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The impact of counterparty risk on credit default swap pricing dynamics

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As observed throughout the financial crisis in 2008, credit default swaps (CDSs) are exposed not only to the credit risk of the underlying reference entity but also to the counterparty risk of the protection seller. Conducting a panel regression analysis based on CDS contracts from 2004 to 2009 in Europe and North America for 198 reference entities, we find that market-oriented counterparty risk measures are reflected in the pricing of CDS contracts. The impact of counterparty risk decreases when increased creditworthiness of the underlying reference entity occurs. We show that counterparty risk had already been incorporated in the CDS spreads for North American reference entities prior to the financial crisis, whereas, for European reference entities, the pricing impact only intensified with the outbreak of the financial crisis in September 2008. Market-based counterparty risk measures have a higher impact on the pricing of CDS contracts compared with measures that rely on the correlation structures of asset returns of reference entities and CDS counterparties.

1 INTRODUCTION

During the recent financial crisis, in addition to widening credit default swap (CDS) spreads, investors were faced with the unexpected termination of CDS contracts due to the default of protection sellers. During the weeks prior to the Lehman Brothers default, for example, it was reported that CDS traders paid lower CDS spreads in cases where Lehman Brothers acted as a protection seller. It became clear to the protection buyers of CDS contracts that they are not only exposed to the credit risk of the reference entity but also to the default probability of the protection seller. We therefore define counterparty risk as the default probability of the protection seller. Previously, financial literature on the valuation of credit default swaps has recommended a default correlation framework in the style of Merton (1974) to capture counterparty risk. This approach relies on long-term *ex ante* asset correlations in order to assess *ex interim* default correlation between the protection seller and the underlying reference entity. As observed throughout the financial crisis, this framework was not able to fully reflect the counterparty risk exposure of CDS contracts.[1]

Against this background, our paper aims to introduce and empirically test two different proxies for counterparty risk. Our first measure directly reflects changes in market perceptions of counterparty risk, and refers to the credit risk of the banks trading CDS contracts (average banks' CDS spreads) adjusted according to the corresponding CDS index level. We thereby create abnormal counterparty spreads in excess of market levels. For our second measure we follow the approach of modeling default correlations between the reference entity and the protection seller based on asset return correlation structures (see Hull and White (2001)).

The recent financial crisis has shown that the dominating pricing models for CDS contracts do not fully reflect the risk exposure of the CDS contracts. We contribute to the existing literature by extending the framework for modeling counterparty risk by proposing a short-term market-oriented perspective. By introducing our market-based measure we are able to reflect the current market conditions of counterparties more accurately and do not have to rely only on long-term *ex ante* data. This allows us to immediately mirror changing market conditions such as increasing credit risk or volatility spikes.

In order to test this hypothesis empirically, we conduct a panel regression analysis based on CDS contracts from 2004 to 2009 in Europe and North America. We adjust for entity-fixed and time-fixed effects and develop two counterparty default measures, which are analyzed both individually and in the context of additional determinants of CDS spreads.

Our results have three dimensions. First, it is shown that counterparty default risk measures, which have been adjusted for the level of the respective CDS index, have a negative impact on CDS spreads in Europe and in North America in the specified period of time. Abnormal counterparty CDS spreads lead to lower CDS spreads for the protection buyer, whereas the impact of counterparty risk decreases as the creditworthiness of the underlying reference entity increases. Second, we find that counterparty risk had already been reflected in the CDS spreads for North American reference entities prior to the financial crisis, whereas, for European reference entities, the pricing impact only intensified with the outbreak of the financial crisis in September 2008.

[1] There is, however, a growing literature on the sophisticated evaluation of CDS contracts with models that can be calibrated to market data (see, for example, Mahfoudhi (2011)).

Third, market-based counterparty risk measures have a higher impact on the pricing of CDS contracts than do measures that rely on the correlation structures of asset returns of reference entities and CDS counterparties. Our results are of particular interest for investors, but also for regulators demanding a higher degree of transparency in credit derivative markets.

The remainder of the paper is organized as follows. Based on a literature review in Section 2, in Section 3 we introduce the data used, and in Section 4 we present the applied methodology of counterparty risk. Section 5 gives a presentation of the empirical results, and these are then discussed in Section 6. Section 7 concludes the paper.

2 LITERATURE REVIEW

A large body of financial literature has emerged on the subject of the pricing structure of CDS spreads. Against the background of our main research question, two strands of literature can be distinguished: first, literature relating to modeling the counterparty risk of CDS contracts; and second, research focusing on additional pricing determinants of CDS contracts, which will be used later in the paper as control variables for our model.

Duffie (1999) develops a pricing model for credit default swaps, modeling the hazard rate as a Poisson process arrival rate of default, where the reference entity's default process is determined by the first jump time of the specified Poisson process. Extending the reduced-form model by Duffie (1999) with regard to counterparty default risk, Jarrow and Yu (2001) apply the primary–secondary framework. Hence, the default process of a primary firm is exclusively dependent on macrovariables. Secondary firms' default processes, however, are not only dependent on macrovariables but also on the primary firms' default processes. Leung and Kwok (2005) further incorporate interdependent default correlations between the protection buyer, the protection seller and the reference entity. Relating to this literature, recent work by Gündüz and Uhrig-Homburg (2011) provides an empirical comparison of structural and reduced-form credit risk frameworks by assessing the out-of-sample prediction quality on time series of CDS prices. The authors find that the model's prediction power is quite close to average, with an outperformance of reduced-form approaches for investment grade names and longer maturities.

Hull and White (2000, 2001) develop a direct pricing model for credit default swaps with counterparty default risk. Whereas Duffie (1999) models the hazard rate as the probability that the bond will default within a time frame between t and $t + \Delta t$, given no earlier default, Hull and White (2000) define the probability density function as seen at the issuance of the CDS contract at time zero. By incorporating default correlations between different entities, Hull and White (2001) extend their valuation model by taking into account counterparty default risk and compute the default correlation between two firms from their respective credit index correlation. The higher the default correlation between the buyer and the seller of the CDS and the lower the credit quality of the issuer, the higher the impact of the default correlation on counterparty default risk. Mahfoudhi (2011) proposes a CDS tree model that simplifies and unifies the CDS valuation based on the incorporating of extended market data, which might also help to incorporate counterparty default components assuming that these are contained in market prices.

The second branch of literature deals with pricing determinants of CDS spreads. A wide range of microeconomic and macroeconomic factors have been analyzed in this context. Early empirical research shows that, besides the rating of the underlying being the most powerful source of information, other factors, such as risk-free interest rate, stock return of the reference entity, interest rate volatility, maturity and exercise price, should be incorporated into models (see Skinner and Townend (2002)).

