**	1.720	**0.423**
GlaxoSmithKline	11.268	0.196		2.520	0.112		-	-	-	-
Heineken	18.236	0.019	**	2.731	0.098	***	7.922	0.005	15.317	0.000
Imperial Tobacco Group	37.428	0.000	*	1.112	0.292		31.918	0.000	35.147	0.000
Nokia	13.836	0.088	***	2.687	0.101		4.527	0.033	11.050	0.004
Northern Rock	8.568	0.407		1.133	0.287		-	-	-	-
Novartis	24.331	0.002	*	8.800	0.003	*	-	-	-	-
Pearson	26.492	0.001	*	3.177	0.075	***	19.564	0.000	22.019	0.000
Pernod Ricard	17.077	0.029	**	3.784	0.052	***	0.001	**0.975**	3.155	**0.206**
Repsol	32.348	0.007	*	5.273	0.558		1.462	**0.227**	2.395	**0.302**
RWE	6.767	0.605		1.376	0.241		-	-	-	-
Saint-Gobain	24.991	0.001	*	1.728	0.189		5.520	0.019	14.848	0.001
Shell	9.825	0.294		3.485	0.062	***	-	-	-	-
Siemens	11.776	0.168		2.790	0.095	***	-	-	-	-
Solvay	28.506	0.023	**	4.125	0.724		2.073	**0.150**	2.628	**0.269**
Stena	15.952	0.043	**	1.458	0.227		1.799	**0.180**	3.072	**0.215**
TDC	13.030	0.114		3.387	0.066	***	-	-	-	-
Telenor	16.517	0.035	**	0.833	0.361		13.054	0.000	13.996	0.001
TeliaSonera	18.603	0.016	**	0.525	0.469		16.122	0.000	17.780	0.000
ThyssenKrupp	6.679	0.615		2.267	0.132		-	-	-	-
Vattenfall	11.421	0.187		3.752	0.053	***	-	-	-	-
Veolia Environment	9.612	0.312		3.014	0.083	***	-	-	-	-
Vodafone	9.896	0.289		3.844	0.050	**	-	-	-	-
Volkswagen	34.532	0.003	*	8.434	0.218		2.361	**0.124**	19.219	0.000

6.2. Vector error correction model

Now that the existence of the long-run equilibrium is confirmed for the firms, the short-run relationship is analysed with the vector error correction model. The adjustment coefficients of the vector autoregressive model are used to calculate the Gonzalo-Granger (GG) measure that depicts the share in which the two market participate in the price discovery process. The adjustment coefficients (λ_1 & λ_2) of the VEC-model, their t-statistics as well as the GG-measures of the cointegrated spread pairs are reported tables 8 – 10 for the three examination periods. As explained in the methodology section a significant and negative λ_1 coefficient implies that the CDS market adjusts to the price discrepancies and a significant and positive λ_2 coefficient suggests that the bond market adjusts to the price changes in the CDS market.

Overall, in period 1 the price discovery process is found to be a two-way process for 6 entities and a one-way process for 17 entities. In 7 of the 17 one-way processes the CDS market is adjusting to the changes in the bond market, while for 10 entities the CDS market leads the price discovery process. All of the one-way processes are significant at least at 5 % level, while in 3 of the two-way processes one coefficient is significant at only 10 % level. For example, in the case of Adecco the λ_1 is significant at 1% level, whereas the λ_2 coefficient is significant 10 % level. In a similar manner, a reverse case is discovered for Gas Natural SDG and Vodafone, where their λ_2 coefficients are significant at 5 % and 1 % level, respectively.

The crisis period results imply that overall the CDS spreads lead the price discovery. As evidenced by the GG-measure the CDS market dictates the price discovery in most of the cases. In fact, already the examination of the 10 restricted spread pairs shows that there are seven companies on which the CDS spreads are the sole contributor to the price discovery process, whereas the bond market only solely affects the process on three cases. In the rest of the 11 cases both markets contribute, while the CDS spreads still lead the price discovery process on average. More precisely, in 7 of the 11 cases the CDS market contributes more to the process, which is implied by a GG-measure higher than 0.50. Still despite the GG-measure indicating a leading status on either direction, there are two occasions where the two markets contribute to the price changes nearly equally, i.e. the GG-measures of RWE and Gas Natural are 0.53 and 0.45 respectively. In addition, there are two companies (Telenor & Veolia Environment) on which the results are not possible to interpret as the GG-measure is not within its upper and lower bounds. This is due to the negative sign of their λ_2 coefficients, which should have a positive value. Moreover, as the λ_1 coefficients are negative and significant their price discovery process is led by the bond market. However, the CDS market is the leading contributor to the price discovery process in 14 of the 23 cases, i.e. 61 % of the cases as represented by the GG-measure.

Table 8. Vector Error Correction Model results for sub-period 1 (15.9.2008 - 28.6.2010). This table reports the speed of adjustment coefficients (λ1 & λ2) from equation 20, their t-statistics as well as the Gonzalo-Granger measure (GG) (equation 21). Significance at 1%, 5% and 10 % levels is presented with *, ** and *** respectively.

	λ_1	t-stat		λ_2	t-stat		GG
Accor	0.000	0.000		0.018	3.530	*	1.00
Adecco	-0.054	-2.839	*	0.083	1.905	***	0.61
British American Tobacco	-0.027	-1.967	**	0.081	3.413	*	0.75
Commerzbank	-0.064	-1.425		0.164	3.233	*	0.72
Deutsche Bank	0.000	0.000		0.312	6.265	*	1.00
E.ON	-0.080	-4.935	*	0.012	0.444		0.13
Fortum	0.000	0.000		0.042	4.059	*	1.00
Gas Natural SDG	-0.081	-1.908	***	0.065	2.315	**	0.45
GlaxoSmithKline	-0.039	-3.856	*	0.021	0.803		0.35
Heineken	-0.017	-1.006		0.077	3.584	*	0.82
Imperial Tobacco Group	-0.062	-3.628	*	0.025	1.978	**	0.28
Nokia	-0.027	-4.318	*	0.000	0.000		0.00
Pearson	-0.003	-0.431		0.114	4.016	*	0.97
Repsol	-0.046	-4.087	*	0.000	0.000		0.00
RWE	-0.053	-3.514	*	0.061	2.106	**	0.53
Shell	0.000	0.000		0.041	2.968	*	1.00
Solvay	0.000	0.000		0.073	4.419	*	1.00
Stena	0.000	0.000		0.063	3.599	*	1.00
Telenor	-0.045	-3.731	*	-0.017	-0.975		-0.58
TeliaSonera	0.000	0.000		0.051	5.053	*	1.00
Veolia Environment	-0.053	-4.283	*	-0.025	-1.599		-0.91
Vodafone	-0.042	-1.929	***	2.370	7.901	*	0.98
Volkswagen	-0.057	-4.203	*	0.000	0.000		0.00

A closer look into the results among industry sectors does not reveal significant resemblances between companies in the same sector since the results vary greatly in certain sectors. For example, the three electric utility companies E.On, Fortum and RWE have their credit risk priced differently as the bond market dominates the price discovery process on E.On (0.13), the CDS market is the sole contributor for Fortum (1.00) while the credit risk of RWE is valued in both markets (0.53). Similarly, in the oil and gas industry, the bond market leads the process for Repsol (0.00), CDS spreads do the same for Shell (1.00), whereas both markets contribute in the case of Gas Natural SDG (0.45).

Still, in three sectors the price discovery process is either led or solely decided by CDS market. For example in the services sector the CDS market is the sole contributor for Accor (1.00), dominates the process for Pearson (0.97) and leads the lead-lag relation for Adecco (0.61). Other CDS dominated sectors with at least two entities were the financial and telecommunications industries.

In period 2 a two way price discovery process is discovered for only 2 entities, BNP Paribas and Imperial Tobacco Group. Moreover, in 8 of the 9 one-way processes the CDS market contributes to the price discovery, while only in the case of Edison the bond market is found to dominate the process. Similar to the crisis period GG results, the CDS market is the leading contributor to the price discovery process also after the crisis. In fact, the derivatives markets role is found to increase significantly as 10 out of 11 examined spread pairs had a GG-measure close to 1.0, i.e. in 91 % of the cases. Furthermore, all six of the restricted VEC-models implied a sole contributor's role for the CDS market. The only bond market led entity was Edison, whose credit risk pricing is clearly dominated by the cash market, as implied also by the GG-measure of 0.06. Thus, unlike during the crisis none of the entities have their credit risk priced equally in both of the markets after the crisis despite the fact that in two cases a two-sided price convergence process is confirmed.

Table 9. Vector Error Correction Model results for sub-period 2 (29.6.2010 - 9.4.2013). This table reports the speed of adjustment coefficients from equation 20, their t-statistics as well as the Gonzalo-Granger measure (GG) (equation 21). Significance at 1%, 5% and 10 % levels is presented with *, ** and *** respectively.

