Estimating Systematic Counterparty Risk in the Credit Default Swap Market

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ABSTRACT

We examine the impact of systematic counterparty default risk on the credit default swap (CDS) market. Using a comprehensive panel data set of 114 US companies from 2001 to mid-2012 we show that systematic counterparty risk is statistically and economically significant in the CDS market. We develop two proxies for systematic counterparty risk: the first proxy refers to the correlation structure between the average equity return of 14 major CDS dealers and the stock return of individual firms. We model the dependence using Student t-copulas that can also account for tail dependence between observed returns. The second proxy is the simple arithmetic mean of the major CDS dealers' CDS spread. We find systematic counterparty risk is mainly driven by changes in credit risk of large CDS dealers. Our findings also suggest that in the aftermath of the financial crisis the impact of systematic counterparty risk is higher, because recently the CDS market is even more concentrated among few CDS dealers. We also conduct robustness checks and perform a cointegration analysis subsequent to the multivariate regression. The findings of the cointegration analysis confirm the existence of a long-run relation among exogenous and endogenous variables of our regression models. Our findings have strong implications for the regulation of the credit default swap market and, especially for the introduction of a central counterparty for CDS clearing.

JEL classification: G21, G15, G12, G01

Keywords: Counterparty Risk, Systematic Risk, Credit Default Swaps, Copulas, Regulation

1. INTRODUCTION

The recent financial turmoil highlighted that counterparty risk represents a substantial risk for the stability of the financial industry with important implications for all other industries due to spill-over effects. The bankruptcy of Lehman Brothers in 2008 and the bailout of American International Group (AIG) are prominent examples of the dramatic impact of systematic counterparty risk. Both companies were highly involved in the credit default swap market and held huge exposures of CDS obligations.

A CDS contract is a simple insurance contract on the event that a specific firm defaults on its debt. Typically company A buys credit protection on debtor C from counterparty bank B. A pays B an annual insurance premium, and in case of default event by C, B pays A the difference between par value and the post-default value of the receivable held by A. But in case of a default by B within the lifetime of the insurance contract, A will face a severe loss. Therefore, A needs to assess the additional costs due to the default probability of its' counterparty B. The credit risk of the individual counterparty B is defined as individual counterparty risk. Given the credit risk of B is higher than the credit risk of other counterparties; A will pay less for B's CDS contract than for insurances from counterparties with lower credit risk. Therefore, individual counterparty risk creates a downward pressure on CDS spreads.

Similarly, we define systematic counterparty risk as the market wide counterparty risk represented by a risk factor as in the standard capital asset pricing model.[1] Given a joint increase in the credit risk of all counterparties, a good insurance is hard to find. The remaining counterparties will ask for a higher risk premium to cover the additional risk. Hence, an increase of systematic counterparty risk in financial markets leads to increasing CDS spreads of the reference entities. Using the systematic counterparty risk approach we are able to capture the cascading or systemic effect of default chains which are hard to model quantitatively.

In the recent past, most banks were CDS protection sellers and protection buyers. Therefore, the default of the top protection seller would create a chain of further defaults and lead to systemic default of the banking industry. Lehman and AIG can be considered as top protection seller. Both companies sold CDS protection to many other companies. Due to the subprime crisis large numbers of reference entities of these contracts defaulted and created a loss of $US 3.3 billion for Lehman and $US11 billion for AIG in 2007. Subsequently, Lehman filed for bankruptcy on 15 September 2008. As Lehman was counterparty in CDS-contracts for many other banks throughout the world, the fears of further bank defaults or a spill-over effect to other industries was significantly heightened and the CDS spreads of financial companies increased dramatically.

However, one day later, on 16 September 2008, the US government announced the bailout of AIG. AIG received approximately $US 150 billion from the US government by December 2008. The fears of systematic defaults in the aftermath of the Lehman default were so extreme the US government agreed to the biggest bailout in American history.

Despite the obvious significance of counterparty risk, hardly any empirical studies exist in literature concerning the measurement and magnitude of counterparty risk. Moreover, the empirical studies are apparently contradictory. Arora et al. (2012) analysed the impact of individual counterparty risk on CDS pricing and find that individual counterparty risk is negatively priced in the credit default swap market. However, their results are fairly weak indicating that an increase of 645 bps of the dealer's spread results in a decline of 1 bps in the price of credit protection.

[1] see Pu et al. (2009), p. 62.

Jorion and Zhang (2009) find evidence that systematic counterparty risk is positively priced and results in increasing CDS-spreads for creditors around the announcement of a debtor's default event. As they employ ordinary event study methodology, their results provide only a short-time view on the impact of systematic counterparty risk.

According to Pu et al. (2011) systematic counterparty risk in financial markets significantly increases CDS-spreads of others industries. They use the spread between LIBOR and Repo rates as a proxy for the systematic counterparty risk. Given the recent LIBOR-affair their proxy might be significantly biased resulting in an underestimation of counterparty risk. To address this issue we develop proxies to estimate the effect of systematic counterparty risk that are unbiased and straightforward. The first proxy refers to the default correlation structure between the average equity return of 14 major CDS dealers and the stock return of individual firm i using a Student t-copula. The second proxy is the simple arithmetic mean of major CDS dealers' CDS spread. We create easily observable proxies for systematic counterparty risk and, therefore, our study contributes to the correct pricing of credit default swaps.

Although the credit default swap market experienced a rapid growth since its inception in 1992, there remains hardly any regulation of CDS-contracts. CDS-contracts are individually negotiated agreements that are traded over the counter. Learning from the recent financial crisis international regulation authorities are trying to create a suitable regulation policy for CDS-contracts. These attempts include the creation of central counterparties (CCP) for CDS clearing to mitigate the systematic counterparty risk. As we develop a new method for the estimation of the magnitude of systematic counterparty risk, our research also contributes to the effectiveness of any new central counterparty regulation in the credit default swap market. Our findings are in line with Duffie and Zhu (2009) who find that the introduction of a central counterparty may increase the credit risk in the market under certain circumstances. Given the chosen margins are too high, smaller financial firms are not able to take part in the CDS without a dealing agent and the market may become more concentrated, resulting in an increased systematic counterparty risk. On the other hand systematic counterparty risk will be reduced via multilateral netting. Furthermore, our findings suggest that introducing a multinational counterparty would be more effective than the introduction of several national counterparties. This occurs because the systematic counterparty risk is driven by US as well as European large CDS dealers.

2. LITERATURE

2.1 PRICING CREDIT DEFAULT SWAPS

A CDS contract is an insurance contract against the default of a reference debt instrument, for example a bond. The protection buyer pays a periodic premium and in case of default on the reference bond, the protection seller pays the difference between par value and the post-default value of the bond.[2] Therefore, the value of a CDS contract can be best thought of as the difference between the expected cash flow of two legs, the fixed and the default one. We assume that the CDS-contract is valued from the protection buyer's point of view and that par value is normalized as unity. In the default event the protection buyer receives par value minus recovery rate R.[3]

Following the model by Hull and White (2000), the fixed leg represents all payments by the protection buyer and is given by:

[2] see Longstaff et al. (2005), S. 2216.

[3] see Hull and White (2000), p. 34.

$$V_{fixed} = w * \int_0^T q(t)\big(u(t) + e(t)\big)dt - (1 - \int_0^T q(t)\, dt\,)wu(T)$$

The protection buyer needs to pay until a credit event or until the end of the lifetime of the credit default swap T, whichever is sooner. If a default occurs at time t (t < T), the present value of the payments is $w\big(u(t) + e(t)\big)$, otherwise it is $wu(T)$.[4]
The expected amount of payment received by the protection buyer in case of a credit event defines the default leg: [5]

$$V_{default} = \int_0^T (1 - R - A(t)R)q(t)v(t)dt$$

Hull and White (2000) point out that the value of the Credit Default Swap is simply the difference between the two legs.

$$V_{CDS} = \int_0^T (1 - R - A(t)R)q(t)v(t)dt - (\int_0^T (q(t)\big(u(t) + e(t)\big)dt + (1 - \int_0^T q(t))wu(T))$$

with
T: Lifetime of CDS
q(t): Risk-neutral default probability density at time t
R: Expected recovery rate on the reference bond in a risk-neutral world.
u(t): Present value of payments at the rate of $1 per year on payment dates between time zero and time t
e(t): Present value of an accrual payment at time t equal to t − t∗ where t∗ is the payment date immediately preceding time t.
v(t): Present value of $1 received at time t
w: Total payments per year made by credit default swap buyer
A(t): Accrued interest on the reference obligation at time t as a percent of face value

The CDS spread is the value of *w*, which is obtained by solving the following equation: [6]

$$\frac{V_{default}}{V_{fixed}} = \frac{\int_0^T (1-R-A(t)R)q(t)v(t)dt}{w*\int_0^T q(t)\big(u(t)+e(t)\big)dt+(1-\int_0^T q(t)dt\,)wu(T)} = 0$$

The CDS spread s represents the total of the payments per year, as a percent of the notional principal, for a newly issued credit default swap.[7]
The equations above do not account for the counterparty risk. Models that ignore counterparty risk produce mispricing.[8] Several studies tried to account for default correlations by including a set of macroeconomic variables.[9] These macroeconomic variables are not able to explain the clustering of defaults around an economic recession.[10]

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4 see Hul and White (2000), p.34.
5 see Hull and White (2000), p.34.
6 see Hull and White (2000), p. 34.
7 see Hull and White (2000), p.34.
8 see Jarrow and Yu (2001), p. 1790.
9 see Duffee and Singleton (1999), p. 692. , see Lando (1998), p.99.
10 see Jarrow and Yu (2001),p. 1765.

Assume that counterparty risk ($\phi(t)$) is defined as the probability of default by the counterparty within the lifetime of the CDS in case there is no earlier default by the reference entity. Similarly, $\theta(t)$ denotes the probability of default by reference between times t and the lifetime of the CDS in case there is no earlier default by the counterparty. In case of a default by the counterparty, there is no final payment.[11]

According to Hull and White (2001) the equation above can then be extended to the following expression:

$$\frac{V_{default}}{V_{fixed}} = \frac{\int_0^T (1 - R - A(t)R)\theta(t)v(t)dt}{w * \int_0^T \big(\theta(t)u(t) + \theta(t)e(t)\big) + \phi(t)u(t))dt + \pi w u(T)} = 0$$

A credit default swap is an insurance contract against the default of a reference entity. Therefore, the periodic insurance premium or the CDS spread reflects the credit risk of the reference entity and should be equal to the credit spread of the reference entity's bond.[12] Therefore, the literature on credit spreads is useful for the pricing of CDS spreads, as well. Additionally, there is much more literature on credit spreads than on CDS spreads.

All theoretical models concerning credit spreads or CDS pricing in literature are either structural models inspired by Merton (1974) or reduced form models. These two types of default risk models differ significantly in the calculation of the default probability *q(t)*. Structural models assume that the probability of default is endogenous. In contrast to this, reduced form models assume that probability of default is exogenous.[13]

Structural models are based on the option pricing model by Black and Scholes (1973) and its formalization by Merton (1974). According to the structural model a zero bond defaults when the value of the entity is lower than the value of the bond at maturity or the leverage ratio is close to unity.[14] Subsequently the main determinants of CDS spreads in structural models are financial leverage, volatility and the risk-free term structure.[15]

Reduced form models assume a risk-neutral investor is indifferent between a risk-free treasury bond and a corporate bond if the present value of the expected cash flows equals the price of the treasury bond. To be able to calculate the expected value of the corporate bond, the probability of default and the recovery rate of the entity need to be determined.[16] According to reduced form models the Credit spread is determined by the probability of default, the recovery rate and the risk-free asset's yield.

However, many empirical studies find that both structural and reduced form models fail to fully explain all of the credit spread variations.[17] Several studies have tried to explain the residual spread. For example Longstaff et al. (2005) and De Jong and Driessen (2006) find that the residual spread can be explain by a liquidity premium. Other studies included macroeconomic variables, such as the gross domestic product, equity indices or inflation.[18] In the CDS market there are many more limitations than in the corporate bond market. Blanco et al. (2005) find that variables of the structural models

[11] see Hull and White (2001), p. 16.

[12]A Credit spread is the difference in yields between a corporate bond and a risk-free asset such as a Treasury bond, see Friewald et al. (2012),p.19.

[13] see Yawitz (1977),p.581.

[14] see Merton (1974),p. 458.

[15] see Pu et al. (2011), p.61.

[16] see Yawitz (1977), p.483, see Jonkart (1979), p.257.

[17] see Black and Cox(1976), p.351, see Kim et al.(1993),p.118, see Collin-Dufresne and Goldstein (2001),p. 1931,see Huang and Huang (2003), p.4.

[18] see Koopmann and Lucas (2005), p.316.

only explain about 25% of the changes in the CDS spread. Typically, CDS are traded over-the-counter; are highly specialized and usually not liquid for smaller names. Therefore, CDS spreads should be affected by a significant liquidity premium. Another complication is the existence of counterparty risk in CDS market. Counterparty risk is particular to the credit derivatives markets, it is not existent in the cash markets.[19]

Empirical studies show that counterparty risk affects CDS spreads in two ways. First, individual counterparty risk can be defined as the risk that the protection buyer does not receive the promised protection payment from a specific counterparty. Therefore, the protection buyer will pay less for a contract with a high-risk counterparty than for a contract with a low-risk counterparty. This creates a downward pressure on CDS prices.[20]

Arora et al. (2012) analysed the impact of individual counterparty risk on CDS-pricing and they find that individual counterparty risk is indeed negatively priced in the CDS market. However, their results are fairly weak indicating an increase of 645 bps of the dealer's spread results in a decline of 1 bps in the price of credit protection. Unfortunately, Arora et al. (2012) use a proprietary data set and, therefore, their proxy for individual counterparty risk cannot be used for other studies.

Second, systematic counterparty risk is defined as the joint credit risk of all counterparties. In the recent past, many protection buyers were protection sellers for other companies. Therefore, the unexpected default of the top protection seller counterparty might create a domino effect of defaults at other institutions. The bankruptcy of the US-bank Lehman Brothers in 2008 and the bailout of the US-insurance company American International Group (AIG) are prominent examples of the dramatic impact of systematic counterparty risk. Lehman Brothers was a protection seller for many other banks that were in turn protection sellers to other parties. The fears of systematic defaults in the aftermath of the Lehman default were so extreme that the US government agreed to the biggest bailout in the American history. Therefore, the magnitude of systematic counterparty risk in the credit default swap market should be much higher than the impact of individual counterparty risk.

