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ABSTRACT

By investigating the determinants of CDS spreads on European contracts before and after the recent crisis we observe significant differences in the explanatory power of market and firm-specific variables. Before the crisis, the underlying credit risk in the overall CDS market is sufficient to explain credit risk. During the crisis investors have a differing view on the risk of financial and non-financial contracts; whereas non-financial CDS contracts reflect the credit risk of the counterparty, financial contracts do not. Our results suggest that in case of default of financial firms, investors expect the government to intervene to alleviate credit risk of the counterparty and fears of systemic risk.

Keywords: Co-integration; Counterparty Risk; Credit Default Swaps; Credit Risk; iTraxx Index

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I. INTRODUCTION

Bond markets have been traditionally regarded as appropriate indicators to evaluate the creditworthiness of a borrower. The risk underlying these bonds is observed in the spread between the risky and risk free bond yields. Empirical models motivated from structural form equations describing fixed income prices have been used to explain variation on bond spreads. Collin-Dufresne et al. (2001) and Avramov et al. (2007) are within this group of articles. These authors use in particular, the risk free rate, volatility and leverage.

The illiquidity of bond markets and the choice of appropriate measures to proxy the risk free bond rate make the bond spread not very suitable to analyze credit risk at high (monthly, daily) frequencies. Recently, the interest has shifted to studying credit risk indirectly by looking at derivative markets, in particular Credit Default Swap (CDS) contracts. A CDS is an insurance agreement between a protection buyer and a seller written on the default risk of a reference entity or obligation. Under the agreement, the buyer makes periodic payments to the seller until the occurrence of the credit event or maturity, and if a credit event occurs the seller compensates the buyer with the amount that is equal to the difference between the par value and recovery of the reference obligation**.**

The study of CDS spreads for gauging credit risk can be theoretically and empirically motivated. As documented by Blanco et al. (2005) and Zhu (2004), CDS and bond spreads converge to each other in the long run but there are significant differences between each other in the short run. These differences are due to the higher liquidity of the CDS market that is able to reflect changes in market conditions faster than bond spreads. Also, in contrast to bond prices CDS contracts are standardized products designed to reflect credit risk of the reference entity.

Bond prices, on the other hand, differ depending on the characteristics of the bond, the structure of coupon payments or the maturity of the debt.

Aunon-Nerin et al. (2002) is one of the first studies that concentrates on CDS spreads to explain credit risk. These authors, following the structural model approach as in Collin-Dufresne et al. (2001), use market variables as well as credit ratings and explain 82% of variation in CDS spreads. The choice of explanatory variables for the analysis of credit risk from CDS spreads is also an important issue highly debated in the empirical literature. Thus, Benkert (2004) describes CDS spreads by mainly concentrating on volatility measures. This author observes that the effect of option-implied volatility is higher on CDS spreads compared to the effect of historical volatility, that is, forward-looking measures of risk have a higher impact on CDS prices than historical measures. Further to Benkert (2004), Cao et al. (2006) conclude that the relation between option-implied volatility and CDS market is especially stronger when CDS spreads are more volatile, the rating of the reference entity is low and options are more liquid. Zhang et al. (2009) mainly investigate the relationship between equity return and CDS market and specifically explore the effect of stochastic volatility and jumps on CDS spreads. By calculating historical volatility from equity return data and the contribution of the jump using high frequency data, their results imply that volatility risk can alone explain 50% of CDS spread variation, while jump risk can predict 19% of the variation.

Greatrex (2009) sheds important doubts on the conclusions derived from the analysis of CDS spreads in levels obtained in other articles, the reason being the existence of spurious regression analyses that invalidate any statistical inference; Greatrex (2009) proposes instead the analysis of changes on CDS spreads. By generating a rating based index based on CDS spreads and a structural form model incorporating market variables, this author explains 35% of variation in

CDS spread changes. Ericsson et al. (2009) also analyze CDS spreads in levels and changes using structural form variables. These authors explain 23% of variation in CDS spread changes and up to 70% of variation in CDS spread levels.

Although there are many studies on the credit risk of the reference entity, there are not many on the credit risk of the protection seller. The analysis of this risk (counterparty risk) gains importance when the seller cannot fulfill its obligations under the occurrence of default of the reference entity. Some of the theoretical studies incorporating the effect of counterparty risk when pricing CDS contracts are Jarrow and Yu (2001), Hull and White (2001) and Yu (2007). To the best of our knowledge, the only empirical work on analyzing this effect is Arora et al. (2010). Further, since the financial crisis of 2007-2009 counterparty risk has become more apparent due to the collapse of the main counterparties such as Bear Sterns, Lehman Brothers and the bailouts of many other financial institutions. CDS contracts have been observed to amplify and spread uncertainty in the financial sector by reducing investors' confidence and also leading to financial contagion due to interconnectedness of the main counterparties. This is the reason why understanding the dynamics of credit spreads on these markets is now more important than ever as this financial derivative has played a critical role in the unfolding of the financial crisis.

The aim of this study is to find the drivers of credit risk by analyzing credit default swap spreads from April 2005 to November 2010. To do this we consider counterparty risk and a CDS market index (iTraxx Europe), that plays the role of the market portfolio in the standard asset pricing models, in addition to the variables considered so far in the literature. We also explore the analysis of CDS spreads not only in levels but also in changes using appropriate econometric techniques for each series. The main contributions of this study can be summarized as follows.