Longstaff *et al* (2005) find that implied CDS spreads significantly exceed market spreads due to treasury specifications, illiquidity in corporate bond markets and the presence of counterparty credit risk. Das *et al* (2009) compare the explanatory power of accounting-based and market-based models of CDS spreads and find that models including both accounting and market information perform better than separate models. Alexander and Kaeck (2008) demonstrate that, in times of economic turbulence, CDS spreads react more sensitively toward equity volatility, whereas CDS spreads are usually more sensitive with regard to equity returns.

Ericsson *et al* (2009) conclude that theoretically implied variables, such as leverage and volatility, explain a significant proportion of CDS variations. In contrast to the majority of empirical analyses on the determinants of CDS spreads, Pires *et al* (2008) apply a quantile regression approach in order to model the distribution of CDS spreads. The authors reveal that results differ significantly between lower- and higher-rated firms and claim that, besides traditional variables, a transaction costs perspective should be included in the regression model.

Additionally, Fabozzi *et al* (2007) analyze the variables of risk-free term structure, industry, credit rating and liquidity and find a positive relationship between the liquidity factors and CDS premiums. By establishing liquidity proxies capturing adverse selection, inventory costs and search frictions, Tang and Yan (2007) provide evidence that liquidity risk and liquidity level explain a significant proportion of CDS spread variation.

Byström (2005) and Zhang *et al* (2008) specifically investigate the impact of equity returns and volatility of the reference entity on the CDS premium. Exploring the relationship between the CDS index market and the stock market, Byström (2005) shows that CDS spreads tighten in response to increasing stock prices and that stock price volatility is positively correlated with CDS prices. Having controlled for historical default probabilities and by calibrating a structural valuation model with stochastic equity volatility and jump risks, Zhang *et al* (2008) explain 73% of the variation of CDS spreads.

Houweling and Vorst (2001) conduct an empirical analysis comparing CDS spreads implied by a simple reduced-form framework with market CDS spreads derived from the underlying bond's credit spread. Using swap or repurchasing agreements (repo) curves instead of the treasury rate as a proxy for the riskless interest rate, they maintain an outperformance of model-implied CDS spreads compared with market practice.

3 DATA SAMPLE

The ensuing analysis on the impact of counterparty risk on CDS spread levels is based on a data sample of 198 different reference entities. Our data set includes both European and North American reference entities, and all are derived from the major CDS indexes. The CDS contracts analyzed are taken from the Markit iTraxx Index Series 1 for the European market and from the Markit CDX Investment Grade Index Series 3 for the North American market. Our analysis focuses on the most liquid and most frequently traded contracts in terms of transaction volume. Thus, we are able to exclude any potential bias relating to company size or trading volume, since all CDS contracts are written on large blue chip companies. The time period of this analysis is restricted to the trading period of the selected indexes and ranges from September 2004 to December 2009. In terms of maturity structure and underlying securities we follow existing finance literature and use CDS contracts on corporate senior debt with a fixed maturity of five years.

Following Zhang *et al* (2008), where monthly data is favored in order to minimize the effect of autocorrelation resulting in a mitigation of an estimation bias, we apply monthly data for our panel analysis. As Zhang *et al* (2008) suggest, high CDS spreads, which indicate the existence of bilateral agreements on upfront payments observations with spreads above 15%, are removed from the data.[2] We excluded all reference entities that were either not publicly listed (so that no information regarding the equity returns and volatility could be retrieved) or had CDS spreads quoted for less than twenty-four months. All data is retrieved from Bloomberg.[3] Our reference entities

[2] For Europe, two outliers with CDS spreads exceeding the 15% threshold are deleted, and, for North America, fourteen observations are deleted.

[3] Markit iTraxx Europe Index Series 1 comprises 125 CDS contracts on senior unsecured debt with maturity of five years on investment grade entities distinguished by the subindexes autos, consumer goods, energy, industrial goods, TMT (which stands for telecommunications, media and technology), financials, nonfinancials and high volatility. Markit CDX Dow Jones CDX Investment Grade Index North America comprises 125 CDS contracts of senior unsecured debt with maturity of five years on investment grade firms. Subindexes are clustered by high volatility, consumer goods, energy, financial, industrial goods and TMT. Both Markit indexes roll every six months.

TABLE 1 Overview of yearly mean CDS spreads across rating categories.

	AAA–A		BBB		BB–C		Total	
Year	**CDX**	**iTraxx**	**CDX**	**iTraxx**	**CDX**	**iTraxx**	**CDX**	**iTraxx**
2004	29.88	25.68	47.09	53.12	57.74	42.99	41.03	39.57
2005	27.41	26.05	45.47	53.19	86.43	79.39	42.93	44.69
2006	20.61	17.32	34.47	41.33	96.96	66.47	36.36	34.27
2007	21.82	20.77	35.36	42.20	138.16	76.91	42.46	37.99
2008	93.84	94.98	143.78	159.50	483.56	328.88	163.53	154.68
2009	157.68	108.05	241.73	166.48	635.96	454.78	252.68	181.91
Total	46.82	48.56	75.73	85.68	211.97	178.59	80.28	82.06

Time-weighted average CDS spreads of the respective index constituents per year for the three rating clusters ranging from AAA–A, BBB and BB–C ratings. Overall, CDS spreads in lower rating classes exceed the AAA rating classes and CDS spreads increase significantly in 2008 and 2009 in the CDX and iTraxx index.

originate from different industries as well as incorporating different rating classes, which further reduces the probability that our results are affected by a selection bias. Rating values are assigned according to a Standard & Poor's rating or, if this is not available, the Moody's credit rating is used. In total, the iTraxx data sample consists of 5379 observations and the CDX data sample consists of 5053 observations. For the subsequent regression analysis we further excluded observations with differenced CDS spreads exceeding the 10% limit in order to ensure that individual events such as low liquidity levels do not affect our empirical results. Despite this, the total number of excluded CDS spreads is on a very modest level.

Table 1 presents an overview of the yearly mean CDS spreads across the different rating categories. The aforementioned negative relationship between quality of rating class (eg, low default probability) and level of CDS spreads is also confirmed for our data sample. Additionally, we detect an already well-documented trend of decreasing mean CDS spreads until 2006–7 and a sudden increase with the beginning of the financial crisis in 2008.

Table 2 on page 70 displays summary statistics of the CDS pricing determinants. We divided the results into two parts (Europe and North America) and listed both the counterparty risk measure and the control variables accordingly. In this context it becomes obvious that the characteristics for the CDS markets in North America and in Europe are quite different (eg, higher liquidity and leverage for the US sample). Thus, we will separate our regression analysis into a US and a European sample. We also observe that the financial crisis has a significant impact on the different pricing components of CDS spreads with the pricing conditions tightening after September 2008.