	λ_1	t-stat	λ_2	t-stat	GG
BAE Systems	0.000	0.000	0.018	4.216 *	1.00
BNP Paribas	-0.017	-2.153 **	0.047	4.967 *	0.73
Deutsche Bank	-0.009	-1.189	0.059	6.056 *	0.86
Edison	-0.102	-3.675 *	0.006	0.164	0.06
Gas Natural SDG	-0.019	-1.027	0.048	4.016 *	0.71
Imperial Tobacco Group	-0.020	-2.187 **	0.080	4.044 *	0.80
Pernod Ricard	0.000	0.000	0.062	3.802 *	1.00
Repsol	0.000	0.000	0.040	3.270 *	1.00
Saint-Gobain	0.000	0.000	0.043	3.050 *	1.00
Solvay	0.000	0.000	0.045	4.619 *	1.00
Telenor	0.000	0.000	0.122	3.721 *	1.00

Overall there are 5 companies for which interpretable GG-measures can be calculated in both sub-periods. This enables a small sample analysis of the changes in the lead-lag relation between the two periods. During the crisis period both markets lead the price discovery process in 2 cases, while in one occasion both markets contribute equally. As shown in the overall results of the post-crisis period, the CDS market dominates the price discovery in sub-period 2 also in the smaller sub-sample. Interestingly, significant shifts towards CDS dominated price discovery processes are detected as for example the GG-measure of Repsol jumps from 0.00 in period 1 to 1.00 in period 2, while the GG-measure of Imperial Tobacco Group shifts from 0.28 to 0.80. Similarly, Gas Natural SDG's previously detected equal contribution (0.45) shifts towards the clear leadership role of the CDS market (0.71) in period 2. The only case where the CDS market loses some of its share in terms of contribution is Deutsche Bank, whose GG-measure slightly drops from 1.00 in period 1 to 0.86 in period 2.

Table 10. Vector Error Correction Model results for full sample lenghts. This table reports the speed of adjustment coefficients (λ1 & λ2) from equation 20, their t-statistics as well as the Gonzalo-Granger measure (GG) (equation 21). Significance at 1%, 5% and 10 % levels is presented with *, ** and *** respectively..The significance level is not presented if the sign of the speed of adjustment coefficient is not correct.

	λ_1	t-stat		λ_2	t-stat		GG
Accor	0.010	2.643		0.027	4.287	*	1.61
Adecco	-0.021	-2.309	**	0.046	2.624	*	0.69
British American Tobacco	-0.023	-2.258	**	0.072	4.047	*	0.76
Commerzbank	-0.007	-2.096	**	-0.029	-2.933		1.32
Deutsche Bank	0.000	0.000		0.095	5.455	*	1.00
Edison	-0.047	-2.964	*	0.048	2.061	**	0.50
Gas Natural SDG	0.001	0.056		0.052	4.882	*	1.02
GDF Suez	0.000	0.000		0.026	4.164	*	1.00
Heineken	0.007	1.393		0.031	3.718	*	1.31
Imperial Tobacco Group	-0.040	-4.878	*	0.023	3.020	*	0.37
Nokia	0.010	2.608		0.018	3.112	*	2.19
Pearson	-0.010	-2.249	**	0.080	4.213	*	0.89
Pernod Ricard	0.000	0.000		0.026	3.185	*	1.00
Repsol	-0.040	-4.976	*	0.000	0.000		0.00
Saint-Gobain	-0.024	-3.368	*	0.019	2.924	**	0.43
Solvay	0.000	0.000		0.036	4.675	*	1.00
Stena	0.000	0.000		0.044	3.366	*	1.00
Telenor	-0.026	-3.939	*	0.004	0.337		0.12
TeliaSonera	-0.015	-3.321	*	0.027	2.566	**	0.65
Volkswagen	-0.027	-4.123	*	0.013	2.061	**	0.32

Table 10. presents the VECM results for the full sample lengths. Interestingly, the longer sample lengths result in more two-way price discovery processes as for 8 entities both markets contribute to the process. However, the CDS market is still the sole contributor in most of the one-way processes as the bond market adjusts to the discrepancies in 9 cases, while the CDS market is the adjusting market in 3 cases. Overall, the full sample results display a larger number of coefficients with a wrong sign than the two sub-samples. For example, the λ_1 coefficient is positive in 4 cases and λ_2 is negative in one case during the full sample tests, whereas in sub-period 1 there are 2 cases where the λ_2 coefficient is negative. Moreover, such cases are not existent in period 2.

Interestingly, the GG-measures in the full sample show that that the CDS market dominates the price discovery process in 4 of the 8 two-way processes, while the bond market leads the process for 3 companies. In the case of Edison both markets are found to contribute equally, as evidenced by the GG measure of 0.50. Notably, also the price

Table 11. Summary of VECM test outcomes. This table summarizes the outcomes of tables 8 - 10. Two-way price discovery process is confirmed for entities for which $\lambda 1 < 0$, $\lambda 2 > 0$ and both are significant at 1%, 5% or 10 % level (t-stat > 1.645). Similarly, a one-way price discovery process where CDS market adjusts to price discrepancies is confirmed if only $\lambda 1 < 0$ and significant. Moreover, if only $\lambda 2 > 0$ and is significant, a one-way process where bond market adjusts is confirmed.

Price discovery process	#	Entities
Panel A: Period 1	**23**	
Two-way $\lambda_1 < 0$ and $\lambda_2 > 0$	6	Adecco, British American Tobacco, Gas Natural SDG, Imperial Tobacco, RWE, Vodafone
One-way: CDS market adjusts only $\lambda_1 < 0$	7	E.On, GlaxoSmithKline, Nokia, Repsol, Telenor, Veolia Environment, Volkswagen
One-way: Bond market adjusts only $\lambda_2 > 0$	10	Accor, Commerzbank, Deutsche Bank, Fortum, Heineken, Pearson, Shell, Solvay, Stena,TeliaSonera
Panel B: Period 2	**11**	
Two-way $\lambda_1 < 0$ and $\lambda_2 > 0$	2	BNP Paribas, Imperial Tobacco
One-way: CDS market adjusts only $\lambda_1 < 0$	1	Edison
One-way: Bond market adjusts only $\lambda_2 > 0$	8	BAE Systems, Deutche Bank, Gas Natural SDG, Pernod Ricard, Repsol, Saint-Gobain, Solvay, Telenor
Panel C: Full Sample lenghts	**20**	
Two-way $\lambda_1 < 0$ and $\lambda_2 > 0$	8	Adecco, British American Tobacco, Edison, Imperial Tobacco Group, Pearson, Saint-Gobain,TeliaSonera, Volkswagen
One-way: CDS market adjusts only $\lambda_1 < 0$	3	Commerzbank, Repsol, Telenor
One-way: Bond market adjusts only $\lambda_2 > 0$	9	Accor, Deutsche Bank, Gas Natural SDG, GDF Suez, Heineken, Nokia, Pernod Ricard, Solvay, Stena

discovery process of Saint-Gobain is rather equally divided between the two markets, while it still slightly edges towards the lead of the bond market (GG: 0.43).

Table 11. summarizes the VECM results. A unified factor between all of the three analysis periods is the CDS markets' leading role in price discovery. The CDS market is not only the dominating market in the majority of the one-way processes but also leads the price discovery also in most of the two-sided processes. Another interesting feat in the VECM results is the lack of entities for which any kind of price discovery process is not detected.

6.3. Granger causality

The crisis period Granger causality test results are presented in table 12. The results imply that on 5 of the 14 entities a two-sided Granger causality exists between the CDS and credit spreads. More precisely, the two-sided causality is detected for BNP Paribas, Daimler, Saint-Gobain, Vattenfall and Volvo. However, the causality from credit spreads to CDS is only detected at 10 % level for Vattenfall and Volvo. Similarly, the causality from CDS to CS is significant at 10 % level for BNP Paribas and Saint-Gobain, while other detected causalities are significant at least at the 5 % level. One sided causality is detected for three companies, as the CDS spreads are found to cause the credit spreads for Barclays Bank and Pernod Ricard, while the bond market causes CDS spreads for Siemens. Thus, overall the causality from CDS to CS is more common in the sample with 8 cases, while causality from bonds to CDS is found on 6 occasions. Also, in 5 cases no causality relationships are detected.

Due to the relatively low number of cointegrated spread pairs in sub-period 2, the Granger causality tests cover a total of 19 entities, whose results are reported in table 12. A two-sided causality is detected in 7 cases, for E.On, Nokia, RWE, Shell, Siemens, TDC and Vattenfall. While a one sided causality from CDS to CS is found for 8 entities, there are no companies with a one-sided causality from CS to CDS. Moreover, four companies have no causality relationships to either direction. Notably, the significance of the post-crisis results is higher than the ones of the crisis period as in 18 of the 38 tests the null hypothesis is rejected at 1 % level. Furthermore, in four tests the null is rejected at 5 % level, while there are no cases where the null is rejected at the 10 % level.

Table 12. Granger causality test results for sub-period 1 (15.9.2008 - 28.6.2010). This table presents the test statistics and p-values for Granger causality tests. Significance at 1%, 5% and 10 % levels is presented with *, ** and *** respectively.