Taylor (2009) analyses this kind of counterparty risk using the difference between LIBOR and the Overnight-Index-Swap spread as a proxy for the systematic counterparty risk. He finds that systematic counterparty risk increases CDS spreads.[21] Jorion and Zhang (2009) find evidence that systematic counterparty risk is positively priced and results in increasing CDS spreads for creditors around the announcement of a debtor's default event. As they employ ordinary event study methodology, their results provide only a short-time view on the impact of systematic counterparty risk.[22] According to Pu et al. (2011) systematic counterparty risk in financial markets significantly increases CDS spreads of others industries. They use the spread between LIBOR and Repo rates as a proxy for the systematic counterparty risk. Given the recent LIBOR-affair both Pu's (2011) and Taylor's (2009) proxies might be significantly biased resulting in underestimation of the counterparty risk.

2.2 REGULATION OF THE CDS MARKET

Before the recent financial crisis there was hardly any regulation of the credit default swap market. The first organization that tried to increase transparency in the credit default swap market was the

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19 see Pu et al. (2011), p. 62.
20 see Arora et al. (2012), p. 280.
21 see Taylor (2009), p. 15.
22 see Jorion and Zhang (2009), p. 2063.

International Swaps and Derivatives Association (ISDA). ISDA was founded in the 1990s and its board of directors comprises mainly CEOs from the financial industry. However, guidelines developed by the ISDA remained the only framework for standardized master agreements for a long time.[23] Master agreements allow all contracts between two counterparties to be netted and, therefore, mitigate counterparty risk.[24]

Another important way to mitigate counterparty risk before the financial crisis was the use of collateralization agreements. Due to the varying credit risk of the reference firm the value of the CDS contract differs significantly from zero over the lifetime of the CDS. Subsequently, each counterparty could be faced by a severe mark-to-market liability to the other. To mitigate this risk, the financial industry regulated itself by requiring full collateralization or over-collateralization.[25] Arora (2012) argues that the latter rather enhanced instead of mitigating counterparty risk. However, in the aftermath of the financial crisis several new regulation authorities and frameworks emerged. The two new major regulation approaches arising from the Pittsburgh Summit in 2009 are the introduction of a central counterparty, and the increase of capital requirements concerning CDS contracts that were not executed by a central counterparty (CCP). Currently, the ICE Trust, the EUREX and a joint venture between Chicago Mercantile Exchange and Citadel Investment Group offer CCP services for CDS contracts.[26]

The concept of a CCP is to replace the bilateral contract between two counterparties by two new contracts with the CCP. Subsequently, the credit risk is concentrated in the CCP and the market participants do not need to assess the credit risk of their bilateral counterparties anymore.[27] Additionally, CCPs allow for multilateral netting, so counterparty risk is theoretically reduced in a highly efficient way.[28]

However, several recent theoretical studies have emerged analysing whether a central counterparty increases or decreases counterparty risk.[29] Duffie and Zhu (2009) study whether a central counterparty could improve credit mitigation mechanisms such as bilateral netting. They find that a central counterparty might actually increase the amount of counterparty risk in markets. Furthermore, they point out that it is always more efficient to clear multiple derivative asset classes on the same central counterparty than on different ones.[30]

Biais et al (2012) suggest that CCPs are able to insure against idiosyncratic risk but not against systematic risk. In case that the latter is most important, protection buyers need to find robust counterparties, whose low default risk makes it possible to withstand aggregate shocks.[31]

Another important paper analysing this issue is Bliss and Steigerwald (2006). They conclude that in some cases a CCP might be the best alternative but in other cases it may not. Concerning CCPs in the Credit Default Swap market, there is the problem that CDS contracts are highly specialized. Unfortunately, CCPs need a sufficient volume to be of value for a particular market. Therefore, one of the biggest advantages of CCPs the increase in liquidity will not appear in the CDS market.[32]

Other studies argue that potential benefits of CCPs may be less obvious for buy-side firms than for sell-side firms. Due to their size and credit profile many buy-side firms will only have access to CCPs

[23] see Bliss and Kaufmann(2006), p. 58.
[24] see Arora et al. (2012), p. 283.
[25] see ISDA Margin Survey (2009), p. 2.
[26] see Meechan and Hodgson (2009), p.1.
[27] see Bliss and Steigerwald (2006), p. 25.
[28] see Cecchetti et al.(2009),p. 49.
[29] see Duffie and Zhu (2009), p. , see Monnet (2010), p. 1, see Mcllory (2010), p. 303, see Biais et al. (2012), p. 193,see Cerulus, S. (2012), p. 212.
[30] see Duffie and Zhu (2009),p. 25.
[31] see Biais et al. (2012), p. 193.
[32] see Bliss and Steigerwald (2006), p. 26.

via a third party member that passes the trades to a CCP. The third party member is likely to offer this service at a price that is prohibitive because it is faced with increased risk and additional infrastructure requirements. Therefore, smaller companies generally will be precluded from accessing CCPs.[33]

Additionally, the capacity of a CCP to absorb risk is determined by the equity injected by its members. CCPs collect an initial margin from members and if this margin is no longer sufficient to cover future exposures, the CCPs also collect a variation margin.[34] These fees might be too costly for small buy-side firms. Last but not least, the trading profile of most buy-side firms does not offer a large potential for netting positions.[35] These issues may result in a minor interest of buy-side firms to trade on CCPs in contradiction of the regulators' objective that all CDS contracts are traded on central counterparties.

Another notable new law in the US is the Dodd-Frank Wall Street Reform and Consumer Protection Act, signed in 2010. This act aims to promote the financial stability of the US by improving transparency in the financial system.[36]

The Dodd-Frank Act focuses on the systemic risk in financial markets and especially in the CDS market. Main features of the Dodd-Frank Act are the introduction of the Office for Financial Research (OFR), the Systemic Risk Council (SRC) and the Financial Stability Oversight Council (FSOC). According to the Dodd-Frank act all existing and new CDS contracts need to be registered at the OFR. The OFR collects the data on CDS contracts, analyses and reports it to other regulatory authorities. The SRC is authorized to identify, review and shut down a company with a high systemic risk exposure. The FSOC is responsible for identifying and observing systemic risks, for example large CDS dealers.[37] Acharya (2011) states that the Dodd-Frank Act is unquestionably the most ambitious and far-reaching reform of financial regulation in the United States since the 1930s, but there still some key areas left uncovered by the Dodd-Frank Act. For example, these include systemic risk arising from collections of smaller institutions.[38] Although, there are many new regulatory policies, it is not clear whether they will be efficient.

3. DATA

This study is based on sample of all firms including in the CDX North American Investment Grade Index Series 18. The CDX North American Investment Grade Index includes 125 firms. The CDS spreads are obtained from Bloomberg. Bloomberg offers many CDS contracts for each reference entity. The contracts differ in maturity, currency and seniority. Following Jorion and Zhang (2009), only five-year contracts are included in the sample, as these are the most liquid accounting for over 85% of the entire CDS market. Furthermore, only $US nominated senior contracts are included into the sample. The daily CDS data covers the period between January 2001 and June 2012. Rating histories of the reference entities are obtained from Standard and Poor's. Interest rates, macroeconomic and equity data are obtained from Thomson Reuters Datastream. After matching the CDS data with Thomson Reuters Datastream data, 266,606 daily observations are included into the sample.

33 see Meechan and Hodgson (2009), p. 2.
34 see Cecchetti et al.(2009), p. 50.
35 see Meechan and Hodgson (2009), p. 2.
36 see Dodd Frank Wall Street Reform and Consumer Protection Act (2010), p.1.
37 see Acharya et al.(2011), p. 45.
38 see Acharya et al.(2011), p. 56.

The total number of observations for the *Default_corr_dealers* variable is reduced to 246,188 observations due to the rolling window approach which is explained in detail in Section 4.

Table 1 shows the descriptive statistics for the variables used in the regression analysis. On average the CDS spread of the CDXNAIG firms is 87.99 bps and the mean CDS spread of the 14 main CDS dealers is 92.45 bps. In contrast, the average CDS spreads as well as the standard deviations of the 100 financial firms and the industry indices are much are higher. This reflects the fact that the 100 financial firms and the industry indices include Investment Grade firms as well as Non-Investment Grade firms. The median of the sample firms' ratings is 8, which equals a BBB+ long term rating by Standard and Poor's. The average equity volatility is 2% and the average leverage of the sample firms is 31.05%, which is in line with Pu et al. (2011).

On average, the bid-ask spread (*Liquidity*) of the sample firms is 7.26 bps. In the period between 2001 and 2012, the average spread between the London Interbank Offered Rate (LIBOR) and the Overnight Swap Index is 34 bps and the average difference between the LIBOR and the repo rates is 64 bps. The average interest rate is 1.89% and the growth of the real gross domestic product (*GDP*) is 1%.

Table 1: Descriptive Statistics

	mean	median	min	max	std. dev.
CDS_spread	87.99	58.67	4.35	2531.19	98.02
Default_corr_dealers	0.49	0.51	-0.42	0.89	0.17
Mean_CDS_dealers	92.45	76.63	11.02	324.23	77.71
0.25quantile_CDS_dealers	56.62	47.85	5.31	202.16	49.03
0.75quantile_CDS_dealers	141.34	127.18	18.69	647.50	120.94
LIBOR_OIS	33.95	14.30	-0.06	364.38	0.44
LIBOR_Repo	63.74	44.00	-60.88	511.88	0.66
CDS_financials	155.33	126.73	22.32	724.91	145.89
CDS_industry	202.40	139.07	10.20	8717.72	292.20
Equityvola	0.02	0.01	0.00	0.29	0.01
Leverage	31.05	30.17	24.16	41.64	5.00
Rating	7.55	8.00	1.00	12.00	1.94
Liquidity	7.26	5.33	-116.94	415.00	7.05
Interest	1.89	1.25	0.25	5.25	1.83
GDP	0.01	0.01	-0.01	0.02	0.01

Note: Table 1 shows descriptive statistics for CDS spreads as well as for all independent variables used in the regression analysis. All variables are based on daily data.CDS spread or LIBOR related variables are expressed in basis points.

4. METHODOLOGY

The impact of the systematic counterparty risk on the economy of the US is modeled by a multivariate regression model. The dependent variable is the daily CDS spread of company *i* at time *t*. The level of CDS spreads can be considered as an indicator of the financial health of the underlying reference entity. High CDS spreads indicate financial distress while low CDS spreads indicate a low bankruptcy risk.[39]

[39] see Flannery et al. (2010),p. 2100.

Conceptually, the regression model of this study refers to the structural model developed by Merton (1974) as well as to the reduced-form model by Hull and White (2001).
The multivariate regression model was estimated as:

$$CDS\_spread_{it} = c + \beta_1 * Counterparty\_risk_t + \beta_2 * CDS\_financials_t + \beta_3 * CDS\_industry_{it} + \beta_4 * Equityvola_{it} + \beta_5 * Leverage_{it} + \beta_6 * Liquidity_{it} + \beta_7 * Rating_{it} + \beta_8 * Interest_t + \beta_9 * gdp_t + \varepsilon_{it}$$

The variable $Counterparty\_risk_t$ denotes the proxies for systematic counterparty risk and can be either *Default_corr_dealers, Mean_CDS_dealers, 0.25_quantile_CDS_dealers, 0.75_quantile_CDS_dealers, LIBOR_OIS* or *LIBOR_Repo.*
Hull and White (2001) find that equity return correlations can be used as a proxy for the counterparty credit risk in the markets. Thus, the variable *Default_corr_dealers* was included in to the regression model. *Default_corr_dealers* is defined as the default correlation between the arithmetic mean of the equity returns of 14 major CDS dealers which give quotes for the firms included in the CDX North America Investment Grade index by MARKIT and the stock return of firm i at time t. The 14 CDS dealers are used as a proxy for the major counterparties in the CDS market. According to the European Central Bank (ECB), a small number of large CDS dealers account for a significant portion of gross notional trading volume of the CDS market.[40]
Morkoetter et al. (2012) use an ordinary correlation coefficient to capture the dependence structure between banks and industry companies. A major drawback of their approach is that simple correlation coefficients usually do not appropriately describe the dependence between financial assets.[41] Asset returns tends to be more highly correlated during market downturns.[42] Therefore, a bivariate time-varying t-copula is fitted to the data in order to describe the dependence structure between the stock returns of the 14 CDS dealers and the equity returns of firm *i*. In contrast to an ordinary correlation coefficient, a Student-t copula is able to capture symmetric tail dependencies and typically fits the dependence structure between equity return data very well.[43]
The copula concept was initially introduced by Sklar (1959) and has successfully been applied to financial data by e.g. Cherubini and Luciano (2001), Jondeau and Rockinger (2006), Junker et al (2006), Patton (2006), Genest and Rémillard (2009), just to name a few. A copula combines marginal distributions to form a joint multivariate distribution. Let $X = (X_1, \dots, X_n)'$ be a random vector of real-valued random variables whose dependence structure is completely described by the joint distribution function:

$$F(x_1, \dots x_n) = P\ (X_1 < x_1, \dots, X_n < x_n)$$

The copula C of vector X is obtained via component-wise transformation of each continuous variable X with its own distribution function F:

$$F(x_1, \dots x_n) = P\ (X_1 < x_1, \dots, X_n < x_n) = P\big(F_1(X_1) < F_1(x_1), \dots, F_n(X_n) < F_n(x_n)\big)$$

40 see ECB (2009), p. 4.
41 see Cherubini and Luciano (2001), p. 249, Jondeau and Rockinger (2006), p.829, Junker et al. (2006), p. 1188.
42 see Longin and Solnik (2001), p. 670.
43 see Jondeau and Rockinger (2006), p. 840. We performed the same estimations with the Clayton and the Gumbel copula and found that the reported results were not altered by the change of the copula. Results are available upon request.

$$= C(F_1(x_1), \ldots, F_n(x_n))$$

The Student t-copula is denoted by:

$$T_{\Sigma,v}(u_1, \ldots, u_d) = t_{\Sigma,v}(t_v^{-1}(u_1), \ldots t_v^{-1}(u_d))$$

where $t_{\Sigma,v}$ denotes the multivariate Student t distribution with v degrees of freedom and the correlation matrix Σ. Low values of the parameter v indicate strong tail dependencies. The Student t-copula belongs to the family of elliptical copulas. In contrast to Archimedian copulas, elliptical copulas can only be implicitly denoted but explicitly constructed and, therefore, they can be simulated comparatively easily.