4 METHODOLOGY

4.1 Counterparty risk and credit default swaps

In what follows, we introduce two different measures for including counterparty risk in a CDS pricing model. The first variable (CPDR1) does not rely only on default correlation patterns derived from Merton (1974) style *ex ante* asset/debt returns but mimics *ex interim* market conditions. The second variable offers a solution incorporating asset correlation structures as introduced by Hull and White (2000, 2001). In a second step we introduce a series of additional control variables that are all derived from the existing literature and have exhibited significant pricing power for determining CDS spreads. As discussed above, default risk has a negative impact on CDS premiums (see Hull and White (2001)). Furthermore, the interdependent risk of default between the underlying reference entity and the issuing counterparty are to be considered. As counterparty specific quotes for single CDS quotes are not available in the common CDS databases (eg, Markit) provided by Bloomberg, Datastream or Reuters, two proxies for aggregate counterparty default risk are computed.[4]

With the first proxy we try to overcome this lack of data transparency by designing an average measure for counterparty risk by adjusting for market sentiment. The Markit platform provides an overview of the banks contributing to the iTraxx and CDX index.[5] Thus, we compute the first proxy of counterparty default risk by taking the arithmetic mean of CDS spreads of all banks contributing to the specific index implying the overall creditworthiness of the contributing counterparties on an actual-to-actual basis. In a second step, we extract the general market sentiment in order to create our first measure for counterparty risk (CPDR1). At each trading point we subtract the corresponding quote of the iTraxx index or the CDX index from the arithmetic mean of CDS spreads of all counterparties. Counterparties are defined as banks contributing to the respective iTraxx or CDX index as quoted by Bloomberg. In this way we are able to isolate changes of the relevant CDS counterparties from the index level resulting in abnormal counterparty risk spreads:

$$\mathrm{CPDR1}_t = \frac{\mathrm{CDS}_{1t} + \mathrm{CDS}_{2t} + \cdots + \mathrm{CDS}_{Nt}}{N} - \mathrm{index}_t \tag{4.1}$$

[4] The reasons why banks contributing trading data to Markit do not want the individual quotes to be published are easy to comprehend: they would be exposed to market suspicion in times of financial turbulence, as experienced by Lehman Brothers in August/September 2008, when, within the interbanking market, the Lehman Brothers counterparty risk did indeed lead to higher CDS spreads compared with other CDS contracts for the very same reference entity and maturity structure.

[5] The CDS index is a list of twenty-five banks in total providing their CDS spreads for the index constituents to Markit Financial Information Services.

TABLE 2 Summary statistics of CDS pricing determinants. [Table continues on next page.]

(a) Europe

	Total sample		Sample before September 2008		Sample after 2008	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**
CDS spread	81.4385	111.3020	49.2941	49.1746	168.2149	170.2088
CPDR1	–9.9087	42.7219	–0.4392	19.5362	–38.2361	68.2777
CPDR2	0.3528	0.8734	0.3291	0.8513	0.4284	0.9674
Liquidity	0.1189	0.0792	0.1334	0.0870	0.0812	0.0347
$\text{Return}^{\text{firm}}$	0.0013	0.0887	0.0044	0.0647	–0.0077	0.1327
Equity volatility	0.0096	0.1301	0.0121	0.1486	0.0104	0.1711
$\text{Return}^{\text{market}}$	0.0020	0.0500	0.0053	0.0382	–0.0080	0.0713
Market volatility	0.0960	0.6106	0.1163	0.6951	0.1040	0.4088
Leverage	0.4315	0.3321	0.4151	0.3272	0.4784	0.3425
Index	66.7479	79.0198	31.0526	16.7400	165.2437	95.6990
Interest^{10}	4.0085	0.6322	4.1332	0.6077	3.7176	0.6090
Interest^{2}	4.6285	12.2151	5.1163	12.1871	3.1774	11.8048
Slope	–0.6200	12.1870	–0.9831	12.1761	0.5402	11.7732
Swap rate	3.6998	1.7998	3.8434	1.2433	3.3410	2.7664
Swap spread	0.3087	1.7021	0.2897	1.1496	0.3766	2.6824

Thus, CPDR1_t reflects the pooled default risk of the contributing banks, minus the overall credit risk in the market.[6] By doing so, our pricing model reflects current market conditions of counterparties and does not rely on *ex ante* data only. This allows us to immediately mirror changing market conditions such as increasing credit risk or volatility spikes. As observed throughout the financial crisis, the approach of Hull and White (2001) had the drawback that it was not able to immediately adjust for the increase in credit risk of the major counterparties. Additionally, we also derived our measure from observed market prices for credit risk and do not solely rely on an indirect link via asset returns.

[6] The importance of counterparty risk is even accentuated by the fact that modern banks use CDS-based credit value adjustments as a measurement of counterparty credit risk on over-the-counter derivative transactions and to adjust their liabilities based on their own credit quality. They do this by adjusting the discount rate curve by the counterparty CDS spread curve. This approach is only reasonable for good counterparties, but it necessitates the analysis presented in this paper.

TABLE 2 Continued.

(b) North America

	Total sample		Sample before September 2008		Sample after 2008	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**
CDS spread	79.6419	134.6668	53.1857	73.2905	240.2657	256.2292
CPDR1	−14.7062	28.5680	−16.5283	16.9726	−3.6435	62.3251
CPDR2	0.2988	0.8556	0.3275	0.8802	0.1248	0.6615
Liquidity	0.1406	0.0857	0.1515	0.0874	0.0739	0.0208
Return$^{\text{firm}}$	−0.0070	0.1133	0.0028	0.0718	−0.0665	0.2354
Equity volatility	0.0080	0.3600	0.0092	0.3885	0.0004	0.0008
Return$^{\text{market}}$	−0.0039	0.0466	0.0034	0.0279	−0.0482	0.0917
Market volatility	0.0066	0.0209	0.0073	0.0225	0.0028	0.0031
Leverage	0.5179	0.1934	0.5019	0.1882	0.6151	0.1964
Index	77.9836	80.0116	0.8802	30.1370	249.0356	75.3505
Interest^{10}	4.1990	0.6351	4.3854	0.4193	3.0673	0.5416
Interest^{2}	3.4804	1.3294	3.8709	0.9767	1.1092	0.3957
Slope	0.7186	0.7649	0.5144	0.6124	1.9582	0.2647
Swap rate	1.3283	0.1037	1.3299	0.1098	0.2647	0.0520
Swap spread	2.8709	0.6713	3.0556	0.4836	0.0520	0.5496

Mean and standard deviation for the dependent and independent variables in the total European sample ($n = 5379$) and the total North American sample ($n = 5053$), and for samples before September 2008 and samples after 2008.