	H0: CS does not cause CDS			H0: CDS does not cause CS		
	F-statistic	p-value		F-statistic	p-value	
BAE Systems	0.380	0.538		1.196	0.275	
Barclays Bank	1.205	0.302		3.031	0.051	**
BNP Paribas	3.078	0.047	**	2.485	0.085	***
Daimler	5.667	0.004	*	10.139	0.000	*
Edison	0.949	0.389		4.934	0.008	*
GDF Suez	0.627	0.535		0.679	0.508	
Northern Rock	1.473	0.231		0.386	0.680	
Novartis	0.599	0.550		1.957	0.143	
Pernod Ricard	0.721	0.487		10.345	0.000	*
Saint-Gobain	4.275	0.015	**	2.782	0.063	***
Siemens	4.674	0.031	**	2.102	0.148	
ThyssenKrupp	0.688	0.408		0.613	0.434	
Vattenfall	2.536	0.057	***	12.693	0.000	*
Volvo	2.996	0.051	***	23.547	0.000	*

Table 13. Granger causality test results for sub-period 2 (29.6.2010 - 9.4.2013). This table presents the test statistics and p-values for Granger causality tests. Significance at 1%, 5% and 10 % levels is presented with *, ** and *** respectively.

	H0: CS does not cause CDS			H0: CDS does not cause CS		
	F-statistic	p-value		F-statistic	p-value	
Accor	0.003	0.997		5.536	0.004	*
Barclays Bank	1.472	0.230		7.220	0.001	*
Carlsberg Breweries	1.742	0.176		20.869	0.000	*
Commerzbank	2.299	0.130		1.398	0.237	
E.ON	5.416	0.005	*	6.686	0.001	*
GDF Suez	0.401	0.752		23.825	0.000	*
Heineken	0.037	0.847		1.408	0.237	
Nokia	9.679	0.000	*	13.853	0.000	*
Pearson	0.848	0.358		0.982	0.322	
RWE	5.394	0.005	*	9.358	0.000	*
Shell	3.692	0.025	**	4.661	0.010	*
Siemens	6.113	0.002	*	7.785	0.001	*
TDC	2.900	0.034	**	15.319	0.000	*
TeliaSonera	1.667	0.190		3.786	0.023	**
ThyssenKrupp	2.317	0.131		1.015	0.316	
Vattenfall	6.055	0.003	*	4.448	0.012	**
Veolia Environment	0.545	0.651		21.283	0.000	*
Volkswagen	0.545	0.580		23.410	0.000	*
Volvo	0.001	0.999		8.536	0.000	*

The results for the full sample lengths in table 14. depict a similar pattern as the two sub-periods. First of all, the CDS market Granger causes the bond market in 12 of the 16 cases, while in 8 cases the bond market has a similar effect to the CDS market. Moreover, a two-way causality is confirmed for 6 entities, one-way causality from CDS to bonds for 6 firms and a one-way causality from the bond market to the CDS market for 2 companies. In addition, in 2 cases a causality to either direction cannot be confirmed.

Table 14. Granger causality test results for full sample lenghts. This table presents the test statistics and p-values for Granger causality tests. Significance at 1%, 5% and 10 % levels is presented with *, ** and *** respectively.

	H0: CS does not cause CDS			H0: CDS does not cause CS		
	F-statistic	p-value		F-statistic	p-value	
BAE Systems	0.005	0.943		2.594	0.108	
BNP Paribas	0.259	0.904		6.911	0.000	*
Daimler	5.492	0.005	*	9.699	0.000	*
E.ON	1.818	0.163		2.574	0.077	***
Fortum	0.999	0.369		6.045	0.003	*
GlaxoSmithKline	4.258	0.014	**	8.771	0.000	*
Northern Rock	2.570	0.078	***	0.184	0.832	
Novartis	0.060	0.942		3.310	0.037	**
RWE	5.154	0.006	*	3.877	0.021	**
Shell	0.589	0.555		14.429	0.000	*
Siemens	5.920	0.001	*	10.886	0.000	*
TDC	2.601	0.051	*	13.399	0.000	*
ThyssenKrupp	0.449	0.503		0.020	0.889	
Vattenfall	5.162	0.000	*	17.483	0.000	*
Veolia Environment	0.865	0.459		18.297	0.000	*
Vodafone	2.011	0.091	***	1.665	0.156	

Table 15. summarizes the Granger causality test results. Similar to the VECM results the summary of the causality tests confirms the leading role of the CDS market in credit risk pricing. Causality from the CDS market to the bond market is found in 71.4 percent of the analysed spread pairs, while a causality from the bond market to the CDS market is confirmed only on 43 percent of the spread pairs. Moreover, the importance of the CDS market is more evident when we compare the shares of the one-way causality relationships (CDS → bond 34 % vs. bond → CDS 6 %).

Table 15. Summary of Granger causality test outcomes. This table reports the outcomes of tables 12 - 14.

Granger causality	#	Entities
Panel A: Period 1	**14**	
Two-way	5	BNP Paribas, Daimler, Saint-Gobain, Vattenfall, Volvo
One-way: CDS causes bond	3	Barclays Bank, Edison, Pernod Ricard
One-way Bond causes CDS	1	Siemens
No causality	5	BAE Systems, GDF Suez, Northern Rock, Novartis, ThyssenKrupp
Panel B: Period 2	**19**	
Two-way	7	E.On, Nokia, RWE, Shell, Siemens, TDC, Vattenfall
One-way: CDS causes bond	8	Accor, Barclays Bank, Carlsberg Breweries, GDF Suez, TeliaSonera, Veolia Environment, Volkswagen, Volvo
One-way Bond causes CDS	0	
No causality	4	Commerzbank, Heineken, Pearson, ThyssenKrupp
Panel C: Full Sample lenghts	**16**	
Two-way	6	Daimler, GlaxoSmithKline, RWE, Siemens, TDC, Vattenfall
One-way: CDS causes bond	6	BNP Paribas, E.On, Fortum, Novartis, Shell, Veolia Environment
One-way Bond causes CDS	2	Northern Rock, Vodafone
No causality	2	BAE Systems, ThyssenKrupp

6.4. Comparison with earlier studies

Studies by Blanco et al. (2005) and Zhu (2006) showed that European corporate entities had their credit risk priced equally in the bond and CDS markets in early the 2000's. The results of this thesis show that the leadership role has shifted to the CDS market as it was involved in the price discovery process for majority of the analysed companies in all three test periods, a result much like the ones on U.S. companies in the two aforementioned studies. Moreover, the results on the two-way processes show that the CDS market has increased its role from the early 2000's. For example, Blanco et al. (2005) and Zhu (2006) suggested that around 70 – 80 % of the U.S. corporate price discovery contribution comes from the CDS market while the corresponding share on the European entities was 50 %. Our results on the European corporates show that the average shares in period 1, period 2 and full sample were 65 %, 83 % and 67 % respectively. The larger role of the CDS market is further presented in the Granger causality results as a causality from the CDS market to the bond market is not only more common but also more significant in majority of the tests.

Coudert et al. (2011) reported that the credit risk of financial corporates was mainly priced in the CDS market during the European debt crisis. Our small sample of financial entities demonstrates a similar outcome, as for example the bond market solely adjusts to price discrepancies for Commerzbank and Deutsche Bank during the crisis. Similarly, the CDS spreads are found to Granger cause the credit spreads of Barclays Bank during and after the crisis.

Also the crisis period seems to have an effect to the number of cointegrated spreads pairs detected as the long-run equilibrium is confirmed for 23 firms in the crisis period while it exists only on 11 during the post crisis period. In a similar manner, Fontana et al. (2010) discovered that the long-run equilibrium did not exist before the crisis for their sample of European sovereigns, while in the crisis period it was found to exist for all entities. Thus, the crisis and thereby also the more volatile spreads seem to lead towards a more evident equilibrium relationship. On the contrary, the steadier spread levels in the post crisis period also lead to smaller adjustments between the two markets which to certain extent accounts for the lower number of cointegrated spread pairs.

Still, the amount of detected long-run equilibriums in the sample of this thesis is small compared to the previous studies. More precisely, the previous studies have shown that the equilibrium relationship existed on most of the analysed entities, which could indicate either lack of liquidity in the corporate bond or CDS markets. Another possibility, is the somewhat inaccurate way of interpolating the 5-year bond yields especially for entities whose bonds were trading significantly above or below par and for which only a few contracts were available.

7. CONCLUDING REMARKS

The previous studies on the equilibrium relation between the credit default swap and bond markets have focused on U.S. firms and sovereign entities. This thesis will, thus extend the literature on European corporate entities, while focusing on the 2007–2013 period. Furthermore, the earlier studies from a similar time period have mainly analysed European countries, thereby resulting in scarce results from the corporate credit risk markets. The empirical studies have shown that the financial crisis period has affected the equilibrium relation and especially the price discovery process. These findings on the price discovery process suggest that the growth of the CDS market has made the CDSs the main trading instrument for credit risk, thus the roles of the two markets for the corporate entities are an issue to be analysed. Especially, since the financial crisis has resulted in mixed results in the late 2000's for high and low risk European countries' price discovery processes as a result of the flight-to-liquidity effect.

The thesis follows the methodology used in the studies of Blanco et al. (2006) and Zhu (2005). First, the spreads are tested for cointegration by determining the stationarity of the CDS basis. Secondly, the cointegrated spreads are analysed with a vector error correction model (VECM) to determine the speed coefficients for the two markets. These coefficients are then used to calculate Gonzalo-Granger information share measure for more precise results on the price discovery process. Also, the causality between spreads that are not cointegrated will be analysed with the Granger-causality test.