In the bivariate case, the dependence parameter rho of the Student t-copula can be calculated as a function of Kendall's Tau τ. Genest and Rémillard (2009) show that this function yields a consistent estimator of the dependence parameter

$$rho = \sin(\frac{\pi\tau}{2})$$

where τ denotes Kendall's sample τ which is given by the following equation:

$$\tau = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j>i} A_{ij}$$

A_{ij} denotes the indicator variables for the estimation of τ from a random sample o f n pairs (Xi,Yi), i = 1,...,n. $A_{ij}$is given by:

$$A_{ij} = sgn(X_i - X_j)(Y_i - Y_j)$$

To obtain daily values of rho and to investigate the nature of dependence through time, a rolling time frame approach of 126 days is applied.[44] High values for rho indicate high default correlations and, therefore, a high systematic counterparty risk for firm i. Thus, the credit spread of firm i is expected to increase when *Default_corr_dealers* increases.

Daily equity return data is obtained from Datastream and the copula dependence parameters are estimated via MatLab.

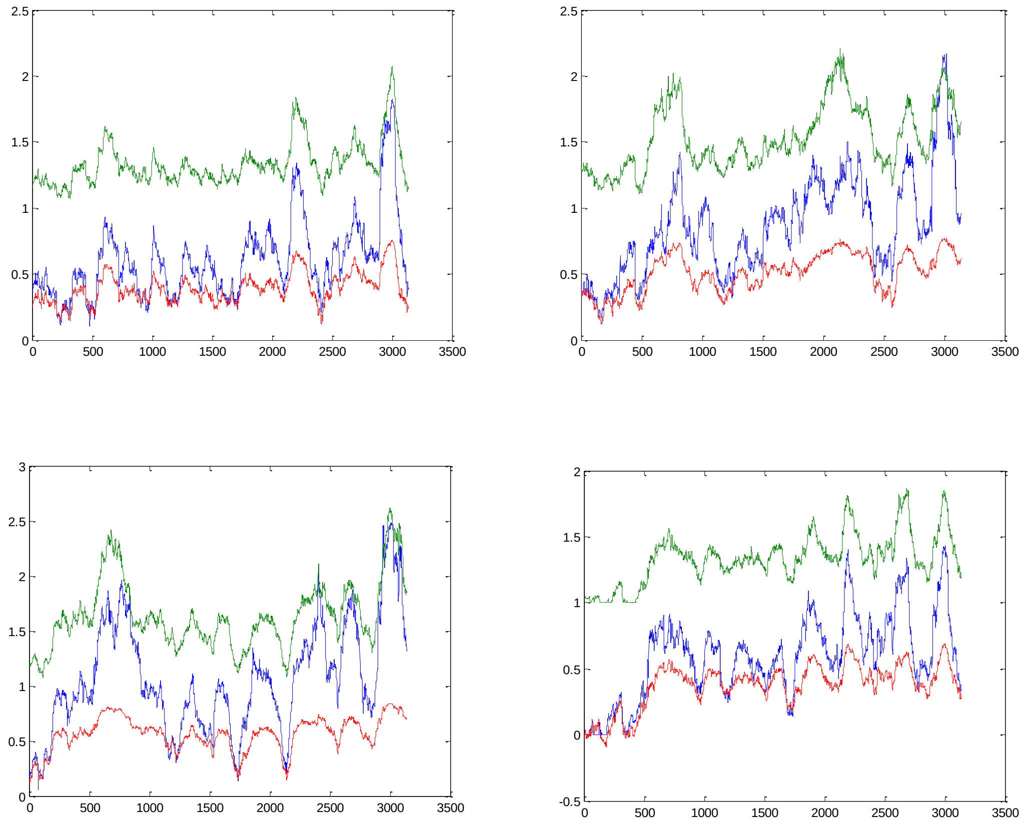
Figure 1 plots the results of the copula parameter estimations for the Clayton (blue), Gumbel (green), and Gaussian and Student t (red) copula for a six month rolling window period with start dates from Juni 27, 2000 up to July 6, 2012. The graphs show the results for dependence structure between daily returns for 14 large CDS dealers and ACE LTD (upper left panel), ATENA INC (upper right panel), ALCOA INC (lower left panel) and AMERICAN ELECTRIC POWER (lower right panel). The parameters are estimated for each firm i= 1,..,108. The results of the panel regression analysis presented in this study are based on the estimations for the Student t copula parameter rho.

The variable *Mean_CDS_dealers* is calculated as the daily average of the 14 major CDS dealers' credit spreads mentioned above. In a similar manner, *0.25_quantile_CDS_dealers* and *0.75_quantile_CDS_dealers* are calculated as the average of major CDS dealers with CDS spreads below the 0.25 quantile or above the 0.75 quantile for each day. In the period between 2001 and 2012, 16 large banks from the US, Great Britain, France and Germany were quote-giving banks for MARKIT. Due to mergers or bankruptcies in the aftermath of the financial crisis, two large banks (Lehman Brothers and Merrill Lynch) were replaced by two other banks, namely by Nomura and

[44] see Giacomini et al. (2009), p. 236, Grégoire et al. (2008), p. 67.

Wells Fargo. The mean of the CDS dealer spreads and the quantiles are estimated based on the 14 CDS dealers that were quote giving at time *t*. Given that these 14 CDS dealers are responsible for a large portion of systematic counterparty risk in the financial markets, CDS spreads of all other companies in the US should significantly increase when the dealers' CDS spreads increase.

Figure 1: Copula parameters



Notes: Figure 1 reports the copula parameter estimations for the Clayton (blue), Gumbel (green), and Gaussian and Student t (red) copula for a six month rolling windowperiod with start dates from Juni 27, 2000 up to July 6, 2012. The graphs showthe results for dependence structure between daily returns for 14 large CDS dealers and ACE LTD (upper left panel), ATENA INC (upper right panel), ALCOA INC (lower left panel) and AMERICAN ELECTRIC POWER (lower right panel). The parameters are estimated for each firm i= 1,..,108. The results of the panel regression analysis presented in this study are based on the estimations for the Student t copula parameter rho.

It is crucial for this study to notice that the 14 CDS dealers are dealing CDS contracts on reference entities, which are chosen as sample firms for this study. Therefore, an increasing counterparty risk of the protection sellers also leads to an increase of the reference entities' risk via the increasing risk of the protection buyers. This linkage reflects the cascading effect of systematic counterparty risk.

To be able to analyse whether the effect on the CDS spreads is driven by low-risk or high-risk dealers the regression model is re-estimated with the *0.25_quantile_CDS_dealers* and *0.75_quantile_CDS_dealers* variables. The "above 0.75 quantile" or the high-risk dealers are expected to have a stronger positive linkage to the CDS spreads of the other firms than the low-risk dealers.

Alternatively, two other variables are introduced to estimate the effect of systematic counterparty risk. Taylor (2009) points out that the difference between the LIBOR and Overnight Swap Index is a good representation of systematic counterparty risk. The Overnight Index Swap is a measure of the market expectations concerning the spread between the Federal Fund rate and the LIBOR. Since the OIS is subtracted from the LIBOR, the spread between LIBOR and OIS is corrected for all expectation effects and simply reflects level of financial stress due to counterparty risk in the market.[45]

An increased LIBOR- OIS spread is associated with increased costs of borrowing due to increased counterparty risk and, therefore, with increased CDS spreads. The variable *LIBOR_OIS* is the spread between the three-month LIBOR and the three-month Overnight Index Swap. Data is obtained from Thomson Reuters Datastream.

In addition to the LIBOR-OIS indicator Taylor (2009) developed another proxy for systematic counterparty risk based on the interest rate spread between secured and unsecured loans. Following Taylor (2009), Pu et al. (2011) used governmental-backed repo rate as a proxy for secured loans and the three-month LIBOR as representative for unsecured loans. They find a positive relation between the LIBOR_Repo spread and CDS spreads.[46] In this study, the variable *LIBOR_Repo* is calculated as the difference between the three-month LIBOR and the repo rates.

However, these measures might be biased because they are LIBOR-based measures.It was recently revealed that some big banks have manipulated the LIBOR for several years. The LIBOR is based on interest rates reported by major banks. The LIBOR is also used in the US derivatives market and underpins $US 350 trillion in derivatives. On June 27, 2012 Barclays was the first of approximately 20 banks that was fined $US 200 million when it was found to have artificially lowered the LIBOR. Since the financial crisis, the bank had reported a lower interest rate than the rate it was actually able to borrow at to make the bank look healthier. The crucial implication is that the LIBOR is traditionally considered to be a reliable proxy for overall business conditions. When the confidence in the market increases, banks report lower interest rates. When the confidence is low, banks report higher interest rates. Because the reported LIBOR in the period from 2008 to 2012 was lower than it should have been, both the LIBOR-OIS spread and the LIBOR-Repo spread were also smaller than they should have been, indicating a smaller counterparty risk in the markets. Therefore, these alternative measures are expected to have a weaker nexus to the CDS spreads than the *Mean_CDS_dealers* variable.

CDS_Financials denotes the daily average CDS spread of 100 financial institutions included in Russell 1000 index. If a financial institution is also a leading CDS dealer, it has been excluded from the calculation. The *CDS_Financials* variable is introduced to distinguish between the effect of the CDS dealers' spread variations and the variations in financial industry as a whole. Acharya (2011) states that there may be a portion of systematic counterparty risk created by smaller institutions, as well. Therefore, the average CDS spread of financial industry is expected to be positively linked to the CDS spreads of the other industries. However, the relationship is expected to be weaker than the nexus between the latter and *Mean_CDS_dealers* because the portion of systematic risk is predicted to be higher for the leading CDS dealers than for the smaller financial institutions.[47]

To control for increases in credit risk within a specific industry, the *CDS_Industry* variable is introduced. *CDS_Industry* is measured by the CDS spreads of each firm's sector indices provided by CMA. It is predicted that the CDS spread of firm *i* is positively linked to its sector CDS spread. The data is obtained from Thomson Reuters Datastream.

As mentioned above, this regression model is inspired by Merton's model (1974). Therefore, the idiosyncratic default risk of the reference entities is modeled by firm specific variables. In Merton's model the main determinants of credit risk are volatility, leverage and the risk-free asset.

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[45] see Taylor (2009), p. 13.
[46] see Pu et al. (2011), p. 69.
[47] see Acharya et al. (2011), p. 56.

Equity return volatility is closely related to the volatility of the underlying firm asset value, which directly effects the default probability of an entity. Therefore, an increase in volatility decreases the value of risky debt and increases CDS spreads.[48]

$Equityvola$ is computed from daily stock returns for firm *i* at day t, using an exponentially weighted moving average (EWMA) model. Daily stock return data are obtained from Thomson Reuters Datastream. EWMA type models have been suggested in the literature by various authors to model conditional heteroscedasticity and related risk measures such as VaR for stock returns, for example see Akgirav (1989), Balaban et al (2006), Guermat and Harris (1996), JP Morgan (1996). The creditability of JP Morgan's popular RiskMetrics, which uses an EWMA model to monitor and forecast volatility in equity markets, suggests the approach can be considered as a standard technique in financial risk management. The volatility of the considered companies is measured by applying an EWMA model using a value of lambda=0.94 as suggested by JP Morgan (1996).

In the structural approach, default is a function of the firm's capital structure. In the default event, the leverage ratio reaches unity.[49] Therefore, there should be a positive nexus between a firm's leverage and its CDS spread. The leverage ratio $Leverage$ for each firm at day *t* is computed as the book value of debt divided by the book value of debt plus the market value of equity. The data is obtained from Bloomberg. Since equity return volatility and leverage ratio data is available only on a monthly basis, a linear interpolation is used to obtain daily estimates as in Collin-Dufresne et al. (2001).

This study also uses a rating-based variable to capture further firm specific default risk. Ratings are closely related to CDS spreads as they are indicators for the financial health of a company.[50] A good rating and a low CDS spread imply a low default risk. To be able to analyse the effect of variations in the rating categories on CDS spreads, each rating class was attributed a number between 1 and 22 denoting the best rating class with 1, second best with 2 and so on. As such, an increase in variable *Rating* is associated with an increase in CDS spreads. The rating histories of the reference entities are obtained from Standard and Poor's. The Level of the CDS spreads might also be affected by the firm-specific liquidity of the CDS. Some studies state that CDS of smaller companies are not liquid.[51]

To account for different levels of liquidity, the variable *Liquidity* was included into the regression model. Several studies showed that the bid-ask spread is a good representation for the liquidity of a bond.[52] Subsequently, the daily bid-ask spread of the CDS of firm I was used as proxy for liquidity. The bid-ask data was provided by Bloomberg.

Following the structural approach, many studies find a strong negative link between the risk-free asset and CDS spreads.[53] An increase in interest rates reduces the default risk and decreases the CDS spreads. To capture this, the variable *Interest* based on the daily US Federal Funds Target Rate was used as proxy for the risk-free asset.

Merton (1974) showed that the volatility of a firm's value is dependent on the overall business climate. To capture macroeconomic influences on the CDS spread, a macroeconomic variable is included in the model, as well. In literature, the increase of the real gross domestic product is mentioned as an effective measure for the overall business condition.[54] Therefore, the variable *GDP* was created denoting the changes of the real gross domestic product.

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[48] see Pu et al. (2011), p. 66.
[49] see Merton (1974), p. 453.
[50] see Flannery et al. (2010), p.2098.
[51] see Pu et al. (2011),p. 63.
[52] see Longstaff et al. (2005), p. 2242.
[53] see Duffee (1998), p. 2240. Annaert et al. (2000),p.6, Düllmann et al. (2000), p.385, Leake (2003), p.23, Papageorgiou and Skinner (2006), p. 421.
[54] see Koopmann and Lucas (2005), p. 316., see Hackbarth et al. (2006), p. 548.