There is, however, a risk-mitigation technique in place that might reduce counterparty risk, ie, margin calls that become effective with a deterioration of credit quality of the counterparty if the contract is closed under standard swap agreements based on International Swaps and Derivatives Association rules. We argue, however, that margining always carries severe risks, as it is usually triggered by a counterparty rating migration. Ratings are long-term and stable by definition (through-the-cycle, Altman and Rijken (2004)) and have been heavily criticized for not reflecting current market evaluation (see, for example, the Lehman Brothers case). Therefore, margining helps to avert a slow but steady path to default, but does not mitigate the risk of a default overnight. A second proxy for counterparty default risk is computed by measuring the default correlation of the individual CDS i at time t:

$$\mathrm{CPDR2}_{it} = \mathrm{DEFCOR}_{it} \tag{4.2}$$

The default correlation proxy DEFCOR_{it} is constructed as the correlation coefficient between the firm equity returns and the arithmetic mean of the equity returns of the counterparties at the trading point in time t applying a regression analysis over a rolling time frame of twenty-four months prior to time t. Since it incorporates *ex ante* correlation patterns it is in line with the existing financial literature on CDS counterparty risk pricing (Hull and White (2000, 2001)).

4.2 Control determinants

Based on Das *et al* (2009) we organize the control determinants into three groups: market-based, firm-specific and trade-specific determinants.

4.2.1 Market-based determinants

With regard to the risk-free rate of return, a negative correlation is expected and may be explained by the existence of lower spot rates during recessionary times, implying a higher number of corporate defaults (Benkert (2004)). Hence, the increased probability of default of the reference entity would result in an enhanced CDS premium. The long-term risk-free rate is approximated by ten-year Treasury bond yields and the short-term rate is approximated by two-year Treasury bond yields. For the European sample the Treasury bond yields of the respective country of the underlying are applied. From a macroeconomic perspective, the impact of the slope of the term structure on CDS spreads is ambiguous and may be interpreted both as an indicator for the future economic conditions (Estrella and Mishkin (1996)) and an inflation indicator (Zhang *et al* (2008)). On the one hand, a higher slope of the term structure would imply an anticipated improvement of the overall economy resulting in lower default probabilities and therefore decreasing CDS spreads. On the other hand, a higher slope of the term structure would be associated with increasing inflation rates, implying restrictive central bank initiatives resulting in a worsening of business conditions and consequently higher CDS premiums. In accordance with Ericsson *et al* (2009) the slope of the term structure is computed as the difference between the ten-year (long) and the two-year (short) risk-free interest rates of the respective country of origin.

Increasing market returns reflect improving conditions in the overall economy that consequently result in decreasing CDS spreads. Furthermore, inclining market volatility implies increasing uncertainty regarding the economic conditions. Therefore, high market volatility would have a positive effect on CDS premiums (Zhang *et al* (2008)). Moreover, the respective CDS index (index_t) also serves as an indicator for market development. The index is defined as the equally weighted average of the constituent CDS spreads. Therefore, an increase in the CDS index is expected to be positively correlated with the CDS premium. In order to establish consistency to the drawn sample over time, the European index equals the Markit iTraxx Index Series 1 and the North American index equals the Markit CDX Investment Grade Index Series 3.

4.2.2 Firm-specific determinants

The rating class is used as a proxy of the underlying firms' credit quality. A good credit rating implies a lower probability of default and, hence, results in a decreased CDS premium (Daniels and Jensen (2005)). For the underlying firms' credit ratings the Standard & Poor's long-term issuer credit rating is retrieved, if available, and in the other cases the Moody's senior debt rating is used. In line with Cossin and Hricko (2001) the ratings will either be analyzed by introducing dummy variables for each rating class or by assigning numeric values (rating_i) to each rating class ranging from 1 for the highest rating (AAA or Aaa) to 17 for the lowest rating class (C).

A firm defaults if the value of its assets drops below the value of its debt (Merton (1974)). By implication, the leverage ratio of the reference entity is crucial for determining the distance to default as a high leverage would imply a higher probability of crossing the default barrier. In other words, an increase in leverage results in an increased probability of default and consequently in an increase of the CDS premiums. In line with Ericsson *et al* (2009) the leverage ratio of the reference firm is computed as:

$$\text{leverage}_{it} = \frac{\text{total liabilities}_{it} + \text{preferred equity}_{it}}{\text{market value (equity)}_{it} + \text{total liabilities}_{it} + \text{preferred equity}_{it}} \tag{4.3}$$

whereas total liabilities and preferred equity are book values being quoted on a quarterly basis and the market value of equity equals the market capitalization defined as the factor of the last equity price and the number of shares outstanding at the end of month t. In accordance with the influence of leverage on CDS spreads, positive firm-specific equity returns augment the value of equity and, hence, diminish the leverage of the firm. Accordingly, the CDS spread is supposedly negatively impacted by equity returns (see Zhang *et al* (2008)).

Black and Scholes (1973) define equity as a European call option on the underlying firm's assets, where the level of debt constitutes the strike price. Thus, enhanced asset volatility would increase the probability that the asset value will fall below the debt level and accordingly leads to an augmented default probability. Therefore, asset volatility positively influences CDS spreads. Following the approach of Cossin and Hricko (2001), the equity volatility eqvol_{it} is computed first by applying the geometric Brownian motion as a scaling measure using the mean return μ_t and standard deviation σ_t over the twenty-four months prior to time t. Analogously, historical market volatility marketvol_{it} is estimated.

4.2.3 Trade-specific determinants

In bond markets higher liquidity generally results in decreased compensation for liquidity risk and hence in a diminished yield spread (see Amihud and Mendelson (1991)). Tang and Yan (2007) document a comparable pattern for CDS markets. In line with their research we use relative bid–ask spreads divided by the mid-market last price quote of the traded instruments in order to obtain a proxy for the liquidity from a transaction costs perspective. The monthly last mid, bid and ask quotes are derived for each CDS contract.

5 EMPIRICAL RESULTS

5.1 Baseline regressions

In order to determine the impact of the cross-sectional and time-series variables described in the previous section, a panel data analysis is conducted for a multi-factor model. To obtain unbiased and efficient results we test whether the time series model variables exhibit autocorrelation by the Lagrangian multiplier test (Wooldridge (2002)) and to what extent individual exogenous variables are related to each other due to multicollinearity. In order to adjust for serial autocorrelation of order one as well as for nonstationary attributes, the first differences approach is applied. Multicollinear attributes were removed from the selection of pricing determinants: short-term interest rate ($d\ \text{interest}^2_{it}$), slope of the term structure ($d\ \text{slope}_{it}$) and market volatility ($d\ \text{eqvol}_{it}$). Nevertheless, the impact of the excluded variables is analyzed separately in the robustness section. As the variable rating_i only captures the cross-section, the variable drops out in the panel regression approach but will be analyzed in more depth later on. Based on a Hausman test, a fixed-effects model is specified for the analysis of the determinants of CDS spreads for our regression model. Additionally, relying on a joint Wald test, the model is adapted so that not only entity-fixed but also time-fixed effects are taken into account.[7] Taking these adjustments into account and adapting them with the different control variables, the general regression model is designed as:

$$\begin{aligned} d\ \text{CDSspread}_{it} = c &+ \beta_1 d\ \text{CPDR1}_t + \beta_2 d\ \text{CPDR2}_{it} + \beta_3 d\ \text{interest}^{10}_{it} \\ &+ \beta_4 d\ \text{return}^{\text{firm}}_{it} + \beta_5 d\ \text{return}^{\text{market}}_{it} + \beta_6 d\ \text{eqvol}_{it} \\ &+ \beta_7 d\ \text{leverage}_{it} + \beta_8 d\ \text{liquidity}_{it} + a_i + a_y + u_{it} \end{aligned} \tag{5.1}$$

with a_i and a_y representing entity-fixed and time-fixed effects.

