The Empirical Relationship between CDS Prices and Bond Yields after the Financial Crisis

Master's Thesis

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Executive Summary

This paper contributes to the literature analysing the empirical relationship between CDS spreads and bond yields. In theory, the prices of these assets are linked through an arbitrage relationship. The paper employs a sample of 32 companies covering the period from the beginning of 2010 until the end of 2011 obtained from the publicly available data sources Bloomberg and Datastream. It then creates artificial 5-year bond yields by linear interpolation and estimates the basis spread, which should be zero if the arbitrage relationship holds perfectly. Subsequently, several econometric concepts are employed to investigate the relationship between the series, including cointegration analysis, Granger-causality, half-life of deviations and price discovery measures.

Several findings emerge. In contrast to previous researchers, this paper finds that yields on government bonds serve as better proxy for the risk-free rate instead of the swap rates. Increased overall risk in the financial sector after the financial crisis and especially in European institutions during the European sovereign debt crisis is a potential explanation for this result.

In line with previous research, the paper finds that the arbitrage relationship holds reasonably well on a medium- to long-term perspective. In the short-term however, the spreads can move away significantly from their equilibrium values. Additionally, there are a few exceptional cases which constantly show large non-zero basis spreads and constitute mainly financial institutions. Furthermore, several differences emerge when grouping companies by rating, country and distinguishing between financial and non-financial companies.

Additionally, in line with previous research, CDS markets seem to lead bond markets. However, this relationship weakens for lower graded entities and reverses during times of crisis. Two theories might explain this finding. First, trading in investment-grade bonds might increase during times of crisis, such that bond prices provide more information. Second, increased counterparty risk inherent in CDS might disturb CDS spreads such that the information value of CDS prices is decreased.

From a technical point of view, this paper argues for employing the Schwarz Bayesian Criterion in contrast to the widely used Akaike Information Criterion for cointegration analysis, because the latter tends to have superior properties in this context. Furthermore, weekly instead of daily observations seem to be more appropriate for cointegration analysis, because of less microstructural noise.

Preface

I would like to thank my supervisor Assistant Professor Mads Stenbo Nielsen from Copenhagen Business School for providing me with insightful thoughts, useful sparring and valuable guidance throughout the entire creation process of my thesis. Furthermore, I would like to thank Professor Ian W. Marsh from Cass Business School for discussing his research in more detail with me.

Copenhagen, July 2012

Marko Celic

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List of Abbreviations

AIC: Akaike Information Criterion

AR: Auto-Regressive

BGN: Bloomberg Generic Price

BIC: Bayesian Information Criterion

BVAL: Bloomberg Valuation Services

CDO: Collateralized Debt Obligation

CDS: Credit Default Swap

CMA: Credit Market Analysis Ltd.

CS: Component Share

CTD: Cheapest-To-Deliver

DTCC: Depository Trust & Clearing Corporation

FINRA: Financial Industry Regulatory Authority, Inc.

IS: Information Share

ISDA: International Swaps and Derivatives Association

MSE: Mean Squared Error

NASD: National Association of Securities Dealers, Inc.

OTC: Over-The-Counter

PT: Permanent-Transitory

TRACE: Trade Reporting and Compliance Engine

USD: United States Dollar

VAR: Vector Autoregression

VECM: Vector Error-Correction

WFE: World Federation of Exchanges

WRDS: Wharton Research Data Services

1. Introduction

Although they have been suspect to much criticism after the recent financial crisis, credit derivatives have become an integral part of the modern financial market. Almost twenty years after inception, the total gross notional value of outstanding credit derivates was estimated to be USD 25.5 trillion at the end of 2010 by the Depository Trust & Clearing Corporation (DTCC). Single-name credit default swaps (CDS) make up more than half of that with a total outstanding amount of USD 14.6 trillion. By comparison, the World Federation of Exchanges (WFE) reported total outstanding non-financial corporate bonds of only USD 6.5 trillion at the end of 2010.

However, the CDS market went through turbulent times as one can see from figure 1, which depicts data from the International Swaps and Derivatives Association (ISDA). According to their market surveys, the outstanding amount of credit default swaps has risen from as little as USD 0.9 trillion in 2001 to a spectacular USD 62.2 trillion at the end of 2007 just before the financial crisis. Since then it has continuously fallen to USD 26.3 trillion at the end of the first half of 2010, when the last ISDA market survey was published.

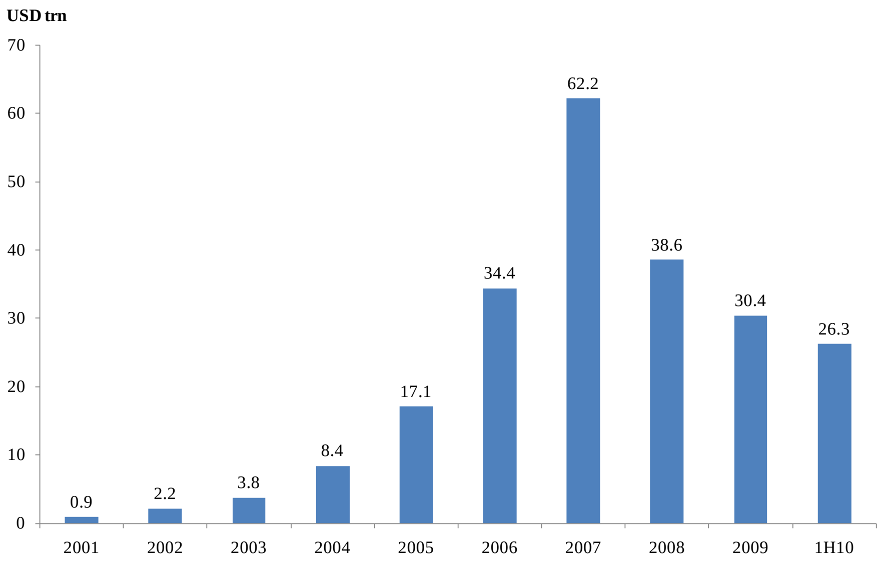

Figure 1: Total Gross Notional Outstanding CDS[1]

This paper analyses the empirical relationship between a CDS contract and the corresponding bond for a sample covering the period from the beginning of 2010 until the end of 2011. In theory, these two securities are linked through a relatively simple arbitrage argument. A portfolio consisting of a

[1] see ISDA (2010).

long position the in the bond and the CDS is theoretically risk-free. This is because in the event of the bond issuer defaulting, the CDS should cover for all incurring losses to the investor. Thus, the return of this portfolio should equal the risk-free rate. This relationship is investigated in this paper.

In contrast to previous research, it is observed that the arbitrage argument seems to hold better if treasury yields are used as proxy for the risk-free rate instead of swap rates. Increased risk in the overall financial sector after the financial crisis and during the European sovereign debt crisis could be one explanation for this finding. The arbitrage relationship holds reasonably well on average, apart from a few exceptional cases which are mainly financial institutions. These cases can be explained by limits to the arbitrage argument, which are discussed in the paper. Several findings emerge when considering groups of observations by rating, region and distinguishing financial and non-financial companies. One of the most interesting findings concerns the price discovery relationship between markets. CDS markets seem to lead bond markets, but the relationship is weaker when considering lower graded entities. Moreover, during volatile times, the relationship seems to reverse and bonds assume price leadership. Two explanations are presented in this paper. First, trading in bonds increases during crises such that bond prices incorporate more information than CDS. Second, increased counterparty risk inherent in CDS due to increased risk of dealers and central counterparties impedes the informational value of CDS such that investors focus rather on bond prices.

2. Overview of Credit Default Swaps

Credit derivatives constitute one of the most important developments of the derivatives markets allowing market participants to trade credit risk in the same way they trade market risks. Banks and other financial institutions assuming credit risk had only two choices before the invention of credit derivatives[2]: In most cases they would bear the credit risk until maturity implicitly assuming that the majority of debtors would be able to serve their debt successfully. In some cases, banks would try unwind loans at discounts to other financial institutions. Using credit derivatives opens new possibilities to financial institutions to actively manage their credit risk by adding positions in the derivatives market to protect themselves from credit events in their loan portfolio. Accordingly the largest participants in the market constitute banks which appear mainly on the buy- or long side of the derivative contracts while the other major part of the market is filled by insurance companies entering short positions in the CDS market.

[2] see Hull (2012), p. 546.

2.1. Formal Structure of Credit Default Swaps

Credit derivatives can be categorized as single- or multi-name securities. A popular form of multi-name securities is the collateralized debt obligation (CDO). This is a security whose cash-flow depends on a complex structure of a portfolio of debt instruments and different categories of investors, so-called tranches, which are specified by their seniority in the cash flow right order. The most popular single-name instrument is the credit default swap (CDS). This constitutes a contract which provides insurance against the default of a so-called reference entity. There are two sides in each CDS contract: a long (buyer) and a short (seller) position. When two sides enter a CDS contract, the long position agrees to make a periodic payment during the contract period to the seller in the form of an insurance premium. In case of no default until maturity, the relationship between both parties ends without any obligations. In case the specified entity, for example a company or a country, defaults on its obligations, the protection seller is obliged to compensate the protection buyer for the incurred loss. This process is described in detail in the following paragraphs.[3]

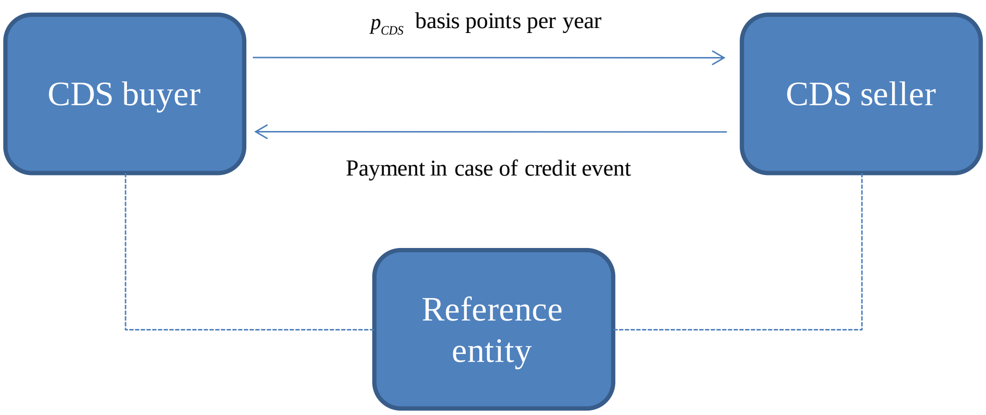

Figure 2: Credit Default Swap Structure

Figure 2 illustrates the relationship between the parties in a CDS contract. The CDS contract provides insurance against the risk of default by a particular company or country. This company or country is the so-called reference entity and a default by the reference entity is known as a credit event. The long side of the CDS contract obtains the right to sell a pre-specified amount of bonds issued by the reference entity at face value, i.e. the principal amount of the bond that is due at maturity, if a credit event occurs. The short side of the contract agrees to buy the bonds at face value in case of a credit event. The total face value of bonds that can be sold is the so-called

[3] see Hull (2012), pp. 547-548.

notional principal. In exchange for the right to sell the bonds in a credit event, the buyer of the CDS contract makes periodic payments to the seller until maturity of the CDS or a credit event occurs. In most cases, these payments are due in arrear every quarter but the payment schedule can vary for different contracts from payments every month to twelve months or even payments in advance. In the case of a credit event, the settlement can be executed via physical delivery or cash settlement. Cash settlement, which is the usual settlement form, leads to an auction process organized by the ISDA to determine the mid-market value of bond, which is deemed the reference obligation. Physical delivery entails the protection buyer to deliver bonds of the reference entity with the face value of the notional principal to the seller, which in turn has to make a payment in amount of the notional principal. Importantly, most CDS contracts allow choosing among several available bonds for settlement. Different characteristics of the bonds w.r.t. to seniority, liquidity or other factors lead to price differentials between those bonds such that the buyer will optimally choose the cheapest available bonds. This option, the so called cheapest-to-deliver (CTD) option causes some difficulties when valuing a CDS contract and deviations from the arbitrage relationship investigated in this paper. The insurance premium paid by the protection buyer ceases in case of a credit event but most contracts involve in arrear payments, such that a final accrual payment is made by the protection buyer. The total insurance premium per year is the so-called CDS spread and is calculated in percent of the notional amount of the CDS contract. Maturities of CDS contracts can vary from one to ten years with maturities of five years being the most popular maturity.[4] Although CDS are over-the-counter (OTC) financial instruments, they are regulated by the ISDA. The ISDA is a global trade organization of financial market participants for OTC derivatives and offers definitions of terms and conditions for CDS contracts. The organization exhibits more than 830 members from 59 countries on six continents. They constitute a broad range of financial market participants, from international banks, insurance companies, government entities to clearing houses and other service providers.[5] The ISDA focuses on three aspects in regulating OTC derivatives. It aims on reducing counterparty credit risk, increasing transparency of the CDS market and on improving the market's operational infrastructure. A key aspect of a CDS contract is the definition of a credit event. According to the ISDA the following events qualify as credit events[6]

1. Bankruptcy
2. Obligation Acceleration

[4] see Hull (2010), p. 549.
[5] see ISDA (2012), pp. 1-9.
[6] see ISDA (2003), pp. 30-34.

3. Obligation Default
4. Failure to Pay
5. Repudiation/Moratorium
6. Restructuring

CDS allow participants to trade credit risk of the reference entities without entering positions in securities issued by the reference entities. CDS protection buyers speculate on worsening credit conditions of the reference entities, while CDS sellers expect the financial stability of the reference entity to improve. The objectives of the CDS depend on the entire portfolio of the parties. The major market participants constitute banks, insurance companies, securities houses and hedge funds. Major bond holders like pension funds or insurance companies enter long positions in CDS to the limit their credit exposure in bond investments of the reference entities. This strategy is particularly interesting for recently downgraded bonds where buyers might be hard to find or demand large discounts. Additionally, banks buy CDS to eliminate their credit exposure of their loans instead of securitizing loans to lower their capital requirements. Finally, CDS are also used for speculation by market participants, mainly hedge funds.[7]

According to the Bank for International Settlements, the largest participants in the single-name CDS market in the end of 2011 with a share of 63% were reported dealers whose head offices are located in the G10 countries and which participate in the BIS' semi-annual derivatives market statistics. CDS with central counterparties accounted for a share of 15%. Banks and security firms represent a share of 13% in the CDS market. Finally, insurance companies and other financial firms represent a share of 6% in the market while hedge fund constitute 3% in the market and the remaining 1% is represented by non-financial firms. A caveat has to be noted to these statistics, because they do not represent net positions. In practice, when an investor enters a CDS with a dealer, the dealer will try to enter an offsetting position. In case he finds no willing investor, the dealer will enter a CDS with another dealer. This process is repeated until a willing investor is found and can easily take eight or more iterations. Accordingly, the statistics are overstated for dealer positions.[8]

CDS contracts can be used to hedge positions in bonds of the reference entity. This will be illustrated in the following example: Suppose an investor buys a 5-year bond with a face value of USD 10 million offering a 7% yield and enters a long position in a 5-year CDS contract with the bond issuer as reference entity, a notional principal of USD 10 million and a credit spread of 2% or

[7] see Hull (2012), pp. 549-555.
[8] see BIS (2012), p. 25.

200 bps. The CDS converts the corporate bond to an approximately risk-free bond with a yield of 5%. In case of no credit event, the investor earns 7% interest on the risky bond less 2% insurance for the credit default swap. If the bond issuer defaults on his obligations, the investor earns 5% interest up until the credit and then receives the face value in exchange for the bond. Accordingly, the excess rate of an n-year bond over the respective n-year CDS contract must equal the risk-free rate to prevent arbitrage opportunities. If this spread is significantly larger than the risk-free rate, then an investor could earn an arbitrage profit by borrowing at the risk-free rate and purchasing the mentioned portfolio. In the case that the spread is significantly less than the risk-free rate, the investor should short-sell the bond, sell CDS protection and invest the available funds at the risk-free rate to obtain an arbitrage profit. This relationship implies, that the excess rate of an n-year bond over the risk-free rate should equal the n-year CDS spread. The difference between the excess rate and the CDS spread is the so-called CDS-bond basis and should be close to zero according to the arguments above.

2.2. Critique During and After Financial Crisis

The financial crisis from 2007 until 2009 was accompanied by the largest destruction in financial wealth since the Great Depression. Many individuals, including economists, financial market participants and media representatives have argued that CDS have been an important driver for the evolvement of the crisis. They argue that there are three fundamental issues in CDS that amplified if not even caused the credit crisis.[9] The first argument is that CDS made the credit boom possible which eventually led to the financial crisis. They argue that banks have been able to increase their loans without increasing capital by entering CDS contracts at the same time. This, they argue, has led to a separation of risk-bearing and funding such that banks were reluctant to conduct the required credit analysis when issuing loans to debtors, because they were able to hedge their risk through CDS. Secondly, many financial institutions had amassed large positions in CDS that led to interrelations among them and resulted in significant system risk. These interrelations contributed to a crisis in confidence in the entire financial system after the collapse of Lehman Brothers in September 2008. Finally the lack of transparency in the market gave certain participants the power to manipulate the view about the conditions of financial institutions. According to the critics, these manipulations were partly responsible for the failure of Bear Stearns and Lehman Brothers. A further argument is that the problem lies not in CDS itself but rather in the way they are traded.

[9] see Stulz (2009), pp. 2-4.

Under this view, CDS should not be over-the-counter securities anymore but rather traded on large exchanges.

These arguments however disregard several important points when considering the role of CDS in the financial crisis. First of all, the ability of banks to hedge their loans has positive effects. For example, financial institutions are able to supply corporations with access to debt beyond their own desirable level of exposure through the use of CDS. This leads to better credit availability for debtors. Furthermore, it was shown in previous research that only a minor share of the outstanding CDS were used to hedge loans by banks.[10] Additionally, CDS often provide more liquid markets for trading credit risk than then underlying bond markets. This is because they do not require large amounts of capital to be funded and CDS are often standardized by ISDA regulations. Thus they can be used to hedge all different types of issued bonds or receivables of the reference entity. Usually, it is also more difficult and costly to enter a short position in the bond of a reference entity instead of entering long position in CDS. Thus the availability of CDS should improve the capital allocations in the market. More importantly, the CDS market worked remarkably well during the first year of the credit crisis. Notably, the DTCC registered USD 72 billion of notional principal of CDS contracts on Lehman Brothers on the day of its bankruptcy and CDS sellers were obliged to pay 91.4 % of the face value to protection buyers. The settlement of the contracts was completed successfully also because net positions were so small such that only USD 5.2 billion needed to be exchanged. Finally, one has to note that the financial distress at Bear Stearns, Lehman and AIG was not caused by credit default swaps. Investors and financial institutions incurred large losses because they have often falsely believed that AAA-tranches of securitized loan portfolios had small probabilities of default. These tranches were held by levered institutions which effectively resulted in reduced confidence in the financial system. Although derivatives exposure of these financial institutions was not known during this time which may have increased uncertainty about them, CDS also made it possible to hedge and reduce the risk of their investments and thus resulting in more secure institutions.[11]

On 10th of May, 2012, JPMorgan Chase & Co. announced a USD 2 billion loss, which could become larger over time, from a CDS portfolio. The portfolio was intended to hedge the bank against a downward trend in the global economy, but according to CEO Jamie Dimon the “strategy was flawed, complex, poorly reviewed, poorly executed and poorly monitored.” Critics argue that

[10] see Minton, Stulz, Williamson (2009), pp. 1-31.
[11] see Stulz (2009), pp. 5-6.

this is the latest sign of credit default swaps being a potential threat to the overall financial system. Academic research has not yet been able to provide convincing empirical evidence for neither of both sides. This shows that there is a lot of room for potential future research about this topic.[12]

3. Theoretical Framework

The valuation of credit default swaps is led by two different approaches. Structural models belong to the first category and base on the work of Black and Scholes (1973) and Merton (1974).[13] In these models, the outstanding debt of company is treated in the way of an option on the company's assets. Accordingly, the firm value needs to be modelled employing stochastic processes. Default occurs when the stochastic process hits the boundary which is determined by the level of debt of the company. Examples of the use of those models for the valuation of credit derivatives are Das (1995) and Pierides (1997).[14] A major drawback of the models lies in the poor empirical performance and the representation of the firm value through stochastic processes.[15] Another approach that has been used extensively to value credit default swaps are the so-called reduced-form or intensity-based models which are represented by Fons (1994), Jarrow, Lando and Turnbull (1997), Duffie (1999) and Hull and White (2000). These models build a direct connection between CDS risk premia and bond spreads and are based on the no-arbitrage approach and the risk-neutral default probability assumption. In the following section the two most famous reduced-form models will be discussed in more detail.[16]

3.1. Valuation of Credit Default Swaps using Reduced-Form Models

Hull and White (2000) provides one of the most famous reduced-form models to value credit default swaps. It starts out by estimating the risk-neutral probability of the reference entity defaulting at different times. For this, the model assumes that the only reason for a price differential between a riskless and risky bond is the probability of default of the issuer of the latter bond. Accordingly this price differential is equivalent to the present value of the cost of default of the

[12] see JPMorgan Chase (2012), p.1.
[13] see Black and Scholes (1973), pp. 637-654; Merton (1974), pp. 449-470.
[14] see Das (1995), pp. 7-23; Pierides (1997), pp. 1579-1611.
[15] see Eom et al. (2004), pp. 499-544; Huang and Huang (2004), pp.1-57;
[16] see Duffie (1999), pp. 73-87; Fons (1994), pp. 25-32.; Jarrow et al. (1997), pp. 481-523; Hull, White (2000), pp. 29-40.

reference entity. Assuming a specific recovery rate and using bonds with different maturities the model then estimates the probability of the company defaulting at different future times.[17]

More formally the model assumes a set of N bonds of the reference entity with the maturity of the ith bond being t_i, with $t_1 < t_2 < ... < t_N$. It then estimates the risk-neutral default probability density function $q(t)$ of the company assuming that $q(t) = q(t_i)$ for $t_{i-1} < t < t_i$ and using the following equation

$$q(t_j) = \frac{G_j - B_j - \sum_{i=1}^{j-1} q(t_i)\beta_{ij}}{\beta_{jj}}$$

where G_j is the current price of a risk-free bond maturing at t_j, B_j is the current price of the companies jth bond and β_{ij} represents the present value of the loss from a default on the jth bond at time t_i as a share of the value of a corresponding risk-free bond and is set to

$$\beta_{ij} = \int_{t_{i-1}}^{t_i} v(t)\left[F_j(t) - \hat{R}C_j(t)\right]dt$$

where $v(t)$ is the present value of certainly receiving USD 1 at time t, $F_j(t)$ is the forward price of the jth risk-free bond delivered at time t, $\hat{R}$ is the expected recovery rate (independent of j and t) while $C_j(t)$ represents the claim made by holders of the jth bond in case of default at time t. To value a CDS with a notional principal of USD 1, one needs to define the risk-neutral probability $\pi(T)$ of no credit event until maturity of the credit default swap T, which is

$$\pi(T) = 1 - \int_0^T q(t)dt$$

Total payments per year made by the protection buyer w last until a credit event or the end of the contract at time T, whichever is sooner. In the case of no default during the lifetime of the CDS, the present value of the payments is $wu(T)$, where $u(T)$ is the present value of annual payment stream of USD 1 between time 0 and T. In the case of default at time $t\,(t < T)$, the present value of the

[17] see Hull, White (2000), pp. 29-40.

payments is $w[u(t)+e(t)]$, where $e(t)$ is the present value of an accrual payment at time t. Accordingly, the expected value of the payments can be expressed as follows[18]

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

Assuming that the claim of protection buyer in case of default equals the face value of the bond L and accrued interest, the payoff of a CDS would be

$$L - \hat{R}L(1 + A(t)) = L\left(1 - \hat{R} + \hat{R}A(t)\right)$$

where $A(t)$ is the accrued interest on the reference obligation at time t expressed as a share of L and since $L = 1$ in this example, the present value of the expected payoff of a CDS can be expressed as follows

$$\int_0^T \left[1 - \hat{R} + \hat{R}A(t)\right] q(t) v(t) dt$$

and the total value of the CDS to the buyer is equal to the difference between the expected payoff the buyer and the present value of the payments to the protection seller which can be formalized as follows

$$\int_0^T \left[1 - \hat{R} + \hat{R}A(t)\right] q(t) v(t) dt - w\int_0^T q(t)[u(t)+e(t)]dt - \pi w u(t)$$

and when entering the contract neither of both parties makes a cash payment. Accordingly, the value of the CDS to both parties has to be zero at inception, which is ensured by choosing $w = p_{CDS}$ as follows

$$p_{CDS} = \frac{\int_0^T \left[1 - \hat{R} + \hat{R}A(t)\right] q(t) v(t) dt}{\int_0^T q(t)[u(t)+e(t)]dt + \pi u(t)}$$

[18] see Hull, White (2000), pp. 29-40.

where p_{CDS} is the credit default swap spread and represents the value of total payments by year as a share of the notional principal of the CDS.