The data used within this study is panel data and, therefore, requires the estimation of robust standard errors to account for residual correlations. In panel data sets, the OLS standard errors may be biased due to residual correlations across firms or across time.[55] As a result, t-statistics that are based on biased standard errors may also be biased. In literature, there are many approaches that deal with robust standard errors.[56] However, most of these are biased.[57]

Petersen (2009) examines the different approaches and he finds that for residual dependence created by a firm effect only clustered standard errors are unbiased. He also states that for correlations due to time effect only the Fama and Macbeth (1973) method is unbiased. Therefore, for the appropriate method, it is important to distinguish between the two versions of underlying residual dependencies.[58]

The data set in this study consists of firm characteristics provided by 114 firms for 2560 days on average. Therefore, the firm effect is more eminent than the time effect. Following Peterson (2009), the regression model is estimated by panel regression with robust standard errors using the clustered standard errors approach to take the firm clusters into account. These standard errors account for cross-sectional dependencies in the error terms of the pooled data sample, but they may be biased downwards for the time-series correlations because they only can account for either the cross-sectional or the time dimension at the same time.[59]

According to Farrar and Glauber (1967), the results of a multiple regression might be affected by multicollinearity. Multicollinearity occurs when two or more independent variables in a regression models are highly correlated. Typical complications that are related to multicollinearity are unstable coefficients. A small change in the regression model results in large changes in the predictor coefficients.[60]

Table 2 presents the pairwise correlations between the variables. Obviously, the variables *Mean_CDS_dealers, 0.25_quantile_CDS_dealers* and *0.75_quantile_CDS_dealers* are highly correlated. This is because these variables are based on the same time series. To generate regression results that are not affected by multicollinearity, these highly correlated variables are not included together within the same regression model.

The variables *Mean_CDS_dealers* and *CDS_Financials* are also highly correlated. As the firms included in the *Mean_CDS_dealers* variable are financial firms, the observed correlation can be explained by the fact that both variables are based on the same industry. The aim of this study is to show that the largest dealers account for the biggest portion of counterparty risk in the market. Therefore, the joint coefficients of both variables in the same regression model are necessary to distinguish between the portions of counterparty risk explained by each variable. To capture this, the variables are separately as well as together estimated.

For the sake of completeness, it should be added that the variable *Interest* is significantly negatively correlated with some other variables. The level of correlation is somewhat lower than the other variables mentioned above, so no separate regression analysis is performed.

[55] see Petersen (2009), p. 435.
[56] see Fama and Macbeth (1973),p. 607, see White (1984), p. 817, see Newey and West (1987), p. 703, see Rogers (1993), p. 19.
[57] see Petersen (2009),p. 436.
[58] see Petersen (2009), p. 475.
[59] see Petersen (2009), p. 457.
[60] see Farrar and Glauber (1967),p. 93.

Table 2: Correlations Matrix

	Mean	0.25_quantile	0.75_quantile	Libor_OIS	Libor_Repo	Default_corr	Financials	Industry	Equityvola	Leverage	Liquidity	Rating	Interest	GDP
Mean	1													
0.25_quantile	0.977	1												
0.75_quantile	0.986	0.930	1											
Libor_OIS	0.497	0.369	0.601	1										
Libor_Repo	0.103	-0.015	0.204	0.682	1									
Default_corr	0.435	0.429	0.426	0.242	0.043	1								
Financials	0.796	0.716	0.830	0.626	0.251	0.370	1							
Industry	0.422	0.374	0.443	0.345	0.143	0.257	0.526	1						
Equityvola	0.438	0.356	0.491	0.596	0.359	0.290	0.632	0.419	1					
Leverage	0.196	0.188	0.194	0.107	0.023	0.150	0.212	0.125	0.248	1				
Liquidity	0.250	0.207	0.274	0.268	0.143	0.208	0.394	0.308	0.590	0.336	1			
Rating	0.095	0.105	0.086	0.006	-0.033	-0.009	0.070	0.136	0.095	0.020	0.155	1		
Interest	-0.694	-0.724	-0.642	-0.147	0.102	-0.290	-0.619	-0.295	-0.237	-0.191	-0.196	-0.099	1	
GDP	-0.502	-0.401	-0.585	-0.694	-0.398	-0.181	-0.619	-0.346	-0.498	-0.104	-0.232	-0.024	0.087	1

Note: Table 2 shows the bivariate correlations coefficients between the independent variables used in the regression analysis

5. STATIONARITY

Since this study uses e.g. CDS spread level data, there might be some concerns about stationarity.
A stochastical process is considered be to be stationary, if its joint probability distribution does not change when shifted in time or space. Consequently, parameters such as the mean and variance, if they exist, also do not change over time or position. For the use of econometric models, weak stationarity is often sufficient. Weak stationarity of a time series X_t is characterized by the following equations:

$$E(X_t) = \mu$$
$$Var(X_t) < \infty$$
$$Cov(X_{t1}, X_{t2}) = Cov(X_{s+t1}, X_{s+t2})$$

According to Granger and Newbold (1974), non-stationarity can lead to spurious regression results. Typically, the use of non-stationary time series in regressions results in inefficient coefficients and, therefore, invalid empirical tests.[61]
The spurious regression problem holds even in panel framework. However, it might be less of a problem because it is reduced by averaging across sections. Using pure non-stationary time series in regressions leads to non-consistent OLS estimators and diverging t-statistics. In contrast, regressing non-stationary panel data may provide consistent long-run regression coefficients because by pooling the cross-section and the time series observations, the strong effect of the residuals in the regression is smoothed.[62] However, even if the average long-run regression coefficients might be consistent, the t-statistics are still diverging.[63] Therefore, in this study a unit root test is conducted before performing the regression analysis. Unit root tests conduct the null hypothesis of a unit root in time series. Hence, when the null hypothesis is rejected, the time series is stationary.
Several studies find that ordinary time series unit root tests have limited power in panel data sets. Therefore, a large strand of literature concerning panel unit root tests emerged.[64] The main difference between panel unit root tests and ordinary time series tests is that panel tests consider a time dimension T as well as a cross-sectional dimension N.
One of the most commonly used panel unit root tests in literature is the test proposed by Levin, Lin and Chu (2002). They test the null H_0: each time series contains a unit root against H_1: each time series is stationary. The H_0 is very restrictive, as it does not allow for the intermediate case, where some cross-sections have unit root whereas other have not. However, the lag order *p* is permitted to vary across individuals. The test procedure involves four steps. In a first step, an augmented Dickey-Fuller (1979) (ADF) test is run for each cross-section. The test involves estimating the following regression:

$$\Delta Y_{it} = \alpha_{mi} d_{mt} + \gamma_i Y_{it-1} + \delta_{i1} \Delta Y_{it-1} + \cdots + \delta_{ip-1} \Delta Y_{it-p+1} + \varepsilon_{it}$$

Second, the individual residuals e_{it} and v_{it-1} are obtained by estimating the following equations:

$$\Delta Y_{it} = \alpha_{mi} d_{mt} + \delta_{i1} \Delta Y_{it-1} + \cdots + \delta_{ip-1} \Delta Y_{it-p+1} + e_{it}$$

61 see Granger and Newbold (1974), p. 111.
62 see Phillips and Moon (1999),p. 1080.
63 see Kao (1999), p. 6.
64 see Levin et al. (2002), p. 2 , see Im et al. (2003), p.54, , see Hadri (2002), p. 149.

$$Y_{it-1} = \alpha_{mi}d_{mt} + \delta_{i1}\Delta Y_{it-1} + \cdots + \delta_{ip-1}\Delta Y_{it-p+1} + v_{it-1}$$

The third step is the standardisation of the residuals by performing

$$\tilde{e}_{it} = e_{it}/\sigma_{\varepsilon i}$$

and

$$\tilde{v}_{it-1} = v_{it}/\sigma_{\varepsilon i}$$

where $\sigma_{\varepsilon i}$ denotes the standard error from each ADF regression. Finally, the following pooled OLS regression is performed:

$$\tilde{e}_{it} = \gamma\tilde{v}_{it-1} + \tilde{\varepsilon}_{it}$$

Under the null that the panel has a common unit root γ equals zero.

Table 3 shows the results of the Levin, Lin and Chu (2002) test for all firm specific variables. The results indicate that for most of the panel time series the first differences of the time series are stationary and, therefore, first order integrated (I(1)).

Table 3: Panel Unit Root Test Results

Variable	Level		1st Differences	
CDS_spread	0.0483		-325.408	***
Default_corr_dealers	2.99111		-635.074	***
Mean_CDS_dealers	10.5264		-66.2834	***
0.25quantile_CDS_dealers	8.0798		-381.142	***
0.75quantile_CDS_dealers	6.61331		52.5363	
LIBOR_OIS	-7.45692	***	59.9843	
LIBOR_Repo	-46.9953	***	356.509	
CDS_financials	-4.80595	***	-13.3473	***
CDS_industry	0.48361		-357.237	***
Equityvola	-1.11455		-561.947	***
Leverage	-1.13355		-664.057	***
Rating	-1.96339	**	-63.734	***
Liquidity	-14.0362	***	-61.9656	***
Interest	2.42955		-35.9387	***
GDP	-23.8093	***	-1.35754	*

*Note: Table 3 shows the ADF t-statistics of the panel unit root test proposed by Levin et al. (2002). The left column shows the test results for the time series levels and the right column reports the test statistics for the first difference of the time series used in the regression analysis. A large negative ADF t-statistic indicates the rejection of the null and therefore stationarity of the time series. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

The test has high power if T is relatively large. However, if T is very large, then Levin et al. (2002) suggest running separate unit root tests for each individual time-series. As in this study T=2500 on average, both a panel unit root test and an individual unit root test are applied.

Table 4 shows the results of the modified augmented Dickey-Fuller test proposed by Elliot, Rothenberg and Stock (1996) for each firm's CDS spread time series and all other variables used in the regression analysis, respectively. The test is similar to the augmented Dickey-Fuller (1979) test,

Table 4(I): Individual Uni Root Test Results

Panel A : Firm Characteristics

firm	name	CDS spreads	Default_corr	Equityvola	Leverage	Liquidity	Rating
1	ACE LTD	-1.021	-3.175 **	-3.514 ***	-0.526	-0.675	-2.063
2	AETNA INC	-1.608	-4.267 ***	-5.379 ***	-1.722	-1.383	-1.007
3	ALCOA INC	-2.477	-1.962	-2.804 *	-2.262	-2.705 *	-1.258
4	AMERICAN ELECTRIC POWER	-2.771 *	-2.162	-4.428 ***	-2.264	-3.720 ***	-0.991
5	AMERICAN EXPRESS CO	-2.789 *	-2.809 *	-2.541	-1.972	-3.160 **	-1.157
6	AMERICAN INTERNATIONAL GROUP	-3.907 ***	-3.011 **	-3.310 **	-1.113	-4.709 ***	-1.318
7	AMGEN INC	-2.678 *	-3.125 **	-1.321	-1.866	-1.609	
8	ANADARKO PETROLEUM CORP	-3.846 ***	-3.010 **	-3.724 ***	-2.675 *	-4.291 ***	-0.905
9	ARROW ELECTRONICS INC	-1.821	-2.231	-3.907 ***	-1.737	-2.069	-1.538
10	AT&T INC	-1.487	-3.180 **	-1.441	-2.236	-0.627	-1.682
11	AUTOZONE INC	-2.976 **	-2.260	-3.346 **	-2.305	-3.597 ***	80.624 ***
12	AVNET INC	-1.086	-2.242	-3.530 ***	-2.378	-2.991 **	-1.602
13	BARRICK GOLD CORP	-2.948 **	-3.927 ***	-3.573 ***	-2.101	-3.002 **	-1.190
14	BAXTER INTERNATIONAL INC	-2.933 **	-3.000 **	-6.123 ***	-2.733 *	-4.866 ***	-1.543
15	BEAM INC	-1.267	-3.367 **	-4.175 ***	-1.996	-1.359	-1.530
16	BERKSHIRE HATHAWAY INC-CL A	-1.310	-2.528 *	-2.091	-3.600 ***	-1.334	-1.604
17	BOEING CO/THE	-2.222	-2.299	-4.119 ***	-1.382	-3.777 ***	-1.187
18	BOSTON SCIENTIFIC CORP	-2.566 *	-3.007 **	-4.516 ***	-1.496	-1.886	-0.617
19	BRISTOL-MYERS SQUIBB CO	-2.618 *	-2.384	-1.155	-0.738	-4.838 ***	
20	CA INC	-1.357		-2.620 *	-1.965	-1.113	-1.158
21	CAMPBELL SOUP CO	-1.464	-2.882 *	-1.846	-1.527	-1.092	-1.233
22	CANADIAN NATURAL RESOURCES	-1.482	-3.998 ***	-3.398 ***	-2.344	-1.281	-1.723
23	CAPITAL ONE FINANCIAL CORP	-1.287	-2.890 **	-2.543	-3.065 **	-1.533	-0.598
24	CARDINAL HEALTH INC	-3.450 **	-2.600 *	-4.500 ***	-1.978	-3.680 ***	-0.893
25	CATERPILLAR INC	-2.854 **	-1.904	-4.140 ***	-2.227	-2.870 **	-1.344
26	CBS CORP-CLASS B NON VOTING	-2.727 *	-2.624 *	-2.142	-1.360	-2.531	-1.641
27	CENTURYLINK INC	-0.397	-3.079 **	-2.912	-2.039	-1.087	-1.544
28	CIGNA CORP	-2.885 **	-3.233 **	-4.360 ***	-2.455 *	-2.239	47.781 ***
29	CISCO SYSTEMS INC	-2.121	-1.893	-2.873 **	-0.750	-1.817	
30	COMCAST CORP-CLASS A	-1.918	-2.939 **	-1.519	-1.380	-1.826	-1.056
31	COMPUTER SCIENCES CORP	-1.388	-2.413	-4.813 ***	-1.825	-4.390 ***	-1.542
32	CONAGRA FOODS INC	-2.139	-2.697 *	-4.273 ***	-2.955 **	-1.977	-1.730
33	CONOCOPHILLIPS	-1.769	-3.240 **	-3.974 ***	-2.089	-3.765 ***	-0.830
34	COX COMMUNICATIONS INC-CL A	-2.287			-2.182	-4.802 ***	-1.294
35	CSX CORP	-1.931	-2.228	-3.200 **	-1.962	-2.907 **	-1.120
36	CVS CAREMARK CORP	-2.267	-3.013 **	-3.754 ***	-2.894 **	-1.835	-1.038
37	DARDEN RESTAURANTS INC	-1.489	-2.435	-2.831 **	2.376	-1.197	-1.488
38	DEERE & CO	-2.346	-1.697	-2.817 *	-2.125	-2.543	-0.994
39	DELL INC	-2.041	-1.944	-1.339	0.809	-3.178 **	-1.673
40	DEVON ENERGY CORPORATION	-1.390	-3.722 ***	-4.111 ***	-1.533	-3.816 ***	-0.604
41	DUKE ENERGY CORP	-0.692	-2.233	-4.130 ***	-1.102	-1.090	82.441 ***
42	EASTMAN CHEMICAL CO	-2.641 *	-2.011	-3.844 ***	-2.336	-0.777	-2.163
43	EXELON CORP	-2.112	-2.866 **	-3.716 ***	-1.244	-0.716	-1.788
44	EXPEDIA INC	-1.569	-2.674 *	-3.34 **	-1.519	-1.211	-1.793
45	FIRSTENERGY CORP	-2.265	-3.174 **	-3.157 **	-1.243	-4.279 ***	-1.366
46	FREEPORT-MCMORAN COPPER	-1.545			-2.162	-1.565	-1.73
47	GATX CORP	-1.68	-2.622 *	-1.566	-1.921	-1.583	-1.513
48	GENERAL ELECTRIC CO	-2.624 *	-2.997 **	-2.116	-1.302	-5.204 ***	-0.867
49	GENERAL MILLS INC	-2.668 *	-2.816 *	-3.631 ***	-1.19	-2.322	-0.918
50	GOODRICH CORP	-1.271	-1.995	-4.021 ***	-2.132	-0.93	-1.322
51	HJ HEINZ CO	-2.596 *	-1.844	-3.237 **	-1.496	-1.583	
52	HALLIBURTON CO	-0.832	-4.421 ***	-3.792 ***	-2.153	-2.858	-1.424
53	HEWLETT-PACKARD CO	-0.978	-1.972	-1.674	-0.661	-1.554	-1.068
54	HONEYWELL INTERNATIONAL INC	-2.399	-2.192	-4.639 ***	-2.126	-4.387 ***	82.578 ***
55	INGERSOLL-RAND PLC	-1.105	-1.526	-3.901 ***	-2.065	-2.521 *	
56	INTL BUSINESS MACHINES CORP	-2.383			-2.228	-3.927 ***	86.551 ***
57	INTERNATIONAL PAPER CO	-3.04 **	-2.282	-3.21 **	-1.747	-2.036	84.198 ***
58	JOHNSON CONTROLS INC	-2.35	-1.678	-1.569	-2.959 **	-2.455	-2.118
59	KINDER MORGAN ENERGY PRTNRS	-1.777	-3.558 ***	-2.607 *	-2.067	-1.638	-1.787
60	KOHLS CORP	-2.211			-1.575	-1.82	-2.966