The data provides an interesting setting for the study. The sample of covers 41 corporate entities from 12 countries across 12 different industries. Due to the lack of available bond data, the sample lengths vary between entities, averaging at 3.4 years. This still enables an analysis of two sub periods, the crisis period (15^{th} September 2008 to 28^{th} June 2010) and the post-crisis period (29^{th} June 2010 – 9^{th} April 2013). The data reveals that majority of the entities experience a negative average CDS basis during the crisis period, which is in many cases mostly accountable to the large rise in the credit spread levels after the collapse of Lehman Brothers in September 2008. Moreover, the pricing discrepancies between the bond and CDS markets steadily decrease towards mid-2010 as the credit spreads drop to the levels of CDS spreads. Furthermore, the CDS spreads are valued higher in the post-crisis period, which is depicted by the low number of entities with a negative average basis (5 out of 36).

In the empirical part the Augmented Dickey-Fuller tests confirm the first-difference stationarity of the spread pairs in majority of the cases in all examination periods.

However, the Johansen cointegration tests reveal major differences between the analysis periods, as the long-run equilibrium is detected for 23 entities in the crisis period and for only 11 entities in the post-crisis period. Thus, the theoretical equilibrium relationship seems to mostly exist during more volatile market conditions, such as the debt crisis.

Vector error correction model tests show that the price discovery is mainly led by the CDS market during both the crisis and post-crisis periods. The CDS market solely contributes to the process in 10 of the 23 cases during the crisis, while a one-way bond market led process is discovered for 7 entities. In addition, there are 6 cases where both markets contribute to the process, while the CDS market leads the price discovery process in 4 of them. The post-crisis results demonstrate a more significant leadership role for the CDS market as in 8 of 11 cases the CDS market solely contributes to the process. Moreover, the bond market is the sole contributor for price discovery for one entity, while the CDS market is the clear leader in both of the 2 two-way processes discovered.

In a similar manner, also the Granger causality test results show that the causality from the CDS market to the bond market is more common among the sample companies. However, in the crisis period a two-way causality relationship is detected for majority of the entities. Still, the one-sided causality from the CDS market is already more common than the two-sided causality in the post-crisis period. This finding supports the VECM results which also implied a dominating leading role of the CDS market in the price discovery process during and even more so after the crisis period.

Overall, the debt crisis has had an effect in the pricing of credit risk. Most importantly, the crisis seems to have resulted in market dynamics that are in line with the theory. However, as the two markets had adjusted to the pricing discrepancies, the long-run equilibrium is not detected that often in the post-crisis period. Similarly, the CDS market gains a more significant leading role in the price discovery process in the small sample of cointegrated spread pairs after the crisis. This could be a sign of investors shifting back to the CDS market and thus reducing the amount of trades in the bond market.

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APPENDIX 1. Bond data

Table 16. Bond data. This table presents the bond contracts used for the bond yield calculations. The year of issue, coupon rate and maturity date are reported respectively.

Accor
- 2009 7 1/2% 04/02/14
- 2009 6 1/2% 06/05/13
- 2009 6.039% 06/11/17

Adecco
- 2006 4 1/2% 25/04/13
- 2009 7 5/8% 28/04/14

BAE Systems
- 2001 6.4% 15/12/11
- 2005 5.2% 15/08/15
- 2009 4.95% 01/06/14
- 2011 3 1/2% 11/10/16

Barclays Bank
- 2004 1 1/2% 18/07/16
- 2008 6% 23/01/18 164
- 2009 4 7/8% 13/08/19
- 2009 4% 14/03/16
- 2009 6 1/2% 06/10/14
- 2010 4% 20/01/17

British American Tobacco
- 2004 4 3/8% 15/06/11
- 2006 4 3/8% 15/09/14

BNP Paribas
- 2007 4 1/2% 30/05/14
- 2007 4 7/8% 15/10/14
- 2007 4 3/8% 01/02/17
- 2008 5.2% 20/06/13
- 2008 5 3/4% 27/06/18

Carlsberg Breweries
- 2009 6% 28/05/14
- 2010 3 3/8% 13/10/17
- 2012 2 5/8% 15/11/22

Commerzbank
- 2000 6.66% 26/07/16
- 2005 3 1/8% 15/09/15
- 2007 5.12% 25/09/20
- 2007 5.19% 15/02/18
- 2007 5.2% 26/09/22
- 2008 6 1/4% 30/09/14

Daimler
- 2009 4 5/8% 02/09/14
- 2010 3% 19/07/13
- 2010 4 1/8% 19/01/17

Deutsche Bank
- 2004 4.155% 10/11/14
- 2005 2 1/2% 30/06/15
- 2007 5 1/8% 31/08/17
- 2008 5 3/8% 07/05/18
- 2008 4 3/8% 30/12/16

E.ON
- 2007 5 1/8% 02/10/12
- 2008 5 1/4% 06/06/14
- 2008 5 1/4% 08/09/15
- 2008 5 1/8% 07/05/13
- 2009 4 3/8% 24/02/16

Edison
- 2009 4 1/4% 22/07/14
- 2010 3 1/4% 17/03/15
- 2010 3 7/8% 10/11/17

Fortum
- 2003 4 5/8% 19/11/10
- 2003 5% 19/11/13
- 2006 4 1/2% 20/06/16
- 2009 4 5/8% 20/03/14
- 2009 6% 20/03/19
- 2011 4% 24/05/21

Gas Natural SDG
- 2009 3 1/8% 02/11/12
- 2009 4 3/8% 02/11/16
- 2009 6 3/8% 09/07/19
- 2009 5 1/4% 09/07/14
- 2010 3 3/8% 27/01/15
- 2010 4 1/8% 26/01/18

GDF Suez
- 2003 5 1/8% 19/02/18
- 2008 6 1/4% 24/01/14
- 2008 6 7/8% 24/01/19
- 2009 5 5/8% 18/01/16
- 2009 6 3/8% 18/01/21

GlaxoSmithKline
- 2005 3% 18/06/12
- 2007 5 1/8% 13/12/12
- 2007 5 5/8% 13/12/17
- 2009 3 7/8% 06/07/15

Heineken
- 2003 5% 04/11/13
- 2009 4 5/8% 10/10/16
- 2009 7 1/8% 07/04/14

Imperial Tobacco Group
- 2006 4 3/8% 22/11/13
- 2008 7 1/4% 15/09/14
- 2009 8 3/8% 17/02/16
- 2011 4 1/2% 05/07/18
- 2011 5% 02/12/19

Nokia
- 2009 5 1/2% 04/02/14
- 2009 6 3/4% 04/02/19
- 2009 5 1/2% 04/02/14
- 2009 6 3/4% 04/02/19

Northern Rock
- 2005 3 5/8% 20/04/15
- 2006 3 7/8% 18/10/11
- 2006 3 5/8% 28/03/13
- 2007 4 1/8% 27/03/17

Novartis
- 2009 5 1/8% 10/02/19
- 2009 4 1/8% 10/02/14
- 2010 1.9% 24/04/13
- 2010 2.9% 24/04/15
- 2010 4.4% 24/04/20

Pearson
- 2004 5.7% 01/06/14
- 2003 4 5/8% 15/06/18
- 2008 5 1/2% 06/05/13
- 2008 6 1/4% 06/05/18

Pernod Ricard
- 2006 4 5/8% 06/12/13
- 2009 7% 15/01/15
- 2010 4 7/8% 18/03/16

Repsol
- 2003 5% 22/07/13
- 2004 4 5/8% 08/10/14
- 2007 4 3/4% 16/02/17

RWE
- 2001 6 1/4% 20/04/16
- 2002 6 1/8% 26/10/12
- 2003 5 1/8% 23/07/18
- 2004 4 5/8% 23/07/14
- 2008 6 5/8% 31/01/19
- 2009 5% 10/02/15

Saint-Gobain
- 2006 4 1/4% 31/05/11
- 2006 4 7/8% 31/05/16
- 2007 4 3/4% 11/04/17
- 2008 7 1/4% 16/09/13

Shell
- 2007 4 5/8% 22/05/17
- 2009 3 3/8% 09/02/12
- 2009 3% 14/05/13
- 2009 4 1/2% 09/02/16
- 2009 4 3/8% 14/05/18

Siemens
- 2008 5 1/4% 12/12/11
- 2008 5 3/8% 11/06/14
- 2008 5 5/8% 11/06/18
- 2009 4 1/8% 20/02/13
- 2009 5 1/8% 20/02/17

Solvay
- 2003 4 5/8% 27/06/18
- 2003 4 7/8% 10/01/14
- 2009 5% 12/06/15

Statoil
- 1994 9 1/8% 15/07/14
- 1996 7 3/8% 01/05/16
- 2004 5 1/8% 30/04/14
- 2009 5 1/4% 15/04/19
- 2010 3 1/8% 17/08/17

Stena
- 2003 9 5/8% 01/12/12
- 2005 7% 01/12/16

TDC
- 2009 5 7/8% 16/12/15
- 2011 3 1/2% 23/02/15
- 2011 4 3/8% 23/02/18
- 2012 3 3/4% 02/03/22

Telenor
- 2002 5 7/8% 05/12/12
- 2006 4 1/2% 28/03/14
- 2007 4 7/8% 29/05/17
- 2010 4 1/8% 26/03/20