Additionally to the valuation, the authors show that the arbitrage argument between CDS and bond holds only approximately and deteriorates significantly for non-flat interest rate structures, for bonds that are not trading close to par and in high interest rate environments. Furthermore, they have made several assumptions for their model including the non-existence of transaction costs, taxes and counterparty risk and the mutual independence of default probabilities, interest rates and recovery rates which altogether may impede the empirical application of the model.[19]

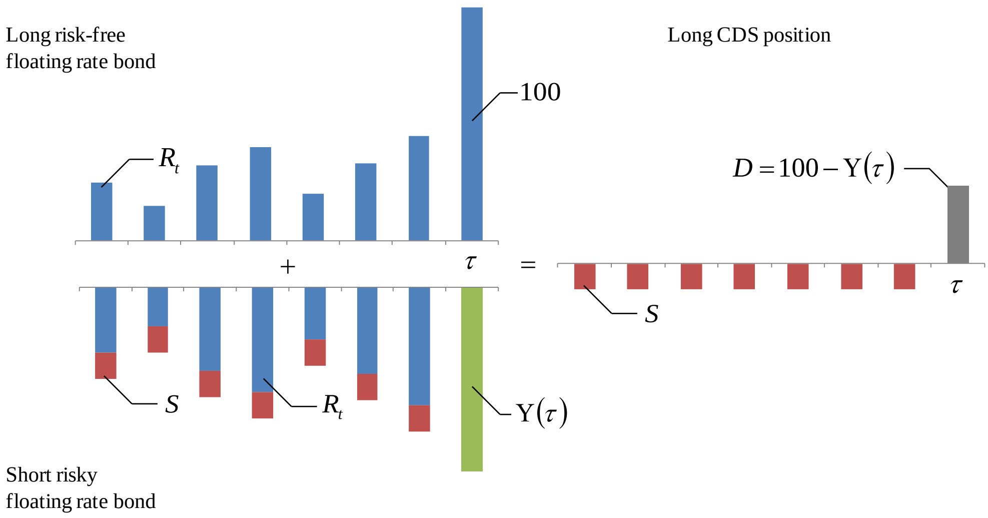

Figure 3: Replicating Strategy for CDS on Risky Floating Rate Bond[20]

Duffie (1999) represents another major reduced-form model and is based on the following no-arbitrage approach. Several assumptions are made to create a replicating portfolio of a CDS, which is depicted in figure 3: A risk-free floating rate bond exists with floating rate R_t at date t. The CDS involves a constant swap rate p_{CDS}, i.e. there is no interest rate swap involved. In case of default, the protection buyer does not have to pay the accrued protection premium. The reference obligation is a par floating-rate note with the same maturity as the CDS and a coupon rate of $R_t + S$, where S is a constant spread. The reference obligation can be shorted on the issue date and be bought both at

[19] see Hull and White (2000), pp. 29-40.
[20] see Duffie (1999), p. 76.

maturity and in case of a credit event. There exist no transaction costs in cash markets for both bonds. In case of a credit event, the payment by the protection seller is made on the following coupon date of the reference obligation and the CDS is settled by physical delivery. Finally, tax effects can be ignored. In this environment, an investor can build a short position in the reference obligation at $t = 0$ for an amount of USD 100. Subsequently, this amount can be invested in the risk-free floating rate bond. Accordingly, the investor receives R_t from his investment in the risk-free rate and has the obligation to pay $R_t + S$ from his short position in the reference obligation such that the net outflow is S. In the case of no credit event, both bonds mature at par such there will be no net cash flow to be made by the investor. In case of a credit event, the investor sells the risk-free bond for an amount of USD 100 and buys the reference obligation for its market value $\mathrm{Y}(\tau)$ at time τ. The difference $D = 100 - \mathrm{Y}(\tau)$ equals the amount that has to be paid in case of a credit event to a protection buyer. Accordingly, the CDS spread p_{CDS} has to be equal to the spread S of the reference obligation over a risk-free bond. However, the author also points out that the arbitrage argument only works approximately when transaction costs exist, the reference obligation trades at a discount to par and accrued swap premiums have to be paid. Furthermore, the maturity of CDS and underlying bonds often differ and short-selling the underlying bond may be very costly. Finally, the CTD option increases the value of the CDS and thus makes the arbitrage imperfect.[21]

3.2. Relationship between CDS and Credit Spreads

Using two further simplifying assumptions, a mathematical equivalence relationship can be established. This approach assumes a par risk-free bond with a fixed coupon rate R and a risky par reference obligation with a fixed coupon rate C, where both bonds have a face value of USD 100. Again, $q(t)$ is defined as the risk-neutral default probability density function, such that the probability of survival of the reference entity until τ is defined as $\pi(\tau) = 1 - \int_0^{\tau} q(t)dt$. The fixed CDS spread amounts to p_{CDS} and the payment dates coincide with the coupon payments of the bonds $t_1, t_2, \ldots, T$ until maturity T or a credit event τ. Finally, the market value of the reference obligation equals D_t at time t. The present value of the expected premium payments equals the sum of all discounted payments until maturity or a credit event

[21] see Duffie (1999), pp. 74-75.

$$\sum_{i}^{T} e^{-rt_i} \pi(t_i) p_{CDS}$$

while the expected value of the insurance payment in case of a credit event is

$$\int_{0}^{T} e^{-rt} (100 - D_t) \pi(t) dt$$

Furthermore, at inception the value of the CDS contract has to be zero because no cash payments are exchanged between the two parties. Accordingly the value of the two above payments has to be equal, such that

$$\sum_{i}^{T} e^{-rt_i} \pi(t_i) p_{CDS} = \int_{0}^{T} e^{-rt} (100 - D_t) \pi(t) dt$$

and the present value of the reference obligation consists of three parts. The first component is the present value of the coupon payments. The present value of the final payment of the bond in case of no default represents the second component, while the expected market value at default is the last component. Thus, the value of the bond can be formalized as follows[22]

$$100 = \sum_{i}^{T} e^{-rt_i} \pi(t_i) c + 100 e^{-rT} \pi(T) + \int_{0}^{T} e^{-rt} D_t \pi(t) dt$$

and the replication strategy resembles the case with floating rate bonds. The investor establishes a long position in the risk-free bond for an amount of USD 100, which is funded by a short position in the reference obligation by the same amount. During the lifetime of the bonds, the coupon obligation by the short position is met using the payments from the long position. In case of no default, both bonds mature at T and there is no net cash-flow needed. In case of a credit event, the long position is liquidated for USD 100 and the risky bond is acquired for its market value of D_t. Since the initial net payment is zero, the no-arbitrage condition requires the expected value of the payments of the portfolio to equal zero, i.e.

[22] see Zhu (2006), pp. 211-235.

$$0=\sum_{i}^{T}e^{-rt_i}\pi(t_i)r+100e^{-rT}\pi(T)+\int_{0}^{T}e^{-rt}100\pi(t)dt-\sum_{i}^{T}e^{-rt_i}\pi(t_i)c-100e^{-rT}\pi(T)-\int_{0}^{T}e^{-rt}D_t\pi(t)dt$$

$$\Rightarrow\sum_{i}^{T}e^{-rt_i}\pi(t_i)(c-r)=\int_{0}^{T}e^{-rt}(100-D_t)\pi(t)dt$$

and subtracting this from the equation above, which formalizes the equivalence of CDS payments, one can find the following

$$p_{CDS}=c-r$$

which indicates that CDS spread should equal the credit spread of bond yields above the risk-free rate. The equation can be restated as follows

$$p_{CDS}-(c-r)=0$$

where the left side of the equation represents the so-called basis spread and should be equal to zero. However, it has to be noted that the arbitrage relationship is lacking the same limitations as discussed in the previous section.[23]

4. Econometric Concepts

This section will give an overview over the econometric concepts used in the paper and will be focused on the most important points of the techniques to give the reader an intuition of the interpretation of the results.

4.1. Cointegration

Cointegration analysis focuses on a potential equilibrium relationship between a set of variables. This relationship should be reflected in the fundamental fact that the variables which are deemed to be linked through a theoretical economic relationship should not diverge from their equilibrium values in the long run. Those variables may drift away from their equilibrium values in the short-term but one cannot infer an equilibrium relationship between those variables if they diverge without any bound. Thus the divergence from their equilibrium values must be stochastically

[23] see Zhu (2006), pp. 211-235.

bounded and diminishing over time. Cointegration analysis provides a statistical measure of the existence of such a measure and it should not be confused with correlation.[24]

The foundation of cointegration analysis is stationarity. A time series $\{x_t\}$ is said to be strictly stationary if the joint distribution of $(x_{t_1},...,x_{t_k})$ is identical to that of $(x_{t_{1+m}},...,x_{t_{k+m}})$ for all m, where k is an arbitrary positive integer and $(t_1,...,t_k)$ is a collection of k positive integers. This implies that strict stationarity requires the joint distribution of $(x_{t_1},...,x_{t_k})$ to be invariant under a time shift. Since this is a very strong assumption and very hard to verify empirically, a weaker version of stationarity is often assumed. A time series $\{x_t\}$ is called weakly stationary if both the mean of x_t and the covariance between x_t and x_{t-l} are time invariant, where l is an arbitrary integer. Formally, $\{x_t\}$ is weakly stationary if

$$E(x_t) = \mu \text{ and } Cov(x_t, x_{t-l}) = \gamma_l$$

where μ is a constant and γ_l depends solely on l. In practice, if one would observe T data points $\{x_t | t = 1,...T\}$, weak stationarity would imply that the time plot of the data would show that the T values fluctuate with constant variation around a fixed level. In applications, weak stationarity allows to make inference concerning future observations. Weak stationarity implicitly assumes that the mean and variance of x_t are finite. Thus a strictly stationary x_t whose first two moments are finite, is also weakly stationary. The opposite does not hold in general, but if x_t is normally distributed then weak stationarity is equal to strong stationarity. The covariance $\gamma_l = Cov(x_t, x_{t-l})$ is called the lag-l autocovariance of x_t and has the following two important properties

$$\gamma_0 = Var(x_t) \text{ and } \gamma_{-l} = \gamma_l,$$

where the second property holds because

$$Cov(x_t, x_{t-(-l)}) = Cov(x_{t-(-l)}, x_t) = Cov(x_{t+l}, x_t) = Cov(x_{t_1}, x_{t_1-l}),$$

where $t_1 = t + l$.[25]

[24] see Banerjee et al. (1993), pp. 136-137.
[25] see Tsay (2010), p. 30.

However, time series analysis is not only restricted to stationary or weakly stationary time series. In fact, most of the time series including CDS spreads, bond yields and interest rates analysed in economics are non-stationary time series. This has substantial impact to well-accepted techniques used in econometric analysis as for example OLS regression.[26]

A non-stationary time series, which can be transformed to a stationary time series by differencing once, is said to be integrated of order 1 and is denoted by $I(1)$. Accordingly, a series is said to be $I(k)$ if it needs to be differenced k times to become stationary. A random walk process y_t is $I(1)$, while a stationary process x_t is $I(0)$, because the series does not need to be differenced to become stationary. Furthermore, the $I(k)$ series $(k \neq 0)$ is called a difference-stationary process. The variance and covariance among variables represents the fundament for most of the econometric analysis. For example, when estimating an OLS regression of y_t on x_t, the coefficient of x_t is the ratio of the covariance between y_t and x_t to the variance of x_t. That means that conventional asymptotic theory is not applicable if the variances of the variables behave differently. In the case, where y_t is $I(1)$ and x_t is $I(0)$ the OLS estimator from a regression of x_t on y_t converges to zero asymptotically. This is because the denominator of the OLS estimator, the variance of y_t, increases as t increases. Thus it dominates the numerator, which is the covariance between x_t and y_t. This implies that the estimator does not exhibit the conventional asymptotic distribution and is said to be degenerate with the conventional normalization of $\sqrt{T}$. Instead, one has to employ the normalization of T instead of $\sqrt{T}$.[27]

The concept of cointegration was introduced by Granger (1981) and it states that two variables are cointegrated if each of them taken individually is $I(1)$ but a linear combination of them is $I(0)$.[28] Formally, if x_t and y_t are $I(1)$ then they are said to be integrated if a β exists such that $y_t - \beta x_t$ is $I(0)$ which is denoted by saying that x_t and y_t are $CI(1,1)$. Generally, if y_t is $I(d)$ and x_t is $I(b)$, then y_t and x_t are $CI(d,b)$ if there exists a β such that $y_t - \beta x_t$ is $I(d-b)$ where $b > 0$. This implies that the regression equation $y_t = \beta x_t + u_t$ makes sense because y_t and x_t do not drift too far apart from each other over time. This means that one can infer a long-run equilibrium relationship

[26] see Appendix A.2
[27] see Maddala, Kim (1999), pp. 24-26.
[28] see Granger (1981), pp. 121-130.

between the variables. In the case that the two series are not cointegrated one would find that $y_t - \beta x_t = u_t$ is also $I(1)$ and the two time series y_t and x_t would drift apart from each other over time. Furthermore, the relationship obtained between the two variables in an OLS regression would be spurious in that case.[29]

One can extend the concept of cointegration to different orders of integrated variables. There may exist linear combinations of $I(2)$ variables which lead to differently integrated time series and as such represent different types of cointegration. For example, linear combinations of $I(2)$ variables can lead to $I(1)$ or $I(0)$ time series. Furthermore, linear combinations of $I(1)$ variables can be cointegrated with first-differences of $I(2)$ variables to produce an $I(0)$ time series.[30]

4.1.1. Johansen Cointegration Test

Several methods have been proposed by academics to test for the existence of a cointegration relationship between variables, most notably the Engle-Granger method and the Johansen reduced rank regression.[31] The former test uses a single-equation approach and essentially employs unit root tests like the Augmented Dickey Fuller method to test whether the error term u_t of the regression $y_t = \beta x_t + u_t$ is $I(0)$. If the test supports the hypothesis of a stationary error term u_t, then it suggests that the variables x_t and y_t are cointegrated. However, testing for cointegration using a single equation involves several disadvantages. In general, one does not know the number of cointegrating vectors before analysing the relationship between the variables. Furthermore, in the beginning one should allow all variables included in the analysis to be endogenous and possibly test for exogeneity later. The Johansen test procedure does not exhibit these problems such that the paper will focus on this method in the following.[32]

The starting point of the Johansen approach is a multivariate autoregression model. Define a vector $\mathbf{z_t}$ of n potentially endogenous variables and specify the following unrestricted vector autoregression (VAR) model

$$\mathbf{z_t} = \mathbf{A_1 z_{t-1}} + \ldots + \mathbf{A_p z_{t-p}} + \mathbf{u_t}, \qquad \mathbf{u_t} \sim IN(0, \Sigma)$$

[29] see Granger, Newbold (1974), pp. 111-121.
[30] see Maddala, Kim (1999), p. 27.
[31] see Engle, Granger (1987), pp. 251-276; Johansen (1988), pp. 231-254.
[32] see Harris (1995), pp. 27-72.

where p is the number of lags to be chosen, $\mathbf{z_t}$ is a $n \times 1$ vector, $\mathbf{u_t}$ is a $n \times 1$ vector of error terms which and each $\mathbf{A_i}$ is a $n \times n$ matrix of parameters to be estimated. This type of VAR model has been used extensively to estimate dynamic relationships among jointly endogenous variables without imposing strong a priori assumptions such as the exogeneity of variables or specific structural relationships. Each variable in $\mathbf{z_t}$ is regressed only on lagged values of both itself and all the other variables in the system. This implies that OLS represents an appropriate way to estimate each equation in the system. The system can be rewritten in the vector error-correction (VECM) form in the following way

$$\mathbf{\Delta z_t} = \mathbf{\Gamma_1 \Delta z_{t-1}} + \ldots + \mathbf{\Gamma_{p-1} \Delta z_{t-p+1}} + \mathbf{\Pi z_{t-p}} + \mathbf{u_t}$$

where $\mathbf{\Delta z_t}$ represents the first-differenced value of $\mathbf{z_t}$, while $\mathbf{\Gamma_i} = -(\mathbf{I} - \mathbf{A_1} - \ldots - \mathbf{A_i})$, $i = 1,\ldots,k-1$ and $\mathbf{\Pi} = -(\mathbf{I} - \mathbf{A_1} - \ldots - \mathbf{A}_k)$ comprise of the parameters to be estimated. The estimates of $\mathbf{\hat{\Gamma}_i}$ and $\mathbf{\hat{\Pi}}$ contain information on both the short- and long-run adjustment to changes in $\mathbf{z_t}$, respectively. The matrix $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$, where $\boldsymbol{\alpha}$ represents the speed of adjustment to disequilibrium, while $\boldsymbol{\beta}$ is a matrix of long-run coefficients such that the term $\boldsymbol{\beta}'\mathbf{z_{t-p}}$ represents up to $n-1$ cointegration relationships in the multivariate model which ensure that $\mathbf{z_t}$ converges to its long-run equilibrium. Assuming that $\mathbf{z_t}$ is a vector of non-stationary $I(1)$ variables, then all the terms in the above equation which involve $\mathbf{\Delta z_{t-1}}$ must be stationary. Furthermore, $\mathbf{\Pi z_{t-p}}$ must also be stationary for $\mathbf{u_t}$ to be stationary. There are three cases when the requirement that $\mathbf{\Pi z_{t-p}}$ is $I(0)$ is met [33]

1. All variables in $\mathbf{z_t}$ are stationary
2. There is no cointegration between the variables such that $\mathbf{\Pi}$ is a $n \times n$ matrix of zeros
3. There exists up to $n-1$ cointegration relationships where $\mathbf{\Pi z_{t-p}} \sim I(0)$

While the former two cases are not particularly interesting, the last case implies that r cointegrating vectors in $\boldsymbol{\beta}$ exists, i.e. r columns of $\boldsymbol{\beta}$ form r linearly independent combinations of the variables in $\mathbf{z_t}$, each of which is stationary. Furthermore, $n-r$ vectors form non-stationary series in combination with $\mathbf{z_t}$. Since $\mathbf{\Pi z_{t-p}}$ has to be $I(0)$, only the cointegration vectors of $\boldsymbol{\beta}$ enter the above VECM such that the last $n-r$ columns of $\boldsymbol{\alpha}$ have to be zero. Thus determining how many

[33] see Harris (1995), pp. 77-78.

cointegration vectors exist in $\boldsymbol{\beta}$ amounts to determining the number of zero columns in $\boldsymbol{\alpha}$. Accordingly, this translates in finding the rank of $\boldsymbol{\Pi}$, i.e. the number of linearly independent columns in $\boldsymbol{\Pi}$. If the rank of $\boldsymbol{\Pi}$ is zero, then the variables in $\mathbf{z_t}$ are not cointegrated, while the variables in $\mathbf{z_t}$ are stationary if $\boldsymbol{\Pi}$ has full rank. The interesting case appears, when $\boldsymbol{\Pi}$ has rank $0 < r < n$, which implies r cointegrating vectors. In general, it is not possible to employ OLS regressions to estimate the equations in the VECM since the obtained estimate of $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta'}$ will be $n \times n$, but $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ can be reduced in dimension to $n \times r$. Thus employing the Johansen reduced rank regression obtains estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. For this, the VECM has to be rewritten to[34]

$$\boldsymbol{\Delta z_t} + \boldsymbol{\alpha\beta' z_{t-p}} = \boldsymbol{\Gamma_1 \Delta z_{t-1}} + \ldots + \boldsymbol{\Gamma_{p-1} \Delta z_{t-p+1}} + \mathbf{u_t}$$

and to correct for short-run dynamics, $\boldsymbol{\Delta z_t}$ and $\mathbf{z_{t-p}}$ have to be regressed separately on the right-hand side of the rewritten VECM, i.e. the following regressions have to be performed

$$\begin{aligned} \boldsymbol{\Delta z_t} &= \mathbf{P_1} \boldsymbol{\Delta z_{t-1}} + \ldots + \mathbf{P_{p-1}} \boldsymbol{\Delta z_{t-p+1}} + \mathbf{R_{0t}} \\ \mathbf{z_{t-p}} &= \mathbf{T_1} \boldsymbol{\Delta z_{t-1}} + \ldots + \mathbf{T_{p-1}} \boldsymbol{\Delta z_{t-p+1}} + \mathbf{R_{pt}} \end{aligned}$$

where the residual vectors $\mathbf{R_{0t}}$ and $\mathbf{R_{pt}}$ can be used to create the following residual matrices

$$\mathbf{S_{ij}} = T^{-1} \sum_{i=1}^{T} \mathbf{R_{it} R'_{jt}}, \qquad \mathrm{i, j = 0, p}$$