[7] In order to test for the presence of homoskedasticity, that is, that the error terms e_{it} have a constant variance for i and t, a modified Wald test for grouped heteroskedasticity is performed with the null hypothesis that the variance of one group i equals the overall variance ($\sigma_i^2 = \sigma^2_{\text{overall}}$). The null hypothesis is rejected on high significance levels in all cases. In order to control for heteroskedasticity, a heteroskedasticity-robust error variance matrix is employed (White (1980)).

Based on the general regression model in formula (5.1) we now investigate in detail the impact of our two measures for counterparty risk on CDS spreads. The main aim of this model (see Table 3 on the next page) is to test whether the inclusion of counterparty measures in addition to the well-documented CDS pricing determinants contributes to a better understanding of CDS pricing dynamics. If so, we would expect that counterparty risk or the corresponding measures CPDR1 and CPDR2 have a significant impact on CDS spreads. The multiple regressions of Table 3 on the next page all rely on time- and entity-fixed effects. Again, we divide our data sample into a European part ($n = 5379$) and a North American part ($n = 5053$). The applied data points correspond to the data sample presented throughout Section 3.

Before discussing the coefficients of the explanatory variables, the models will be analyzed with regard to their overall goodness of fit. For all models, high F-statistics indicate that all model parameters are different from zero. For the European sample, the R^2 values vary between 22.7% and 23.0%, whereas the corresponding R^2 values for North America are slightly lower and range between 19.45% and 19.50%. As documented in the robustness section, higher values are difficult to obtain since we decided to exclude the rating factor due to their static attributes as an independent variable whose inclusion would have driven up the corresponding R^2 values. With regard to both the control variables and the counterparty risk measures, we again detect diverging results for the European and North American data sample.

5.1.1 Europe

First, the results of the European panel regression model are discussed. We observe that our two counterparty risk measures have a significant impact on the CDS spreads. By applying CPDR1 to the data sample, counterparty risk is isolated from the general market sentiment. Based on the coefficients for CPDR1, we observe the expected results: the lower the protection sellers' credit quality, the lower the corresponding CDS spread. Therefore, we are able to empirically show a link between counterparty risk and the risk of the underlying reference entities. On an α-level of 5%, the default correlation between the individual firm equity returns and the arithmetic mean of the equity returns of the counterparties also prove to be significant (CPDR2) with a high coefficient. Based on the observed positive coefficients for CPDR2, we are able to confirm the findings of Hull and White (2000, 2001) and agree that a higher correlation between reference entity and counterparty positively impacts the CDS spread levels.

With regard to the set of control variables we now focus on liquidity and the leverage factor. In addition to the counterparty risk measures, these variables are the only components with a statistically significant impact on the CDS spreads within our multi-factor model. We show that higher debt leverage leads to higher CDS spreads, whereas liquid CDS contracts carry lower CDS spreads. As suggested by empirical studies on

TABLE 3 Multiple panel data regression model. [Table continues on next page.]

Variables	Europe (1) CDS spread	Europe (2) CDS spread	Europe (3) CDS spread	Europe (4) CDS spread	North America (1) CDS spread	North America (2) CDS spread	North America (3) CDS spread	North America (4) CDS spread
d CPDR1	−0.699**	−0.847***	—	—	−1.048**	−0.992**	—	—
	(−2.461)	(−3.017)	—	—	(−2.194)	(−2.012)	—	—
d CPDR2	10.45**	—	10.45**	—	−6.182	—	−6.002	—
	(2.362)	—	(2.362)	—	(−0.856)	—	(−0.831)	—
d liquidity	−55.41***	−55.01***	−55.41***	−55.01***	−33.22	−34.01	−33.65	−34.40
	(−2.930)	(−2.890)	(−2.930)	(−2.890)	(−1.335)	(−1.367)	(−1.351)	(−1.382)
d return$^{\text{firm}}$	−3.907	−1.686	−3.907	−1.686	−87.72**	−89.73**	−86.67**	−88.67**
	(−0.178)	(−0.0764)	(−0.178)	(−0.0764)	(−2.499)	(−2.533)	(−2.484)	(−2.520)
d return$^{\text{market}}$	38.90	36.59	38.90	36.59	126.4	161.2	426.3	444.6
	(1.506)	(1.415)	(1.506)	(1.415)	(0.240)	(0.305)	(0.739)	(0.763)
d eqvol	−1.996	−1.069	−1.996	−1.069	−0.101	−0.106	−0.102	−0.107
	(−1.584)	(−1.592)	(−1.584)	(−1.592)	(−0.398)	(−0.438)	(−0.380)	(−0.417)
d leverage	16.82***	16.67***	16.82***	16.67***	99.52	97.38	99.11	97.04
	(2.596)	(2.580)	(2.596)	(2.580)	(1.466)	(1.429)	(1.457)	(1.422)

TABLE 3 Continued.

Variables	Europe (1) CDS spread	Europe (2) CDS spread	Europe (3) CDS spread	Europe (4) CDS spread	North America (1) CDS spread	North America (2) CDS spread	North America (3) CDS spread	North America (4) CDS spread
d index	−0.425	−0.775	−0.0771	−0.353	−0.163	−0.180	−0.0496	−0.0717
	(−0.665)	(−1.238)	(−0.153)	(−0.716)	(−0.418)	(−0.456)	(−0.123)	(−0.177)
d interest[10]	−10.66	−10.68	−10.66	−10.68	−41.26	−43.76	−54.99	−56.71
	(−1.200)	(−1.202)	(−1.200)	(−1.202)	(−0.825)	(−0.868)	(−1.124)	(−1.156)
Constant	−3.472	−4.086*	−3.518	−4.141*	−3.214	−1.399	15.05	15.87
	(−1.460)	(−1.745)	(−1.476)	(−1.766)	(−0.108)	(−0.0468)	(0.459)	(0.479)
Observations	5379	5379	5379	5379	5053	5053	5053	5053
R^2	0.230	0.227	0.230	0.227	0.196	0.194	0.195	0.194
Number of CDS_id	91	91	91	91	107	107	107	107