TeliaSonera
- 2005 3 5/8% 09/05/12
- 2005 4 1/8% 11/05/15
- 2007 4 3/4% 07/03/17
- 2009 5 1/8% 13/03/14
- 2011 4 1/4% 18/02/20

Tesco
- 2008 5 5/8% 12/09/12
- 2008 5 7/8% 12/09/16
- 2009 5 1/8% 24/02/15
- 2011 3 3/8% 02/11/18

ThyssenKrupp
- 2004 5% 29/03/11
- 2005 4 3/8% 18/03/15
- 2009 8% 18/06/14
- 2009 6 3/4% 25/02/13
- 2009 8 1/2% 25/02/16

Vattenfall
- 2003 5% 18/06/18
- 2008 5 3/4% 05/12/13
- 2008 6 3/4% 31/01/19
- 2009 4 1/4% 19/05/14
- 2009 5 1/4% 17/03/16

Veolia Environment
- 2002 5 7/8% 01/02/12
- 2003 4 7/8% 28/05/13
- 2005 4% 12/02/16
- 2009 5 1/4% 24/04/14
- 2005 4% 12/02/16
- 2006 4 3/8% 16/01/17

Vodafone
- 2002 5 3/8% 30/01/15
- 2003 4 5/8% 15/07/18
- 2003 5% 16/12/13
- 2006 5 3/4% 15/03/16
- 2007 5 5/8% 27/02/17

Volkswagen
- 2002 5 3/8% 25/01/12
- 2003 4 7/8% 22/05/13
- 2003 5 3/8% 22/05/18
- 2009 3 1/2% 02/02/15

Volvo
- 2007 5% 31/05/17
- 2009 9 7/8% 27/02/14

APPENDIX 2. Descriptive statistics

Table 17. Descriptive statistics by industry. This table reports the descriptive statistics for period 1 (15.9.2008 - 28.6.2010). Mean, maximum and minimum values as well as the standard deviation are reported for CDS spread and credit spread, respectively. In addition, the average CDS basis, average absolute basis and number of observations are presented in the last three columns.

	CDS	MAX	MIN	STD	CS	MAX	MIN	STD	AB	AAB	OBS
Automobile											
Daimler	103.00	145.00	68.97	17.12	90.48	156.34	59.82	22.89	12.52	17.23	217
Volkswagen	166.71	416.93	65.71	75.65	131.92	355.59	17.85	84.17	34.79	42.03	466
Volvo	269.20	576.00	141.92	103.20	318.86	974.50	77.81	222.29	-49.66	94.02	346
Average	**179.64**	**379.31**	**92.20**	**65.32**	**180.42**	**495.48**	**51.83**	**109.78**	**-0.79**	**51.10**	**343**
Basic Materials											
Solvay	87.49	165.25	52.25	32.54	97.34	217.26	-24.30	57.32	-9.85	31.90	466
ThyssenKrupp	341.03	494.00	195.94	83.62	322.63	540.50	196.96	98.30	18.40	138.93	346
Average	**214.26**	**329.62**	**124.10**	**58.08**	**209.99**	**378.88**	**86.33**	**77.81**	**4.28**	**85.41**	**406**
Financial											
Barclays Bank	102.02	182.64	71.97	28.82	486.44	688.69	316.96	78.30	-384.43	384.43	188
BNP Paribas	76.37	148.00	47.25	21.62	138.04	257.24	48.35	56.87	-61.67	72.24	412
Commerzbank	87.94	160.90	53.35	26.58	241.39	341.33	164.60	49.33	-153.45	153.45	153
Deutsche Bank	99.92	184.43	67.69	26.05	123.58	249.92	48.99	37.43	-23.66	29.95	296
Northern Rock	310.00	550.00	147.50	111.43	247.32	349.80	114.43	69.59	62.68	70.85	364
Average	**135.25**	**245.19**	**77.55**	**42.90**	**247.36**	**377.40**	**138.67**	**58.30**	**-112.11**	**142.19**	**283**
Consumer Goods											
British American Tobacco	83.14	183.33	52.54	29.53	173.09	359.95	41.47	92.02	-89.95	92.47	395
Heineken	111.54	150.00	85.25	20.43	82.15	114.06	44.06	13.06	29.39	29.39	238
Imperial Tobacco Group	203.61	465.00	86.21	114.87	243.32	600.75	25.66	183.25	-39.72	71.71	466
Pernod Ricard	184.40	275.00	129.31	40.97	225.99	325.45	156.43	39.65	-41.59	48.36	238
Average	**145.67**	**268.33**	**88.33**	**51.45**	**181.14**	**350.06**	**66.90**	**81.99**	**-35.47**	**60.48**	**334**
Electric Utilities											
E.ON	70.69	151.25	46.67	19.21	73.14	180.19	-8.37	45.27	-2.45	26.20	466
Edison	91.23	143.89	67.96	12.83	89.75	127.83	22.57	17.74	1.48	12.80	236
Fortum	66.39	160.00	42.05	24.87	82.26	177.82	2.41	51.58	-15.87	30.56	466
Gas Natural SDG	123.08	258.60	62.51	43.71	110.37	214.41	56.62	40.36	12.71	14.90	238
RWE	58.10	110.83	36.37	15.25	52.06	133.33	-9.48	39.47	6.04	24.98	466
Vattenfall	61.99	105.00	42.61	13.61	60.63	165.38	-4.26	45.56	1.35	31.11	387
Average	**78.58**	**154.93**	**49.69**	**21.58**	**78.04**	**166.49**	**9.92**	**39.99**	**0.54**	**23.43**	**377**
Healthcare											
GlaxoSmithKline	59.51	105.00	38.00	20.47	36.26	135.82	-24.34	38.06	23.25	28.16	466
Novartis	44.93	75.00	25.00	13.65	37.28	144.33	-4.16	37.54	7.64	23.69	363
Average	**52.22**	**90.00**	**31.50**	**17.06**	**36.77**	**140.07**	**-14.25**	**37.80**	**15.44**	**25.93**	**415**
Industrial Goods											
BAE Systems	109.37	297.50	43.00	53.14	198.23	434.06	53.93	106.32	-88.86	102.08	466
Saint-Gobain	210.63	525.00	92.63	111.09	217.48	476.75	68.59	129.67	-6.85	40.20	466
Siemens	98.82	248.33	50.33	43.88	60.87	186.62	-25.16	53.77	37.95	40.95	466
Veolia Environment	117.05	210.00	65.57	35.50	133.40	340.22	36.83	79.65	-16.36	40.64	466
Average	**133.97**	**320.21**	**62.88**	**60.90**	**152.50**	**359.41**	**33.55**	**92.35**	**-18.53**	**55.97**	**466**
Oil & Gas											
Gas Natural SDG	123.08	258.60	62.51	43.71	110.37	214.41	56.62	40.36	12.71	14.90	238
Repsol	180.06	516.67	73.43	105.84	173.34	395.79	74.74	92.21	6.72	33.12	466
Shell	57.34	95.09	42.65	12.22	26.48	83.17	-8.26	21.09	30.86	31.13	346
Average	**120.16**	**290.12**	**59.53**	**53.92**	**103.39**	**231.12**	**41.03**	**51.22**	**16.76**	**26.38**	**350**
Services											
Accor	172.25	274.94	119.80	36.93	231.98	506.31	130.98	85.85	-59.73	61.61	346
Adecco	155.92	211.70	123.00	19.38	274.83	455.80	165.30	78.15	-118.91	118.91	295
Pearson	68.63	187.50	35.00	29.24	299.90	658.77	84.98	156.29	-231.27	231.27	466
Tesco	99.10	185.00	61.83	25.43	102.92	333.99	6.37	93.67	-3.82	63.26	454
Average	**123.97**	**214.78**	**84.91**	**27.75**	**227.41**	**488.72**	**96.91**	**103.49**	**-103.43**	**118.76**	**390**
Technology											
Nokia	62.62	108.33	35.66	17.89	64.66	210.05	-11.48	50.66	-2.05	39.37	346
Telecommunications											
Telenor	114.02	234.33	59.14	47.17	136.00	331.41	-19.77	111.61	-21.98	61.61	466
TeliaSonera	67.95	121.85	40.69	21.30	109.08	264.28	10.56	69.66	-41.14	50.33	466
Vodafone	72.70	133.03	55.22	15.67	199.79	632.29	50.80	72.32	-127.08	127.33	238
Average	**84.89**	**163.07**	**51.68**	**28.05**	**148.29**	**409.33**	**13.87**	**84.53**	**-63.40**	**79.76**	**390**
Transportation											
Stena	645.57	1288.46	244.89	265.20	857.54	1333.09	427.67	303.55	-211.96	233.43	448

APPENDIX 2. Descriptive statistics CONT'D

Table 18. Descriptive statistics by industry. This table reports the descriptive statistics for period 2 (29.6.2010 - 9.4.2013). Mean, maximum and minimum values as well as the standard deviation are reported for CDS spread and credit spread, respectively. In addition, the average CDS basis average absolute basis, and number of observations are presented in the last three columns.