The maximum likelihood estimate of $\boldsymbol{\beta}$ is then obtained as the eigenvectors corresponding to the r largest eigenvalues from solving the following equation

$$\left| \boldsymbol{\lambda} \mathbf{S_{pp}} - \mathbf{S_{p0} S_{00}^{-1} S_{0p}} \right| = 0$$

which yields the n eigenvalues of $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$ and the corresponding eigenvectors $\hat{\mathbf{V}} = (\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \ldots, \hat{\mathbf{v}}_\mathbf{n})$. The elements in $\hat{\mathbf{V}}$ which represent linear combinations of stationary relationships are the r cointegrating vectors $\hat{\boldsymbol{\beta}} = (\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \ldots, \hat{\mathbf{v}}_\mathbf{r})$. This is because the eigenvalues are the largest squared canonical correlations between $\mathbf{R_{0t}}$ and $\mathbf{R_{pt}}$. This implies that all $\hat{\mathbf{v}}_\mathbf{i}' \mathbf{z_t}$ $(i = 1, \ldots, r)$ combinations have high correlations with the stationary $\boldsymbol{\Delta z_t}$ elements. This in turn

[34] see Harris (1995), p. 79.

can only be true if the combinations $\hat{\mathbf{v}}_{\mathbf{i}}'\mathbf{z}_{\mathbf{t}}\ (i=1,...,r)$ themselves are $I(0)$, which implies that $(\hat{\mathbf{v}}_{\mathbf{1}},\hat{\mathbf{v}}_{\mathbf{2}},...,\hat{\mathbf{v}}_{\mathbf{r}})=\hat{\boldsymbol{\beta}}$. Thus the magnitude of $\hat{\lambda}_i$ is a measure of how strongly the cointegration relations $\hat{\mathbf{v}}_{\mathbf{i}}'\mathbf{z}_{\mathbf{t}}$ are correlated with the stationary part of the model. Since, the last $n-r$ combinations $\hat{\mathbf{v}}_{\mathbf{i}}'\mathbf{z}_{\mathbf{t}}$ represent non-stationary combinations, $\hat{\lambda}_i=0$ for $i=r+1,...,n$. Thus the test that $r=1$ is in fact a test whether $\hat{\lambda}_2=\hat{\lambda}_3=...=\hat{\lambda}_n=0$ and $\hat{\lambda}_1>0$. Furthermore, since $\hat{\lambda}_i=\hat{\boldsymbol{\alpha}}_{\mathbf{i}}'\mathbf{S}_{\mathbf{00}}^{-1}\hat{\boldsymbol{\alpha}}_{\mathbf{i}}$ this implies testing $\hat{\boldsymbol{\alpha}}_{\mathbf{i}}=0$ for $i=r+1,...,n$. Finally, the estimates of the speed of adjustment to disequilibrium are obtained by $\hat{\boldsymbol{\alpha}}=\mathbf{S}_{\mathbf{0k}}\hat{\boldsymbol{\beta}}$.[35]

Formally, the test of the null hypothesis that there are at most r cointegration vectors amounts to

$$H_0:\lambda_i=0,\qquad i=r+1,...,n$$

where only the first r eigenvalues are non-zero. This restriction can be imposed for different values of r and then the log of the maximized likelihood function can be compared to the log of the maximized likelihood function of the unrestricted model and a standard likelihood test with a non-standard distribution can be computed. That means that the null hypothesis can be tested using the so-called trace statistic

$$\lambda_{trace}=-2\log(Q)=-T\sum_{i=r+1}^{n}\log\left(1-\hat{\lambda}_i\right),\qquad r=0,1,2,...,n-2,n-1$$

where Q represents the ratio of the restricted maximized likelihood to the unrestricted maximized likelihood and critical values for rejecting the hypothesis are provided in Osterwald-Lenum (1992). An additional test of significance of the largest λ_r is the so-called maximal eigenvalue or $\lambda_{\max}$ statistic

$$\lambda_{\max}=-T\log\left(1-\hat{\lambda}_{r+1}\right),\qquad r=0,1,2,...,n-2,n-1$$

which tests that there are r cointegration relationships against the alternative that $r+1$ exist. In practice, this test is exercised sequentially for $r=0,r=1,...,r=r^*$ where $r=r^*$ represents the last

[35] see Harris (1995), p. 79; Johansen (1992), pp. 313-34.

r for which the null hypothesis is rejected in this process. This is the number of cointegration relationships that can be assumed between the variables.[36]

4.1.2. Information Criteria

One parameter that has to be selected when forming vector autoregressive models is the number of lags to be incorporated in the estimations. The material question behind this choice is which number of lags fits the data best. Whilst the inclusion of additional lags will necessarily reduce the sum of the squared residuals it will also entail estimating additional coefficients and a loss of degrees of freedom. Furthermore, adding extraneous coefficients will reduce the forecasting performance of the fitted model. There exist several so-called information criteria, which trade-off the benefit of lower sum of squared residuals against the cost of a less parsimonious model. Two of the most commonly used information criteria are the Akaike Information Criterion (AIC)[37] and the Schwartz Bayesian Information Criterion (BIC)[38]. They are calculated with the following formulas

$$AIC = T\ln(SSR) + 2n$$
$$BIC = T\ln(SSR) + n\ln(T)$$

where T is the number of usable observations, n is the number of parameters estimated and SSR is the sum of squared residuals. When increasing the number of lags, some observations are lost necessarily. Nevertheless, then number of observations T in the formulas should be kept fixed to adequately compare the alternative models. Otherwise, one would compare the performance of the models over different sample periods. Furthermore, decreasing the number of observation T has the direct effect of decreasing both the AIC and the BIC. However, this is in contrast to the goal of estimating the information criteria. One should not choose the models with the smallest number observations but rather the model that fits the data best. As the fit of the model improves, both the AIC and the BIC will approach $-\infty$. Thus for an ideal model the AIC and the BIC will be as small as possible or even negative. Accordingly, model A is said to fit better than model B if the AIC or/and the BIC for A is smaller than for B. For each information criterion, the inclusion of an additional lag should have the effect of decreasing the sum of squared residuals SSR and thus decreasing the information criterion. If this is not the case, i.e. if the additional regressor does not have significant explanatory power, then the information criterion will increase because n increases

[36] see Harris (1995), pp. 87-88; Osterwald-Lenum (1992), pp. 461-472.
[37] see Akaike (1977), pp. 27-41; Akaike (1978), pp. 217-235.
[38] see Schwarz (1978), pp. 461-464.

in the formulas. In most cases, $\ln(T)$ will be larger than 2 since it is unlikely that sample sizes will be smaller than 8 observations. This implies that the BIC will always prefer fewer lags than the AIC. This is because the marginal cost of adding an additional lag is larger for the BIC than for the AIC, while the marginal benefit for both models is the same. Furthermore, the BIC has superior large sample properties. If the true order of a data generating process is $n*$ and one uses the AIC and the BIC to estimate the all models of order $n \geq n*$, then both criterions will choose models of order greater than or equal $n*$ as the sample size approaches infinity. But the BIC criterion is asymptotically consistent, while the AIC is biased toward selecting an overparameterized model.[39]

4.1.3. Price Discovery Measures

If a security is traded in only one market, then all new information with respect to that security is immediately processed in this market. However, if two closely linked securities are traded in different markets, then the information processing is split. In this case, one of the two can lead the other market in the price discovery process. This means that new information is mainly processed in one of the two, while the other market follows the price movements of the information processing market. Price discovery measures estimate whether one of the two markets leads the price discovery process. Two popular measures are used to investigate in the price discovery relationships between markets: The Hasbrouck measure and the Gonzalo-Granger measure.[40] Both measures rely on the fact that the prices of two closely linked securities are cointegrated $I(1)$ variables, which implies that the price series share one or more common stochastic factors. Because of that they are so-called common factor models and they are based on the two error correction models of the following form

$$\Delta p_{1,t} = \lambda_1 \left(p_{1,t-1} - \alpha_0 - \alpha_1 p_{2,t-1} \right) + \sum_{j=1}^{p} \beta_{1j} \Delta p_{1,t-j} + \sum_{j=1}^{p} \delta_{1j} \Delta p_{2,t-j} + \varepsilon_{1,t}$$

and

$$\Delta p_{2,t} = \lambda_2 \left(p_{1,t-1} - \alpha_0 - \alpha_1 p_{2,t-1} \right) + \sum_{j=1}^{p} \beta_{2j} \Delta p_{1,t-j} + \sum_{j=1}^{p} \delta_{2j} \Delta p_{2,t-j} + \varepsilon_{2,t}$$

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[39] see Enders (2004), pp. 69-70.
[40] see Gonzalo, Granger (1995), pp. 27-35; Hasbrouck (1995), pp. 1175-1199.

where $p_{1,t}$ and $p_{2,t}$ are the two cointegrated price series, $\lambda_i, \alpha_i, \beta_i$ and δ_i are parameters to be estimated, p is the number of lags to be chosen and $\varepsilon_{1,t}$, $\varepsilon_{2,t}$ are serially uncorrelated innovations with the following covariance matrix Ω

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$$

where σ_1^2 (σ_2^2) is the variance of $\varepsilon_{1,t}$ ($\varepsilon_{2,t}$) and ρ is the correlation between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$.

Despite this similarity, the Hasbrouck (1995) and the Gonzalo, Granger (1995) define price discovery differently.[41] The Hasbrouck measure defines the term as the variance of the innovations to the common factor. Accordingly it measures each market's relative contribution to this variance. This so-called information share is calculated as follows for the market of security $p_{1,t}$

$$HAS_1 = \frac{\lambda_2^2\left(\sigma_1^2 - \dfrac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2},$$

$$HAS_2 = \frac{\left(\lambda_2\sigma_1 - \lambda_1\dfrac{\sigma_{12}}{\sigma_2}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}$$

while there is no single value for the Hasbrouck measure, HAS_1 and HAS_2 build a lower and upper estimate for the price discovery measure of Hasbrouck. Furthermore, it has been noted that the average provides a sensible estimate of the price discovery relationship between the two markets. [42]

In contrast, Gonzalo and Granger (1995) consider only the error correction process described by the two coefficients λ_1 and λ_2. This involves only permanent shocks that result in a disequilibrium instead of transitory shocks. Accordingly, the so-called permanent-transitory (PT) model defines each market's contribution to the common factor as a function of the two error correction coefficients as follows[43]

[41] see Gonzalo, Granger (1995), pp. 27-35; Hasbrouck (1995), pp. 1175-1199.
[42] see Baillie et al. (2002), pp. 309-321; Hasbrouck (1995), pp. 1175-1199.
[43] see Gonzalo, Granger (1995), pp. 27-35.

$$GG = \frac{\lambda_2}{\lambda_2 - \lambda_1}$$

For both models, a value of the price discovery measure above 0.5 indicates that the market of $p_{1,t}$ leads the price discovery process while a lower value than 0.5 indicates that $p_{2,t}$ leads the price discovery process. Researchers have not been able to determine whether one of the two measures is superior to the other such that both measures are used in most studies.[44]

4.2. Granger Causality

The Granger Causality Test investigates in the forecasting relationship between two variables and was proposed by Granger (1969) and further popularized by Sims (1972) but has less statistical power than the cointegration relationship.[45]

The question investigated in the Granger Causality Test is whether a time series x_t can help to forecast the future values of another time series y_{t+s}. If it does not, then x_t does not Granger-cause y_t. Formally, x_t fails to Granger-cause y_t if for all $s > 0$ the mean squared error (MSE) of a forecast of y_{t+s} based on $(y_t, y_{t-1}, ...)$ is the same as the MSE of a forecast of y_{t+s} that uses both $(y_t, y_{t-1}, ...)$ and $(x_t, x_{t-1}, ...)$, i.e.

$$MSE\left[\hat{E}\left(y_{t+s} \middle| y_t, y_{t-1}, ...\right)\right] = MSE\left[\hat{E}\left(y_{t+s} \middle| y_t, y_{t-1}, ..., x_t, x_{t-1}, ...\right)\right]$$

where $\hat{E}(y_t)$ is the estimated expected value of y_t. Furthermore, if x_t fails to Granger-cause y_t, y_t is said to be exogenous in the time series sense with respect to x_t or x_t is not linearly informative about future y_t.

The idea behind this test is that if the event X is the cause for another event Y, then the event X should happen before the event Y. Although this argument intuitively makes sense, there can be several obstacles when implementing the test in empirical applications with aggregated time series data.[46]

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[44] see Baillie et al. (2002), pp. 309-321; Harris et al. (2002), pp. 277-308; Hasbrouck (2002), pp. 329-339; Harris et al. (2002b), pp. 341-348; Jong (2002), pp. 323-327; Lehmann (2002), pp. 259-276; Ronen, Yaari (2002), pp. 349-390.
[45] see Granger (1969), pp. 424-438; Sims (1972), pp. 540-552.
[46] see Hamilton (1994), pp. 302-304.

The econometric test of Granger causality can be based on a bivariate autoregressive model of the following form

$$y_t = c_1 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + u_t$$

where p represents the lag length to be chosen. Subsequently, one can perform an F-test of the null hypothesis $H_0 : \beta_1 = \beta_1 = ... = \beta_p = 0$ which can be implemented using the sum of squared residuals of the bivariate model $RSS_2 = \sum_{t=1}^{T} \hat{u}_t^2$ and the sum of squared residuals of a univariate model $RSS_1 = \sum_{t=1}^{T} \hat{\upsilon}_t^2$ of $y_t = c_1 + \sum_{i=1}^{p} \alpha_i y_{t-i} + u_t$ which is estimated by OLS. The relevant F-statistic is

$$S_1 = \frac{(RSS_1 - RSS_2)/ p}{RSS_1 /(T - 2p - 1)}$$

which is $F(p, T - 2p - 1)$ distributed. If the F-statistic is greater than the 5% critical value of an $F(p, T - 2p - 1)$ distribution, one can reject the null hypothesis that x_t does not Granger-cause y_t, i.e. if S_1 is sufficiently large the test suggests that x_t Granger-causes y_t. The test is only valid asymptotically, because of the lagged dependent variables.

However, even if the test suggests Granger-causality between two variables one should be cautious about concluding true causality between two variables. Researchers have found that Granger-causality tests serve well for statements about the predictability of a particular series. On the other hand, they are sceptical about the explanatory power when considering Granger-causality tests for establishing the direction of causation between two arbitrary time series. Thus, the test seems to be better described by the question of whether x_t helps to forecast y_t instead of whether it causes y_t.[47]

5. Overview of Existing Literature

Credit default swaps have received increased attention during the last decade due their importance in today’s financial markets. In the early stage of research about CDS, academics have focused on the technical aspects when valuing CDS contracts. Subsequent research has focused on the

[47] see Hamilton (1994), pp. 305-306.

comparison of different valuation models for CDS, the relation between CDS, bond and equity markets and the determinants of CDS spreads, especially liquidity and credit rating changes.[48]

This paper is going to focus on a subcategory of the existent research, which studies the relationship between the closely related CDS and bond markets. The literature on this topic is relatively scarce compared to the rest of the research on credit default swaps.

Blanco et al. (2005) represents a very well-received paper and constitutes the basic framework for the empirical estimations applied in this paper. In their paper, the authors analyse the empirical relationship between CDS and bonds of 33 corporate entities from the beginning of 2001 through mid-2002.[49]

They find a relatively low average basis spread of 5.5 bps across their entire sample, when using the swap rate as reference rate. They argue that the swap rate has several advantages over government yields, including virtually unlimited availability and the quoting in constant maturities. They also find several entities with basis spreads significantly larger than zero. They argue that this is likely to be due to two factors. First, the difficulty of borrowing the bond in the market leading to non-zero repo costs which in turn results in underestimating the true credit spread. Second, the CTD option inherent in some credit default swap contracts, which increases the CDS spread. Furthermore they find evidence for a cointegration relationship for all U.S. entities and the majority of EU companies in their sample. Apart from the CTD option and non-zero repo costs they suspect that large bid-ask spreads result in the prices moving in seemingly unrelated ways during their relatively short sample period. Subsequently, they test for market leadership in price discovery using vector-error-correction models and find that on average the CDS market contributes to 80% of price discovery. Finally, they test several firm-specific and macroeconomic variables for their effect on CDS and credit spreads. These tests support their findings on the leadership of CDS markets. Furthermore, they find that credit spreads react more to macroeconomic variables while CDS spreads react more to firm-specific variables. However, they note that since both variables are linked trough the arbitrage argument, both CDS and credit spreads should react equally on firm-specific factors. And this, they argue, is brought about by credit spreads following CDS spreads which is supported by their empirical evidence. Lastly, they note that the explanatory power of their models still leaves the majority of variance in spreads unexplained, which indicates a missing factor in their estimations.

[48] see Abid, Naifar (2006), pp. 23-42; Arora et al. (2012), pp. 280-293; Bongaerts et al. (2011), pp. 203-240; Chen et al. (2008), pp. 123-160; Joriona, Zhang (2007), pp. 860-883; Norden, Weber (2004), pp. 2813-2843.
[49] see Blanco et al. (2005), p. 2260.

The authors conclude that the price discovery takes place mainly in the CDS market, because it is the most convenient market to trade credit risk and that informed participants mainly trade in this market. The CDS market benefits from its synthetic nature, which allows entering both large long and short positions in CDS contracts. Furthermore, since CDS incorporate counterparty risk, the CDS market is restricted to professional institutions with high credit ratings. Finally, they conclude that transaction costs, repo costs and the synthetic nature of the 5-year bond yield used to estimate the credit spread could cause the estimated basis spread to be different from zero.[50]

Ammer, Cai (2011) analyses the relation between CDS and credit spreads for nine emerging market sovereign entities from the beginning of 2001 until the beginning of 2005. The authors focus on the implications of the CTD option on basis spreads. They present evidence of a significant impact of the CTD option on basis spreads. They find that the basis tends to be higher for entities where the value of the option ex-post is larger. Furthermore, they find larger basis spreads for riskier entities with higher credit spreads and lower credit ratings. While they also find CDS markets leading the price discovery process in some instances they also find the opposite in other cases. The important factor in deciding which market leads seems to be the liquidity, i.e. the authors find the more liquid market to lead the discovery process. Thus in the case of emerging markets, the CDS market does not seem to be the clear leader in the price discovery process.[51]

Bai, Collin-Dufresne (2012) studies the relationship of CDS and credit spreads of 484 companies during the financial crisis from January 2006 until September 2009. Their estimation of the credit spread analysis differs from the linear interpolation method used for example in Blanco et al. (2005) and they do not restrict their sample to investment-grade bonds such that they are able to create a significantly larger data sample compared to other publications. The authors find that the basis spread across their sample becomes extremely negative during the financial crisis, especially for non-investment grade bonds. Although they are not able to provide a compelling theory why the basis spread turns negative, they provide evidence for several explanations of a non-zero basis spread. They find that measures of counterparty, collateral quality, funding and bond trading liquidity risk can explain variation in the basis spreads. Furthermore, they find that the CDS market leadership in price discovery dramatically weakens during crisis times.[52]

[50] see Blanco et al. (2005), pp. 2260-2288.
[51] see Ammer, Cai (2011), pp. 369-387.
[52] see Bai, Collin-Dufresne (2012), pp. 1-63.

Houweling, Vorst (2005) compares theoretical CDS spreads derived from reduced-form models to their market prices for 225 corporate and sovereign entities from May 1999 to January 2001, ranging from AAA-rated to unrated entities. They find that model-estimated prices produce significantly lower basis spreads for investment-grade securities and speculative-grade bonds (76.3 bps vs. 179.6 bps). Furthermore, they find that observed basis spreads in the market are lower when using swap rates instead of government bonds as reference rate for investment-grade bonds (1.2 bps vs. -27.6 bps) but higher speculative-grade bonds (157.6 bps vs. 179.6 bps). They argue that this presents evidence for the government curve to be no longer seen as the reference risk-free rate but that swap rates have taken this position.[53]

Hull et al. (2004) examines the relationship between CDS spreads, bond yields and credit rating announcements of 1599 entities from January 1998 until May 2002, covering investment- and speculative grade corporations as well as sovereign entities from the U.S., EU, Asia, Africa and Australia. To determine which rate to use as reference rate, they estimate the basis spread on a subsample of 31 entities, which exhibits a relatively complete CDS quote history. They find that the implied risk-free rate from their CDS and bond yield observations is 62.8 bps higher than the treasury yields and only 6.5 bps lower than the swap rates. Thus they conclude that swap rates serve as reference rates. Subsequently, they analyse the relationship between CDS spreads and credit rating announcements. They find that reviews for downgrade contain information while actual downgrades and negative outlooks do not and that all three types are anticipated by the market. Furthermore, they find that all three types have high probabilities when accompanied by large CDS spread changes. Finally, they find less explanatory power for positive rating announcements which could be due to the limited existence of such announcements in the sample.[54]

Longstaff et al. (2005) estimate the share of corporate bond yields that is due to default risk for a proprietary data set of 68 actively traded firms in the credit derivatives market during the March 2001 to October 2002 period. The authors use CDS spreads to measure the size of default- and non-default risk inherent in corporate yields spreads. They find lower basis spreads using swap rates instead of treasury rates for AAA- and AA-rated (5 bps vs. -53.1 bps), A-rated (-13.4 bps vs. -70.4 bps), BBB-rated (-14.7 bps vs. -72.9 bps), and BB-rated (-10.3 bps vs. -70.1 bps) companies. Furthermore, they find that the default component represents the majority of corporate spreads although they also present evidence of a significant non-default component in corporate spreads.

[53] see Houweling, Vorst (2005), pp. 1200-1225.
[54] see Hull et al. (2004), pp. 2789-2811.