Results of the multifactor panel data regressions applying the fixed effect model with robust error variance matrix to the differenced sample for Europe ($n = 5379$) and North America ($n = 5053$); overall R^2 fluctuates between 22.7% and 23.0% (Europe) and between 19.4% and 19.6% (North America); model significance provided by a significant F-statistic. We use monthly changes for both the dependent and independent variables. The analyzed time period covers 2004 to 2009. Robust t-statistics in parentheses, *** denotes $p < 0.01$, ** denotes $p < 0.05$ and * denotes $p < 0.1$.

bond markets, higher liquidity implies decreasing liquidity risk and consequently results in a lower yield spread (Fabozzi *et al* (2007)). With liquidity being defined as the relative bid–ask spread, this relationship also holds for our referenced CDS sample. With regard to leverage, the implied negative correlation of the leverage ratio on the distance to default is also approved as CDS spreads are positively correlated with the leverage measure. Moreover, the equity returns ($\text{return}^{\text{firm}}$) are negatively correlated with the CDS spreads, whereas the positive market returns ($\text{return}^{\text{market}}$) come as a surprise. The coefficient of the iTraxx index_t in the European sample exhibits negative correlation, however, at a statistically insignificant level. As a consequence of increased volatility in the financial markets throughout the analyzed time period, therefore, the iTraxx index does not serve as a reliable market-based determinant in the European case.

5.1.2 North America

As documented for Europe, CPDR1 also has a significant negative impact on the CDS pricing levels for the North American panel. Contrasting the results with Europe, however, only CPDR1 incorporates pricing power.

With regard to the control variables we also detect significantly different results. Individual firm equity returns, rather than liquidity and leverage, mainly drive the CDS spreads in addition to CPDR1. In the North American model, $\text{return}^{\text{firm}}$ exhibits a strongly negative coefficient that is statistically significant at the 5% level and in line with the theoretically expected impact that high equity returns indicate a higher distance to default. Therefore, we may conclude that, in the US market, the change of market returns serves as an indicator for the anticipated business conditions and that these conditions adversely affect the level of CDS premiums (even if we specifically ignore potential lag structures). For the North American data we are therefore able to confirm the earlier work of Norden and Weber (2004). The coefficients of the CDX index_t in the multiple panel regressions of the North American sample have a negative sign, albeit at a statistically insignificant level. Therefore, in an analogous way to the European sample, the CDX index does not serve as a reliable market-based determinant in the North American case for the time span considered within the scope of this analysis.

5.2 Effects of the financial crisis

In the case of analyzing CDS spread levels, the financial crisis has proven to be a significant factor affecting the spread level, resulting in an exponential increase of CDS spreads. The default of Lehman Brothers and the near default of AIG also highlighted the counterparty risk in the case of CDS trading activities. Consequently, we aim to investigate whether the impact of counterparty default risk on the pricing of CDS swaps has changed after the collapse of Lehman Brothers and the bailout of AIG in September 2008. Hence, Table 4 on the next page controls the findings of the multiple regression model (5.1) for two different time periods: June 2004 to September 2008 (pre-crisis) and September 2008 to December 2009. It is noteworthy that the lagged variable market return is removed from the model as it exhibits a high degree of collinearity in the post-crisis subperiod for the US sample. In order to create consistent and comparable findings, the market return has been dropped accordingly.

Looking at the European sample, we find that both counterparty risk measures are significantly correlated with CDS spreads in the subperiod before September 2008, with CPDR1 being significant at the 1% level. However, in the pre-crisis period, CDS spreads are positively correlated with the defined counterparty measure. The coefficient for CPDR1 is only negative in the *ex post* time period (during the financial crisis), as documented in Table 4 on the next page. Following the argument that CPDR1 allows us to isolate the idiosyncratic risk of CDS trading counterparties, we find that buyers only began to demand a discount on CDS spreads in case of higher counterparty risk in the context of intensifying financial crisis protection. In other words, only the Lehman Brothers default and AIG bailout raised the awareness of protection buyers enough that they actually demanded lower CDS spreads due to the existence of counterparty risk. For CPDR2 we find stable results in terms of significance with a strongly increased coefficient for the time period after the financial crisis (from 4.11 to 22.63). This result might be interpreted as a strong indicator of the increased awareness of correlation in the market and the corresponding need to be compensated for this correlation-driven counterparty risk. With respect to control variables, we observe that liquidity is only important in pre-crisis times, which might be due to comparably wide bid–ask spreads in the time period at the beginning of the financial crisis.

Additionally, we see that the CDS index lost impact during the financial crisis, which might be explained by high spread volatility. The impact of leverage, in turn, remains constant. With regard to stock price volatility, the findings of previous empirical studies regarding the increased impact of stock price correlation on CDS spreads in times of crisis (Alexander and Kaeck (2008)) are not supported for either the European or the North American parts of Table 4 on the next page.

The results from the North American sample differ from the European findings. Regarding the measures of counterparty default risk, we observe a negative correlation in terms of idiosyncratic counterparty risk (CPDR1) in both subsamples, albeit not statistically significant in both samples. Hence, this analysis gives diverging results for the two parts. In the European sample, CPDR1 is only negative after September 2008, whereas in the North American sample, CPDR1 is negative throughout the entire period. With regard to the correlation measure (CPDR2), it becomes obvious that the differentiation in the two samples provides no further insight compared with the

TABLE 4 Effects of the financial crisis.

(a) Europe

	Before September 2008		After September 2008	
	Coefficient	t-value	Coefficient	t-value
d CPDR1	2.93***	6.97	–0.57***	–7.72
d CPDR2	4.11*	1.73	22.63*	1.69
d interest^{10}	2.61	0.58	–19.33	–1.31
d index	0.39***	4.48	–0.13	–2.50
d leverage	5.02**	2.51	61.54**	1.87
d return$^{\text{firm}}$	2.85	0.50	1.06	0.03
d eqvol	–0.92*	1.80	–36.04	–1.15
d liquidity	–37.65***	–3.66	–78.23	–0.76
Constant	–6.46***	–3.34	–4.32	–1.33
R^2	0.4369	—	0.1961	—
prob $> F$	0.0000	—	0.0000	—

(b) North America

	Before September 2008		After September 2008	
	Coefficient	t-value	Coefficient	t-value
d CPDR1	–1.50	–1.55	–0.98	–0.92
d CPDR2	–6.89	–0.88	–9.96	–0.42
d interest^{10}	–37.34	–0.74	–146.96	–1.32
d index	–0.88	–1.06	–0.55*	–1.68
d leverage	–8.32	–0.23	527.38**	2.38
d return$^{\text{firm}}$	–59.89**	–2.16	–84.89	–1.61
d eqvol	–0.09	–0.29	–743.38	–0.35
d liquidity	–43.39***	–3.68	–76.38	–0.17
Constant	–6.9602	–1.26	130.2534	1.19
R^2	0.1849	—	0.2026	—
prob $> F$	0.0000	—	0.0000	—

Results of the multifactor panel data regressions comparing two subsamples: before and after the financial crisis; applying the fixed effect model with robust error variance matrix to the differenced sample for Europe and North America; model significance provided by a significant F-statistic. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

baseline regression as the coefficients are comparable, show the same direction and are not significant.