*Note: Table 4 reports the t-statistics of the unit root test proposed by Elliot, Rothenberg and Stock(1996) for each individual time-series. A significant t-statistic indicates that the time-series is stationary. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

Table 4(II): Individual Uni Root Test Results - continued

Panel A : Firm Characteristics							
firm	name	CDS spreads	Default_corr	Equityvola	Leverage	Liquidity	Rating
61	KRAFT FOODS INC-CLASS A	-2.539	-3.866 ***	-2.269	-2.215	-2.95 **	-2.046
62	LOCKHEED MARTIN CORP	-1.178	-4.291 ***	-3.242 **	-0.003	-3.644 ***	-1.498
63	LOEWS CORP	-1.249	-2.438	-3.54 ***	-1.462	-0.606	-1.156
64	LOWE'S COS INC	-2.011	-2.482	-1.653	-2.166	-2.451	-0.502
65	MACY'S INC	-2.729 *	-2.570 *	-2.989 **	-2	-2.347	-1.299
66	MARRIOTT INTERNATIONAL-CL A	-2.448	-1.795	-3.499 ***	-2.032	-1.428	-1.668
67	MARSH & MCLENNAN COS	-1.879	-1.804	-3.624 ***	-1.427	-2.315	-1.773
68	MCDONALD'S CORP	-2.892 **	-2.404	-3.975 ***	-1.052	-2.468	-1.072
69	MCKESSON CORP	-3.8 ***	-3.845 ***	-1.461	-1.587	-1.95	-1.626
70	METLIFE INC	-1.976	-2.239	-2.217	-2.668 *	-1.791	-1.537
71	MOTOROLA INC	-2.137			-1.111	-2.611 *	-1.595
72	NATIONAL AUSTRALIA BANK LTD	-2.11	-2.950 **	-1.925 **	-0.848	-2.79 *	-1.425
73	NEWELL RUBBERMAID INC	-2.608 *	-3.157 **	-3.554 ***	-2.19	-1.443	-1.542
74	NORDSTROM INC	-2.744 *	-2.823 *	-3.001 **	-1.867	-2.214	-1.732
75	NORFOLK SOUTHERN CORP	-2.235	-4.326 ***	-1.924	-2.047	-1.208	-1.607
76	NORTHROP GRUMMAN CORP	-0.594	-4.330 ***	-4.322 ***	-2.511	-0.509	-1.019
77	OMNICOM GROUP	-1.911	-2.315	-3.276 ***	-2.488	-1.117	-1.703
78	PFIZER INC	-2.856 **	-2.445	-2.371	-1.577	-1.452	-1.567
79	PITNEY BOWES INC	1.033			-1.89	-2.403	-2.666 *
80	QUEST DIAGNOSTICS INC	-1.836			-0.401	-1.286	
81	RAYTHEON COMPANY	-0.864	-3.465 ***	-4.072 ***	-0.067	-2.771 **	-1.74
82	REYNOLDS AMERICAN INC	-2.936 **	-3.051 **	-3.371 ***	-1.248	-3.598 ***	-1.692
83	RYDER SYSTEM INC	-1.994	-1.549	-1.604	-1.588	-2.125	-1.206
84	SAFEWAY INC	0.415	-2.557 *	-3.135 **	-1.239	-0.341	-1.386
85	SARA LEE CORP	-3.514 ***			-1.343	-4.216 ***	-1.49
86	SEMPRA ENERGY	-0.587	-2.280	-4.316 ***	-1.366	-0.58	-1.092
87	SIMON PROPERTY GROUP INC	-2.761 **	-3.289 **	-2.845 **	-2.2	-2.579 **	
88	SLM CORP	-2.921 **	-1.711	-2.641 *	-0.678	-3.93 ***	
89	SOUTHWEST AIRLINES CO	-2.923 **	-2.811 **	-4.473 ***	-2.006	-2.496	
90	STARWOOD HOTELS & RESORTS	-1.813	-2.217	-3.964 ***	-1.732	-0.811	
91	TARGET CORP	-2.873 ***	-3.188 **	-2.388	-2.047	-3.443 **	
92	CHUBB CORP	-2.379	-2.912 **	-2.979 **	-1.786	-0.685	-1.789
93	ALLSTATE CORP	-3.022 **	-3.143 ***	-2.887 **	-1.779	-2.438	83.242 ***
94	DOW CHEMICAL CO/THE	-3.487 ***	-1.965	-3.325 **	-2.004	-3.088 **	-1.206
95	GAP INC/THE	-0.503	-2.207	-4.54 ***	-1.306	-1.534	-1.36
96	HARTFORD FINANCIAL SVCS GI	-2.404	-2.244	-4.002 ***	-2.375	-1.875	83.244 ***
97	HOME DEPOT INC	-2.181	-2.725 ***	-2.112	-1.107	-1.928	
98	KROGER CO	-1.859	-3.350 **	-3.859 ***	-2.235	-6.666 ***	
99	SHERWIN-WILLIAMS CO/THE	-1.986	-1.827	-2.806 *	-3.063 **	-1.437	
100	WALT DISNEY CO/THE	-2.552 *	-1.366	-1.812	-1.747 *	-2.485	
101	TIME WARNER INC	-2.646 *	-3.169 **	-1.81	-0.794	-3.391 **	
102	TRANSOCEAN LTD	-2.61 *	-3.226 **	-2.256	-1.477	-3.07 **	
103	TYSON FOODS INC-CL A	-2.443	-3.297 **	-3.337	-2.908 **	-2.678 *	
104	UNION PACIFIC CORP	-2.65 *	-2.859 **	-2.718 **	-2.587 *	-3.284 **	
105	UNITED PARCEL SERVICE-CL B	-1.689	-2.368	-2.394	-3.707 ***	-1.474	
106	UNITEDHEALTH GROUP INC	-1.306	-3.917 ***	-4.255 ***	-1.121	-0.888	
107	VALERO ENERGY CORP	-2.468	-3.382 **	-3.405 **	-1.462	-2.877 **	
108	VERIZON COMMUNICATIONS INC	-1.075	-2.658 *	-2.887 **	-2.13	-1.05	
109	VIACOM INC-CLASS B	-1.534	-3.007 **	-2.36	-0.719 *	-1.588	
110	VORNADO REALTY TRUST	-1.018	-2.803 *	-2.55 *	-2.028 *	-3.76 ***	
111	WAL-MART STORES INC	-2.705 *	-2.562	-1.524	-2.934 **	-2.177	
112	WHIRLPOOL CORP	-3.048 **	-1.710	-2.976 **	-2.96 **	-3.277 **	
113	XEROX CORP	-1.572	-2.855 **	-3.435 ***	-1.458	-3.689 ***	
114	YUM! BRANDS INC	-1.579	-2.859 **	-4.594 ***	-1.72	-1.713	
1%		6	15	50	2	23	8
5%		15	33	21	8	16	0
10%		18	14	7	8	5	1
no significance		75	52	36	96	70	105

*Note: Table 4 reports the t-statistics of the unit root test proposed by Elliot, Rothenberg and Stock(1996) for each individual time-series. A significant t-statistic indicates that the time-series is stationary. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

except the time series is transformed via a Generalized least squares (GLS) regression instead of an Ordinary least squares (OLS) regression. According to Elliot Rothenberg and Stock (1996), this test is more powerful than the augmented Dickey-Fuller test.

Analogous to the augmented Dickey-Fuller test, the modified augmented Dickey Fuller test performs the following regression but on GLS-detrended data:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1} \Delta Y_{t-p+1} + \varepsilon_t$$

The null hypothesis of the test is that Y_t is a random walk, possibly with drift and, therefore, H_0: $\gamma = 0$. Alternatively, Y_t can be stationary about a linear time trend or Y_t is stationary with a possibly non-zero mean but with no linear time trend.

According to Table 4, the vast majority of time series levels used in the regression analysis are not stationary. Hence, the results of the modified ADF test confirm the results of the Levin et al. (2003) panel unit root test.

The panel time series used in the multivariate regression analysis are level data. Therefore, the regression results may be affected by spurious regression. To check our results for spurious regression, we also perform a cointegration analysis. The results of the cointegration analysis are discussed in Section 7.

Table 4(III): Unit Root Test Results- continued

Panel B : Aggregate Time Series

Industry Indices			Other Aggregate Variables		
Auto	-2.545	*	Interest	-0.88	
Banks	-3.183	**	GDP	-3.431	**
Basic Resources	-3.064	**	Financials	-1.931	
Chemicals	-2.452		Mean_CDS_dealers	-1.951	
Construction/ Materials	-2.261		0.25_quantile_dealers	-2.055	
Financials	-2.548	*	0.75_quantile_dealers	-1.937	
Food	-2.189		LIBOR_OIS	-2.452	
Healthcare	-2.37		LIBOR_REPO	-5.69	***
Industrial G&S	-3.922	***			
Insurance	-2.733	*			
Media	-2.405				
OilGas	-2.219				
PSNL HHLD	-2.93	**			
Realestate	-1.202				
Retail	-3.084	**			
Technologies	-2.319				
Telecommunication	-2.304				
TravelLeisure	-1.841				
Utilities	-1.788				

*Note: Table 4 reports the t-statistics of the unit root test proposed by Elliot, Rothenberg and Stock(1996) for each individual time-series. A significant t-statistic indicates that the time-series is stationary. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

6. RESULTS

6.1 MAIN FINDINGS

Before performing a multivariate regression analysis, a univariate regression analysis is set up. Table 5 shows the results of the univariate regression analysis for the counterparty risk proxies. The dependent variable is the CDS spread level of firm *i* at day *t*. To account for firm clusters, robust standard errors are used for the calculation of the *t* values. The first line of the table denotes the coefficient for each variable and the second line reports the robust standard error. ***,**,* represent the significance levels of the *t*-values at 1%,5%,10% respectively.

Results show that all systematic counterparty risk proxies are significant and are of correct sign. R^2 ranges between 18.42% and 1.24% indicating that the variables explain a good portion of variations in the CDS spread levels. Compared to the other counterparty risk proxies, the LIBOR_Repo variable explains the smallest portion of CDS spread level changes (1.24%) and 0.75_quantile_dealers explains the highest portion (18.42%). Therefore, the results of the univariate analysis indicate that systematic counterparty risk in CDS-pricing is best approximated by the CDS spread level changes of the high-risk large CDS dealers.

Table 5: Univariate Analysis

	I	II	III	IV	V	VI
Default_corr_dealers	**150.97** ***					
	23.82					
Mean_CDS_dealers		**0.53** ***				
		0.05				
0.25_quantile_dealers			**0.76** ***			
			0.07			
0.75_quantile_dealers				**0.35** ***		
				0.03		
LIBOR_OIS					**77.87** ***	
					7.65	
LIBOR_Repo						**16.51** **
						2.68
cons		**39.35** ***	**45.12** ***	**38.82** ***	**-56.43** ***	**77.47** **
		3.55	3.55	3.56	20.73	3.79
Obs.	246,188	266,606	266,606	266,606	266,606	266,606
F	40.16 ***	109.23 ***	107.05 ***	105.27 ***	103.55 ***	37.95 ***
R^2	7.05%	17.40%	14.34%	18.42%	12.52%	1.24%

*Notes: Table reports the univariate regression results for the entire sample. Dependent variable is the CDS spread level of firm i at day t. To account for firm clusters, robust standard errors are used for the calculation of the t values. The first line of the table denotes the regression coefficient for each variable and the second line reports the robust standard error. All variables are calculated from daily data. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

Table 6 shows the results of the multivariate regression analysis for the entire sample. The dependent variable is the CDS spread level of firm i at day t. The first row of the table denotes the coefficient for each variable and the second line reports the robust standard error. All variables are calculated from daily data. Rating is a dummy variable equal to 1 for a reference entity rated AAA, 2 for AA+ and so on. ***,**,* represent the significance levels of the t-values at 1%,5%,10%, respectively.