Their results suggest, that this non-default component is strongly related to bond-specific illiquidity, which is measured by the bid-ask spread and the outstanding principal amount of the bond. Furthermore changes in the non-default component are related to the overall liquidity level of the fixed-income market.[55]

Nashikkar et al. (2011) analyse the effect of bond liquidity on basis spreads using the so-called "latent liquidity", which is defined as the weighted average turnover of funds holding the bond, where the weights are their fractional holdings of the bond. Their combined database covers 1,167 companies for the period from July 2002 to June 2006. Using swap rates they find an average basis spread across their entire sample of 41.1 bps which ranges widely for each company from -620.9 bps up to 5,738.3 bps. They show that the latent liquidity measure has more explanatory power for the basis than other bond characteristics or measures of realized liquidity. Their results suggest that an increase in latent liquidity of bonds leads to an increased basis spread due to lower bond yields. Interestingly, they find that this relationship reverses for the most illiquid bonds where decreased liquidity increases the basis spread.[56]

Norden, Weber (2009) examines the co-movement between equity and credit markets for 58 companies from the U.S., EU and Asia for the years 2000-2002 from AA-rated to BB-rated entities. Once again, the authors find lower basis spreads using swap rates instead of government yields for AA-rated (21.0 bps vs. 60.6 bps), A-rated (55.2 bps vs. 106.0 bps), BBB-rated (115.6 bps vs. 160.0 bps) and BB-rated companies (325.4 bps vs. 366.6 bps). Further, they find that stock movements are least predictable and bond movements are most predictable at daily, weekly and monthly frequencies. Accordingly, they find that in the majority of cases CDS spreads Granger-cause credit spreads. In line with Blanco et al (2005), they find that the majority of CDS and credit spreads support the cointegration relationship and that CDS markets lead the price discovery process, while the latter observation is more pronounced for U.S. companies than their European counterparts.[57]

Finally, Zhu (2006) investigates the relationship between CDS and credit spreads of 24 U.S., EU and Asian corporations from 1999-2002, ranging from AA- to BBB-rated companies. The author finds lower basis spreads using swap rates across their entire sample (14.9 bps vs. -52.3 bps), although this reverses in the last year of their sample (32.2 bps vs. -20.4 bps). Furthermore, the results in the paper suggest a cointegration relationship between CDS and bond markets although

[55] see Longstaff et al. (2005), pp.2213-2254.
[56] see Nashikkar et al. (2011), pp. 627-656.
[57] see Norden, Weber (2009), pp. 529-562.

the spreads can differ substantially in the short run. The author argues that these deviations are largely to different responses of CDS and bonds to changes in the credit quality of the reference entity. Additionally, as found by other researchers as well, the author confirms that CDS markets seem to lead in the price discovery process. Lastly, the author notes a persistence of the short-term deviations mentioning that only 10% vanish within one day and that they can exist for up to three weeks.[58]

This paper differs from prior research mainly because it employs the most recent dataset, which is very important as Blanco et al. (2005) note that their "results are not necessarily representative of the period before or after our relatively short span of data." The articles considered above focus on the years from 1999-2009, while the data in this paper covers the recent period from 2010-2011. The results presented in this paper are very interesting, because they document potential changes that might have occurred because of the financial crisis from 2008-2009. Furthermore, the data spans the parts of the European sovereign debt crisis, which gives further interesting details into the relationship between CDS and bond markets during crises. The results of this paper can thus help to understand the development spreads during periods of crisis and their accurate interpretation. Additionally, this paper uses only publicly available data in contrast to the prevailing literature which uses proprietary datasets. Thus the paper can be seen as a test of the appropriateness of publicly available CDS and bond yield data for relationship analysis. Finally, this paper exhibits the largest sample size compared to prior research employing comparable restrictions on data consistency, rating and estimation methods.

6. Data Description

To analyse the relationship between bonds and CDS, consistent price data of preferably liquid bonds and CDS contracts is needed. As a starting point for potential sample candidates, all reported bond trades to the Trade Reporting and Compliance Engine (TRACE) from January 1st, 2010 until December 30th, 2011 were downloaded via the Wharton Research Data Services (WRDS). This included trades of bonds from 641 issuing companies. TRACE was introduced by the self-regulatory organization Financial Industry Regulatory Authority, Inc. (FINRA) formerly known as the National Association of Securities Dealers, Inc. (NASD) in July 2002 to increase the price transparency of the corporate debt market in the United States. TRACE collects and publishes data about all over-the-counter market activity in investment grade, high yield and convertible corporate

[58] see Zhu (2006), pp. 211-235.

debt. Although the system only captures trades happening in the U.S., not only U.S. bonds but issuers from a wide variety of countries are represented in the sample.

6.1. CDS Spreads

For the issuers in the TRACE sample, daily mid-market quotes of 5-year CDS contracts at "close of business" were downloaded using Bloomberg, because five years represent the most liquid maturity in the CDS market.[59] 245 companies out of this sample had at least 500 out of the possible 521 daily observations in the period from January 1st, 2010 through December 30th, 2011. Strong restrictions with regards to missing values were employed to draw attention to only the most liquid CDS contracts. The few missing values in the sample were replaced by observations of the previous day. The prices are quoted in basis points and are for a notional of USD 10 million and based on the standard ISDA regulations for settlement. The CDS spreads of the final sample were checked for suspicious values and for general confirmation using two additional data sources. The first dataset was downloaded from Datastream and uses data from the Credit Market Analysis Ltd. (CMA), which is a data provider for OTC market data. Unfortunately, this sample ends in September 31st, 2010. The second dataset uses Datastream's own sources and runs throughout the whole sample period, although with more missing values than the Bloomberg data and missing decimal separators. Both datasets confirm the price patterns of the CDS prices with a few exceptions, where one can observe the same pattern but a spread between the CDS prices. Moreover, it shows that the Bloomberg data is the best with regards to consistency and missing values and therefore a good source for the estimations in this paper.

6.2. Bond Yields

To set the CDS in relation to their corresponding bonds, five-year bond yields are needed for each of the companies. To achieve this, for each reference entity Bloomberg was searched for one bond with time to maturity of more than 7 years and one bond with a maturity of less than 5 years at the start of the sample period. The obtained yields were then linearly interpolated to estimate an artificial 5-year bond yield. To keep the prices comparable, only "plain vanilla" bonds were included in the search. This means that all bonds with special features, e.g. embedded options, deferred coupons or sinking funds were excluded. For bonds satisfying the requirements, the mid-quote for the bond yield to maturity holding at "close of business" was downloaded. Where several

[59] see Bai, Collin-Dufresne (2012), p. 15; Longstaff et al. (2005), p. 2217.

price sources were available, the Bloomberg Generic Price (BGN) was preferred. Liquidity is the main criteria for a BGN price to be generated. BGN is a market consensus price for bonds. It is calculated using prices contributed to Bloomberg through a polling process. The goal of the methodology is to produce "consensus" pricing. If BGN prices were not available, prices reported to TRACE were used. Lastly, if none of those sources were available, Bloomberg Valuation Services (BVAL) prices were used. BVAL prices are calculated for securities, where no direct market observations exist. BVAL uses observations of comparable securities and their correlations to the target security. Using the correlations it then estimates weights for the price impact of each security on the target security. The BVAL price is then calculated as a weighted sum of the prices of the comparable securities. BVAL prices were available for all bonds in the sample. Where a choice between bonds was available, the bond trading closest to par and having the shortest available maturity satisfying the above mentioned requirements was chosen. This is due to the weakening of the arbitrage relation through larger discounts and maturities of the bonds discussed in section 3. Missing values were again replaced by observations of the previous day. None of the presented results change significantly when dropping all trading days where the bond or the CDS observation is missing. According to Bloomberg 45 out of the 245 companies issued bonds satisfying the requirements with regards to data source, type and maturity. BGN is the main source of price data, providing prices for 49 out of 90 (two for each company) bonds of the sample. TRACE provides 27 out of 90 bonds. Finally, BVAL prices exhibit 14 out of 90 bonds. This represents a good distribution of price sources, as data concerns are lowest for BGN prices and their existence indicates liquidity of the used bonds. The bond yield data was checked against up to three different data sources. First, for each bond, yields were downloaded using BGN, BVAL and TRACE as price source where available. Second, Datastream was used to check for suspicious values and for general confirmation of the data. The yield data is confirmed by the additional data sources. It exhibits the same pattern and occasionally shows a spread but no large inconsistencies. More importantly, using the alternative datasets does not significantly change the empirical results presented in this paper. Although one has to acknowledge that the use of different price sources is not perfect, it represents the best non-proprietary data source currently available. To account for the prevailing data and liquidity issues, companies with an average basis spread of more than 100 bps (10 companies), bond yield observations of less than 400 out of 521 (2 companies) and rating changes below BBB during the sample period (1 company) were dropped from the sample. Thus the final sample consists of 32 companies. Table I presents a description of the sample and gives further details of the cleansing process. The final dataset is well-balanced with regards to the geographical origin of the countries. 43.8% of the sample companies consist of U.S. companies while the rest are European companies. While A-rated companies represent the largest fraction of the companies with 46.9% of the sample, AAA-AA- and BBB-rated companies are not significantly underrepresented with shares of 18.8% and 34.4% respectively. Lastly, due to the cleansing process a fraction of the financial companies is dropped, such that they represent roughly one third of the final sample with non-financials making up the rest. Non-financial companies cover a wide range of industries from agriculture over media to pharmaceuticals with no particular overrepresentations.

6.3. Risk-Free Rate

The risk-free rate is required to calculate the credit spread of the bond yields for each company. In general, yields on government bonds are deemed good proxies for the risk-free rate. Therefore five-year government bond mid-market yields were downloaded from Bloomberg. Treasuries were employed for U.S. entities and German government bonds for EU companies. These bonds were used to calculate the so-called Bloomberg Generic Bond 5-year constant maturity yield.

However, prevailing literature mentions several disadvantages which make the government bonds not an ideal proxy for the risk-free rate. Main problems constitute different taxation treatment, repo costs and scarcity premia. For example, government bonds require financial institutions to hold less capital compared to other securities that exhibit low credit risk. Additionally, financial institutions need to hold government bonds to fulfil certain regulations. Finally, interest on U.S. government bonds is not taxed on the state level while it is taxed for other interest-paying securities. All these factors do not directly affect the credit risk of the issuing entity, but ceteris paribus favour demand for government bonds and thus should decrease bond yields demanded by investors.[60]

A widely used alternative is the 5-year swap for the respective currency. Swap rates are synthetic and almost unlimitedly available but they also contain credit premia and counterparty risk. As an alternative reference rate, 5-year swap rates for USD and EUR were downloaded via Bloomberg for the sample period.[61]

[60] see Duffee (1996), pp. 527-551; Hull et al. (2004), pp. 2795-2801; Reinhart, Sack (2002), pp. 298-328.
[61] see Blanco et al. (2005), p. 2261.

	Country	Sector	Rating	Observations CDS	Bond Yield
Altria	US	Agriculture	BBB	520	500
American Express	US	Financial	BBB+	520	501
Bank of America	US	Financial	A-	521	518
Caterpillar	US	Machinery	A	518	503
Comcast	US	Media	BBB+	520	462
GE	US	Manufacturing	AA+	520	501
Goldman Sachs	US	Financial	A-	521	521
Johnson & Johnson	US	Pharmaceuticals	AAA	519	411
Kraft Foods	US	Food	BBB	520	501
Morgan Stanley	US	Financial	A-	513	500
News America	US	Media	BBB+	520	429
Pfizer	US	Pharmaceuticals	AA	520	430
Philip Morris	US	Agriculture	A	515	497
Wal-Mart	US	Retail	AA	520	495
Abbey National	ES	Financial	AAA	521	521
Aegon	NL	Financial	A-	521	521
Atlantic Richfield	GB	Energy	A	521	521
AXA	FR	Financial	A	521	519
Barclays	GB	Financial	A	521	521
British Telecom	GB	Communications	BBB	521	521
Credit Agricole	FR	Financial	A	521	521
Deutsche Telekom	DE	Communications	BBB+	521	521
Enel	IT	Utilities	BBB+	521	521
France Telecom	FR	Communications	A-	521	521
GlaxoSmithKline	GB	Consumer	A+	521	521
Marks & Spencer	GB	Consumer	BBB-	521	521
Nokia	FI	Communications	BBB-	521	521
Santander	ES	Financial	A	521	521
Standard Chartered	GB	Financial	A+	521	521
Statoil	NO	Energy	AA-	521	521
Telefonica	ES	Communications	BBB+	521	521
Vodafone	GB	Communications	A-	521	521

Number of Companies			
All	45	Cleansed	32
AAA-AA	9	AAA-AA	6
A	22	A	15
BBB	13	BBB	11
US	17	US	14
EU	28	EU	18
Financial	19	Financial	11
Non-Financials	26	Non-Financials	21

Table I: Sample Description

7. Empirical Results

This part of the paper is going the present the results of the empirical estimations. Section 7.1 discusses the average pricing of credit risk by analysing average basis spreads of the sample entities and testing CDS and credit spreads for cointegration. Subsequently, Section 7.2 estimates the half-life of deviations from equilibrium of the basis spreads and provides first insights into the lead-lag relationship between CDS and bonds. Afterwards, Section 7.3 discusses the price discovery process of the two markets in detail. In this section Vector Error-Correction Models (VECM) are estimated and with the help of Hasbrouck and Gonzalo-Granger measures the lead-lag relationship between

CDS spreads and credit spreads is further analysed. Section 7.4 presents the robustness checks, which are employed to check the significance of the estimated results. The paper chooses several subsamples as well as different estimation settings to check whether the results are robust to changes in the sample environment. Finally, section 7.5 discusses the implications of the empirical results and potential explanations.

7.1. Average Basis Spreads

If the arbitrage relationship holds, then both the CDS as well as the bond should price credit risk equally. This in turn should result in equal CDS and credit spreads for the same entity and maturity. The credit spread of a bond is calculated as the difference between the bond yield and the respective risk-free rate. Following the arbitrage argument the difference between the CDS spread and the credit spread should be zero. Thus, defining this difference as the basis spread, one can obtain the following relationship:

$$basis_t^{cash} = p_{CDS,t} - p_{CS,t}^{cash} = p_{CDS,t} - \left(\hat{y}_t - r_t^{cash}\right)$$
$$basis_t^{swap} = p_{CDS,t} - p_{CS,t}^{swap} = p_{CDS,t} - \left(\hat{y}_t - r_t^{swap}\right)$$

where $basis_t^{cash}$ and $basis_t^{swap}$ are defined as the basis spread at time t, based on the treasury yields or the swap rates respectively. $p_{CDS,t}$ denotes the CDS spread rate of the reference entity at time t. $p_{CD,t}^{cash}$ and $p_{CD,t}^{swap}$ are defined as the credit spread of the issuer at time t, respectively based on the treasury yields or the swap rates. The credit spreads are calculated as the difference between the interpolated 5-year bond yield $\hat{y}_t$ of the issuer at time t and the respectively applicable (U.S. or EU) treasury yield r_t^{cash} or swap rate r_t^{swap}.

Figures 4 and 5 plot the cross-sectional average of the CDS spreads, credit spreads and basis spreads over the entire sample period. Looking at the graphs, one can observe several interesting patterns. Bond yields and credit spreads indeed seem to have a close relationship. One can observe that they follow a similar pattern, although exhibiting a non-zero basis spread. Furthermore, bond yields as well as credit spreads did rise substantially towards the end of the sample. The cross-sectional average CDS spread reaches its sample minimum already on 11th of January, 2010 with 72.9 bps while having its maximum on the 25th of November, 2011 with 245.0 bps which implies it more than tripled during a period of less than two years. Credit spreads have evolved in a similar way. Using treasury yields as a proxy for the risk-free rate, the average credit spread reaches its maximum on the 16^{th} of December, 2011 with 277.4 bps. However, compared to CDS spreads, credit spreads reach their minimum much later on the 3^{rd} of May, 2011 with 71.8 bps. Yet this is not so much due the effect of lower bond yields but rather higher treasury rates. Those characteristics have some very interesting implications on the development of the basis spread curve. First of all, the curve of the basis spread constantly fluctuates in cycles around zero. It reaches its maximum with 33.1 bps on 21^{st} of April, 2011 and its minimum with -69.0 bps on 5^{th} of December, 2011. Second, when looking at the average level of CDS spreads and bond yields compared to the basis spread, one can observe that the deviations from zero increase with the level of CDS spreads and bond yields. For example, during the period from the 1^{st} of January, 2010 until the 4^{th} of May, 2010 the average CDS and credit spread were 90.6 bps and 83.6 bps respectively. This resulted in a relatively small average basis spread of 7.0 bps. In contrast to that, during the period from the 1^{st} of August, 2011 through 30^{th} December, 2011 CDS and credit spreads ran at a hefty average of 200.9 bps and 240.3 bps respectively. Comparing to the previous period this resulted in an average basis spread of -39.4 bps, which represents a more than fivefold increase in the absolute basis spread.

Looking at figure 5, where swap rates are employed, one can observe several differences compared to the previous case. Again, bond yields and credit spreads seem to have a close relationship to each other. However, the credit spread stays below the bond yield during the entire sample period. During the beginning of the sample, the credit spread stays relatively low until the 5^{th} of May, 2010 with an average of 56.4 bps then quickly increasing to its first peak at 131.5 bps on the 6^{th} of July, 2010. Afterwards, it constantly decreases to its minimum of 40.3 bps on the 14^{th} of April, 2011 from which on it again increases suddenly reaching its sample maximum of 210.7 bps on the 4^{th} of October, 2011. This results in a constantly positive basis spread in contrast to the case with treasury yields, where the basis spread changes its sign several times over the sample period. Furthermore, one can observe that the deviations from zero in this case are much larger than previously, which is confirmed by the higher average of 32.6 bps compared to -9.7 bps in the case with treasury yields. One more interesting observation is that the relationship of higher basis spreads in times of higher bond yields and credit spreads does not seem to hold in the case of swap rates. Indeed during the beginning when bond yields and credits spreads have been relatively low, the average basis spread was as high as 34.4 bps, but during the period from the 1^{st} of September, 2012 until the end of the sample the average credit spread was 186.8 bps, yet the average basis spread even decreased to 22.9 bps during this period. Furthermore, considering the entire sample period, the average basis spread using treasury yields with -9.7 bps was lower compared to 32.6 bps in the case using swap rates. This also holds true when considering absolute basis spreads, in which case average spreads using treasury yields increase to 20.1 bps but still stay lower than the 32.6 bps of the spreads using swap rates. The latter does not increase when considering absolute average spreads, because the average basis spread is positive throughout the entire sample period.

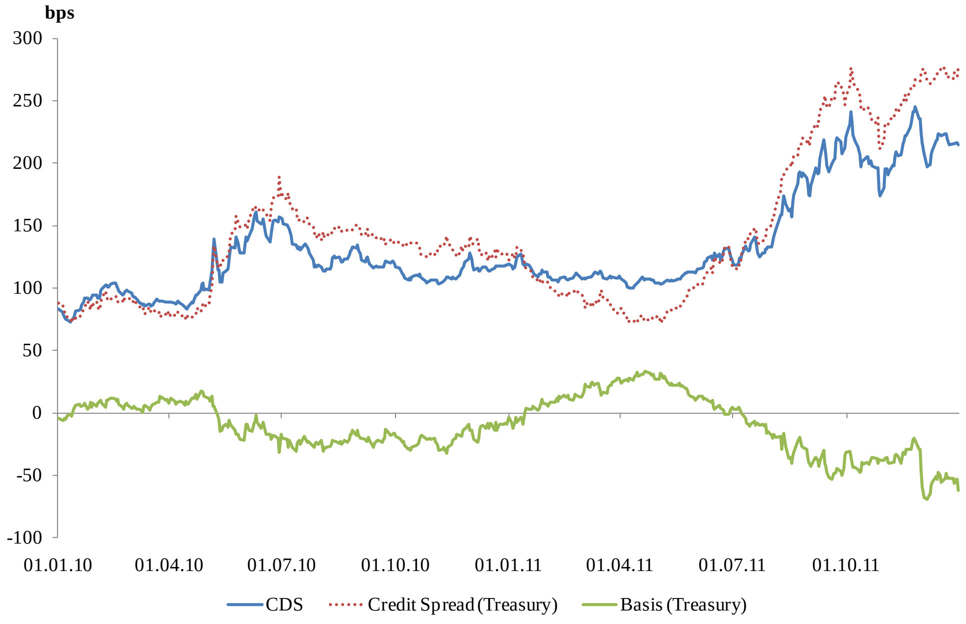

Figure 4: Cross-Sectional Averages using Treasury Yields

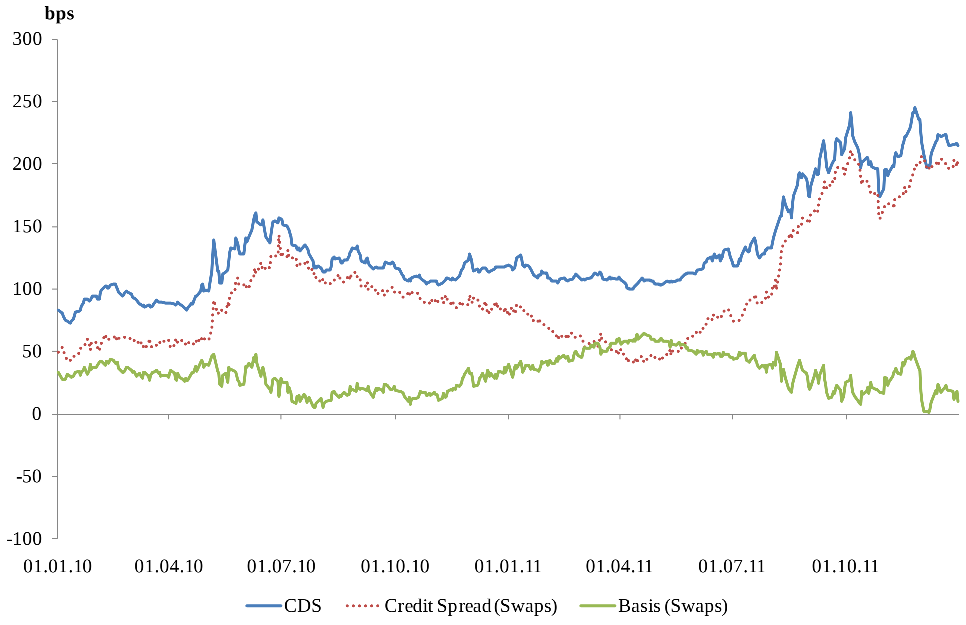

Figure 5: Cross-Sectional Averages using Swap Rates

Table II shows the summary statistics of the sample and thus gives a more granular view. It confirms the general pattern of the cross-sectional averages but show some important differences when looking at the companies individually. First of all, one can observe that the average basis spread based on treasury yields differs widely across firms. The maximum basis spread is at 71.0 bps with Abbey National and the minimum at -93.8 bps with Barclays, both financial companies. As mentioned earlier, financial companies do exhibit the most extreme basis spreads. In fact, 7 out of the 10 companies which were dropped because of a too large basis spread are financial companies. Still, after cleaning for outliers, financial companies incorporate the extremes in the sample w.r.t. basis spreads. Both considering the average spread (-16.7 bps vs. -6.0 bps) and the absolute average spread (58.2 bps vs. 41.0 bps) financial companies display larger basis spreads than non-financial companies. Interestingly, comparing US and EU companies shows no large differences, neither w.r.t. the average basis spread (-7.4 bps vs. -11.5 bps) nor the average absolute basis spread (46.7 bps vs. 47.0 bps). Previous studies indicate larger differences, for example Blanco et al. (2005) find an average absolute basis spread of 59.5 bps for US companies whereas EU entities only have a spread of 33.2 bps.[62] This might be a sign of increasing convergence of the global financial system.