Table 4 on the facing page also shows that CDS liquidity is also losing its impact for the North American sample in the time period after September 2008. It is also worth mentioning that the R^2 figures remain constant for the North American sample, but, for the European sample, we observe a significant drop from 43.69% to 19.61%.[8]

5.3 Effects across rating categories

In a second step we control our results by comparing three different subsamples according to the rating categories AAA–A, BBB and BB–C, as we would like to further analyze where the shown effects come from. The results of counterparty default risk measure CPDR1, illustrated in Table 5 on the next page, are robust for the European data sample across the different rating categories, with no linear relationship across the rating classes. To investigate whether the negative impact of counterparty risk intensifies for clusters with lower rating, we pooled the data and attributed dummies to the rating categories BBB and BB–C. This allowed the calculation of interaction terms between our counterparty risk measures (CPDR1 and CPDR2) and the two relevant rating classes. As can be seen from Table 5 on the next page, there is a highly significant interaction term between CPDR1 and the lowest rating category BB–C. This provides enhanced proof of differentiation across rating categories. In particular, it shows the increased importance of the lowest rating class (compared with the other rating classes) for the relevance of counterparty risk measures. This implies an increased importance of counterparty risk for underlying reference entities with a higher probability of default.

For the second measure, in contrast with Table 3 on page 76, we find a negative (though not significant) coefficient for the rating class with the highest credit quality. It is unsurprising, however, that, in the case of a very good reference entity rating, a high default correlation actually leads to decreasing counterparty risk, since it indirectly means that the counterparty also has a very good rating, which, in turn, should lower the CDS spreads by definition. This observation also makes perfect sense from an economic point of view as protection buyers would not buy protection from a counterparty that carries a rating below the rating of the reference entity. With regard to the lowest rating class we also find that the correlation-driven counterparty risk measure becomes relevant and significant. This again supports the above finding that

[8] Besides the above-discussed test for the effect of the financial crisis, we tested the significance and relevance of our two parameters in a single factor panel regression with entity-fixed and time-fixed effects on an updated sample ranging until September 2011. We find that both the level of the coefficients and the high significance for Europe and the nonexistent significance for the US sample are robust.

TABLE 5 Results across rating categories. [Table continues on next page.]

(a) Europe

	AAA–A		BBB		BB–C		Total	
	Coefficient	***t*-value**	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**
d CPDR1	−0.25***	−3.97	−1.15***	−3.28	−0.80***	−5.50	−0.352	−1.406
d CPDR2	−1.068	−0.580	1.928	0.470	32.75*	1.670	18.44	1.579
d CPDR1 × BBB	−0.0426	−0.495	—	—	—	—	—	—
d CPDR2 × BBB	−6.884	−0.841	—	—	—	—	—	—
d CPDR1 × BB–C	0.310***	3.08	—	—	—	—	—	—
d CPDR2 × BB–C	−11.83	−1.171	—	—	—	—	—	—
d interest^{10}	10.925	1.200	−4.732	−0.430	−60.525	−1.340	−0.0357	−0.004
d $\text{return}^{\text{market}}$	−37.027	−1.350	−6.960	−0.180	219.39**	2.150	32.17	1.251
d index	−0.07*	−1.850	−1.32*	−1.70	0.015	0.100	−1.025**	−2.199
d leverage	7.359	1.360	8.137	0.960	28.92*	1.870	8.811	1.101
d $\text{return}^{\text{firm}}$	1.391	0.170	9.391	0.880	−16.563	−0.280	−4.115	−0.189
d eqvol	0.487	1.120	−1.79*	−1.88	−601.27**	−2.25	−2.110	−1.641
d liquidity	−50.39***	−4.80	−143.93***	−4.16	−226.860	−1.430	−79.69***	−3.834
Intercept	−2.92*	−1.90	−9.82*	−1.81	6.089	0.830	−22.90	−0.869
R^2	0.3743	0.4570	0.3851	0.2410	—	—	—	—
prob $> F$	0.0000	0.0000	0.0000	0.0000	—	—	—	—

TABLE 5 Continued.

(b) North America

	AAA–A		BBB		BB–C		Total	
	Coefficient	***t*-value**	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**
d CPDR1	3.748	0.51	–4.57***	–4.19	–3.826	–1.09	–0.627	–0.977
d CPDR2	2.097	0.46	–5.884	–1.05	11.720	0.96	3.920	0.324
d CPDR1 $\times$ BBB	–0.0527	–0.600	—	—	—	—	—	—
d CPDR2 $\times$ BBB	–0.358	–0.043	—	—	—	—	—	—
d CPDR1 $\times$ BB–C	–0.0883	–0.668	—	—	—	—	—	—
d CPDR2 $\times$ BB–C	–5.257	–0.521	—	—	—	—	—	—
d interest[10]	–586.306	–0.63	–73.24***	–3.42	8.13272	0.06	–67.73	–1.399
d $\text{return}^{\text{market}}$	588.84*	1.72	–1300.59*	–1.78	–2677.067	–1.46	269.8	0.477
d index	–1.462	–0.78	–1.43***	–4.78	–2.789104	–0.9	–0.352	–0.915
d leverage	25.400	0.31	148.02**	2.27	243.10*	1.87	208.0*	1.907
d $\text{return}^{\text{firm}}$	–36.653	–0.46	–41.66**	–2.18	–100.9577	–1.61	–50.16	–1.26
d eqvol	197.690	1.3	68.99***	2.44	1.949237	0.77	–0.0736	–0.308
d liquidity	–26.515	–0.86	–167.01***	–5.71	–726.47***	–2.73	–34.63	–1.347
Constant	433.808	0.53	–138.87***	–2.53	–95.2023	–0.47	6.563	0.204
R^2	0.1785	0.3162	0.4093	0.2190	—	—	—	—
prob $>F$	0.0000	0.0000	0.0000	0.0000	—	—	—	—

Results of the multifactor panel data regressions comparing three subsamples: reference entities with rating AAA–A, BBB, BB–C; applying the fixed effect model with robust error variance matrix to the differenced sample for Europe (AAA: $n = 2266$. BBB: $n = 2107$. BBC: $n = 673$.) and North America (AAA: $n = 2028$. BBB: $n = 2163$. BBC: $n = 647$.) model significance provided by a significant F-statistic. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

a differentiation across rating categories makes perfect sense as the lowest rating class contributes most to our empirical findings. However, we could not confirm this result at a significant level with regard to the respective interaction term.