Table 6: Regression Results Entire Sample

	I	II	III	IV	V	VI	VII	VIII
Default_corr_dealers	**49.55 *****							
	12.82							
Mean_CDS_dealers		**0.24 *****					**0.21 *****	
		0.04					0.02	
0.25_quantile_dealers			**0.36 *****					
			0.06					
0.75_quantile_dealers				**0.14 *****				
				0.02				
LIBOR_OIS					**-6.61**			
					6.70			
LIBOR_Repo						**-5.90 ****		
						2.44		
CDS_Financials	**0.00**	**-0.04**	**-0.02**	**-0.04**	**0.02**	**0.02**		**0.01**
	0.06	0.07	0.07	0.07	0.06	0.06		0.06
CDS_Industry	**0.01**	**0.01**	**0.01**	**0.01**	**0.02**	**0.02**	**0.01**	**0.02**
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Equityvola	**1654.60 ****	**1729.80 ****	**1753.999 ****	**1700.37 ****	**1764.27 ****	**1785.72 ****	**1633.57 *****	**1702.09 ****
	682.40	704.26	706.77	700.01	753.14	725.47	585.37	693.23
Leverage	**82.15 ****	**81.06 ****	**80.70 ****	**81.69 ****	**83.02 ****	**82.68 ****	**81.52 ****	**83.34 ****
	36.59	36.74	36.69	36.80	36.53	36.53	37.02	36.78
Liquidity	**6.91 *****	**7.09 *****	**7.09 *****	**7.07 *****	**6.91 *****	**6.91 *****	**7.06 *****	**6.94 *****
	1.85	1.92	1.93	1.92	1.85	1.87	1.86	1.87
Rating	**7.38 *****	**6.90 *****	**6.83 *****	**6.98 *****	**7.10 *****	**7.06 *****	**7.01 *****	**7.14 *****
	1.90	1.93	1.93	1.93	1.94	1.94	1.81	1.93
Interest	**-6.40 *****	**-2.95 ****	**-2.14 ****	**-3.99 *****	**-6.77 *****	-6.48 *******	**-2.05 ****	**-6.98 *****
	1.73	1.24	1.16	1.36	1.58	**1.58**	0.82	1.73
GDP	**-1072.48 *****	**-203.98**	**-336.81**	**-73.46**	**-1234.07 *****	**-1201.38 *****	**123.47**	**-1013.32 *****
	245.22	264.53	257.28	270.39	292.46	246.98	686.67	245.31
cons	**-80.78 *****	**-82.42 *****	**-84.53 *****	**-78.93 *****	**-56.04 *****	**-54.51 ****	**-88.28 *****	**-57.25 *****
	19.48	18.54	18.49	18.50	17.79	17.77	22.01	18.04
Obs.	178,949	179,493	179,493	179,493	179,493	179,493	179,493	179,493
F	76.06 ***	73.75 ***	73.76 ***	73.52 ***	72.42 ***	73.03 ***	65.65 ***	80.97 ***
R^2	67.34%	67.60%	67.70%	67.39%	66.74%	66.83%	67.54%	66.70%

*Notes: Table reports the multivariate regression results for the entire sample. Dependent variable is the CDS spread level of firm i at day t. To account for firm clusters, robust standard errors are used for the calculation of the t values. The first row denotes the regression coefficient for each variable and the second row reports the robust standard error. All variables are calculated from daily data. Rating is a dummy variable equal to 1 for a reference entity rated AAA, 2 for AA+ and so on. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

Regression models I to V show the effect of the counterparty risk variables on the CDS spread levels. The main finding is that only the *Default_corr_dealers*, *Mean_CDS_dealers*, *0.25_quantile _dealers* and *0.75_quantile _dealers* variables are significant and of correct sign. The *LIBOR-OIS* as well as the *LIBOR-Repo* spreads is no longer significant in the multivariate analysis. Moreover, the coefficients of the LIBOR-OIS and the LIBOR-Repo spreads are negative. These findings support the hypothesis that these measures are biased by the recent LIBOR affair. Subsequently, the findings are contradictory to Taylor (2009) and Pu et al. (2011), who state that the *LIBOR_OIS* spread and the *LIBOR_Repo* spreads are good measures for the portion of systematic counterparty risk in CDS spreads.

To distinguish between the effect of the leading CDS dealers' spread variations and variations in financial industry as a whole, the *CDS_Financials* variable is included in the multivariate regression models. The findings are in line with Acharya (2011) indicating a positive link between the CDS spread variations and CDS spread variations in the financial industry. *CDS_Financials* is of positive sign in almost all regression models.[65] Additionally, the findings confirm that systematic counterparty risk is fundamentally driven by CDS spread variations of the leading 14 CDS dealers. *CDS_Financials* is insignificant in all regression models irrespective of the inclusion of the *Mean_CDS_dealers* variable. Therefore, the results indicate that the portion of systematic counterparty risk created by other financial institutions is relatively lower than the portion of systematic counterparty risk created by leading CDS dealers. The *CDS_Industry* variable has the expected positive sign, but it is insignificant in all regression models. This finding indicates that the impact of an increased risk within a specific industry on CDS spread levels of sample firms of that industry is fairly weak compared to other firm specific or macroeconomic factors.

Firm specific variables implied by the structural model as well as macroeconomic control variables are significant and of correct sign in almost all regression models. R^2 is high, ranging between 66.70 % and 67.70%. The high R^2 indicates that the variables explain a large amount of CDS spread level changes.

6.2 NON-FINANCIAL AND FINANCIAL SUBSAMPLES

The full sample includes financial as well as non-financial firms. Financial statements of banks differ in many ways from those of non-financial firms. For example, banks have a large portion of financial assets on their balance sheets and are exposed to high credit, liquidity and market risks. To take these differences into account, the entire sample was divided into two subsamples. The first one includes all non-financial firms and the second one all financial firms. The latter is the smaller one representing 26,660 observations or 15% of the entire sample. Conversely, the non-financial sample includes 157,946 observations or 85% of the entire sample.[66]

Table 7 reports the multivariate regression results for the non-financial sample. Dependent variable is the CDS spread level of firm i at day t. The first row of the table denotes the regression coefficient for each variable and the second line reports the robust standard error. ***,**,* represent the significance levels at 1%,5%,10%, respectively. The results are similar to the findings of the entire sample. The systematic counterparty risk proxies *Default_corr_dealers*, *Mean_CDS_dealers, 0.25_quantile_dealers* and *0.75_quantile_dealers* are positive and significant at 1% level whereas *LIBOR_OIS* and *LIBOR_Repo* are not. The first ones are of the expected sign whereas the latter ones are not. Therefore, the results of the non-financials subsample support the findings of the entire sample.

However, in contrast to the results of the entire sample, the coefficient of the *CDS_Financials* is negative and significant at least at the 5% level. The results may for to two different reasons. First, the non-financial sample includes no financial firms. Therefore, *CDS_Financials* represents risk variations in a completely different industry, which may affect the CDS spreads of the sample firms contrarily.

Second, the findings support the hypothesis that counterparty risk is mainly driven by big CDS dealers, because of the impact of CDS spread level changes of larger CDS dealers are quite different from the impact of CDS spread variation of financials in general.

[65] The negative coefficient of *CDS-Financials* in regression models II-IV indicates the presence of multicollinearity. Especially *CDS-Financials* and *Mean_CDS_Dealers* are highly correlated. Therefore, the coefficient of CDS-Financials in model VIII is the most valid one.

[66] Numbers are based on 179,493 observations included in the multivariate regression models.

Table 7: Regression Results Non-Financials

	I	I	II	III	IV	V	VI	VII
Default_corr_dealers	**39.21 *****							
	9.18							
Mean_CDS_dealers		**0.28 *****					**0.21 *****	
		0.03					0.03	
0.25_quantile_dealers			**0.43 *****					
			0.05					
0.75_quantile_dealers				**0.17 *****				
				0.02				
LIBOR_OIS					**-5.76**			
					3.75			
LIBOR_Repo						**-6.25 *****		
						1.07		
CDS_Financials	**-0.08 *****	**-0.13 *****	**-0.11 *****	**-0.14 *****	**-0.06 *****	**-0.06 ****		**-0.07 ****
	0.02	0.02	0.02	0.02	0.01	0.02		0.02
CDS_Industry	**0.02 ***	**0.02 ***	**0.02 ***	**0.02 ***	**0.02 ***	**0.02 ***	**0.01**	**0.02 ***
	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Equityvola	**1459.17 *****	**1527.01 *****	**1556.59 *****	**1487.75 *****	**1562.74 *****	**1604.79 *****	**1100.10 ****	**1492.74 *****
	450.63	478.95	478.94	479.53	521.60	495.31	466.46	478.70
Leverage	**46.10 ****	**44.18 ****	**44.14 ****	**44.83 ****	**47.98 ****	**47.74 ****	**43.70 ***	**47.95 ****
	20.14	20.90	20.70	21.14	21.67	21.51	22.36	21.78
Liquidity	**11.47 *****	**12.08 *****	**12.10 *****	**12.00 *****	**11.51 *****	**11.53 *****	**11.52 *****	**11.54 *****
	1.63	1.73	1.73	1.72	1.65	1.64	1.73	1.64
Rating	**4.82 *****	**4.11 *****	**4.02 *****	**4.22 *****	**4.48 *****	**4.41 *****	**4.82 *****	**4.52 *****
	1.15	1.13	1.12	1.15	1.23	1.22	1.29	1.23
Interest	**-8.75 *****	**-4.38 *****	**-3.44**	**-5.56 *****	**-8.95 *****	**-8.62 *****	**-1.29 ***	**-9.12 *****
	0.71	0.73	0.77	0.70	0.70	0.69	0.73	0.72
GDP	**-1716.20 *****	**-682.07 *****	**-848.50 ****	**-503.09 *****	**-1818.80 *****	**-1826.48 *****	**412.69**	**-1628.89 *****
	220.39	185.99	193.63	176.80	159.81	214.59	255.71	227.82
cons	**-52.27 *****	**-64.07 *****	**-66.54 *****	**-60.13 *****	**-33.05 *****	**-31.28 *****	**-82.84 *****	**-33.94 *****
	8.01	8.69	8.62	8.68	8.15	8.02	10.46	8.14
Obs.	156,670	157,128	157,128	157,128	157,128	157,128	157,128	157,128
F	103.48 ***	101.47 ***	102.30 ***	99.80 ***	92.86 ***	94.42 ***	95.10 ***	104.13 ***
R^2	77.27%	78.63%	78.82%	78.21%	76.62%	76.80%	77.54%	76.58%

*Notes: Table reports the multivariate regression results for the "Non-Financials" sample. The Non-Financials sample equals the entire sample deducted by financial firms. Dependent variable is the CDS spread level of firm i at day t. The first rowof the table denotes the regression coefficient for each variable and the second rowreports the robust standard error. All variables are calculated from daily data. Rating is a dummy variable equal to 1 for a reference entity rated AAA, 2 for AA+ and so on. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

Table 8 reports the multivariate regression results for the financial sample. The dependent variable is the CDS spread level of firm *i* at day *t*. The first row of the table denotes the regression coefficient for each variable, while the second row reports the robust standard error. ***,**,* represent the significance levels at 1%,5%,10%, respectively.

The results basically confirm the findings for the full sample. *Default_corr_dealers*, *Mean_CDS_dealers,* and *0.75_quantile _dealers* are positive and significant at the 5% level. The *0.25_quantile _dealers* is insignificant in this subsample, confirming the hypothesis that systematic counterparty risk is driven by the high-risk large CDS dealers. Most variables are of the correct sign, despite LIBOR_Repo and LIBOR_OIS. The latter are negative and more or less insignificant indicating only a weak relation to the dependent variable. Furthermore, firm characteristic variables as well as macroeconomic variables are less significant compared to the entire sample. Somewhat surprisingly, *CDS_Financials* is insignificant in the financials sample insignificant, as well. In general, the explanation power of the estimated regression models is weaker compared to the entire or non-financial samples. However, R^2 still ranges between 61.38 and 63.78%

Table 8: Regression Results Financials Sample

	I	II	III	IV	V	VI	VII	VIII
Default_corr_dealers	**78.98** **							
	35.48							
Mean_CDS_dealers		**0.27** **					**0.34** **	
		0.13					0.13	
0.25_quantile_dealers			**0.38**					
			0.21					
0.75_quantile_dealers				**0.17** **				
				0.08				
LIBOR_OIS					**-1.85**			
					23.84			
LIBOR_Repo						**-6.66**		
						7.06		
CDS_Financials	**0.18**	**0.10**	**0.12**	**0.10**	**0.19**	**0.17**		**0.17**
	0.16	0.17	0.17	0.17	0.16	0.16		0.16
CDS_Industry								
Equityvola	**1676.15**	**1878.80** *	**1912.39**	**1833.47**	**1804.14**	**1874.64**	**2100.04** **	**1801.98** *
	1084.56	1118.49	1134.86	1102.00	1242.01	1144.05	925.11	1079.53
Leverage	**172.35**	**149.23**	**147.57**	**150.91**	**162.35**	**153.92**	**147.24**	**155.29**
	117.98	114.16	114.58	113.90	116.54	113.76	113.31	113.78
Liquidity	**4.24** **	**4.31** **	**4.31** **	**4.31** **	**4.16** **	**4.24** **	**4.30** **	**4.27** **
	1.61	1.62	1.63	1.62	1.71	1.59	1.63	1.61
Rating	**15.14** *	**14.95** *	**14.70**	**15.26** *	**17.29** *	**15.86** *	**14.90**	**16.06** *
	7.98	8.42	8.44	8.44	8.99	8.56	8.30	8.61
Interest	**-1.11**	**0.44**	**0.69**	**-0.47**	**-2.10**	**-2.87**	**-1.74**	**-3.41**
	4.85	3.90	3.62	4.10	5.22	3.75	3.12	4.13
GDP	**-106.66**	**318.62**	**108.67**	**453.62**	**-50.65**	**-752.46**	**-387.50**	**-611.95**
	1204.70	1452.59	1404.80	1494.80	1051.67	1055.46	2093.12	1140.12
cons	**-206.72**	**-173.81**	**-170.79**	**-172.98**	**-175.33**	**-151.54**	**-160.17**	**-155.58**
	132.75	125.86	125.02	126.24	125.56	120.02	128.14	120.71
Obs.	26,660	26,660	26,660	26,660	24,218	26,660	26,660	26,660
F	17.70 ***	10.63 ***	16.54 ***	10.73 ***	6.85 ***	11.42 ***	11.09 ***	10.50 ***
R^2	61.91%	61.79%	63.61%	61.72%	61.53%	61.43%	61.65%	61.38%