Further interesting facts can be observed, when comparing differently rated companies. Perhaps most surprising is the fact, that both the average basis spreads as well as the average absolute spreads decrease with the rating. Whereas AAA- and AA-rated companies show an average basis spread of 46.0 bps, this value decreases for A-rated companies to -12.5 bps and even further to -36.3 bps for BBB-companies. This also holds true for the average absolute basis spread, where AAA- and AA-companies have the largest spread with 55.4 bps, A-rated companies' absolute basis spread decreases to 46.7 bps and the BBB-companies exhibit the lowest absolute basis spread with 42.5 bps. This is somewhat contradicting to the relationship which was observed analysing the cross-sectional average. There one could observe that the average basis spread increases with increasing CDS and credit spreads. Investors demand higher interest rates for increasing risk. Thus one can assume that lower rated companies should have higher CDS and credit spreads. Following this argument, AAA-rated companies should have lower basis spreads than BBB-companies because AAA-companies have lower CDS and credit spreads. However, looking at average CDS and credit spreads for the entire sample, the relationship between rating and CDS/credit spreads seems not to hold. A-rated companies have the highest CDS spreads (153.5 bps) and credit spreads

[62] see Blanco et al. (2005), p. 2265.

(166.0 bps), followed by triple-B-rated companies with CDS spreads of 122.7 bps and credit spreads of 159.0 bps and finally as expected the lowest CDS spreads of 92.7 bps and credit spreads of 46.7 bps for AAA- and AA-rated entities. Why do A-rated bonds exhibit larger credit spreads than BBB-rated bonds? The answer lies in distinguishing financial and non-financial companies. When looking at non-financial companies, the relationship between rating and credit spreads holds. AAA- and AA-rated non-financial exhibit a CDS spread of 78.5 bps and a credit spread of only 37.6 bps, while A-rated companies have average CDS spreads of 85.0 bps and credit spreads of 85.2 bps. Finally, BBB-rated companies show CDS spreads of 125.5 bps and credit spreads of 158.6 bps. Thus one can see why the basis spread decreases with the ratings. The CDS spreads do not increase as much as credit spreads, such that each rating decrease also triggers a decrease in the basis spread. For financial companies, the case looks quite different at first: AAA- and AA-rated companies have an average CDS spread of 163.7 bps and an average credit spread of 92.7 bps. A-rated companies do have larger average CDS spreads of 199.2 bps and credit spreads of 220.0 bps. But then again, BBB-companies show lower than expected CDS spreads of 94.6 bps and credit spreads of 163.2 bps. Again, the explanation lies in further examination of the business focus of the sample companies.

American Express and Capital One, both BBB-rated financial companies from the U.S., are rather focussed on credit card business compared to the rest of the financials, which consist mainly of universal banks. This is also reflected in their lower average CDS spread of 92.8 bps and credit spread of 143.1 bps. Excluding both companies increases the CDS spread of BBB-rated financials to 393.6 bps and credit spread to 176.1 bps. Thus the CDS spreads follow the theoretical relationship of increased spread on lower rating, but the credit spread represents an exception, which is likely due to the underrepresentation of BBB-rated universal banks in the sample. Looking at basis spreads using swap rates generally confirms the pattern observed when using treasury rates. Again, basis spreads decrease with lower ratings (avg. spreads: AAA-AA: 81.3 bps, A: 33.0 bps, BBB: 5.5 bps; abs. avg. spreads: AAA-AA: 84.4 bps, A: 56.4 bps, BBB: 31.6 bps), which is due to the facts mentioned earlier. U.S. and EU companies show larger differences when comparing their average basis spreads (17.9 bps vs. 44.1 bps), but this effect vanishes when looking at absolute basis spreads (47.4 bps vs. 57.6 bps). Financials show lower deviations from zero basis spreads when looking at average numbers (27.9 bps vs. 35.1 bps), but this effect also vanishes when looking at absolute figures (65.2 bps vs. 46.7 bps).

	Treasury rates		Swap rates	
	Average basis	**Average absolute basis**	**Average basis**	**Average absolute basis**
Altria	-44.0	45.6	-18.8	28.8
American Express	-68.6	68.6	-43.4	43.6
Bank of America	-25.9	43.0	-0.7	40.9
Caterpillar	17.8	28.7	43.0	44.5
Comcast	-7.3	25.6	17.9	26.3
GE	68.7	69.1	93.9	94.0
Goldman Sachs	-43.2	56.4	-17.9	43.6
Johnson & Johnson	69.7	69.9	95.0	95.0
Kraft Foods	-56.4	56.5	-31.2	32.2
Morgan Stanley	-70.1	70.3	-44.9	47.3
News America	-2.3	19.9	23.0	25.9
Pfizer	-0.6	13.7	24.7	25.8
Philip Morris	-6.4	19.2	18.9	23.2
Wal-Mart	65.2	67.3	90.4	91.9
Abbey National	71.0	72.2	126.7	126.7
Aegon	61.2	61.4	116.9	116.9
Atlantic Richfield	-38.1	52.4	17.5	37.4
AXA	17.2	46.1	72.9	77.2
Barclays	-93.8	96.6	-38.1	60.4
British Telecom	-75.2	75.2	-19.5	22.6
Credit Agricole	32.5	45.7	88.2	89.1
Deutsche Telekom	-15.7	26.6	40.0	40.0
Enel	-8.1	22.9	47.6	48.1
France Telecom	14.6	33.2	70.2	70.2
GlaxoSmithKline	10.8	28.4	66.5	66.5
Marks & Spencer	-45.9	49.6	9.8	30.6
Nokia	-25.4	26.1	30.2	30.5
Santander	-10.1	24.4	45.5	46.8
Standard Chartered	-54.5	55.3	1.2	24.9
Statoil	1.7	40.4	57.4	73.0
Telefonica	-50.6	50.6	5.1	18.6
Vodafone	0.6	39.5	56.3	56.3
	Treasury rates		**Swap rates**	
	Average basis	**Average absolute basis**	**Average basis**	**Average absolute basis**
Cleansed (32 companies)	-9.7	46.9	32.6	53.1
AAA-AA (6 companies)	46.0	55.4	81.3	84.4
A (15 companies)	-12.5	46.7	33.0	56.4
BBB (11 companies)	-36.3	42.5	5.5	31.6
US (14 companies)	-7.4	46.7	17.9	47.4
EU (18 companies)	-11.5	47.0	44.1	57.6
Financial (11 companies)	-16.7	58.2	27.9	65.2
Non-Financials (21 companies)	-6.0	41.0	35.1	46.7

Table II: Summary Statistics

A further surprising fact is that the absolute credit spread is smaller when using treasury yields (46.9 bps) compared to the case with swap rates (53.1 bps). Earlier research has found swap rates to fit better than government bond yields when trying to proxy for the risk-free rate to estimate credit spreads. Although, Blanco et al. (2005) find an average absolute basis spread based on treasuries of 45.9 bps, which is very close to the 46.9 bps found in this paper, they also find a much lower average absolute basis spread of 15.6 bps compared to 53.1 bps in this paper. Again, looking at the details reveals the solutions to the puzzle. Figure 6 plots the monthly difference between swap rates and treasury yields for U.S. and EU government bonds from January 1999 through May 2012. Both curves peak during two historic crises – during the dotcom crisis in 2000 and the recent financial crisis in 2008. Furthermore, before the end of the financial crisis the swap spread has been always smaller for EU bonds compared to U.S. bonds. However, after the financial crisis, the EU spread soared again exhibiting large volatility starting in the end of 2009 and since then exceeding the U.S. spread. This increase is largely attributable to an increase in overall financial sector risk – i.e. the rise in swap yields is mainly due to an increase in the overall credit risk of the financial sector (i.e. counterparty risk).[63] Especially the euro crisis and its implications for the stability of European financial institutions resulted in an increase in swap rates in Europe. During December 2011, where the EU spread between swap rates and government yields reached its maximum of 97.1 bps, Fitch Ratings announced the downgrade of five European institutions – Credit Agricole (France), Banque Fédérative du Crédit Mutuel (France), Danske Bank (Denmark), OP Pohjola (Finland), Rabobank Group (Netherlands) – which shows the doubts about the financial sector in Europe during this time. Using this knowledge helps to explain the results from Table II. Because EU swap spreads increased dramatically during the sample period, the basis spread for EU companies is much larger (44.1 bps) than for U.S. companies (17.9 bps) when using swap rates. Looking at the entire sample, employing government bond yields as proxy for the risk-free rate seems to produce more reasonable results in estimating basis spreads, which is also due to the majority of companies being from the EU in the sample and the increase in the EU swap spread. Considering these results, this paper will in what follows use yields on government bonds as proxy for the risk-free rate instead of swap rates in contrast to prior academic research.[64]

[63] see Bai, Collin-Dufresne (2012), p. 3, Feldhütter, Lando (2007), p. 397.
[64] see Blanco et al. (2005), p. 2261; Duffie (1999), p. 75-76; Houweling, Vorst (2005), p. 1223; McCauly (2002), p. 956-960.

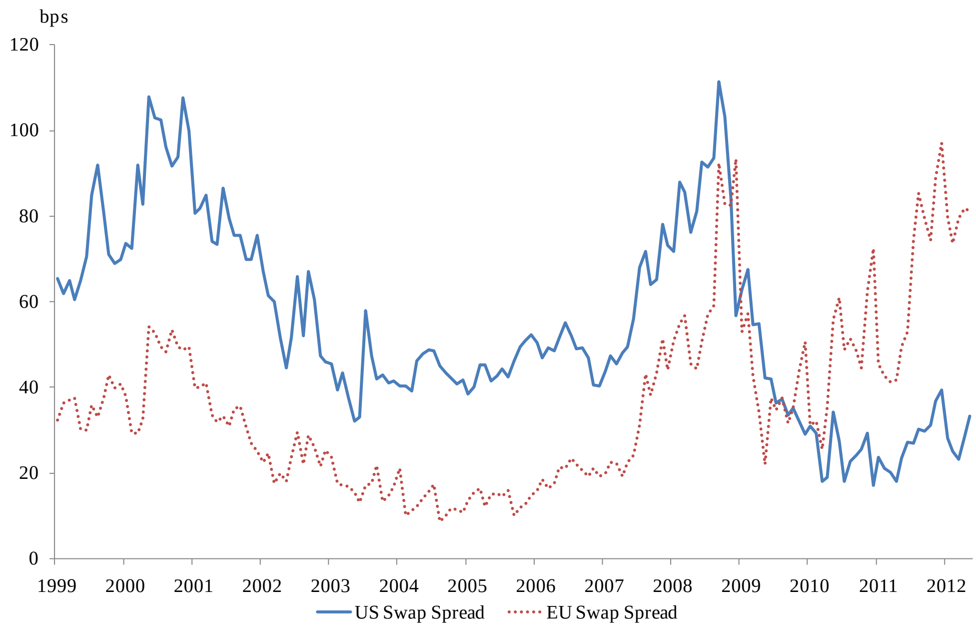

Figure 6: Monthly US and EU Swap Spread

These results from Table II suggest that the arbitrage relationship between bonds and CDS holds reasonably well on average, apart from a few exceptional cases like Barclays and Abbey National. Prior research suggests that persistent and positive biases like in the case of Abbey National can be due to a CTD option in the bonds which leads to increased CDS prices or non-zero repo costs, which result in underestimation of the true credit spread. Other studies have found that limits to capital prevent arbitrageurs to close all basis gaps, such that they focus only on the least risky ones. They have found that trading costs measured by bid-ask spreads, trading liquidity risk and funding liquidity risk seem to be the main sources of cross-sectional variation in the basis spreads.[65]

7.2. Cointegration Relationship

In the following it will be tested whether the two markets price credit risk equivalently over the long-run. This involves testing for cointegration. If the two prices $p_{CDS,t}$ and $p_{CS,t}$ are cointegrated with cointegrating vector $[1,-1,c]$, then the two markets price credit risk equally in the long run. Furthermore, the constant in the cointegrating space c, should be zero. There are several reasons as to why the two processes could possibly not be cointegrated:

[65] see Bai, Collin-Dufresne (2012), p. 5; Blanco et al. (2005), p. 2261; Duffie (1999), p. 75-76; Houweling, Vorst (2005), p. 1223; McCauly (2002), p. 956-960.

1. CDS and cash bond markets price credit differently and this difference is not constant over time
2. At least one of the two market's prices of credit risk contains time-varying non-transient components that are not reflected in the other's market price of credit risk
3. At least one of the two market's prices of credit risk contains a time-varying non-transient measurement error

Rejection because of the first reason is very unlikely as this would mean that the basic theoretical arbitrage relationship between bond and CDS does not hold at all. The second reason for rejection, which is the most likely among the three reasons, can be caused by several limitations in the arbitrage relationship, e.g. capital limits of arbitrageurs or CTD options which are discussed above. The last reason for rejection is more likely to affect the results of this study compared to previous research, as this paper is based on publicly available data sources instead of proprietary data which is used in most of previous articles and is found to be a more reliable data source.[66]

As a first starting point, this paper analyses whether the cross-sectional average of the CDS prices and credit spreads are cointegrated for both all 45 companies as well as the cleansed sample, consisting of only 32 companies. Table III reports the Johansen trace test statistics for both samples using two different information criteria, the Akaike Information Criterion (AIC)[67] and the Bayesian Information Criterion (BIC).[68] It offers a diverse set of results depending on sample structure and information criterion. Three effects can be singled out. First, when employing the BIC criterion a lower number of lags is suggested. Second, decreasing the number of lags increases the probability of rejecting the null hypothesis of no cointegrating vectors. Finally, the cleansed sample favours rejection of the null hypothesis of no cointegrating vectors compared to the raw sample. This results in rejection of the null hypothesis for the cleansed sample under BIC (at 1% significance level) and AIC (at 10% level) and the raw sample under BIC (at 5% level). However, the test fails to reject the hypothesis for the raw sample under AIC.[69]

[66] see Blanco et al. (2005), pp. 2266-2268.
[67] see Akaike (1977), pp. 27-41; Akaike (1978), pp. 217-235.
[68] see Schwarz (1978), pp. 461-464.
[69] see Engle, Granger (1987), pp. 251-252; Johansen (1991), pp. 1551-1580.

				Observations		Treasury rates		Swap rates		Number of cointegrating vectors		Restrictions on vector
	Companies	Information Criterion	Lags	CDS	Bond Yield	Average basis	Average absolute basis	Average basis	Average absolute basis	None	At most 1	[1,-1,c]
All Average	45	BIC	2	521	521	-2.2	18.5	42.0	42.0	17.24**	0.10	14.06***
Cleansed Average	32	BIC	2	521	521	-9.7	20.1	32.6	32.6	23.58***	0.03	20.56***
All Average	45	AIC	4	521	521	-2.2	18.5	42.0	42.0	10.32	0.37	NA
Cleansed Average	32	AIC	4	521	521	-9.7	20.1	32.6	32.6	14.94*	0.15	10.74***

Table III: Cointegration Results (cross-sectional average)[70]

Do these results imply that CDS prices and credit spreads are only cointegrated for a special subsample, which can be identified by having lower basis spreads? This question is equal to the question of whether the AIC or the BIC should be preferred in cointegration analysis of CDS prices and credit spread. Most of the previous studies exploring the empirical relationship between CDS prices and credit spreads employ the AIC for choosing the number of lags, which is why it is tempting to rely on the results produced by the AIC. However, none of the papers specifically states why they choose this information criterion instead of one of the others.[71] Yet, looking at previous research on cointegration analysis, one can find several arguments for choosing the BIC over AIC. Most papers concerned with this issue employ Monte Carlo techniques to study the significance of both information criteria. They find that the AIC often overparameterizes the model by choosing too many lags which reduces the validity of the resulting model.[72] This behaviour was also observed during the estimations for this paper, e.g. the AIC suggested including c.70 lags when having only about 100 observations. Taking previous research and the observed behaviour of the information criteria into account, one can conclude that the BIC yields more reliable results. Thus the following estimation will be based on the BIC. All estimations in this paper have also been done using the AIC. While those results do not entirely contradict the presented results, they exhibit lower significance and are thus less clear to interpret. Accordingly, the results in Table III suggest that the cointegration relationship holds on average. Surprisingly, the test rejects the restriction on the cointegrating vector which is in contrast to previous research.[73]

Although these results seem to prove that the arbitrage relationship between the two markets holds reasonably well on average, one has to take a more detailed look at the securities to infer more

[70] significance at the 10%, 5% and 1% level is indicated by *, ** and *** respectively
[71] see Bai, Collin-Dufresne (2012) p. 5, Blanco et al. (2005), p. 2261; Houweling, Vorst (2005), p. 1223.
[72] see Cheng, Phillips (2012), pp. 7-8; Enders (2004); pp. 69-70; Ho, Sørensen (1996) pp. 726-732; Kapetanios (2000), p. 9; Koehler, Murphree, (1988), pp. 187-195.
[73] see Blanco et al. (2005), p. 2269.

about their relationship. Table IV presents the Johansen test statistics for each security in the cleansed sample. Cointegration is suggested for 20 out of the 32 companies. Interestingly this ratio is remarkably constant throughout all different groups, whether ratings, geographical origin or financial relation are considered. Also considering all 45 companies before the cleansing process, the ratio of confirmed cointegration relationships stays constant. A-rated and BBB-rated companies form an exception to this case, because the former shows a slightly lower rate (53%) while the latter has a slightly higher rate (73%) of cointegrated securities. Surprisingly, the size of the basis spread does not seem to have the expected effect on the cointegration relationship between the securities. The average basis spread between securities, where test results suggest rejection of the cointegration relationship, is 3.5 bps. Firms that suggest cointegration have an average basis spread of -17.7 bps. Furthermore, firms with very small average basis spreads like Telefonica (1.72 bps) and Vodafone (0.59 bps) reject cointegration. In contrast to this, firms like Barclays (-93.8 bps) and Johnson & Johnson (69.7 bps) with very large basis spreads confirm cointegration. The picture does not change significantly when looking at absolute average spreads. Cointegrated securities exhibit an average absolute basis spread of 49.4 bps while rejected companies again show a lower average absolute basis spread of 42.7 bps.

	Number of cointegrating vectors		Restriction on vector
	None	At most 1	[1,1,c]
Altria	11.05	3.69*	NA
American Express	25.57***	3.61*	14.73***
Bank of America	65.43***	0.00	57.75***
Caterpillar	8.97	1.59	NA
Comcast	15.67**	3.86**	4.66**
GE	21.28***	4.16**	5.86**
Goldman Sachs	12.42	0.69	NA
Johnson & Johnson	22.06***	6.62**	1.08
Kraft Foods	24.90***	5.93**	4.85**
Morgan Stanley	40.87***	0.87	28.65***
News America	13.27	2.44	NA
Pfizer	32.42***	1.69	0.00
Philip Morris	9.95	2.00	NA
Wal-Mart	34.25***	2.34	4.86**
Abbey National	3.68	0.06	NA
Aegon	8.96	0.74	NA
Atlantic Richfield	35.36***	5.21**	2.95*
AXA	10.24	0.01	NA
Barclays	35.19***	0.04	32.13***
British Telecom	16.64**	1.00	12.47***
Credit Agricole	23.22***	0.69	13.24***
Deutsche Telekom	15.41*	0.42	11.54***
Enel	29.45***	0.85	20.79***
France Telecom	3.52	0.09	NA
GlaxoSmithKline	17.85**	1.72	14.53***
Marks & Spencer	8.46	0.16	NA
Nokia	27.82***	0.04	8.38***
Santander	34.54***	0.26	11.72***
Standard Chartered	19.52**	0.20	16.08***
Statoil	3.29	0.18	NA
Telefonica	22.14***	0.00	10.45***
Vodafone	8.55	1.66	NA

	All	Sign.(10%)	% Sign.
Cleansed	32	20	63%
AAA-AA	6	4	67%
A	15	8	53%
BBB	11	8	73%
US	14	9	64%
EU	18	11	61%
Financial	11	7	64%
Non-Financials	21	13	62%

Table IV: Cointegration Results (daily observations)[74]

[74] significance at the 10%, 5% and 1% level is indicated by *, ** and *** respectively

Employing swap rates instead of treasury rates does change the picture slightly. Rejected companies now show a larger average basis spread (46.5 bps vs. 24.3 bps) as well as a larger average absolute basis spread (59.7 bps vs. 49.1 bps). Previous research suggests, that cointegration for firms with small basis spreads is rejected because the securities exhibit proportionally large bid-ask spreads which makes the prices to move in seemingly unrelated ways such that no cointegration relationship can be identified.[75]

These results suggest that roughly only two thirds of the companies in our sample are cointegrated. What are potential reasons for these results? Several researchers have pointed out limits to the arbitrage relationship due to specific characteristics like the CTD option. Furthermore, it is reasonable to assume that arbitrageurs are capital-constrained, such that they employ their scarce funds on the best arbitrage opportunities with regards to potential profits and risk. Finally, one has to acknowledge that neither CDS nor cash bond markets are anywhere near to the liquidity inherent in stock capital markets. Thus one could reasonably assume that it takes some time for arbitrage forces to come into effect. This would mean that daily prices incorporate a lot of statistical noise, which would inherently lower the explanatory power of the employed econometric techniques in this paper. To eliminate the noise inherent in daily observations this paper suggests testing for cointegration using weekly (Thursday to Thursday) instead of daily prices. Table V presents the Johansen trace test statistics for each company when considering weekly prices. As expected, when the prices are cleaned for daily noise the test results suggest overwhelmingly support for cointegration. 30 out of the 32 companies in the cleansed sample reject the null hypothesis of having no cointegrating vector. Again, this ratio stays remarkably constant across all groups also when considering the raw sample consisting of 45 companies. U.S. companies show the lowest share of cointegrated companies with 84% of companies, while all AAA-AA-rated and all EU companies confirm the cointegration relationship.