	CDS	MAX	MIN	STD	CS	MAX	MIN	STD	AB	AAB	OBS
Automobile											
Volkswagen	116.58	202.53	67.55	33.76	34.36	90.41	-13.24	22.10	82.22	82.21	549
Volvo	135.30	210.16	100.00	32.97	67.64	154.15	34.32	27.74	67.65	67.63	244
Average	**125.94**	**206.35**	**83.78**	**33.37**	**51.00**	**122.28**	**10.54**	**24.92**	**74.94**	**74.92**	**397**
Basic Materials											
Solvay	120.58	251.21	63.61	46.57	74.56	176.74	14.87	36.94	46.02	46.29	642
ThyssenKrupp	293.74	384.35	192.34	58.17	437.09	583.76	288.91	80.60	-143.35	143.29	123
Average	**207.16**	**317.78**	**127.97**	**52.37**	**255.83**	**380.25**	**151.89**	**58.77**	**-48.66**	**94.79**	**383**
Financial											
Barclays Bank	161.33	282.61	98.00	44.12	240.90	578.28	63.33	116.22	-79.57	117.17	726
BNP Paribas	168.24	361.16	79.16	66.84	139.14	364.96	-61.38	92.88	29.10	78.98	726
Commerzbank	192.30	361.25	83.81	65.02	177.43	561.59	19.08	131.92	14.88	156.87	726
Deutsche Bank	136.57	308.14	82.16	43.01	67.15	192.24	-16.04	44.10	69.41	74.91	726
Average	**164.61**	**328.29**	**85.78**	**54.74**	**156.15**	**424.27**	**1.25**	**96.28**	**8.46**	**106.98**	**726**
Consumer Goods											
Carlsberg Breweries	111.81	153.49	85.26	16.97	81.83	164.40	30.47	31.35	29.98	31.79	650
Heineken	89.54	104.90	73.80	9.17	74.56	92.78	58.99	7.11	14.98	16.91	207
Imperial Tobacco Group	102.55	168.61	82.26	17.37	41.97	186.12	-11.29	40.80	60.58	62.08	726
Pernod Ricard	147.86	252.69	117.68	30.21	207.05	311.25	152.07	36.81	-59.19	59.25	321
Average	**112.94**	**169.92**	**89.75**	**18.43**	**101.35**	**188.64**	**57.56**	**29.02**	**11.59**	**42.51**	**476**
Electric Utilities											
E.ON	74.89	133.82	58.63	11.17	8.81	62.05	-17.25	12.76	66.09	66.03	304
Edison	126.25	180.26	97.27	19.04	126.69	187.60	75.10	31.04	-0.44	14.84	228
Fortum	61.20	126.78	48.37	13.83	13.41	37.37	-9.27	8.21	47.79	47.76	48
Gas Natural SDG	240.91	563.59	137.34	81.98	267.10	601.37	129.17	92.25	-26.18	32.35	545
RWE	97.39	162.57	59.07	23.86	10.16	79.32	-58.80	34.93	87.23	87.18	726
Vattenfall	70.15	106.00	55.04	10.81	11.06	65.41	-38.95	23.96	59.09	59.08	711
Average	**111.80**	**212.17**	**75.95**	**26.78**	**72.87**	**172.19**	**13.33**	**33.86**	**38.93**	**51.21**	**427**
Healthcare											
GlaxoSmithKline	55.06	66.51	46.86	6.11	21.17	46.60	-16.68	15.12	33.90	33.99	254
Novartis	39.78	69.93	26.33	8.22	8.74	36.07	-20.38	9.10	31.04	31.06	608
Average	**47.42**	**68.22**	**36.60**	**7.16**	**14.95**	**41.33**	**-18.53**	**12.11**	**32.47**	**32.53**	**431**
Industrial Goods											
BAE Systems	137.92	230.56	85.17	34.29	128.42	215.60	55.00	45.91	9.50	34.83	635
Saint-Gobain	137.25	259.47	95.10	42.83	100.15	200.81	35.80	36.95	37.10	38.16	374
Siemens	70.82	110.25	54.94	13.81	4.99	63.21	-32.35	17.60	65.83	65.89	380
Veolia Environment	155.82	317.37	80.21	56.42	72.83	181.83	17.21	36.46	82.99	82.95	710
Average	**125.46**	**229.41**	**78.85**	**36.84**	**76.60**	**165.36**	**18.92**	**34.23**	**48.86**	**55.46**	**525**
Oil & Gas											
Gas Natural SDG	240.91	563.59	137.34	81.98	267.10	601.37	129.17	92.25	-26.18	32.35	545
Repsol	149.98	255.14	104.71	30.04	125.03	198.03	76.32	31.73	24.95	26.98	335
Shell	69.64	107.80	47.63	14.86	-3.35	52.25	-43.93	23.93	72.98	72.96	700
Statoil	69.90	115.68	51.37	15.61	20.17	55.05	-12.24	14.12	49.73	49.74	726
Average	**132.61**	**260.55**	**85.26**	**35.62**	**102.24**	**226.68**	**37.33**	**40.51**	**30.37**	**45.51**	**577**
Services											
Accor	122.00	179.16	86.30	26.00	125.59	217.21	33.78	55.73	-3.59	30.84	290
Pearson	67.77	89.93	52.31	9.11	110.51	147.96	77.33	14.93	-42.74	42.81	374
Tesco	92.35	127.16	69.51	14.05	10.17	44.69	-32.56	11.53	82.17	82.13	726
Average	**94.04**	**132.08**	**69.37**	**16.39**	**82.09**	**136.62**	**26.19**	**27.40**	**11.95**	**51.93**	**463**
Technology											
Nokia	124.97	329.70	81.19	58.12	68.04	328.86	12.77	74.22	56.93	56.96	290
Telecommunications											
TDC	102.67	186.01	73.56	25.27	102.61	343.30	22.46	73.83	0.06	39.31	726
Telenor	71.37	104.52	57.56	10.59	33.56	81.69	11.66	13.65	37.81	37.87	328
TeliaSonera	65.70	94.31	47.71	11.45	27.70	89.28	-24.21	27.67	38.00	37.99	726
Vodafone	84.06	126.36	62.88	13.31	54.78	672.29	-4.28	76.22	29.28	59.96	726
Average	**80.95**	**127.80**	**60.43**	**15.15**	**54.66**	**296.64**	**1.41**	**47.84**	**26.29**	**43.78**	**627**

APPENDIX 3. T-test and JB Normality test

Table 19. T-test and Jarque-Bera Normality test of CDS Basis (15.9.2008 - 28.6.2010). T-statistics and p-values for T-test testing for null hypothesis of H0 = mean basis equals 0 are presented in columns 1 and 2. Similarly, skewness, kurtosis and JB normality test p-values are reported in columns 3 - 4. Acceptance of the null hypothesis presented bolded p-values.

	(1)	(2)	(3)	(4)	(5)
Entity	t-statistic	p-value	Skewness	Kurtosis	p-value
Accor	-17.108	0.000	-1.254	3.310	0.000
Adecco	-30.671	0.000	-0.599	2.134	0.000
BAE Systems	-23.119	0.000	0.114	2.739	**0.312**
Barclays Bank	-75.749	0.000	0.259	2.315	**0.056**
British American Tobacco	-26.348	0.000	-0.049	1.643	0.000
BNP Paribas	-21.535	0.000	0.151	2.165	0.001
Commerzbank	-67.648	0.000	-0.337	2.694	**0.174**
Daimler	11.269	0.000	-0.326	2.665	**0.088**
Deutsche Bank	-12.912	0.000	-0.713	3.585	0.000
E.ON	-1.649	**0.100**	-0.604	2.610	0.000
Edison	1.379	**0.169**	-0.490	3.850	0.000
Fortum	-9.442	0.000	-0.418	1.968	0.000
Gas Natural SDG	15.779	0.000	-0.023	4.243	0.000
GDF Suez	16.091	0.000	-0.076	2.258	0.004
GlaxoSmithKline	22.078	0.000	-0.981	4.150	0.000
Heineken	34.008	0.000	0.278	2.412	0.039
Imperial Tobacco Group	-10.744	0.000	-0.338	1.832	0.000
Nokia	-0.844	**0.399**	-0.402	2.183	0.000
Northern Rock	16.338	0.000	0.749	2.940	0.000
Novartis	5.341	0.000	-1.050	3.341	0.000
Pearson	-35.318	0.000	-0.316	1.868	0.000
Pernod Ricard	-18.828	0.000	0.476	3.108	0.011
Repsol	2.989	0.003	0.396	4.985	0.000
RWE	4.526	0.000	-0.341	2.188	0.000
Saint-Gobain	-2.747	0.006	-0.801	3.572	0.000
Shell	39.682	0.000	-0.468	3.041	0.002
Siemens	30.753	0.000	-0.398	2.680	0.001
Solvay	-5.811	0.000	0.410	2.786	0.001
Stena	-29.403	0.000	0.636	3.544	0.000
Telenor	-6.549	0.000	-0.534	1.745	0.000
TeliaSonera	-17.021	0.000	-0.452	2.014	0.000
Tesco	-1.086	**0.278**	-0.921	2.493	0.000
ThyssenKrupp	2.169	0.031	-0.105	1.799	0.000
Vattenfall	0.726	**0.468**	-0.395	2.003	0.000
Veolia Environment	-6.491	0.000	-1.233	3.488	0.000
Vodafone	-32.299	0.000	-1.691	11.117	0.000
Volkswagen	21.311	0.000	-1.493	7.867	0.000
Volvo	-7.113	0.000	-1.170	3.038	0.000

APPENDIX 3. T-test and JB Normality test CONT'D

Table 20. T-test and Jarque-Bera Normality test of CDS Basis (29.6.2010 - 9.4.2013). T-statistics and p-values for T-test testing for null hypothesis of H0 = mean basis equals 0 are presented in columns 1 and 2. Similarly, skewness, kurtosis and JB normality test p-values are reported in columns 3 - 4. Acceptance of the null hypothesis presented with bolded p-values.