*Notes: Table reports the multivariate regression results for the "Financials" sample. The Financials sample equals the entire sample deducted by non-financial firms. Dependent variable is the CDS spread level of firm i at day t. The first rowof the table denotes the regression coefficient for each variable and the second rowreports the robust standard error. All variables are calculated from daily data. Rating is a dummy variable equal to 1 for a reference entity rated AAA, 2 for AA+ and so on. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

6.3 PRE- AND POST-CRISIS SUBSAMPLES

Recent financial turmoil has highlighted that systematic counterparty risk represents a substantial risk for the stability of the financial markets with implications for all other industries due to spill-over effects. The bankruptcy of Lehman Brothers has led to an increased awareness of systematic counterparty risk in the markets since 2008. Subsequently, the effect of systematic counterparty risk on CDS spreads should be stronger in the aftermath of the financial crisis. As stated before, the CDS market is concentrated among a few large dealers. Since the financial crisis there has been further concentration as some dealers merged while others filed for bankruptcy. Therefore, the effect of *Mean_CDS_dealers* is expected to be stronger in the aftermath of the financial crisis. To be able to analyse these time-related effects, the entire sample was divided into two subsamples. The first subsample represents all observations before the recent financial crisis and the second one represents all observations since the financial crisis.

Table 9 reports the multivariate regression results for the pre- and post-crisis subsamples. The left-hand side of the table reports the regression results using all observation before the 15 September 2008, while the right-hand side reports the results using all observations after 15 September 2008. On 15 September 2008 Lehman Brothers filed for bankruptcy. This date marks substantial declines in stock returns throughout the world and, therefore, the depth of the recent financial crisis. The dependent variable is the CDS spread level of firm i at day t. The first line of the table denotes the regression coefficient for each variable and the second line reports the robust standard error. ***,**,* represent the significance levels at 1%,5%,10%, respectively.

The results are in line with the hypothesis that the impact of systematic counterparty risk on CDS spreads is higher in the aftermath of the financial turmoil. Almost all systematic counterparty risk proxies in the pre-crisis subsample are either insignificant or significant at a lower level than the proxies of the post-crisis subsample.[67]

Furthermore, the results show that the increased concentration of CDS dealers in the aftermath of the financial crisis leads to a higher significance of the systematic counterparty risk measured by the *Default_corr_dealers* and the *Mean_CDS_dealers* proxy in the post-crisis subsample. For example, the *Mean_CDS_dealers* coefficient in model II of the pre-crisis subsample is insignificant whereas the coefficient in model I of the post crisis subsample is significant at 1% level.

Additionally, the effect of CDS spread level changes in the financial industry (*CDS_Financials*) on CDS spreads of other industries seems to be stronger before the financial crisis. This finding indicates that systematic counterparty risk is basically driven by few larger CDS dealers, as well.

Somewhat surprising, the nexus between CDS-industry index changes (*CDS_Industry*) and CDS spread level changes of the sample firms is weaker in the post-crisis subsample than in the pre-crisis subsample. The *CDS_Industry* coefficient in the pre-crisis subsample is at least significant at the 5% level whereas the coefficient is insignificant in the post-crisis subsample.

Firm specific variables implied by the structural model as well as macroeconomic control variables are significant and of correct sign in almost all regression models.

The coefficients of macroeconomic variables such as *Interest* and *GDP* in the pre-crisis regression models are insignificant whereas the coefficients of the post-crisis subsample are highly significant. The results show the macroeconomic effects became more important factors for CDS-pricing after the financial crisis. R^2 ranges around 60% for the pre-crisis subsample as well as for the post-crisis subsample.

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[67] Despite this, the LIBOR_Repo variable is negative and significant in the pre-crisis subsample and insignificant in the post crisis subsample.

Table 9: Regression Results Pre- and Post-Crisis Subsamples

	Pre-Crisis								Post-Crisis							
	I	II	III	IV	V	VI	VII	VIII	I	II	III	IV	V	VI	VII	VIII
Default_corr_dealers	**16.05**								**56.34**							
	8.64 *								22.34 **							
Mean_CDS_dealers		**0.08**					**0.19 *****			**0.22 *****					**0.20 *****	
		0.07					0.03			0.03					0.04	
0.25_quantile_dealers			**0.12**								**0.37 *****					
			0.08								0.05					
0.75_quantile_dealers				**-0.01**								**0.14 *****				
				0.03								0.02				
LIBOR_OIS					**-4.39**								**18.94** **			
					4.19								8.22			
LIBOR_Repo						**-0.97** ***								**-1.72**		
						0.34								2.29		
CDS_Financials	**0.19 *****	**0.12 ***	**0.13 ****	**0.22 *****	**0.22 *****	**0.20 *****		**0.20 *****	**-0.02**	**-0.05**	**-0.03**	**-0.06**	**-0.04**	**-0.01**		**-0.01**
	0.04	0.07	0.05	0.05	0.04	0.03		0.03	0.08	0.08	0.08	0.09	0.07	0.08		0.08
CDS_Industry	**0.06 ****	**0.06 ****	**0.06 ****	**0.06 ****	**0.06 ****	**0.06 ****	**0.06 *****	**0.06 ****	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Equityvola	**1406.21 *****	**1423.38 *****	**1417.923 *****	**1431.48 ****	**1450.26 *****	**1434.65 *****	**1426.96 *****	**1429.58 *****	**1835.08 ****	**1887.06 ****	**1857.78 ****	**1907.54 ****	**1859.55 ****	**1918.06 ****	**1769.26 ****	**1913.92 ****
	471.77	473.22	474.27	473.23	484.85	473.89	473.63	473.01	830.56	837.24	837.92	837.67	854.75	840.61	691.44	835.86
Leverage	**43.48 ****	**43.38 ****	**43.38 ****	**43.39 ****	**43.45 ****	**43.38 ****	**43.45 ****	**43.39 ****	**120.20 ***	**120.91 ***	**121.16 ****	**120.99 ***	**122.99 ****	**122.74 ****	**122.05 ***	**122.74 ****
	16.41	16.43	16.44	16.41	16.42	16.41	16.44	16.42	61.15	61.66	61.73	61.58	61.55	61.47	62.18	61.48
Liquidity	**8.14 *****	**8.22 *****	**8.21 *****	**8.23 *****	**8.21 *****	**8.23 *****	**8.20 *****	**8.23 *****	**6.48 *****	**6.59 *****	**6.61 *****	**6.57 *****	**6.54 *****	**6.49 *****	**6.57 *****	**6.50 *****
	2.33	2.33	2.33	2.33	2.34	2.33	2.32	2.33	2.02	2.06	2.06	2.06	2.03	2.04	2.02	2.04
Rating	**5.48 *****	**5.25 *****	**5.25 *****	**5.24 *****	**5.25 *****	**5.24 *****	**5.25 *****	**5.24 *****	**8.08 ****	**8.18 ***	**8.19 ****	**8.17 ****	**8.19 ****	**8.16 ****	**8.36 *****	**8.16 ****
	0.89	0.90	0.90	0.90	0.90	0.90	0.90	0.90	3.11	3.21	3.20	3.21	3.20	3.20	2.98	3.20
Interest	**-0.05**	**-0.27**	**-0.30**	**0.27**	**0.36**	**0.19**	**-1.18**	**0.16**	**-21.92 *****	**-25.86 *****	**-20.46 *****	**-30.43 *****	**-40.38 *****	**-17.55 *****	**-20.27 ****	**-20.41 *****
	1.20	1.31	1.27	1.24	1.14	1.16	0.98	1.16	6.80	7.05	6.86	7.51	6.17	4.43	7.73	6.90
GDP	**305.47**	**275.13**	**243.48**	**393.51 ***	**426.77 ***	**401.07**	**-2.67**	**373.54**	**-1239.94 *****	**-1087.99 *****	**-1312.75 *****	**-836.31 *****	**-371.78**	**-756.22 *****	**-121.97**	**-708.72 ****
	239.30	237.45	242.68	230.55	244.60	238.75	213.43	233.16	389.88	312.49	332.66	305.49	257.26	283.65	1740.82	306.69
cons	**-92.55 *****	**-83.16 *****	**-82.62 *****	**-87.66 *****	**-88.37 *****	**-86.68 *****	**-75.32 *****	**-86.76 *****	**-87.33 *****	**-87.43 *****	**-95.03 *****	**-82.19 *****	**-60.72 ****	**-66.56 ****	**-100.80 *****	**-66.10 ****
	16.54	18.75	18.67	18.14	17.19	17.25	15.98	17.27	30.22	28.56	28.80	28.50	28.10	28.53	26.73	28.51
Obs.	95,296.00	95,208.00	95,208.00	95,208.00	95,208.00	#######	95,208.00	95,208.00	83,739.00	84,285.00	84,285.00	84,285.00	84,285.00	#######	84,285.00	83,883.00
F	61.02 ***	67.22 ***	66.21 ***	59.67 ***	65.74 ***	60.96 ***	65.76 ***	67.07 ***	27.88	30.39 ***	32.66 ***	29.17 ***	35.76 ***	25.58 ***	33.00 ***	25.52 ***
R^2	65.87%	65.73%	65.75%	65.72%	65.73%	65.73%	65.69%	65.72%	62.42%	62.48%	62.52%	62.38%	61.85%	61.75%	62.38%	61.97%

*Notes: Table reports the multivariate regression results for the pre- and post crisis subsamples. The left-hand side of the table reports the regression results using all observations before the September 15, 2008 whereas the right-hand side reports the results using all observations after September 15, 2008. On September 15, 2008 Lehman Brothers filed for bankruptcy. This date marks substantial declines of stock returns all over the world and therefore the peak of the recent financial crisis. Dependent variable is the CDS spread level of firm i at day t. The first line of the table denotes the regression coefficient for each variable and the second line reports the robust standard error. All variables are calculated from daily data. Rating is a dummy variable equal to 1 for a reference entity rated AAA, 2 for AA+ and so on. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

7. COINTEGRATION ANALYSIS

To check whether the regression results are affected by spurious regression due to non-stationary time series, a cointegration analysis is performed subsequent to the regression analysis.

Cointegration refers to the long-run relationship between two or more variables. The intuition is that common non-stationary forces can be eliminated by considering the linear combination. The variables in a p-dimensional system of non-stationary processes are called cointegrated, if a linear combination $v'X_t$ is stationary. In this case, v denotes the cointegrating vector.[68]

Cointegration techniques have been widely used in empirical studies. The most common one is the test proposed by Engle/Granger (1987). They perform a two-step residual-based test. In a first step, the residuals are estimated using an ordinary Least-Squares regression on the dependent and independent variables. Second, the first difference of the residuals is regressed on the lagged level of the residuals without a constant. Under the null that the dependent variable and independent variables are not cointegrated, the residual should be non-stationary. In other words, they perform a Dickey/Fuller (1979) test on the residuals.

One shortcoming of the Engle/Granger test is that it does not permit for more than one cointegration relationship. Therefore, Johansen (1991) developed a test allowing for several cointegrating relations.

However, concerning panel data, traditional tests, such as the augmented Dickey/Fuller test tend to have low power in panel data sets. Levin and Lin (1993) pointed out that the power of panel cointegration tests increases dramatically as the cross-section dimension increases.

In literature, there are two different types of panel cointegration tests. The first group are residual-based tests, such as McCosky and Kao (1998), Pedroni (2004) and Kao (1999). Residual-based tests are based on the time series cointegration test proposed by Engle and Granger (1987). The residuals for the test statistics are obtained by estimating static panel regressions.

A second group of panel cointegration tests are maximum-likelihood-based tests, such as Groen and Kleibergen (2003), Larsson and Lyhagen (1999) and

Larsson et al. (2001). Similar to most of the tests in the first group, they test the null of no cointegration and the decision principle is whether the error process of the equation is stationary or not.

The latest panel cointegration tests are error correction model (ECM) tests developed by Westerlund (2007) and Gengenbach, Urbain and Westerlund (2009). These ECM approaches check whether or not an ECM has an error correction or not.

In this study, cointegration relations are examined by using the panel cointegration test proposed by Kao (1999). Kao (1999) developed two panel cointegration tests: the Dickey/Fuller type and the augmented Dickey/Fuller type test. The null hypothesis is no cointegration for both tests. The tests are limited to the special case where cointegration vectors are homogenous between individuals because the alternative hypotheses does not allow for heterogeneity and these tests can only be applied in a multivariate regression where X>2.

Kao derives the DF test statistic from a simple regression of $\hat{e}_{it}$ on its own lagged value. Similarly, he develops the ADF test statistic by adding the lagged changes in the residuals to the regression mentioned above. This yields to the following equation:[69]

[68] see Johansen (1991), p. 313.
[69] see Kao(1999), p.9.

$$\hat{e}_{it} = \rho\hat{e}_{it-1} + \sum_{j=1}^{p} \varphi_i \Delta\hat{e}_{it-j} + v_{itp}$$

The ADF test statistic is the usual t-statistic of ρ =1 in the above regression and is given by:

$$t_{ADF} = \frac{(\rho - 1)(\sum_{i=1}^{N}(e_i' Q_i e_i))^{\frac{1}{2}}}{s_v}$$

where $Q_i = I - X_{ip}\left(X_{ip}' X_{ip}\right)^{-1} X_{ip}'$ and $s_v^2 = (\frac{1}{NT}) \sum_{i=1}^{N} \sum_{t=1}^{T} v_{itp}$ with X_{ip} being the matrix of observation on the *p* regressors $(\Delta\hat{e}_{it-1}, \dots \Delta\hat{e}_{it-p})$ from the above equation.
Using the sequential limit theory, Kao shows via further computations that the ADF test statistic is asymptotically normal distributed. Kao finds that the test has little power when T is small, but the size distortion disappears quickly when T increases.
Table 10 reports the ADF t-statistics of the panel cointegration test proposed by Kao (1999) for regession models I-VII. A large negative ADF t-statistic indicates the rejection of the null of no cointegration. ***,**,* represent the significance levels at 1%,5%,10%, respectively
The ADF statistics indicate a strong cointegration relationship among CDS spreads and the variables used in each individual regression model.