Where does this increased support for cointegration come from? Figures 7 and 8 try to shed some light on this issue. These figures depict the development of the CDS and credit spread of Goldman Sachs, with the former showing the daily values and the latter only weekly observations. Goldman Sachs is a global investment bank, providing financial advisory, securities and investment

[75] see Blanco et al. (2005), p. 2268

management services to a diverse client base consisting of corporations, financial institutions, governments and high-net-worth individuals.[76]

	Number of cointegrating vectors		Restrictions on vector
	None	At most 1	[1,1,c]
Altria	74.28***	34.57***	0.41
American Express	26.36***	3.33*	11.56***
Bank of America	11.97	0.29	NA
Caterpillar	19.47**	4.26**	4.66**
Comcast	78.23***	1.55	4.80**
GE	95.78***	6.81***	66.40***
Goldman Sachs	50.65***	0.02	39.78***
Johnson & Johnson	19.93**	0.47	1.20
Kraft Foods	70.98***	2.78*	50.37***
Morgan Stanley	56.62***	14.24***	19.41***
News America	12.82	0.97	NA
Pfizer	54.82***	1.33	4.33**
Philip Morris	54.12***	17.12***	19.83***
Wal-Mart	29.30***	1.42	14.41***
Abbey National	65.79***	30.20***	5.45**
Aegon	26.11***	0.09	4.48**
Atlantic Richfield	45.61***	2.76*	29.37***
AXA	15.43**	2.17	0.53
Barclays	48.83***	3.28*	33.49***
British Telecom	67.72***	5.89**	57.10***
Credit Agricole	15.61**	0.02	0.06
Deutsche Telekom	26.23***	0.81	21.53***
Enel	59.37***	8.30***	13.60***
France Telecom	31.44***	0.80	0.02
GlaxoSmithKline	36.16***	0.25	24.19***
Marks & Spencer	24.92***	0.08	0.12
Nokia	15.65**	0.08	3.55*
Santander	55.37***	13.58***	29.14***
Standard Chartered	43.96***	4.91**	23.98***
Statoil	49.28***	0.02	0.01
Telefonica	37.52***	7.24***	0.17
Vodafone	36.48***	3.97**	23.28***

	All	Sign.(10%)	% Sign.
Cleansed	32	30	94%
AAA-AA	6	6	100%
A	15	14	93%
BBB	11	10	91%
US	14	12	86%
EU	18	18	100%
Financial	11	10	91%
Non-Financials	21	20	95%

Table V: Cointegration Results (weekly observations)[77]

[76] see Goldman Sachs Annual Report 2011, p. 26
[77] significance at the 10%, 5% and 1% level is indicated by *, ** and *** respectively

CDS and credits spreads of Goldman Sachs prove to be a good example to show the effects of employing weekly instead of daily data because of several reasons. First, Goldman Sachs is one of the ten companies where the Johansen trace test statistics reject cointegration for daily observations but support a cointegration relationship for weekly observations. Thus the change from daily to weekly data has an effect on the cointegration test results. Second, showing an average basis spread of -43.2 bps and an average absolute basis spread of 56.4 bps, one can assign the company to the group of companies with a relatively large spread. However, as the cointegration test results suggest, this does not have a negative effect on the arbitrage relationship between the two securities. Third, its securities are followed by a large universe of different investors such that it is highly unlikely that they will suffer a liquidity discount or any other price imperfections. Finally, the data source for both bonds is Bloomberg Generic Price, which is considered the best data provider with regards to accuracy and consistency. The availability of BGN prices suggests that the securities exhibit a good amount of liquidity. To sum it all up, the characteristics of the company and its securities make it a highly relevant case to consider it for individual study.

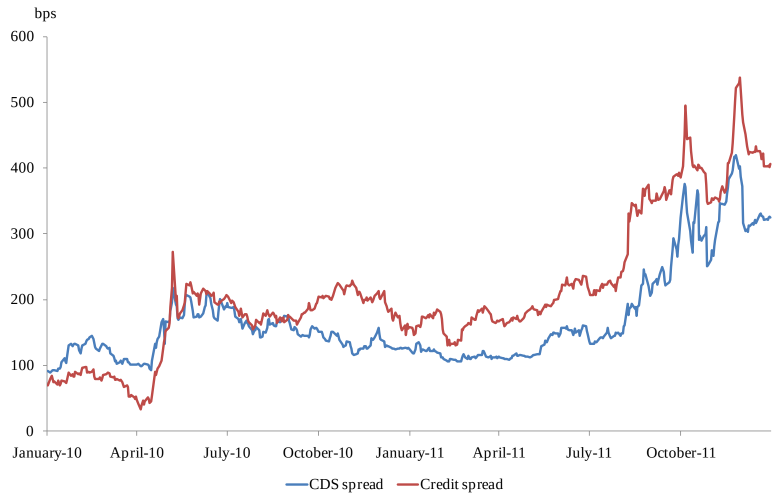

Figure 7: Goldman Sachs CDS and Credit Spread (daily observations)

Looking at weekly prices results in a clearer picture of the relationship between the two securities. Almost all positive and negative peaks of the CDS spreads are covered by peaks in credit spreads in weekly data, while this is not the case for daily observations. These characteristics seem to give much more explanatory power to the Johansen cointegration test. Using Monte Carlo techniques, this observation is also confirmed by previous researchers in studies of cointegration analysis. They suggest that for cointegration analysis the span of the data is much more important than the mere number of observations within that span.[78] This also makes intuitively sense. If one wants to check whether two variables have an equilibrium relationship, statements based on a sample covering monthly observations spanning fifty years have more explanatory power than statements based on a sample spanning one day with continuous observations.

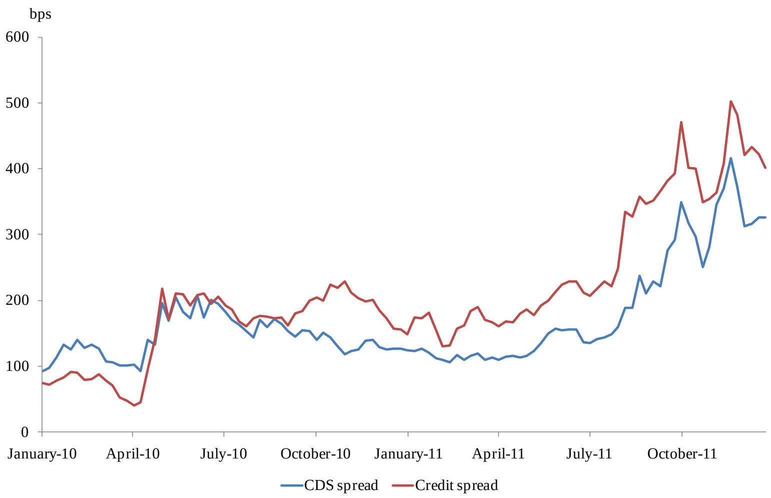

Figure 8: Goldman Sachs CDS and Credit Spread (weekly observations)

Three effects are in place here. First, increasing the number of observations within the data span, increases short-term variation in the variables. This increases probability of rejecting cointegration for variables that are actually cointegrated because of statistical noise. Second, decreasing the number of observations lowers the amount of information analysed and thus increases both possible types of error, i.e. falsely concluding an existing or non-existing cointegration relationship. Finally, increasing the data span of the sample increases amount of information about the behaviour of the variables over time, thus lowers both possible types of errors. These effects influence the optimal sample choice in the following way. First, a longer span of the data should generally be favoured over a shorter data set. In the case of this paper, the theoretical maximum data span would be five years, since it is analysing 5-year CDS contracts. However, it highly unlikely that such long data spans will be achieved in the near future. This is because CDS data has been very scarce in the past and more problematic, the restrictions on maturity and issue dates of bonds to suffice linear

[78] Hakkio, Rush (1991), p. 571.

interpolation are even more difficult to satisfy. Comparing this study to previous research, the increase of the data span by more than 30% already indicates a stronger explanatory power. Second, the number of the observations within that data span has to be optimized to balance the negative effects of increased short-term variation and the positive effects of more information. Furthermore, academic research has shown that sampling too frequently runs the risk of contaminating the data with transitory microstructure noise. Empirically, how often to sample prices to reduce residual correlation appears to be context specific.[79] Scientific research does not provide a specific decision rule for the last choice, but comparing the results of previous studies and the different tests in this paper, weekly observations seem to be an appropriate choice for cointegration analysis.[80]

Summing up the empirical results in this part of the paper, one can conclude that the arbitrage relationship between the two markets holds well in the medium- to long-term for almost all securities. Furthermore, on average the relationship holds also reasonably well in the short-term, i.e. the daily view. However, looking at the companies in full detail one can observe that a substantial fraction of the companies exhibit severe deviations from the equilibrium in the short-term, such that the arbitrage relationship comes into question for these companies.

7.3. Half-Life of Deviations

The previous section dealt with the question of whether an equilibrium relationship between CDS and bond markets exists. This was confirmed for most of the companies in the short-term and for almost all companies in the medium-term. An interesting question to investigate is how long deviations from this equilibrium survive? One way to answer these questions is to estimate the effect of the lagged basis on the change of CDS and credit spreads. This is done in this paper by estimating the following OLS regressions for every company:

$$\Delta CDS_{t,t-1} = \alpha_0 + \alpha_1 BS_{t-1} + \varepsilon_{CDS,t}$$

and

$$\Delta CS_{t,t-1} = \beta_0 + \beta_1 BS_{t-1} + \varepsilon_{CS,t} \,,$$

79 see Andersen et al. (2002), pp. 67-138.
80 see Blanco et al. (2005), p. 2268.

where $\Delta CDS_{t,t-1}$ and $\Delta CS_{t,t-1}$ respectively represent the change of CDS and credit spreads from $t-1$ to t. Further BS_t represents the basis spread at t. If the estimated coefficients α_1 and β_1 are the true values and the basis equals 1 bps in $t-1$, then CDS spreads will change by α_1 bps and credit spreads by β_1 in t. Since the basis spread is the difference between CDS and credit spreads, the change of the basis spread from $t-1$ to t will be the difference of the changes in CDS and credit spreads. This relationship can be formalized as follows:

$$\begin{aligned} BS_t &= BS_{t-1} + \Delta BS_{t,t-1} \\ &= BS_{t-1} + \left(\Delta CDS_{t,t-1} - \Delta CS_{t,t-1}\right) \\ &= BS_{t-1} + \left(\alpha_1 BS_{t-1} - \beta_1 BS_{t-1}\right) \\ &= BS_{t-1}\left(1 + \alpha_1 - \beta_1\right) \end{aligned}$$

From this equation, one can analyse the behaviour of CDS and credit markets in case of deviation from the equilibrium value. As discussed, it is reasonable to assume that the equilibrium value of the basis spread is zero. If CDS and bond markets behave according to this relationship, one can assume that α_1 will be significant and negative and β_1 will be significant and positive. This is because according to the arbitrage relationship a positive basis spread implies that CDS spread are too high or credit spreads are too low. Thus in the case of a positive basis spread, CDS spreads should fall, reflecting a negative and significant α_1, and credit spreads should rise, reflecting a positive and significant β_1. There are even more conclusions one can draw from the results of the above regression. The market, which is accompanied by the larger and more significant coefficient, is more likely to follow the other market. If the basis spread is positive and CDS spreads do not adjust, reflecting an insignificant α_1, but credit spreads do adjust as forecasted, reflecting a positive and significant β_1, then this is likely to show evidence of the following theory: CDS markets lead the price discovery process such that credit spreads follow the CDS spreads to fulfil the arbitrage relationship. In this case higher CDS spreads cause the basis spread to be positive which in turn cause credit spreads to increase until the basis spread is zero again.

Generalizing the above formula, one can derive the size of the basis spread after n periods depending on the size of the basis spread BS_t in t, α_1 and β_1:

$$BS_{t+n} = BS_t\left(1 + \alpha_1 - \beta_1\right)^n$$

This formula gives an insight of how deviations of the basis spread evolve over time. A common measure of this behaviour is the so-called half-life of deviations. This measure states how much time passes from an initial shock that disturbs the variable's equilibrium balance until the initial deviation of the equilibrium value halves in size.

In the application of this paper, the half-life of deviations measures the time that it takes for the basis spread to halve in size after an initial shock that causes the spread to become non-zero. To estimate this measure, one has to substitute BS_{t+n} by $\frac{1}{2}BS_t$ in the above formula and solve for n, which yields the following equation:

$$n = \frac{\ln(0.5)}{\ln(1+\alpha_1-\beta_1)}$$

Table VI presents the results of these estimations. The results present evidence for the existence of an arbitrage relationship, an estimated half-life of 7.6 days across the entire sample and leadership of CDS markets in the price discovery process. On average, the effect of the basis spread explains only 4% of the observed variation in credit spreads.

The majority of coefficients behave as expected with respect to their signs, i.e. 72% percent of α_1 coefficients are negative while 97% of β_1 coefficients are positive. This gives yet more evidence that the suggested arbitrage relationship holds between CDS and bond markets.

Only two companies show statistically significant α_1 values, while 20 companies do show significant β_1 coefficients. This indicates price leadership of CDS markets, as CDS markets do not seem adjust to basis spreads while credit spreads seem to do. Interestingly, all β_1 coefficients are statistically significant for U.S. while this is only the case for a third of the European companies. This indicates that price leadership of CDS markets is strongly present in U.S. markets compared to EU markets. Apart from this, the ratio of significant coefficients is remarkably constant across all groups.

Finally, the average β_1 coefficient varies along different groups, which results in varying estimations of the half-life of deviation for the groups. Interestingly, EU companies show the largest half-life with 30.6 trading days while a value of only 3.7 days. This is surprising as neither the comparison the group's average basis spreads nor the share of cointegrated securities suggested large differences between the two markets.

	Dependent Variable		
Cleansed (32 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.08	7.6
t-statistic	-0.43	3.94	
Adjusted R^2	0.00	0.04	
AAA-AA (6 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.19	3.3
t-statistic	-0.80	6.24	
Adjusted R^2	0.00	0.09	
A (15 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.03	21.9
t-statistic	-0.44	2.54	
Adjusted R^2	0.00	0.02	
BBB (11 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.11	6.0
t-statistic	-0.23	4.58	
Adjusted R^2	0.00	0.05	
US (14 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.17	3.7
t-statistic	-0.40	6.45	
Adjusted R^2	0.00	0.08	
EU (18 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.02	30.6
t-statistic	-0.46	1.98	
Adjusted R^2	0.00	0.01	
Financial (11 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.04	16.0
t-statistic	-0.11	2.80	
Adjusted R^2	0.00	0.02	
Non-Financials (21 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.11	5.9
t-statistic	-0.60	4.53	
Adjusted R^2	0.00	0.05	

Table VI: Avg. OLS Coefficient of Basis Spread

The lowest half-life is estimated for AAA- and AA-rated companies, which show a half-life of only 3.3 days. Surprisingly, A-rated show a relatively high half-life of 21.9 days, while a deviation in the basis spread of BBB-rated seems to halve within 6.0 days. Lastly, financial companies exhibit a longer half-life (16.0 days) than non-financial companies (5.9 days). This conforms to the larger observed average basis spread for financial companied compared to non-financial companies.

These results seem to confirm the expected arbitrage relationship, but they should be interpreted with due care. As explained in the previous section, microstructural noise could cause the results to be biased. Furthermore, as stated, the average explained variance of credit spreads is only 4% while the basis spreads are in fact not able to explain any of the variance in CDS spreads. This gives rise to the existence of other more important factors that influence credit spreads. Finally, the OLS regressions in this case share the disadvantage that they only incorporate one past period in the estimations. The effect of previous periods is omitted, which can severely disturb estimation results. The results in this section of the paper should therefore be treated rather as supporting evidence further confirming the main evidence presented in the previous and next sections of the paper.

7.4. Price Discovery

The previous two sections focused on the long-term arbitrage relationship of the securities and showed that it holds reasonably well. If the two markets are tied to each other, does one market happen to lead the price discovery process? If so, which one of the markets is leading and how much more timely is new information processed in this market? This topic has been briefly discussed in the previous section and the following part of the paper is going to concentrate on it.

The dynamic process by which markets incorporate information is called price discovery. Academic research has been mainly employing two different methods to explore the relationship between multiple markets. Hasbrouck (1995) focused on the variance of the markets, defining the information share (IS) of a market as the proportion of the efficient price information variance attributable to that market. In contrast to that, Gonzalo and Granger (1995) attribute price discovery to the market that adjusts least to price movements in the other market. This measure of price discovery is called the component share (CS).[81] Both models are explained in greater detail in

[81] see Blanco et al. (2005), pp. 2270; Gonzalo, Granger (1995), pp. 27-35; Hasbrouck (1995), pp. 1175-1199; Yan et al. (2010), pp. 1-19.

section 4.1.3. None of the price measures is universally superior to the other. Thus this paper will present both measures.[82]

To estimate both measures of price discovery it is necessary to first estimate the following VECM:

$$\Delta p_{CDS,t} = \lambda_1 \left(p_{CDS,t-1} - \alpha_0 - \alpha_1 p_{CS,t-1} \right) + \sum_{j=1}^{p} \beta_{1j} \Delta p_{CDS,t-j} + \sum_{j=1}^{p} \delta_{1j} \Delta p_{CS,t-j} + \varepsilon_{1,t}$$

and

$$\Delta p_{CS,t} = \lambda_2 \left(p_{CDS,t-1} - \alpha_0 - \alpha_1 p_{CS,t-1} \right) + \sum_{j=1}^{p} \beta_{2j} \Delta p_{CDS,t-j} + \sum_{j=1}^{p} \delta_{2j} \Delta p_{CS,t-j} + \varepsilon_{2,t}$$

where $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ represent i.i.d. shocks. If the cash bond market contributes to the price discovery process, then λ_1 is ought to be negative and statistically significant such that the CDS market adjusts to new information from the cash bond market. In contrast, if λ_2 turns out to be positive and statistically significant, the CDS market contributes to the price discovery process. It is also possible, that both coefficients are statistically significant, in which case both markets contribute to price discovery. The cointegration relationship between the markets implies that at least one of the markets has to adjust by the Granger representation theorem. That market reacts to publicly available information and is thus inefficient.[83]

The Hasbrouck and Gonzalo-Granger measures reveal how much the CDS market contributes to price discovery. Table VI presents the results of these estimations of the price discovery measures. The results confirm previous research, which has found evidence in favour of CDS market leadership. At the 10% level λ_2 is significant in 16 out of 20 cases, which indicates that CDS markets are relevant for price discovery. The relevance of cash bond markets for price discovery seems limited when considering the entire sample. Only 11 out of the 20 companies show significant λ_1 coefficients. British Telecom, Deutsche Telekom, Enel and Telefonica provide exceptions to this case, where bond markets seem to be the main source of price discovery.

[82] see Bai et al. (2012), pp. 1-61; Baillie et al. (2002), pp. 309-321; Blanco et al. (2005), pp. 2255-2281, Booth et al. (1999), pp. 619-643; Chu et al. (1999), pp. 21-34; Harris et al. (1995), pp. 563-57; Harris et al. (2002), pp. 277-308; Harris et al. (2002b), pp. 341-348; Hasbrouck (2002), pp. 329-339; Jong (2002), pp. 323-327; Lehmann (2002), pp. 259-276; Ronen, Yaari (2002), pp. 349-390.
[83] Engle, Granger, (1987), pp. 251-276.

The results present new interesting insights, when considering different groups of companies. Interestingly, while the Hasbrouck and Gonzalo-Granger measure provide conflicting signals for a few individual cases, they are remarkably consistent when considering group averages. First of all, the importance of CDS markets seems to decrease for lower ratings. While all AAA-, AA- and A-rated companies show significant λ_2 coefficients, only 50% of BBB-rated companies do provide significant λ_2 coefficients. Accordingly, the share of significant λ_1 coefficients increases with lower ratings, i.e. 25% of AAA- and AA-rated, 38% of A-rated and 88% of triple-B-rated companies show significant λ_1 values. This is also confirmed, when considering the Hasbrouck and Gonzalo-Granger measures of the group. AAA- and AA-rated companies show a Hasbrouck measure of 0.93 while this value falls to 0.74 for A-rated companies and finally to 0.50 for BBB-rated companies. When considering the Gonzalo-Granger measure, the respective values are 0.90, 0.69 and 0.48. This provides evidence for the hypothesis, that investors rely more on bond prices than on CDS with lower ratings.

Furthermore, the CDS market seems to be more relevant for U.S. companies than for EU companies. All λ_2 coefficients for U.S. companies are significant, while this is only the case for 64% of the EU companies. Accordingly, the cash bond market's importance for price discovery is limited in the U.S. case, a fact that is reflected in the significance of only 33% of λ_1 coefficients for U.S. companies compared to 73% for EU companies. Both the Hasbrouck as well as the Gonzalo-Granger measure confirm this evidence, with U.S. companies showing values of 0.84 and 0.91 respectively, compared to a value of 0.49 for both measures in the EU case.

Finally, the empirical evidence seems to suggest that investors rely slightly more on CDS markets for price discovery of financial companies than of non-financial companies. According to the share of significant λ_2 coefficients, the CDS market is important for price discovery for all financial companies while it is only for 43% of non-financial companies. With regards to the bond markets, λ_1 is significant for 62% of non-financial companies and for only 43% of financial companies. Again, this is confirmed by the companies' Hasbrouck and Gonzalo-Granger measures. Financial companies exhibit a Hasbrouck measure of 0.72 and a Gonzalo-Granger measure of 0.71, while non-financial show values of 0.61 and 0.66 respectively.

12 out of 32 companies reject cointegration when using daily observations. Rejection is possibly due to a CTD option, binding short sale constraints or too much microstructural noise because of

daily sampling. In this case the VECM representation is not valid. For these companies, the simpler concept of Granger causality using a vector autoregressive model is tested as explained in section 4.2. Table VII presents the results of these estimations. 5 out of twelve companies support the hypothesis of CDS spreads Granger-causing credit spreads, while 2 of these cases indicate bi-directional causality. Further 2 cases seem to indicate that only credit spreads Granger-cause CDS spreads. Finally, 5 cases indicate no existing Granger-relationship between the two markets.

					Hasbrouck			
	λ_1	Z-stat	λ_2	Z-stat	Lower	Upper	Mid	GG
American Express	-0.03	-2.2	0.21	3.7	0.62	0.78	0.70	0.87
Bank of America	-0.02	-1.0	0.11	7.2	0.75	0.99	0.87	0.84
Comcast	-0.02	-2.4	0.14	2.3	0.46	0.51	0.49	0.88
GE	-0.02	-2.1	0.05	3.1	0.54	0.74	0.64	0.71
Johnson & Johnson	0.00	0.5	0.39	3.9	0.98	0.99	0.99	1.01
Kraft Foods	0.00	-0.4	0.38	4.3	0.96	0.99	0.98	0.99
Morgan Stanley	-0.01	-0.6	0.15	5.8	0.82	0.99	0.90	0.93
Pfizer	0.00	-0.5	0.21	5.5	0.98	0.99	0.99	0.99
Wal-Mart	0.00	-0.6	0.67	5.6	0.97	0.99	0.98	1.00
Atlantic Richfield	-0.02	-1.3	0.09	5.3	0.93	0.95	0.94	0.83
Barclays	-0.03	-2.5	0.08	4.5	0.55	0.82	0.69	0.69
British Telecom	-0.04	-2.5	0.02	1.5	0.14	0.62	0.38	0.35
Credit Agricole	-0.01	-1.1	0.02	2.7	0.33	0.95	0.64	0.56
Deutsche Telekom	-0.06	-3.8	-0.01	-0.4	0.01	0.05	0.03	-0.22
Enel	-0.06	-3.5	0.02	1.8	0.11	0.58	0.35	0.19
GlaxoSmithKline	-0.04	-3.8	-0.08	-2.3	0.12	0.33	0.23	2.06
Nokia	-0.05	-2.7	0.03	2.2	0.18	0.75	0.46	0.34
Santander	-0.07	-3.7	0.02	2.2	0.13	0.61	0.37	0.23
Standard Chartered	-0.01	-0.6	0.04	3.9	0.76	0.98	0.87	0.86
Telefonica	-0.04	-2.1	0.03	1.9	0.16	0.81	0.48	0.37

	Hasbrouck							
Means	Lower	Upper	Mid	GG	λ_1 sign.	%	λ_2 sign.	%
Cleansed (20 companies)	0.53	0.77	0.65	0.68	11	55%	16	80%
AAA-AA (4 companies)	0.87	0.93	0.90	0.93	1	25%	4	100%
A (8 companies)	0.55	0.83	0.69	0.74	3	38%	8	100%
BBB (8 companies)	0.33	0.64	0.48	0.50	7	88%	4	50%
US (9 companies)	0.79	0.89	0.84	0.91	3	33%	9	100%
EU (11 companies)	0.31	0.68	0.49	0.49	8	73%	7	64%
Financial (7 companies)	0.57	0.87	0.72	0.71	3	43%	7	100%
Non-Financials (13 companies)	0.50	0.72	0.61	0.66	8	62%	9	69%

Table VII: Price Discovery Measures (daily)[84]

[84] The interpretation of GG values greater than unity or smaller than zero is not clear and unambiguous. Thus they were respectively treated as one and zero when computing averages. Significance is measured at the 10% level. λ_1 significant at least at the 10% level.