	(1)	(2)	(3)	(4)	(5)
Entity	T-statistic	p-value	Skewness	Kurtosis	p-value
Accor	-1.675	**0.095**	0.511	2.147	0.000
BAE Systems	5.636	0.000	0.067	2.948	**0.758**
Barclays Bank	-16.734	0.000	-0.596	2.352	0.000
BNP Paribas	8.651	0.000	0.327	1.648	0.000
Carlsberg Breweries	34.909	0.000	-0.114	2.384	0.003
Commerzbank	2.316	0.021	-0.883	2.277	0.000
Deutsche Bank	36.208	0.000	-0.511	2.586	0.000
E.ON	100.262	0.000	0.054	2.863	**0.824**
Edison	-0.373	**0.709**	-0.340	2.347	0.015
Fortum	59.988	0.000	0.812	3.863	0.000
Gas Natural SDG	-19.425	0.000	-0.298	2.640	0.004
GDF Suez	84.271	0.000	-0.207	1.871	0.000
GlaxoSmithKline	26.955	0.000	1.000	2.828	0.000
Heineken	15.828	0.000	-0.198	1.911	0.003
Imperial Tobacco Group	58.827	0.000	-1.166	4.123	0.000
Nokia	50.166	0.000	-1.084	3.690	0.000
Novartis	66.337	0.000	-0.304	2.857	0.007
Pearson	-40.185	0.000	-0.101	2.132	0.002
Pernod Ricard	-53.493	0.000	-0.499	2.679	0.001
Repsol	22.213	0.000	0.165	2.795	**0.348**
RWE	65.274	0.000	0.153	1.841	0.000
Saint-Gobain	27.375	0.000	0.317	2.828	0.035
Shell	78.764	0.000	0.172	2.069	0.000
Siemens	64.031	0.000	0.418	2.687	0.002
Solvay	35.340	0.000	0.495	1.898	0.000
Statoil	71.685	0.000	0.069	2.634	**0.098**
TDC	0.031	**0.975**	-1.327	4.409	0.000
Telenor	85.322	0.000	0.122	2.436	**0.076**
TeliaSonera	47.918	0.000	0.281	1.817	0.000
Tesco	125.426	0.000	0.214	2.229	0.000
ThyssenKrupp	-36.508	0.000	0.209	2.666	**0.481**
Vattenfall	72.635	0.000	0.026	1.931	0.000
Veolia Environment	48.633	0.000	0.234	1.611	0.000
Vodafone	11.018	0.000	-3.535	16.964	0.000
Volkswagen	63.939	0.000	0.816	2.697	0.000
Volvo	70.546	0.000	0.344	2.595	0.039

APPENDIX 4. ADF-test results

Table 21. Augmented Dickey-Fuller Test for subperiod 1 (15.9.2008 - 28.6.2010). Augmented Dickey-Fuller test t-statistics and one-sided MacKinnon p-values are reported for both level (Yt) and first-differenced (ΔYt) CDS and CS time series. Rejection of the null hypothesis at 1% and 5% levels is presented with * and ** respectively.

	H0: Y_t has a unit root				**H0: ΔY_t has a unit root**			
Entity	t(CDS)	p-value	t(CS)	p-value	t(ΔCDS)	p-value	t(ΔCS)	p-value
Accor	-2.394	0.144	-1.584	0.798	-15.557 *	0.000	-17.145 *	0.000
Adecco	-2.349	0.157	-0.985	0.759	-14.798 *	0.000	-18.644 *	0.000
BAE Systems	-1.962	0.304	-1.035	0.742	-9.557 *	0.000	-22.685 *	0.000
Barclays Bank	-2.340	0.410	-2.527	0.111	-12.444 *	0.000	-13.800 *	0.000
British American Tobacco	-1.393	0.586	-0.694	0.416	-17.134 *	0.000	-24.309 *	0.000
BNP Paribas	-2.051	0.265	-1.459	0.842	-16.433 *	0.000	-24.281 *	0.000
Carlsberg Breweries	-	-	-	-	-	-	-	-
Commerzbank	-2.850	0.182	-1.758	0.720	-13.340 *	0.000	-13.453 *	0.000
Daimler	-2.434	0.134	-2.394	0.382	-12.895 *	0.000	-13.512 *	0.000
Deutsche Bank	-1.244	0.656	-0.693	0.416	-16.648 *	0.000	-20.279 *	0.000
E.ON	-2.384	0.147	-1.390	0.588	-21.352 *	0.000	-22.048 *	0.000
Edison	-3.021	0.129	-1.921	0.640	-14.239 *	0.000	-16.283 *	0.000
Fortum	-1.848	0.357	-0.647	0.857	-18.968 *	0.000	-18.789 *	0.000
Gas Natural SDG	0.501	0.999	-0.934	0.949	-11.247 *	0.000	-15.102 *	0.000
GDF Suez	-1.489	0.539	-1.137	0.703	-19.646 *	0.000	-18.920 *	0.000
GlaxoSmithKline	-1.427	0.570	-1.148	0.698	-20.322 *	0.000	-18.982 *	0.000
Heineken	-1.862	0.350	-2.043	0.268	-20.423 *	0.000	-19.188 *	0.000
Imperial Tobacco Group	-3.268	0.073	-2.969	0.142	-7.455 *	0.000	-7.706 *	0.000
Nokia	-0.825	0.810	-1.371	0.868	-15.520 *	0.000	-21.734 *	0.000
Northern Rock	-0.953	0.948	-0.702	0.972	-23.005 *	0.000	-30.249 *	0.000
Novartis	-2.022	0.277	-1.813	0.374	-16.206 *	0.000	-17.111 *	0.000
Pearson	-1.753	0.404	-0.701	0.844	-12.076 *	0.000	-24.327 *	0.000
Pernod Ricard	-1.192	0.909	-1.373	0.866	-13.265 *	0.000	-11.605 *	0.000
Repsol	-1.593	0.486	-2.524	0.316	-18.062 *	0.000	-8.871 *	0.000
RWE	-2.496	0.117	-0.900	0.788	-18.702 *	0.000	-19.837 *	0.000
Saint-Gobain	-1.368	0.599	-2.545	0.306	-16.583 *	0.000	-10.505 *	0.000
Shell	-0.320	0.919	-0.638	0.976	-17.212 *	0.000	-19.538 *	0.000
Siemens	-1.420	0.573	-0.931	0.778	-21.186 *	0.000	-24.868 *	0.000
Solvay	-1.937	0.315	-0.903	0.787	-16.769 *	0.000	-14.408 *	0.000
Statoil	-	-	-	-	-	-	-	-
Stena	-1.281	0.640	-2.438	0.359	-10.151 *	0.000	-5.171 *	0.000
TDC	-	-	-	-	-	-	-	-
Telenor	-1.303	0.629	-0.763	0.828	-20.539 *	0.000	-6.586 *	0.000
TeliaSonera	-1.687	0.437	-0.274	0.926	-18.225 *	0.000	-30.574 *	0.000
Tesco	-4.466 *	0.002	-1.854	0.676	-17.981 *	0.000	-23.831 *	0.000
ThyssenKrupp	-1.990	0.292	-0.864	0.799	-16.077 *	0.000	-11.488 *	0.000
Vattenfall	-2.003	0.285	-1.715	0.743	-16.485 *	0.000	-18.432 *	0.000
Veolia Environment	-2.058	0.262	-0.785	0.822	-19.053 *	0.000	-21.363 *	0.000
Vodafone	-1.642	0.773	-2.785	0.204	-14.760 *	0.000	-15.449 *	0.000
Volkswagen	-1.809	0.376	-0.925	0.780	-8.748 *	0.000	-13.112 *	0.000
Volvo	-2.671	0.250	-1.436	0.849	-14.351 *	0.000	-13.425 *	0.000

APPENDIX 4. ADF-test results CONT'D

Table 22. Augmented Dickey-Fuller Test for subperiod 2 (29.6.2010 - 9.4.2013). Values for Augmented Dickey-Fuller t-statistics and one-sided MacKinnon p-values are reported for both level (Yt) and first-differenced (ΔYt) CDS and CS time series. Rejection of the null hypothesis at 1% and 5% levels is presented with * and ** respectively.