Table 10: Panel Cointegration Test Kao (1999)

Model	ADF-Statistics		Residual Variance	HAC Variance
I	-21.84	***	34.04	51.39
II	-22.71	***	33.75	47.78
III	-22.58	***	33.71	48.80
IV	-22.94	***	33.80	45.87
V	-21.57	***	33.81	50.90
VI	-21.71	***	33.81	51.00
VII	-22.47	***	36.11	50.31
VIII	-21.51	***	33.81	51.05

*Note: Table 10 reports the ADF t-statistics of the panel cointegration test proposed by Kao (1999) for regession models I-VII. A large negative ADF t-statistic indicates the rejection of the null of no cointegration. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

However, Kao's test does not allow for the bivariate case with only one cointegration relation. Therefore, in addition to Kao's test, the panel cointegration test proposed by Pedroni (2004) is performed. Pedroni (2004) considers seven test statistics for the null of no cointegration. He distinguishes between panel and group statistics. The former are based on pooling the data along the within dimension and the latter are based on pooling along the between dimension of the panel.
In a first step, both cases require obtaining the individual residuals $(\hat{e}_{it})$ for each member of the panel via the estimation of the following equation:[70]

[70] see Pedroni (2004), p. 599.

$$Y_{it} = \alpha_i + \delta_i t + \beta_i X_{it} + \hat{e}_{it}$$

where X_{it} is an m-dimensional column vector and β_i is an m-dimensional row vector for each panel member i. The parameters α_i, δ_i and β_i are allowed to vary by individual and, therefore, the cointegrating vectors may be heterogeneous across the panel.
Second, the individual residuals are pooled to various statistics. The panel cointegration statistics are constructed by summing the numerator and the denominator terms over the N dimension separately. Pedroni (2004) mentions the following panel cointegration statistics:

$$Z_{vNT} = \hat{L}_{11}^2 \frac{1}{(\sum_{i=1}^N A_{22i})} \text{ (panel v statistic)}$$

$$Z_{\rho NT} = \frac{\sum_{i=1}^N (A_{21i} - T\hat{\lambda}_i)}{(\sum_{i=1}^N A_{22i})} \text{ (panel rho statistic)}$$

$$Z_{tNT} = \frac{\sum_{i=1}^N (A_{21i} - T\hat{\lambda}_i)}{\sqrt{(\sigma_{NT}^2 \sum_{i=1}^N A_{22i})}} \text{ (panel PP statistic)}$$

where A_i equals $\sum_{t=1}^T \tilde{e}_{it} \tilde{e}_{it}'$ with $\tilde{e}_{it} = (\Delta\hat{e}_{it,} \hat{e}_{it-1})$ defining $\hat{e}_{it,}$ as individual residuals from the initial equation above. Further, $\hat{\lambda}_i = T^{-1} \sum_{s=1}^K w_{sK} \sum_{t=s+1}^T \hat{\mu}_{it} \hat{\mu}_{i,t-s}$ for some choice of lag window with $w_{sK} = 1 - \frac{s}{1-K}$ and $\hat{\mu}_{it} = e_{it} - \rho_i e_{it-1}$. The long-run variance $\tilde{\sigma}_{NT}^2$ is defined as $N^{-1} \sum_{i=1}^N \hat{\sigma}_i^2$ with $\hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i$ where $\hat{s}_i^2 = T^{-1} \sum_{t=2}^T \hat{\mu}_{it}{}^2$.[71]
$\hat{L}_{11}^2 = N^{-1} \sum_{i=1}^N \hat{L}_{11i}^2$ where the nuisance parameter estimator $\hat{L}_{11i}^2$ denotes the individual long-run conditional variance for the residuals η_{it} of the differenced regression and is given as $\widehat{\Omega}_{11i} - \widehat{\Omega}_{21i} \widehat{\Omega}_{22i}{}^{-1} \widehat{\Omega}_{21i}{}'$ using any kernel estimator for Ω. The differenced regression of the original time series for each member equals:[72]

$$\Delta Y_{it} = \beta_i \Delta X_{it} + \eta_{it}$$

The panel v-statistic is a non-parametric variance ratio statistic, the rho statistic is a panel version of the non-parametric Phillips and Perron (1988) ρ- statistic and the t-statistic is a non-parametric average of the Phillips and Perron (1988) t- statistic.
In contrast, the group cointegration statistics are calculated by dividing the numerator by the denominator prior to summing over the N dimension. Therefore the group statistics are simply the average of the individually estimated autocorrelation coefficients. The group mean statistics are:[73]

$$\tilde{Z}_{\rho NT} = \sum_{i=1}^N \frac{(A_{21i} - T\hat{\lambda}_i)}{A_{22i}} \quad \text{(group rho statistic)}$$

$$\tilde{Z}_{tNT} = \sum_{i=1}^N \frac{(A_{21i} - T\hat{\lambda}_i)}{\sqrt{(\sigma_{NT}^2 A_{22i})}} \text{ (group PP statistic)}$$

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[71] see Pedroni (2004), p. 604.
[72] see Pedroni (1999), p. 659.
[73] see Pedroni (2004), p. 604.

Despite the way of construction, the two groups of statistics differ in the alternative hypothesis specification. The panel statistics test for a common autoregressive coefficient $\rho = \rho_i$ for all panel members, whereas the group statistics allow for heterogeneous coefficients under the alternative hypothesis.
The above statistics are non-parametric. Their computation involves the estimation of the following autoregression equation:

$$\hat{e}_{it} = \rho_i \hat{e}_{it-1} + \hat{u}_{it}$$

The residuals $\hat{u}_{it}$ are used to calculate the long-run variance $\hat{\sigma}_i^2$. Pedroni (1999) mentions parametric ADF-type panel and group statistics, as well. He shows that the statistics can be written as:

$$Z_{tNT}^{*} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\widehat{L_{11i}^{-2}} e_{it-1}^{*}\Delta\hat{e}_{it}^{*}}{\sqrt{(\tilde{s}_{NT}^{*2}\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{L}_{11i}^{-2}\hat{e}_{it-1}^{*2})}} \text{ (panel ADF statistic)}$$

$$\tilde{Z}_{tNT}^{*} = \sum_{i=1}^{N}\frac{\sum_{t=2}^{T}\hat{e}_{it-1}^{*}\Delta\hat{e}_{it}^{*}}{\sqrt{(\sum_{t=2}^{T}\hat{s}_{NT}^{*2}\hat{e}_{it-1}^{*2})}} \text{ (group ADF statistic)}$$

The ADF type statistics are obtained by estimating the appropriate autoregression:

$$\hat{e}_{it} = \rho_i \hat{e}_{it-1} + \sum_{k=1}^{K_i}\rho_i \Delta\hat{e}_{it-k} + \hat{u}_{i,t}^{*}$$

The residuals $\hat{u}_{i,t}^{*}$ are used to compute the corresponding long-run variance $\hat{s}_i^{*2}$.
Using the sequential limit theory, all test statistics have standard normal asymptotic distributions under the null hypothesis as T and N grow to infinity. Under the alternative hypothesis the panel v-statistics diverges to positive infinity.
Pedroni (1997) shows that all test statistics have the same power when T>100.
Table 11 shows the test results of the panel cointegration test proposed by Pedroni (1999, 2004) for single cointegration relations between the *CDS_spreads* and the variables used in the corresponding univariate regression model. The left column shows the test results for the panel statistics and the right column reports the group test statistics. A large (negative) test-statistic indicates the rejection of the null and, therefore, cointegration between the two time series. The panel statistics consider the alternative hypotheses of a common autoregressive (AR) coefficient, whereas the group statistics tests for the alternative hypotheses of individual AR coefficients. ***,**,* represent the significance levels at 1%,5%,10%, respectively. The results indicate a strong cointegration relation among *CDS_spreads* and the independent variables.

Table 11: Panel Cointegration Test Pedroni (2004)

	Panel Statistics: Common AR Coeff.				Group Statistics: Individual AR Coeff.		
Independent Variable	v-Statistic	rho-Statistic	PP-Statistic	ADF-Statistic	Group rho-Statistic	Group PP-Statistic	Group ADF-Statistic
Default_corr_dealers	23.72 ***	-20.22 ***	-12.57 ***	-12.33 ***	-12.73 ***	-10.23 ***	-9.65 ***
Mean_CDS_dealers	28.56 ***	-23.39 ***	-13.48 ***	-13.77 ***	-21.92 ***	-15.59 ***	-15.16 ***
0.25quantile_CDS_dealers	24.83 ***	-19.63 ***	-11.85 ***	-11.85 ***	-17.75 ***	-13.07 ***	-12.05 ***
0.75quantile_CDS_dealers	34.01 ***	-31.17 ***	-16.95 ***	-15.57 ***	-30.30 ***	-20.11 ***	-17.76 ***
LIBOR_OIS	24.17 ***	-27.69 ***	-13.37 ***	-13.59 ***	-18.21 ***	-11.64 ***	-12.36 ***
LIBOR_Repo	18.99 ***	-27.69 ***	-15.88 ***	-13.65 ***	-20.87 ***	-14.14 ***	-12.31 ***
CDS_financials	43.87 ***	-35.07 ***	-19.54 ***	-19.95 ***	-30.44 ***	-19.20 ***	-18.87 ***
CDS_industry	49.09 ***	-63.64 ***	-28.61 ***	-17.69 ***	-39.62 ***	-20.06 ***	-16.86 ***
Equityvola	45.27 ***	-51.02 ***	-24.47 ***	-22.71 ***	-41.61 ***	-23.27 ***	-21.90 ***
Leverage	37.12 ***	-27.15 ***	-15.74 ***	-15.20 ***	-19.73 ***	-13.31 ***	-12.13 ***
Rating	22.00 ***	-18.42 ***	-11.37 ***	-12.11 ***	-13.37 ***	-9.47 ***	-9.21 ***
Liquidity	57.76 ***	-2142.64 ***	-247.82 ***	-18.05 ***	-673.15 ***	-111.03 ***	-15.94 ***
Interest	22.72 ***	-18.13 ***	-11.70 ***	-12.48 ***	-14.80 ***	-11.47 ***	-11.42 ***
GDP	26.99 ***	-21.69 ***	-13.37 ***	-14.30 ***	-14.04 ***	-11.48 ***	-11.78 ***

*Note: Table 11 reports the panel and group statistics of the panel cointegration test proposed by Pedroni (2004).The underlying regression model is a univariate regression using CDS_spreads as dependent variable.The left column shows the test results for the panel statistics and the right column reports the group test statistics. A large (negative) test-statistic indicates the rejection of the null and therefore cointegration between the two time series. The panel statistics consider the alternative hypotheses of a common autoregressive (AR) coefficient, whereas the group statistics tests for the alternative hypotheses of individual AR coefficients. ***,**,* represent the significance levels at 1%,5%,10%, respectively.*

8. CONCLUSIONS

Using a comprehensive panel data set with 266,606 observations of 114 US companies over the period from 2001 to mid-2012 we show systematic counterparty risk is statistically and economically significant in credit default swaps market. A change of 42 bps of the average 14 largest CDS dealers spread results in an increase of 10 bps for the sample firm CDS spreads.

To analyse the effect of systematic counterparty risk on CDS spreads, we create and compare several proxies for systematic counterparty risk and set up a multivariate panel regression model, including a set of well-known control variables. To check the findings for robustness, we perform a cointegration analysis subsequently to the multivariate regressions. The findings of the cointegration analysis confirm the existence of a long-run relation among the dependent and independent variables of our regression models.

The proxies for systematic counterparty risk are based on structural as well as on reduced-form models (see Merton 1970, Hull and White 2001). We develop two proxies for systematic counterparty risk: The first proxy refers to the default correlation structure between the average equity return of 14 major CDS dealers and the stock return of individual firm i using a Student t-copula. The second proxy is the arithmetic mean of major CDS dealers' CDS spread. We find that the simple average CDS spread of 14 large CDS dealers reflects the portion of systematic counterparty risk in CDS spreads best. LIBOR based measures seem to be biased by the recent LIBOR affair and, therefore, underestimate the portion of counterparty risk significantly.

Furthermore, we show that systematic counterparty risk is mainly driven by changes in risk of 14 large multinational CDS dealers whereas changes in risk of non-dealing financials have no impact on systematic counterparty risk.

Our findings suggest that in the aftermath of the financial crisis the impact of systematic counterparty risk is higher because the CDS market is even more concentrated among few CDS dealers. These findings have a strong impact on the introduction of a central counterparty in the credit default swap market. As a CCP allows for multilateral netting among the participating CDS dealers, our findings support the hypothesis that a CCP will be able to reduce the portion of systematic counterparty risk significantly. On the other hand, margins should be chosen carefully otherwise smaller financial firms might be excluded from the CDS market resulting in a higher market concentration and, hence, a higher counterparty risk. Therefore, our findings are in line with Duffie and Zhu (2009) who find that a central counterparty might actually increase the amount of counterparty risk in the markets. Furthermore, they point out that it is always more efficient to clear assets on the same central counterparty than on different ones.[74] Our findings are also in line with this argument, because the 14 large CDS dealers, who represent the largest portion of counterparty risk in the markets, are US as well as European banks. Therefore, the introduction of only one international CCP would be most efficient.

It would be interesting to compare the magnitude of individual and systematic counterparty risk within one regression model, as well. Due to the lack of an appropriate proxy for individual counterparty risk, we leave this issue to future research.

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[74] see Duffie and Zhu (2009),p. 25.

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