To sum it all up, the evidence in this case is slightly less in favour of CDS markets than compared to previous research. Again one likely reason for this is the larger microstructural noise in daily data. Evidence of this is reflected by the fact that all five companies that reject Granger-relationships between the two markets in the case of daily data do confirm cointegration in the case of weekly data.

	H_0: CDS do not cause CS			H_0: CS do not cause CDS		
	Sum of sign. coefficients	**F-stat**	**p-value**	**Sum of sign. coefficients**	**F-stat**	**p-value**
Altria	0.78	8.31	0.00	0.00	5.88	0.00
Caterpillar	0.00	1.60	0.20	0.00	5.82	0.00
Goldman Sachs	0.03	28.55	0.00	0.00	1.63	0.20
News America	0.07	16.50	0.00	0.00	3.05	0.05
Philip Morris	0.00	0.71	0.49	0.02	6.95	0.00
Abbey National	0.00	0.56	0.57	0.00	0.72	0.49
Aegon	0.07	2.42	0.09	0.00	0.26	0.77
AXA	0.02	4.59	0.01	0.00	0.01	0.99
France Telecom	0.00	1.43	0.24	0.00	2.09	0.13
Marks & Spencer	0.00	1.52	0.22	0.00	2.29	0.10
Statoil	0.00	0.08	0.92	0.03	2.13	0.12
Vodafone	0.00	0.42	0.66	0.00	0.30	0.74

Table VIII: Granger-Causality (daily)

7.5. Robustness Checks

Several different techniques were employed to check the robustness of the presented results. The techniques tested different potential weaknesses of the estimation, e.g. the data quality or the relevance of certain options of the estimation methods. Summing it all up, the tests do confirm the test results for the testable weaknesses although they show lower statistical significance. However, there are also limitations to the robustness checks that could be only solved by more data.

As a first step to test the robustness of the results, the dependence of the results on the data source was analysed. For this purpose all estimations in this paper were done using different data sources. As explained in the data description for bond yields up to three different sources were available: Bloomberg Generic Prices (BGN), Trade Reporting and Compliance Engine (TRACE) reported prices and Bloomberg Valuation Service prices. Additionally, for CDS spread also up to three different data sources were available: Bloomberg, Datastream and Credit Market Analytics provide prices for CDS contracts. The results confirm the evidence provided in this paper. Average basis spreads change and the Johansen test statistics decrease, which results in lower share of cointegrated securities and decreased overall statistical significance. Finally, half-life of deviations increases slightly on average but price discovery leadership is still suggested for CDS markets.

As a next step, it was tested whether the results depend on the use of government bond yields as proxy for the risk-free rate. Thus the presented estimations in this paper were done using swap rates as proxy for risk-free rates. As already showed in section 7.1 the sample companies' average basis spreads increase when using the swap rates instead of treasury yields. The share of accepted cointegration relationships between the companies' securities is lowered. Again, the share is lower for daily observations compared to weekly observations. Furthermore, half-life of deviations increases substantially. Lastly, price leadership is suggested for CDS markets again but with less statistical significance.

Additionally, all estimations were initially done without imposing restrictions to cleanse the sample. This implied including all 45 companies which were initially in the sample. This was done to prevent the results to be biased by a selection bias. In theory the strong restrictions imposed on the sample could result in an artificial sample, which consists only of companies for which the arbitrage relationship holds, while other companies would be excluded by the restrictions. For example, it could be the case that only companies whose basis spreads stay below certain levels exhibit cointegrated securities. In that case, the share of cointegrated securities should fall.

	Treasury rates		**Swap rates**	
	Average basis	**Average absolute basis**	**Average basis**	**Average absolute basis**
Average (45 companies)	-2.2	76.6	42.0	83.6
AAA-AA (9 companies)	-33.4	101.0	8.7	101.7
A (22 companies)	14.6	77.2	60.6	91.7
BBB (13 companies)	-16.5	57.4	25.2	51.9
US (17 companies)	6.2	56.3	31.4	59.4
EU (28 companies)	-7.2	88.9	48.4	98.2
Financial (19 companies)	-7.4	107.9	40.3	114.5
Non-Financials (26 companies)	1.7	53.8	43.3	61.0

Table IX: Average Basis Spreads (unrestricted sample)

However, the results do not show evidence for such a selection bias. Table IX presents the summary statistics of the unrestricted sample. In fact, the average basis spreads approaches its theoretical equilibrium value from -9.7 bps to -2.2 bps when including all companies. However, this is not caused by tighter basis spreads among companies but rather because of the balance of large negative and positive basis spreads. This is reflected by the fact that the average absolute basis spread increases to 76.6 bps from 46.9 bps when including all companies. Again treasury rates seem to provide a better reference rate as observed by the larger average absolute basis spread 83.6 bps when using swap rates. The relation between absolute average basis spreads and the credit rating of the company still seems to hold. AAA-AA-rated companies show a basis spread of 101.0 bps while for A-rated companies this value falls to 77.2 bps and for BBB-rated companies even further to 57.4 bps. The difference between US and EU companies increases dramatically when including all companies. While they showed only small differences in the cleansed sample (46.7 bps vs. 47.0 bps), US companies exhibit an average absolute basis spread of 56.3 bps compared to 88.9 bps for EU companies. The difference between financial and non-financial companies increases from 17.2 bps in the cleansed sample to 54.1 bps when including all companies. This increase is because the majority of dropped companies (7 out of 13) are European financial institutions.

	Number of companies	**Sign.(10%)**	**% Sign.**
All	45	24	53%
AAA-AA	9	5	56%
A	22	11	50%
BBB	13	8	62%
US	17	10	59%
EU	28	14	50%
Financial	19	9	47%
Non-Financials	26	15	58%

Table X: Cointegration Results (unrestricted sample)

Table X summarizes the results of the Johansen cointegration test when considering the entire sample. Only two of the previously dropped financial companies support the cointegration relationship. Apart from this group, the ratio of cointegrated companies does not fall significantly. The share of cointegrated companies falls from 63% to 53%, while this decrease is most pronounced in the group of financial companies where the share falls from 64% to 47%. Accordingly, the share of cointegrated non-financial companies stays relatively stable.

European financial companies had to face extremely difficult times during the European sovereign debt crisis, which climaxed in the sample during the last quarter of 2011. This could explain the larger basis spreads. With regards to the results of the cointegration results, a possible explanation for this kind of behaviour is that the apparent price leadership of CDS markets breaks down temporarily in times of extreme volatility.

	Hasbrouck							
Means	**Lower**	**Upper**	**Mid**	**GG**	**λ_1 sign.**	**%**	**λ_2 sign.**	**%**
All (24 companies)	0.53	0.77	0.65	0.69	13	54%	19	79%
AAA-AA (5 companies)	0.79	0.92	0.86	0.86	2	40%	5	100%
A (11 companies)	0.55	0.79	0.67	0.76	4	36%	10	91%
BBB (8 companies)	0.33	0.64	0.48	0.50	7	88%	4	50%
US (10 companies)	0.72	0.81	0.76	0.89	4	40%	9	90%
EU (14 companies)	0.39	0.73	0.56	0.56	9	64%	10	71%
Financial (9 companies)	0.56	0.88	0.72	0.71	4	44%	9	100%
Non-Financials (15 companies)	0.51	0.69	0.60	0.69	9	60%	10	67%

Table XI: Price Discovery Measures (unrestricted sample)[85]

Table XI summarizes the results of the VECM estimation of all entities exhibiting cointegrated securities. The results confirm that CDS markets lead the price discovery process. Both Hasbrouck and Gonzalo-Granger measure stay remarkably constant. The largest changes of those measures represent the fall from 0.93 to 0.86 of the Gonzalo-Granger measure of AAA- and AA-rated companies and the increase from 0.49 to 0.56 of Gonzalo-Granger measure of EU companies. Again, in the majority of cases λ_2 is significant, which provides evidence for leadership of CDS markets in the price discovery process.

	CDS	**%**	**CS**	**%**	**Bi-Directional**	**%**
All (21 companies)	5	24%	5	24%	5	24%
AAA-AA (4 companies)	0	0%	0	0%	1	25%
A (11 companies)	3	27%	4	36%	2	18%
BBB (5 companies)	1	20%	1	20%	2	40%
US (7 companies)	0	0%	4	57%	2	29%
EU (14 companies)	4	29%	1	7%	3	21%
Financial (10 companies)	4	40%	2	20%	3	30%
Non-Financials (11 companies)	1	9%	3	27%	2	18%

Table XII: Granger-Causality (unrestricted sample)

[85] λ_1 significant at least at 10% level.

In the case of companies, which do not seem to exhibit cointegrated securities, the evidence towards CDS leadership is once more not as strong as for cointegrated companies.

Table XII presents a summary of the tests for Granger causality of these companies. Only in 48% of the cases, the results suggest that CDS prices Granger-cause credit spreads and in half of those cases, bi-directional causality is indicated. Finally, in 24% of the cases bond markets seem to Granger-cause CDS spreads and in 28% of the cases no Granger relationship is suggested.

	Dependent Variable		
All (45 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.06	10.0
t-statistic	-0.42	3.22	
Adjusted R^2	0.00	0.03	
AAA-AA (9 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.13	5.0
t-statistic	-0.64	4.47	
Adjusted R^2	0.00	0.06	
A (22 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.03	23.8
t-statistic	-0.44	2.26	
Adjusted R^2	0.00	0.01	
BBB (13 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.09	7.2
t-statistic	-0.18	4.09	
Adjusted R^2	0.00	0.04	
US (17 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.14	4.5
t-statistic	-0.45	5.35	
Adjusted R^2	0.00	0.07	
EU (28 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.02	31.0
t-statistic	-0.41	1.93	
Adjusted R^2	0.00	0.01	
Financial (19 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.03	23.3
t-statistic	-0.18	2.17	
Adjusted R^2	0.00	0.01	
Non-Financials (26 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.09	6.9
t-statistic	-0.60	4.00	
Adjusted R^2	0.00	0.04	

Table XIII: Avg. OLS Coefficient of Basis Spread (unrestricted)

Table XIII presents the results of the OLS estimations of the basis spread on the credit spreads and CDS spreads when using the unrestricted sample. Including all companies increases the average half-life of deviations of the basis spread across the sample from 7.6 to 10.0 days. As one could have expected, the rise is mainly pronounced for financial companies. Their half-life increases from 16.6 to 23.3 days. The effect on other groups is negligible, with the second largest change being an increase of 1.9 days for A-rated companies from 21.9 to 23.7 days. The results of the OLS regression give further evidence that CDS markets lead the price discovery process. The majority (51%) of β_1 coefficients is statistically significant, while only three companies show a significant α_1 coefficient. Once again, these ratios stay constant across all groups with the exception of US and EU companies, where 82% of US companies exhibit significant β_1 coefficients while this share is only 32% for EU companies.

As a further robustness check, the sample was divided into two subsamples, with one subsample covering the first half of the sample period and the other covering the second half of the sample period. All estimations presented in this paper were done again to prevent the results being biased by special circumstances, e.g. the worsening European sovereign debt crisis during the second half of the sample.

Table XIV and XV report the summary statistics of the average basis spreads for the first and second half of the sample period. Comparing the average basis spread across the samples only small effects appear. When using first half observations the average basis spread increases slightly from 9.7 to 9.8 bps and accordingly decreases to 9.6 bps when considering the second half of the sample. However, the effect of the European crisis is reflected in the absolute basis spreads. They rise from 40.9 bps in the first half to 52.8 bps in the second half and are most pronounced for financial companies where absolute basis spreads increase from 43.9 to 72.5 bps in the second half.

	Average basis	**Average absolute basis**	**Average basis**	**Average absolute basis**
Cleansed (32 companies)	-9.8	40.9	26.4	43.9
AAA-AA (6 companies)	36.8	53.5	67.9	73.8
A (15 companies)	-9.7	35.9	29.0	42.9
BBB (11 companies)	-35.5	41.0	0.4	28.9
US (14 companies)	-0.2	40.9	23.3	43.7
EU (18 companies)	-17.3	40.9	28.9	44.0
Financial (11 companies)	-17.1	43.9	20.9	45.3
Non-Financials (21 companies)	-6.0	39.4	29.3	43.1

Table XIV: Avg. Basis Spreads (first half)

	Average basis	Average absolute basis	Average basis	Average absolute basis
Cleansed (32 companies)	-9.6	52.8	38.9	62.3
AAA-AA (6 companies)	55.1	57.4	94.9	95.0
A (15 companies)	-15.3	57.6	37.1	69.8
BBB (11 companies)	-37.2	43.9	10.7	34.3
US (14 companies)	-14.6	52.5	12.4	51.0
EU (18 companies)	-5.8	53.1	59.4	71.1
Financial (11 companies)	-16.4	72.5	34.9	85.3
Non-Financials (21 companies)	-6.1	42.6	40.9	50.3

Table XV: Avg. Basis Spreads (second half)

Table XVI and XVII summarize the results of the cointegration test of the first and second half of the sample period. The share of cointegrated securities increases in the second period of the sample (59% vs. 69%). This is surprising, as absolute spreads increase during the second part across all groups. Moreover, the increase in cointegrated companies is mostly pronounced for financial companies (45% vs. 91%), which also happen to exhibit the largest absolute spread in the second period (72.5 bps) as well the largest increase in absolute basis spreads from the first to the second half of the sample (28.6 bps). This indicates a positive relationship between basis spreads and cointegration which is counterintuitive. If the basis spread increases, the arbitrage relationship is more likely not to be fulfilled and this should translate in rejection of cointegration. One explanation of this observation could be that the increased variance in the spreads results in more valuable information. This means that a large increase in CDS spreads which is accompanied by an increase in credit spread gives more evidence for cointegration than relatively stable CDS and credit spreads, although the basis spread can increase during the former case.

	Number of companies	Sign.(10%)	% Sign.
Cleansed	32	19	59%
AAA-AA	6	4	67%
A	15	6	40%
BBB	11	9	82%
US	14	10	71%
EU	18	9	50%
Financial	11	5	45%
Non-Financials	21	14	67%

Table XVI: Cointegration Results (first half)

	Number of companies	Sign.(10%)	% Sign.
Cleansed	32	22	69%
AAA-AA	6	5	83%
A	15	11	73%
BBB	11	6	55%
US	14	11	79%
EU	18	11	61%
Financial	11	10	91%
Non-Financials	21	12	57%

Table XVII: Cointegration Results (second half)

Table XVIII and XIX summarize the price discovery measures of the first and second half of the sample period. Several interesting results emerge when comparing the two periods. During the first half, leadership of CDS markets in the price discovery process is suggested. 74% of the cointegrated companies show significant λ_2 coefficients. Furthermore, both the Hasbrouck's measure of 0.60 and the Gonzalo-Granger measure of 0.59 confirm this evidence. AAA- and AA-rated companies form an exception, where a Hasbrouck's measure of 0.29 and a share of 75% λ_1 significant coefficients suggest bond market leadership in the price discovery process. The Gonzalo-Granger measure of 0.50 suggests no price leadership. Apart from this group, all statistical results provide strong evidence for CDS market leadership in the price discovery process.

This dramatically changes during the second half of the sample. The evidence in this case strongly points to bond markets leading the price discovery process. On average the Hasbrouck measure falls from 0.60 to 0.40, the Gonzalo-Granger measure from 0.59 to 0.52. Additionally, while the share of significant λ_2 coefficients falls from 74% to 41%, the share of significant λ_1 coefficients increases from 37% to 77%. More interestingly, the effect is most pronounced for financial companies, which arguably were most affected by the European sovereign debt crisis. The Hasbrouck measure falls from 0.68 to 0.40 for financial companies, while the Gonzalo-Granger measure falls from 0.59 to 0.45. In addition, the share of significant λ_2 coefficients falls from 80% to 50%. All λ_1 coefficients are significant in the second period compared to one significant λ_1 coefficient in the first half.

The results of the Granger causality test confirm the observations for the companies, where cointegration was rejected. During the first period, only 15% of the companies indicate Granger-causality from bond markets toward CDS markets, while this share increases to 50% in the second period. Accordingly, the share of companies, where CDS spreads Granger-cause credit spreads, falls from 23% to 10% in the second period.

These observations give evidence for a dynamic price discovery relationship between CDS and bond markets. During stable periods with relatively low variance, statistical results suggest that CDS markets lead the price discovery process. In crisis times when markets exhibit much higher levels of variance, the results suggest that this leadership diminishes and bond markets take over the price leadership.

	Hasbrouck							
Means	**Lower**	**Upper**	**Mid**	**GG**	**λ_1 sign.**	**%**	**λ_2 sign.**	**%**
Cleansed (19 companies)	0.52	0.68	0.60	0.59	7	37%	14	74%
AAA-AA (4 companies)	0.25	0.33	0.29	0.50	3	75%	1	25%
A (6 companies)	0.69	0.77	0.73	0.79	1	17%	5	83%
BBB (9 companies)	0.52	0.78	0.65	0.50	3	33%	8	89%
US (10 companies)	0.46	0.68	0.57	0.55	4	40%	7	70%
EU (9 companies)	0.57	0.68	0.63	0.64	3	33%	7	78%
Financial (5 companies)	0.61	0.74	0.68	0.59	1	20%	4	80%
Non-Financials (14 companies)	0.48	0.66	0.57	0.59	6	43%	10	71%

Table XVIII: Price Discovery Measures (first half)

	Hasbrouck							
Means	**Lower**	**Upper**	**Mid**	**GG**	**λ_1 sign.**	**%**	**λ_2 sign.**	**%**
Cleansed (22 companies)	0.29	0.50	0.40	0.52	17	77%	9	41%
AAA-AA (5 companies)	0.30	0.45	0.37	0.60	3	60%	2	40%
A (11 companies)	0.32	0.49	0.40	0.54	10	91%	6	55%
BBB (6 companies)	0.25	0.56	0.41	0.43	4	67%	1	17%
US (11 companies)	0.16	0.38	0.27	0.30	9	82%	2	18%
EU (11 companies)	0.42	0.62	0.52	0.74	8	73%	7	64%
Financial (10 companies)	0.28	0.52	0.40	0.45	10	100%	5	50%
Non-Financials (12 companies)	0.30	0.49	0.39	0.58	7	58%	4	33%

Table XIX: Price Discovery Measures (second half)[86]

Table XX and XXI summarize the results of the OLS regressions and give estimates for the half-life of deviations for the first and second half of the sample.

[86] λ_1 significant at least at 10% level for both tables.

As expected, the average half-life of 3.7 days is much lower during the first period compared to 9.3 days for the second period. Furthermore, during the first period 78% of β_1 coefficients exhibit statistical significance while none of the α_1 coefficients is significant. This confirms the evidence of CDS market leadership in the price discovery process during the first half of the sample. Additionally, all β_1 coefficients behave as expected with respect to their sign, while only 47% α_1 coefficients show negative signs. The half-life differences between the groups follow the same pattern in the entire sample, the first half and the second half.

	Dependent Variable		
Cleansed (32 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.17	3.7
t-statistic	0.05	4.50	
Adjusted R^2	0.00	0.09	
AAA-AA (6 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.28	2.1
t-statistic	-0.17	5.85	
Adjusted R^2	0.00	0.14	
A (15 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.06	10.9
t-statistic	0.20	2.99	
Adjusted R^2	0.00	0.04	
BBB (11 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.26	2.3
t-statistic	-0.06	5.82	
Adjusted R^2	0.00	0.13	
US (14 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.35	1.6
t-statistic	0.07	7.05	
Adjusted R^2	0.00	0.17	
EU (18 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.03	19.8
t-statistic	0.03	2.51	
Adjusted R^2	0.00	0.02	
Financial (11 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.01	0.08	8.6
t-statistic	0.45	3.31	
Adjusted R^2	0.00	0.05	
Non-Financials (21 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.22	2.8
t-statistic	-0.17	5.12	
Adjusted R^2	0.00	0.11	

Table XX: Avg. OLS Coefficient of Basis Spread (first half)

The results of the second period confirm the diminishing importance of CDS markets in the price discovery process. The share of significant β_1 coefficients falls to 47%, while this share rises to 25% for α_1 coefficients. The largest discrepancy lies between European companies which show a share of significant β_1 coefficients of only 17% while this value is 86% for U.S. companies. Furthermore, the share of negative α_1 coefficients rises to 81% while the share of positive β_1 coefficients falls to 75%. Also, the average size of the coefficients indicates a diminishing importance of CDS markets in the price discovery process. The average β_1 coefficient falls from 0.17 to 0.06 in the second period, while the average α_1 coefficient falls from 0.00 to -0.01. Both changes are indicative of a lower importance of CDS markets for the price discovery process.

To sum it all up, the OLS estimations further confirm the observations made when estimating the Hasbrouck and Gonzalo-Granger measures. One possible explanation for the dynamic price discovery relationship is increased trading volume in bonds during volatile market periods.

As a further robustness check, all estimations were done using weekly instead of daily data. As explained in section 7.1 employing weekly data can clean the data from microstructural noise. This is helpful for concepts that focus on the long-term relationship between variables as for example cointegration analysis. However, for concepts that focus on the short-term relationship, employing weekly data has severe drawbacks. This is the case for the price discovery measures estimated in this paper. As these measures try to estimate which market processes information faster, a more detailed data set is beneficial for the explanatory power of the estimation results. Thus one can expect lower explanatory power when employing weekly instead of daily data for these techniques. The results confirm these expectations. Although the CDS market leadership can be confirmed also for weekly data, the results are less convincing w.r.t. significance in this case. For example, the share of significant λ_2 coefficients falls from 80% to 60% in the case of weekly data. Apart from the lower statistical significance, the changes in the results are negligible. Thus the tables will not be presented in this paper.