	H0: Y_t has a unit root				**H0: ΔY_t has a unit root**			
Entity	t(CDS)	p-value	t(CS)	p-value	t(ΔCDS)	p-value	t(ΔCS)	p-value
Accor	-0.946	0.948	-2.222	0.475	-17.210 *	0.000	-23.562 *	0.000
Adecco	-	-	-	-	-	-	-	-
BAE Systems	-1.654	0.770	-1.697	0.752	-15.146 *	0.000	-28.478 *	0.000
Barclays Bank	-2.559	0.102	-2.789	0.202	-21.692 *	0.000	-25.052 *	0.000
British American Tobacco	-	-	-	-	-	-	-	-
BNP Paribas	-1.733	0.414	-0.893	0.955	-17.465 *	0.000	-40.206 *	0.000
Carlsberg Breweries	-1.989	0.606	-1.468	0.840	-26.259 *	0.000	-31.876 *	0.000
Commerzbank	-1.813	0.698	-2.969	0.142	-17.304 *	0.000	-27.777 *	0.000
Daimler	-	-	-	-	-	-	-	-
Deutsche Bank	-2.039	0.578	-2.571	0.294	-19.169 *	0.000	-18.335 *	0.000
E.ON	1.566	1.000	-2.684	0.078	-12.643 *	0.000	-19.587 *	0.000
Edison	-1.860	0.351	-1.151	0.696	-12.643 *	0.000	-20.542 *	0.000
Fortum	0.579	1.000	-3.739 *	0.004	-12.841 *	0.000	-26.546 *	0.000
Gas Natural SDG	-1.561	0.807	-1.936	0.634	-13.895 *	0.000	-11.846 *	0.000
GDF Suez	-1.788	0.387	-2.608	0.092	-17.829 *	0.000	-16.458 *	0.000
GlaxoSmithKline	-4.540 *	0.002	-1.868	0.347	-16.403 *	0.000	-20.053 *	0.000
Heineken	-2.870	0.175	-2.245	0.191	-15.359 *	0.000	-19.824 *	0.000
Imperial Tobacco Group	-1.889	0.338	-1.968	0.301	-25.756 *	0.000	-16.450 *	0.000
Nokia	0.495	0.999	-0.082	0.995	-12.779 *	0.000	-11.852 *	0.000
Northern Rock	-	-	-	-	-	-	-	-
Novartis	-1.611	0.476	-4.609 *	0.001	-22.497 *	0.000	-30.471 *	0.000
Pearson	-1.942	0.631	-3.058	0.118	-17.090 *	0.000	-23.587 *	0.000
Pernod Ricard	-0.663	0.974	-1.134	0.921	-13.642 *	0.000	-16.454 *	0.000
Repsol	-2.850	0.181	-1.240	0.658	-15.751 *	0.000	-18.564 *	0.000
RWE	-1.980	0.296	-0.746	0.833	-21.380 *	0.000	-33.760 *	0.000
Saint-Gobain	-1.108	0.714	-1.841	0.360	-18.471 *	0.000	-11.534 *	0.000
Shell	-1.907	0.329	-2.031	0.273	-27.698 *	0.000	-32.006 *	0.000
Siemens	-1.652	0.455	-2.246	0.190	-15.591 *	0.000	-22.586 *	0.000
Solvay	-1.483	0.542	-1.280	0.640	-20.890 *	0.000	-15.345 *	0.000
Statoil	-1.272	0.894	-3.836 **	0.015	-22.913 *	0.000	-33.519 *	0.000
Stena	-	-	-	-	-	-	-	-
TDC	-2.170	0.505	-2.467	0.345	-26.762 *	0.000	-29.453 *	0.000
Telenor	-1.685	0.756	-3.190	0.088	-15.163 *	0.000	-16.970 *	0.000
TeliaSonera	-1.452	0.845	-2.482	0.337	-28.347 *	0.000	-37.554 *	0.000
Tesco	-2.527	0.109	-4.400 *	0.000	-26.736 *	0.000	-37.278 *	0.000
ThyssenKrupp	-2.049	0.568	-1.823	0.688	-9.420 *	0.000	-8.422 *	0.000
Vattenfall	-1.698	0.432	-1.440	0.564	-25.491 *	0.000	-34.679 *	0.000
Veolia Environment	-1.570	0.497	-1.787	0.387	-22.584 *	0.000	-14.916 *	0.000
Vodafone	-2.520	0.318	-4.312 *	0.001	-21.255 *	0.000	-5.617 *	0.000
Volkswagen	-1.469	0.549	-1.624	0.470	-18.487 *	0.000	-29.558 *	0.000
Volvo	-1.995	0.601	-1.725	0.737	-9.699 *	0.000	-19.205 *	0.000

APPENDIX 4. ADF-test results CONT'D

Table 23. Augmented Dickey-Fuller Test for full sample lenghts. Values for Augmented Dickey-Fuller t-statistics and one-sided MacKinnon p-values are reported for both level (Yt) and first-differenced (ΔYt) CDS and CS time series. Rejection of the null hypothesis at 1% and 5% levels is presented with * and ** respectively.

	H0: Y_t has a unit root				H0: ΔY_t has a unit root			
Entity	t(CDS)	p-value	t(CS)	p-value	t(ΔCDS)	p-value	t(ΔCS)	p-value
Accor	-2.471	0.343	-3.189	0.088	-22.274 *	0.000	-26.763 *	0.000
Adecco	-2.206	0.484	-0.610	0.978	-14.615 *	0.000	-25.798 *	0.000
BAE Systems	-2.701	0.074	-2.038	0.271	-16.735 *	0.000	-39.552 *	0.000
Barclays Bank	-2.754	0.065	-3.951 **	0.011	-18.864 *	0.000	-29.624 *	0.000
British American Tobacco	-2.047	0.267	-0.414	0.904	-20.794 *	0.000	-32.036 *	0.000
BNP Paribas	-1.862	0.350	-0.937	0.950	-21.616 *	0.000	-47.032 *	0.000
Commerzbank	-2.016	0.280	-3.298	0.067	-18.988 *	0.000	-30.724 *	0.000
Daimler	-2.439	0.358	-2.505	0.325	-13.557 *	0.000	-14.157 *	0.000
Deutsche Bank	-2.358	0.154	-2.571	0.294	-19.169 *	0.000	-18.335 *	0.000
E.ON	-2.427	0.135	-2.314	0.425	-28.535 *	0.000	-35.797 *	0.000
Edison	-3.216	0.083	-2.088	0.551	-19.164 *	0.000	-21.767 *	0.000
Fortum	-2.147	0.518	-1.800	0.705	-26.627 *	0.000	-27.699 *	0.000
Gas Natural SDG	-1.428	0.852	-1.921	0.643	-16.878 *	0.000	-14.411 *	0.000
GDF Suez	-2.218	0.200	-1.952	0.309	-35.000 *	0.000	-39.743 *	0.000
GlaxoSmithKline	-1.863	0.673	-2.368	0.396	-28.887 *	0.000	-42.183 *	0.000
Heineken	-2.749	0.217	-2.731	0.070	-27.489 *	0.000	-27.188 *	0.000
Imperial Tobacco Group	-1.852	0.355	-0.858	0.802	-12.472 *	0.000	-16.718 *	0.000
Nokia	1.115	1.000	1.190	1.000	-13.188 *	0.000	-21.156 *	0.000
Northern Rock	-1.918	0.644	-1.267	0.895	-27.016 *	0.000	-37.940 *	0.000
Novartis	-2.743	0.220	-3.265	0.073	-18.923 *	0.000	-27.147 *	0.000
Pearson	-2.729	0.070	-1.849	0.680	-17.356 *	0.000	-35.159 *	0.000
Pernod Ricard	-1.723	0.740	-1.933	0.636	-20.202 *	0.000	-19.807 *	0.000
Repsol	-2.130	0.233	-1.816	0.697	-25.975 *	0.000	-14.345 *	0.000
RWE	-2.315	0.167	-2.285	0.441	-30.931 *	0.000	-50.096 *	0.000
Saint-Gobain	-2.157	0.222	-1.605	0.791	-25.678 *	0.000	-32.534 *	0.000
Shell	-2.038	0.579	-3.354	0.058	-32.467 *	0.000	-27.824 *	0.000
Siemens	-1.732	0.415	-2.306	0.430	-29.152 *	0.000	-35.511 *	0.000
Solvay	-2.115	0.239	-1.860	0.674	-27.303 *	0.000	-20.493 *	0.000
Statoil	-1.272	0.894	-3.836 **	0.015	-22.913 *	0.000	-33.519 *	0.000
Stena	-1.391	0.588	-0.587	0.979	-12.222 *	0.000	-11.334 *	0.000
TDC	-2.847	0.181	-2.486	0.335	-27.294 *	0.000	-29.460 *	0.000
Telenor	-1.744	0.409	-1.714	0.745	-29.092 *	0.000	-9.596 *	0.000
TeliaSonera	-3.244	0.076	-2.095	0.548	-31.799 *	0.000	-54.315 *	0.000
Tesco	-3.400 **	0.011	-1.359	0.872	-30.930 *	0.000	-42.137 *	0.000
ThyssenKrupp	-1.886	0.339	-1.088	0.929	-18.689 *	0.000	-20.543 *	0.000
Vattenfall	-2.583	0.097	-3.046	0.120	-29.489 *	0.000	-29.299 *	0.000
Veolia Environment	-2.332	0.162	-2.355	0.403	-31.605 *	0.000	-15.357 *	0.000
Vodafone	-2.503	0.115	-1.391	0.588	-27.244 *	0.000	-12.241 *	0.000
Volkswagen	-2.734	0.069	-1.536	0.515	-13.839 *	0.000	-22.580 *	0.000
Volvo	-3.655 **	0.026	-10.565 *	0.000	-19.603 *	0.000	-13.121 *	0.000