Not surprisingly, the impact of leverage comes down for the whole robustness check, since determination of rating classes relies heavily on balance sheet structure, which is, in turn, directly reflected in leverage ratios.

With regard to the North American sample, the cross-check for different rating classes reveals that the results for CPDR1 are robust, leading to significant results (1% level) for the BBB spectrum. Relating to CPDR2, Table 3 on page 76 displays an insignificant negative relation. Our cross-check in Table 5 on page 82, however, also shows that this negative correlation is largely driven by the BBB rating class with the other two rating categories displaying positive values. The interaction term for CPDR2 and the lowest rating class additionally indicates that the coefficient for this low rating category would also be negative considering this rating class only; these results are, however, not confirmed at a significant level with regard to interaction between rating class and counterparty risk measure. For the other control variables we observe significant coefficients primarily for the BBB rating class.

5.4 Robustness of the risk-free term structure

We performed several robustness checks in order to control for bias in our results due to the importance of swap rates and the slope of the term structure. Several determinants regarding the risk-free term structure – such as the two-year government bond yield, the slope of the yield curve and the swap rate – were excluded from the multiple regression model (5.1) due to multicollinearity. Therefore, analyses were run to provide further insights on the additional explanatory variables by adopting the robust time-fixed and entity-fixed effects adjusted panel regression model of Table 3 on page 76. Although the regressions are biased by multicollinearity (eg, lower R^2), we show that none of the three previously excluded factors leads to significant coefficients, nor does their inclusion change the explanatory power of the other variables (besides the documented multicollinearity attributes). These tables can be provided by the author upon request.

6 DISCUSSION

In the light of the current criticism of credit derivatives with regard to transparency issues and the interconnectedness of counterparty relations, the empirical analysis of CDS spreads presented here provides evidence for the question of whether counterparty default risk is adequately reflected in CDS spreads. It also addresses the question of whether CDS pricing differs in the European and US credit derivatives markets and whether pricing patterns have been adapted in response to the financial meltdown after the Lehman Brothers bankruptcy.

Reviewing the results of our analysis, we observe that, in particular, CPDR1 adds significantly to the understanding of the CDS pricing structure.[9] The negative coefficients strengthen the general idea that diminishing creditworthiness of protection sellers (eg, measured via increasing CDS spreads of CDS trades) drives up counterparty risk and should lead to lower CDS spreads for the protection buyer.[10] Alternatively, the impact of counterparty risk should decrease if the likelihood of default of the underlying reference entity decreases.

Indeed, according to our analyses for the different rating classes of the CDS reference entities, we find that the demanded discount by protection sellers on the CDS spreads decreases as the credit quality of the reference entity increases. The analysis for our two counterparty risk measures shows, for both Europe and North America, that the lower rating classes contribute more to the relevance of the measure than the higher rating categories do. This means that the lower the rating of the underlying reference entity is, the more important the counterparty risk compensation becomes. Furthermore, correlation matters to an increased extent for the lower market segment.

In the spirit of Hull and White (2000, 2001) we include the correlation structures of asset returns between reference entities and protection sellers as the second measure in our analysis. As displayed earlier, we detect empirical proof for this variable for the European market in particular (on the 5% level for Europe, not significant for North America). Thus, we note that correlation structures of asset returns incorporate explanatory power for counterparty risk. However, the results for this measure seem to be dominated by the previously discussed market-based counterparty risk measures. The importance of correlation in the European market is, however, remarkable in its development over time as it increases strongly after the financial crisis. We see this result as an indicator of increased investor awareness of correlation-driven counterparty risk in the markets after the financial crisis.

There has been much discussion about how, and in which ways, the financial crisis has affected capital markets, and CDS trading activities in particular. In the wake of the Lehman Brothers default, one of the main demands with regard to future regulation was the introduction of a central counterparty (CCP), which would significantly reduce or even totally eliminate the default risk of a CDS protection seller. Analyzing the

[9] Following our empirical results in Table 3 on page 76, we note that a 1 basis point (bp) increase in the underlying credit risk of a protection seller acting as counterparty leads to an average CDS discount for the protection buyer of 0.699bps in Europe (and 1.105bps in the North America, which is not significant).

[10] This result might also be interpreted in such a way that risk-mitigation techniques such as margining are considered to be ineffective by the markets. First, they only react to rating migration, and second, a margin call for already bad counterparties might trigger a default as they turn illiquid.

impact of the financial crisis on the importance of counterparty risk measures, we found that, for Europe, *ex ante* counterparty risk was not as important as it was *ex post*/during the crisis, with significant negative coefficients in the time period from September 2008. It appears as though the financial crisis has alerted market participants to the potential threat of counterparty default. For the North American sample, we observe the awareness of counterparty risk in terms of demanded CDS spread discount at a significant level before the financial crisis, but see insignificant positive coefficients in the months after the Lehman Brothers default. Since the results are not significant, and considering the extreme market turmoil in the US banking industry, we recommend that the importance of the results for North America should not be overstated. For Europe, however, a CCP would make perfect sense considering our empirical results.

However, the discussion on CCPs is controversial since, on the one hand, CCPs might reduce counterparty risk, but, on the other hand, these clearing houses are often operated by the major banks in the country. Even if CCPs bear most of the credit risk in a CDS transaction, the ultimate risk might again be with banks as counterparties, which only strengthens the importance of banks in the market and might inspire the interpretation of our empirical results. This development would obviously contradict current market sentiment and the regulators' attempts to reduce banks' market power and system relevance.

7 CONCLUSION

From the angle of analyzing counterparty risk in CDS trading activities, we propose two different measures in order to better capture the default risk of the CDS protection seller. The market-based measure CPDR1 refers directly to the credit risk of the banks trading CDS contracts focusing on abnormal counterparty CDS spreads. CPDR2 is developed in line with prior research by Hull and White (2000, 2001) and focuses on correlation structures of asset returns between CDS counterparties and traded reference entities. Based on an analysis for Europe and North America from 2004 until 2009, our main findings are as follows. First, we show that idiosyncratic counterparty risk is reflected in the pricing of CDS contracts leading to lower CDS spreads for the protection buyer, whereas the impact of counterparty risk decreases with increased creditworthiness of the underlying reference entity. Second, we find that counterparty risk (CPDR1) had already been reflected in the CDS spreads for North American reference entities prior to the financial crisis, whereas, for European reference entities, the pricing impact only intensified with the outbreak of the financial crisis in September 2008. Third, market-based counterparty risk measures seem to have a higher impact on the pricing of CDS contracts compared with measures relying on the correlation structures of asset returns of reference entities and CDS counterparties. We contribute to the existing literature by extending the framework of modeling counterparty risk by proposing a short-term market-oriented perspective. By introducing our market-based measures we are able to better reflect current market conditions of counterparties and do not have to rely only on long-term *ex ante* data. This allows us to immediately mirror changing market conditions like increasing credit risk or volatility spikes.

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