Finally, all estimations in this paper were done choosing the number of lags based on the AIC and BIC criterion. As explained, employing the AIC criterion drastically increases the number of lags. This results in a lower share of suggested cointegrated relationships. Furthermore, the significance of the remaining results falls. However, the results do not suggest any contradictions to the observations made in the paper. Accordingly, the results will not be presented in detail here.

	Dependent Variable		
Cleansed (32 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.06	9.3
t-statistic	-0.82	2.14	
Adjusted R²	0.00	0.03	
AAA-AA (6 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.16	3.7
t-statistic	-1.53	3.80	
Adjusted R²	0.01	0.07	
A (15 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.03	18.6
t-statistic	-0.88	1.42	
Adjusted R²	0.01	0.01	
BBB (11 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.06	10.0
t-statistic	-0.36	2.21	
Adjusted R²	0.00	0.03	
US (14 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	0.00	0.13	5.0
t-statistic	-0.53	3.99	
Adjusted R²	0.01	0.06	
EU (18 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.02	0.01	25.5
t-statistic	-1.05	0.69	
Adjusted R²	0.00	0.00	
Financial (11 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.04	13.1
t-statistic	-0.62	1.71	
Adjusted R²	0.01	0.02	
Non-Financials (21 companies)	**CDS price**	**Credit Spread**	**Implied Half-Life**
Lagged Basis	-0.01	0.08	8.0
t-statistic	-0.93	2.36	
Adjusted R²	0.00	0.03	

Table XXI: Avg. OLS Coefficient of Basis Spread (second half)

7.6. Discussion

In contrast to the majority of previous research, this paper has found that yields on government bonds serve as better proxies for the risk-free rate than swap rates. A reason for this could be the perception of increased overall risk in the financial sector by investors. This argument seems reasonable as the sample period starts in the aftermath of the financial crisis and covers the beginning of the European sovereign debt crisis. Especially European swap rates have increased dramatically because financial institutions in this region appear at the centre of investor concerns. An observation that supports this theory is that the average basis spreads based on swap rates are much larger for European than for U.S. companies.

Furthermore, the results suggest that the arbitrage relationship holds reasonably well in the medium- to long-term. The average basis spread fluctuates around zero, the estimated half-life of deviations is 7.6 days and cointegration is supported for the majority of companies. As the average level of CDS and credit spreads rises towards the end of the sample, the absolute basis spreads are also found to become larger. Apart from that, some companies show large non-zero basis spreads. Possible explanations for this observation are limits to the arbitrage relationship induced by the cheapest-to-deliver option, non-zero transaction costs especially for short-sales of bonds, the non-flat interest rate term structure, bonds trading at discount to par, capital limits especially to fund bond positions and the lack of liquidity in CDS and bond markets such that it takes time for arbitrage forces to come into effect. Additionally, one has to note that the analysed 5-year bond yields are not traded directly in the market but estimated by linear interpolation which induces a possible measurement error.

Several findings emerge, when grouping observations by region, rating and distinguishing between financial and non-financial companies. Basis spreads based on treasury yields do not differ for European and U.S. companies. However, basis spreads decrease with lower rating of the reference entity. The share of suggested cointegration relationships is remarkably constant across all groups and the basis spread does not seem to have an effect on test results. Employing the BIC produces more reliable results than the AIC. It was found that the AIC tends to result in overparameterized models for cointegration analysis. Furthermore, it was found that employing weekly instead of daily data increases the share of suggested cointegration relationships. Microstructural noise inherent in daily observations seems to be the reason for this observation. Daily observations might be impractical here because a non-proprietary dataset has been used. Apart from that, Bloomberg and

Datastream have proven to be valuable data sources for the analysis of CDS and credit spreads. In OLS regressions the one-day lagged basis spread is able to explain only 4% of the variance in credit spreads on average and practically none of the variance inherent in CDS spreads.

In line with previous research, it was found that CDS markets lead bond markets in terms of price discovery. However, this leadership decreases with lower rating of the reference entity. Furthermore, during the more volatile second half of the sample, the relationship seems to reverse. Previous research suggests that price discovery takes place in the market where informed participants trade most. During normal times, the CDS market represents the easiest venue to trade credit risk. Accordingly, traders focus on CDS markets such that price discovery occurs mainly in this market and trading levels for bonds are lower during times with low variance. The majority of investment-grade bond investors are looking for stable and safe income. As long as their perception of the security of their investment does not change, there are few incentives for them to change the composition of their bond portfolio. Furthermore, bond investors are rather long-term investors and do not adjust their portfolios to small market moves. The nature of CDS contracts give market participants the option to speculate on short swings, because investors can quickly enter CDS positions and realize profits fast by closing the positions through entering opposite contracts. This is an important difference to bond markets, where investors are not able to enter and close positions as fast and have to provide much more capital. However, when volatility increases bond investors adjust their portfolios resulting in larger activity in bond markets. Additionally, one can often observe a flight-to-safety to investment-grade bonds during crisis times, which further increases trading in bond markets. This flow of information increases the relevance of bond markets for price discovery of credit risk of the traded companies. The increased relevance of bond markets results in diminishing importance of CDS markets in the price discovery process and the evidence even suggests that the relationship between the two markets does not become bi-directional but that in fact the bond market takes over and leads the price discovery process. A further important fact is that CDS contain counterparty risk, which increases when financial institutions are perceived as more risky. This relationship can disturb CDS prices during times of high economic uncertainty. Accordingly, the information value of CDS spreads decreases during times of crisis resulting in price discovery mainly occurring in bond markets.

All of the above results have been tested against a battery of different robustness checks, including different data sources, different reference rates, weakening sample restrictions, different information criteria, employing weekly instead of daily data and dividing the sample period into two subsamples. While the significance of results decreases, none of the tests contradicts previous findings. Nevertheless there remain caveats to the results. Importantly, one cannot infer a causal relationship of the group characteristics by comparing the test results of different groups of companies. Furthermore, the sample size of only 32 companies is far from optimal for the purposes of this paper. Finally, the tests implying decreased price discovery in CDS markets during volatile market periods were obtained using an even smaller sample. By splitting the data into two subsamples, the explanatory power diminishes considerably. An important aspect, the time span of the data, is halved in this case. Despite these issues, the results give rise to a potential new understanding of the relationship between bond and CDS markets and should be more thoroughly analysed by future researchers.

8. Conclusion

This paper contributes to the literature on the empirical relationship between CDS and credit spreads analysing the theoretical arbitrage relationship between the securities. It differs from prior research because it covers the most recent period from the beginning 2010 until the end 2011. Accordingly, the results potentially represent changes that occurred after the financial crisis and more importantly developments during the European sovereign debt crisis. Additionally, the dataset spans the largest period of time among previous studies with comparable sample restrictions and bond yield interpolation.

In contrast to previous research, the results in this paper suggest yields on government bonds as reference rate instead of swap rates. A possible explanation for this might be increased risk in the overall financial market, especially for European institutions during the sovereign debt crisis. In line with previous research, it is found that the arbitrage relationship holds reasonably well on average. The average basis spread fluctuates around zero and cointegration is supported for the majority of companies. Apart from that, some companies show large non-zero basis spreads. The paper presents several explanations for this observation, most notably arbitrage limitations in form of the CTD option, transactions costs and lack of liquidity such that it needs time for arbitrage forces to come into effect. Several findings emerge, when considering different groups of companies by rating, region and distinguishing between financial and non-financial companies. Furthermore, the paper argues for employing the BIC and using weekly data when analysing the cointegration relationship between CDS and credit spreads. The AIC tends to results in overfitted models and daily data seems to exhibit too much microstructural noise. However, this might be due to the use of publicly available data. Apart from that, the paper documents the appropriateness of data from Bloomberg and Datastream for the analysis of CDS and credit spreads. Confirming previous research, the paper finds that CDS markets lead bond markets, but the relationship decreases when considering lower ratings. Moreover, the relationship seems to reverse during times of increased volatility. Two different explanations are provided. First, information inherent in bond prices increases during volatile times because bond trading increases in times of economic crises. Second, counterparty risk inherent in CDS results in less information value of CDS spreads due to the increased risk in the overall financial sector. Both effects might explain the observations.

The results can help to develop a further understanding of the relationship between CDS and bond markets and give advice for the interpretation of spreads especially during volatile times. An important implication of the results is, that market participants should focus rather on bond yields instead of CDS spreads during times of high economic uncertainty. A natural point of critique of the estimations is the use of publicly available data from different sources, which seem to provide lower quality data compared to proprietary data. Additionally, the sample size of only 32 companies may seem to be too small to allow valuable inferences. Finally, one cannot convincingly infer a causal relationship between the group characteristics and the differences observed between groups based on the estimations provided in this paper. Despite this justified critique, it has to be acknowledged that the data and the results proved to be consistent against several different robustness checks.

Lastly, several questions were left open in this paper: How important are the different arbitrage limitations in determining the basis spread? What are the main factors driving CDS and credit spreads? Are the group characteristics the true reasons for the differences observed between groups? Does the arbitrage relationship hold for a larger sample? Considering the scarcity of accurate data, the last question will prove to be difficult. It will be left to future research to find convincing answers to these questions.

Appendix A.1 Details of Bonds in Sample

Name	Region	Bloomberg ID	ISIN	Source	Issue	Maturity
Altria	US	EH616183	US02209SAC70	TRACE	10.11.2008	10.11.2013
American Express	US	EH829013	US025816BA65	TRACE	18.05.2009	20.05.2014
Bank of America	US	EG526102	XS0304943938	BGN	11.06.2007	11.06.2012
Boeing	US	EC584237	US09700PBC14	BVAL	20.06.2002	15.06.2012
Capital One Bank	US	ED011059	US14040EHG08	TRACE	13.06.2003	13.06.2013
Caterpillar	US	ED462922	US14911QTY79	BVAL	20.05.2004	15.05.2012
Comcast	US	EC755395	US00209TAA34	TRACE	18.11.2002	15.03.2013
GE	US	EC834306	US369604AY90	TRACE	28.01.2003	01.02.2013
Goldman Sachs	US	EF1053661	XS0231001859	BGN	04.10.2005	04.10.2012
Johnson & Johnson	US	EC984179	US478160AM65	TRACE	22.05.2003	15.05.2013
Kraft Foods	US	EC569652	US50075NAH70	TRACE	20.05.2002	01.06.2012
Morgan Stanley	US	EI0521308	US61747YCK91	TRACE	20.11.2009	20.11.2014
News America	US	ED865493	US652482BG48	TRACE	01.04.2005	15.12.2014
Pfizer	US	ED309655	US717081AR42	TRACE	03.02.2004	15.02.2014
Philip Morris	US	EH364136	US718172AB55	TRACE	16.05.2008	16.05.2013
Wal-Mart	US	EC952399	US931142BT92	TRACE	29.04.2003	01.05.2013
Walt Disney	US	EH499713	XS0382275641	BVAL	19.08.2008	19.08.2013
Abbey National	EU	EF174926	XS0235967683	BVAL	18.11.2005	18.11.2012
Aegon	EU	EH802637	XS0425811865	BGN	29.04.2009	29.04.2012
Atlantic Richfield	EU	MM1325289	US04882PCL13	BVAL	11.03.1992	15.05.2012
AXA	EU	EH6839078	FR0010697300	BGN	19.12.2008	19.12.2013
Barclays	EU	EI0182754	XS0459903620	BGN	28.10.2009	28.01.2013
BNP Paribas	EU	EH8463091	XS0431833119	BVAL	11.06.2009	11.06.2012
British Telecom	EU	EH0458255	XS0332154524	BGN	22.11.2007	22.01.2013
Credit Agricole	EU	EC4860325	FR0000188112	BVAL	10.12.2001	10.12.2013
Credit Suisse	EU	EH5146772	CH0045029870	BGN	15.09.2008	13.09.2013
Deutsche Bank	EU	EG5825609	CH0032119288	BGN	24.07.2007	24.07.2012
Deutsche Telekom	EU	EH216178	JP527613A828	BVAL	22.02.2008	22.02.2013
Enel	EU	ED0048873	XS0170342868	BGN	12.06.2003	12.06.2013
France Telecom	EU	EF4302693	XS0255429754	BGN	24.05.2006	24.05.2012
GlaxoSmithKline	EU	ED9750834	XS0222377300	BGN	16.06.2005	18.06.2012
Lloyds TSB	EU	EC5806962	XS0149620691	BGN	20.06.2002	20.06.2014
Marks & Spencer	EU	EG2985661	XS0293893813	BGN	29.03.2007	29.05.2012
Nokia	EU	EH7057639	XS0411735300	BGN	04.02.2009	04.02.2014
Philips	EU	DD5305659	US718448AB95	TRACE	24.08.1993	15.08.2013
Rabobank	EU	EH9043264	XS0440737905	BGN	27.07.2009	27.07.2012
RBS	EU	EC5477822	CH0014024464	BGN	26.04.2002	26.04.2012
Santander	EU	EF2580779	ES0413900111	BGN	06.02.2006	06.02.2014
Standard Chartered	EU	EH8068858	XS0426682570	BGN	30.04.2009	30.04.2014
Statoil	EU	EC2618154	US656531AL44	TRACE	25.05.2000	15.07.2014
Telecom Italia	EU	EC5522262	XS0146643191	BGN	24.04.2002	24.04.2012
Telefonica	EU	EG1361195	XS0284891297	BGN	07.02.2007	07.02.2014
Total	EU	EG4670378	XS0302705172	BGN	04.06.2007	04.06.2012
UniCredit	EU	EH7988759	XS0425413621	BGN	27.04.2009	27.04.2012
Vodafone	EU	EG5172994	XS0304458564	BGN	06.06.2007	06.06.2014

Table XXII: Detailed Bond List (1/2)

Name	Region	Bloomberg ID	ISIN	Source	Issue	Maturity
Altria	US	EH616187	US02209SAD53	TRACE	10.11.2008	10.11.2018
American Express	US	EG763174	US025816AX77	TRACE	28.08.2007	28.08.2017
Bank of America	US	EH9805902	XS0453820366	BGN	24.09.2009	15.09.2021
Boeing	US	ED158570	US09700WEG42	BVAL	24.09.2003	15.09.2023
Capital One Bank	US	EH874870	US140420MV96	TRACE	25.06.2009	15.07.2019
Caterpillar	US	EH715074	US14912L4E81	TRACE	12.02.2009	15.02.2019
Comcast	US	EC755391	US00209TAB17	TRACE	18.11.2002	15.11.2022
GE	US	EH097013	US369604BC61	TRACE	06.12.2007	06.12.2017
Goldman Sachs	US	EI0163044	XS0459410782	BGN	23.10.2009	23.10.2019
Johnson & Johnson	US	EC984187	US478160AL82	TRACE	22.05.2003	15.05.2033
Kraft Foods	US	EH113355	US50075NAU81	TRACE	12.12.2007	01.02.2018
Morgan Stanley	US	EG1779784	XS0287135684	BGN	14.02.2007	14.02.2017
News America	US	ED865785	US652482BJ86	TRACE	01.04.2005	15.12.2034
Pfizer	US	EC862987	US717081AQ68	TRACE	19.02.2003	01.03.2018
Philip Morris	US	EH364140	US718172AA72	TRACE	16.05.2008	16.05.2018
Wal-Mart	US	EG046533	XS0279211832	BGN	19.12.2006	19.01.2039
Walt Disney	US	EC527035	US25468PBW59	TRACE	28.02.2002	01.03.2032
Abbey National	EU	EF355621	XS0250729109	BGN	12.04.2006	12.04.2021
Aegon	EU	EI079970	XS0473964509	BGN	16.12.2009	16.12.2039
Atlantic Richfield	EU	048825BB8	US048825BB81	BVAL	03.02.1992	01.02.2022
AXA	EU	EC3189817	XS0122028904	BVAL	15.12.2000	15.12.2020
Barclays	EU	EH0910289	US06739GAE98	BVAL	04.12.2007	04.12.2017
BNP Paribas	EU	EC5084354	XS0142073419	BGN	01.04.2005	03.04.2017
British Telecom	EU	TT3189525	XS0052067583	BGN	23.08.1994	26.03.2020
Credit Agricole	EU	EH1847035	XS0343877451	BGN	01.02.2008	01.02.2018
Credit Suisse	EU	EC2963568	XS0118514446	BGN	05.10.2000	05.10.2020
Deutsche Bank	EU	EG7882376	DE000DB5S5U8	BGN	31.08.2007	31.08.2017
Deutsche Telekom	EU	EH6872467	DE000A0T5X07	BGN	20.01.2009	20.01.2017
Enel	EU	EG5612999	XS0306647016	BGN	20.06.2007	20.06.2019
France Telecom	EU	ED2837968	FR0010039008	BGN	23.01.2004	23.01.2034
GlaxoSmithKline	EU	ED9750792	XS0222383027	BGN	16.06.2005	16.06.2025
Lloyds TSB	EU	TT3143472	XS0043098127	BGN	06.04.1993	06.04.2023
Marks & Spencer	EU	EI0628574	XS0471074582	BGN	02.12.2009	02.12.2019
Nokia	EU	EH7057670	XS0411735482	BGN	04.02.2009	04.02.2019
Philips	EU	DD1020823	US718337AC23	BVAL	23.05.1995	15.05.2025
Rabobank	EU	EF0667370	XS0228265574	BGN	30.08.2005	30.08.2029
RBS	EU	ED3861272	US00080QAB14	TRACE	15.03.2004	04.06.2018
Santander	EU	EF6746608	ES0413900145	BGN	08.09.2006	09.01.2017
Standard Chartered	EU	EG8688624	US853250AB48	BVAL	26.09.2007	26.09.2017
Statoil	EU	EH7470220	XS0416848520	BGN	11.03.2009	11.03.2021
Telecom Italia	EU	EC8174871	XS0161100515	BGN	24.01.2003	24.01.2033
Telefonica	EU	EF2508754	XS0241946044	BGN	02.02.2006	02.02.2018
Total	EU	EH8327932	XS0430265693	BGN	02.06.2009	08.12.2017
UniCredit	EU	EI0254413	IT0004547409	BGN	05.11.2009	31.01.2022
Vodafone	EU	EH8499970	XS0432619913	BGN	05.06.2009	05.12.2017

Table XXIII: Detailed Bond List (2/2)

Appendix A.2 Comparison of Stationary and Non-Stationary Processes

Consider the following two processes

$$x_t = \rho x_{t-1} + u_t, \quad |\rho| < 1$$
$$y_t = y_{t-1} + \upsilon_t$$

where u_t and υ_t represent error terms assumed to be normally independently identically distributed with mean zero and unit variance, $u_t, \upsilon_t \sim iin(0,1)$, i.e. purely random processes. Both are autoregressive models of order one, but y_t is a special case of the x_t process where $\rho = 1$ and is called a random walk model. It is also known as AR(1) model with a unit root since the root of the AR(1) equation is 1 (or unit). Although both processes belong to the class of AR(1) model, their statistical behaviour diverges substantially when considering their first and second moments. The processes can be expressed as the sum of the initial observation and the errors by successive substitution[87]

$$x_t = \rho^t x_0 + \sum_{i=0}^{t-1} \rho^i u_{t-i}$$
$$y_t = y_0 + \sum_{i=0}^{t-1} \upsilon_{t-i}$$

which transforms the models from the autoregressive to the moving-average form. If the initial observations are zero, i.e. $x_0 = 0$ and $y_0 = 0$, the first moments of the processes are

$$E(x_t) = 0$$
$$E(y_t) = 0$$

and the variances can be expressed as follows

$$Var(x_t) = \sum_{i=0}^{t-1} \rho^{2i} Var(u_{t-i}) \Rightarrow \lim_{t\to\infty} Var(x_t) = \frac{1}{1-\rho^2}$$
$$Var(y_t) = \sum_{i=0}^{t-1} Var(\upsilon_{t-i}) = t$$

while the lag-l autocovariances take the following form

[87] see Maddala, Kim (1999), p. 20.

$$\gamma_l^x = E(x_t x_{t+l}) = \sum_{i=0}^{t+l-1} \rho^i \rho^{l+i}$$
$$\gamma_l^y = E(y_t y_{t+l}) = t - l$$

because the errors are assumed to be $u_t, \upsilon_t \sim iin(0,1)$ which implies $Cov(u_t, u_s) = Cov(\upsilon_t, \upsilon_s) = 0,\ t \neq s$. Thus, in this case the means are the same but the variances and autocovariance differ substantially.

The most important difference is that the variance and autocovariance of x_t converge to a constant over time, while they are functions of t in the case of y_t. From this it follows, that the variance of y_t increases as t increases while the variance of x_t asymptotically converges to a constant. This shows that the two processes exhibit different statistical behaviour. The variance of stationary stochastic processes converges to a constant, while the variance of non-stationary processes increases over time. But the means of the processes also behave differently, when one adds a constant to each of the processes

$$x_t = \alpha + \rho x_{t-1} + u_t, \quad |\rho| < 1$$
$$y_t = \alpha + y_{t-1} + \upsilon_t$$

which can be rewritten as

$$x_t = \rho^t x_0 + \alpha \sum_{i=0}^{t} \rho^i + \sum_{i=0}^{t} \rho^i u_{t-i}$$
$$y_t = y_0 + \alpha t + \sum_{i=0}^{t-1} \upsilon_{t-i}$$

where the y_t process contains a deterministic trend t. If the initial observations are zero, i.e. $x_0 = 0$ and $y_0 = 0$, then the means of the processes take the following form[88]

$$\lim_{t \to \infty} E(x_t) = \frac{\alpha}{1-\rho}$$
$$E(y_t) = \alpha t$$

[88] see Maddala, Kim (1999), p. 21.

and the second moments (variances and autocovariances) stay the same as in the case without constants. From this one can conclude, that adding a constant to the processes results in the means becoming different in addition to the different variances and autocovariances. Again, the mean and the variance of the x_t process converge to a constant over time, while they increase for y_t over time.

Conventional asymptotic theory cannot be applied to non-stationary time series, because their variance is not constant over time. However, there is a way to analyse these series. One can create stationary time series by differencing non-stationary time series. For example, the random walk series y_t can be transformed to a stationary series by differencing once, i.e.

$$\Delta y_t = y_t - y_{t-1} = (1 - L)y_t = \varepsilon_t$$

where the error term ε_t is assumed to be independently normal and L is a lag operator. Thus the first difference of y_t is stationary, i.e. the variance of Δy_t is constant over the sample period. [89]

[89] see Maddala, Kim (1999), p. 22.

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