First, we aim to compare the explanatory power of firm-specific versus market variables on credit risk. In the literature, only Blanco et al. (2005) analyze both bond and CDS spreads from this perspective. Their results indicate that CDS spreads are more sensitive to firm-specific variables, whereas bond spreads are affected by market variables. Different from this study, our sample involves data from both early stages of the CDS market and the recent financial crisis period. This enables us to investigate the effect of potential breaks in the dataset and see how the recent financial turmoil has changed the way that credit risk is priced in the CDS market. The empirical analysis indicates that before the crisis market variables are sufficient to explain credit risk. In contrast to most of related literature, our study also contemplates the iTraxx index for pricing CDS spreads. Our study reveals that this index, that reflects general market conditions in the European CDS market, is the most important variable for explaining single CDS contracts. However, the outlook completely changes after the crisis. We observe that financial and non-financial firms behave in a very different way. In particular, for the non-financial contracts in our study is it the variables describing the features of the underlying entity (firm-specific variables) as well as counterparty risk what really explain credit risk. For the financial contracts, on the other hand, both market and firm-specific variables lose their predictive power to describe credit risk.

Second, we explicitly analyze the effect of counterparty risk when pricing CDS contracts. As mentioned before, CDS spreads also carry counterparty risk as it is likely that CDS sellers can also default and not fulfill their obligations. Arora et al. (2010) use contemporaneous CDS transaction prices and quotes from fourteen dealers selling CDS on the same reference entity. They consider CDS spread of counterparty as a proxy for the counterparty risk. They find that counterparty risk is priced in the CDS spreads written on non-financial firms, but not on the

financial ones. These authors also observe that the effect of counterparty risk on CDS spreads increases after the collapse of Lehman Brothers. In contrast to these authors we use a different proxy for gauging the influence of the counterparty. Our aim is to answer the following two research questions: Is counterparty risk reflected in CDS prices or the spread is a pure indicator of default risk of the reference entity? Is the effect of counterparty risk on CDS contracts higher after the break produced by the financial crisis? Our findings indicate that before the structural break occurred in each CDS contract counterparty risk is ignored. However, after the crisis, counterparty risk has started to be priced in all contracts except those on financial companies.

Third, we correct an important technical oversight in this literature that considers standard ordinary least squares (OLS) dynamic regressions to describe CDS spreads in levels, see for example Aunon-Nerin et al. (2002), Benkert (2004), or Ericsson et al. (2009). These authors report the coefficient of determination (R^2) to gauge goodness of fit measures for dynamic regression models in levels. All these authors claim to explain over 90% of variation in CDS spread level. However, the CDS spreads in levels are usually modeled as a unit root process, and as such, these processes have a variance that increases to infinity invalidating, in general, statistical analyses and conclusions based on the R^2. To avoid spurious regressions, we analyze CDS spread in levels under a co-integration framework, and also make allowance for the presence of a break to account for possible regime or level shifts in the long run relationship. We conclude that the iTraxx Europe and VIX index for the market variables, and the implied volatility and stock price for the firm-specific variables are co-integrated with CDS spreads.

The remainder of this paper is organized as follows. In Section II, we describe the dataset, present our explanatory variables and their expected relationship with CDS spreads. In Section

III, we explain the econometric methodology followed in this study and report our findings on CDS spread analysis. Section IV concludes. An appendix collects tables and figures.

II. THE DETERMINANTS of CDS SPREADS

This section introduces the dataset used for our empirical analysis; it describes the determinants of CDS spreads and discusses the expected relationship between these variables.

A. CDS Data

In this study, monthly mid quotes of CDS spreads are obtained from Bloomberg which is one of the leading financial data providers. In particular we consider the contracts with the following specifications: senior debt, EURO currency, quarterly premium payment, and five year maturity. The contracts with five year maturity are chosen specifically as it is by far the most commonly traded tenor which leads to the most liquid contracts. The dataset in this study covers the period April 2005 to November 2010. We have selected this period for two reasons: First, CDS market is more mature compared to the beginning of the twenty first century, and second, after experiencing tremendous growth the market started to shrink in 2008 due to the financial crisis all over the world. Therefore, this sample period is ideal to investigate the existence and effect of structural breaks in individual contracts and estimate potential different models for both volatile and tranquil periods. As one of the main aims of this study is to investigate the effect of counterparty risk on CDS spreads, we use data of CDS contracts sold by HSBC Bank PLC which is one of the major counterparties in the CDS Market. The data sample is obtained from

Bloomberg HSBC page which displays CDS quotations on contracts that are priced and sold by HSBC Bank[1].

As we believe that analyzing individual contracts from different sectors will give us more reliable results than pooling the data or taking the average of coefficients as done in the literature, we select for our analysis ten firms representative of the main sectors of economic activity in Europe. The choice of these companies is due to their relative importance in explaining the performance of the sector and data availability. The name of the firms and their corresponding industry information are listed in Table 1. We have two groups in our dataset: Aviva and Deutsche Bank are grouped as financial firms and the other eight firms are grouped as non-financial ones.

Table 1

List of Reference Entities in the Dataset

Reference Entity	Sector	Group
Aviva PLC	Financials-Insurance	Financial
Bayer AG	Pharmaceuticals	Non-Financial
BMW AG	Automotive	Non-Financial
Deutsche Bank	Financials-Bank	Financial
Imperial Tobacco Group PLC	Tobacco	Non-Financial
Philips Electronics N.V.	Technology	Non-Financial
Tesco PLC	Retail	Non-Financial
Total S.A.	Energy	Non-Financial
Vinci PLC	Construction	Non-Financial
Vodafone Group PLC	Telecommunications	Non-Financial

[1] Ideally, this analysis should include data provided by other CDS dealers, and not only HSBC. Unfortunately, only data on CDS spreads traded by HSBC and Royal Bank of Scotland (RBS) are made public in Bloomberg. Since data on RBS CDS spreads have a significant amount of missing observations, we choose to work only with CDS spreads on HSBC Bank.

Figure 1

CDS Spreads of Reference Entities Over Time

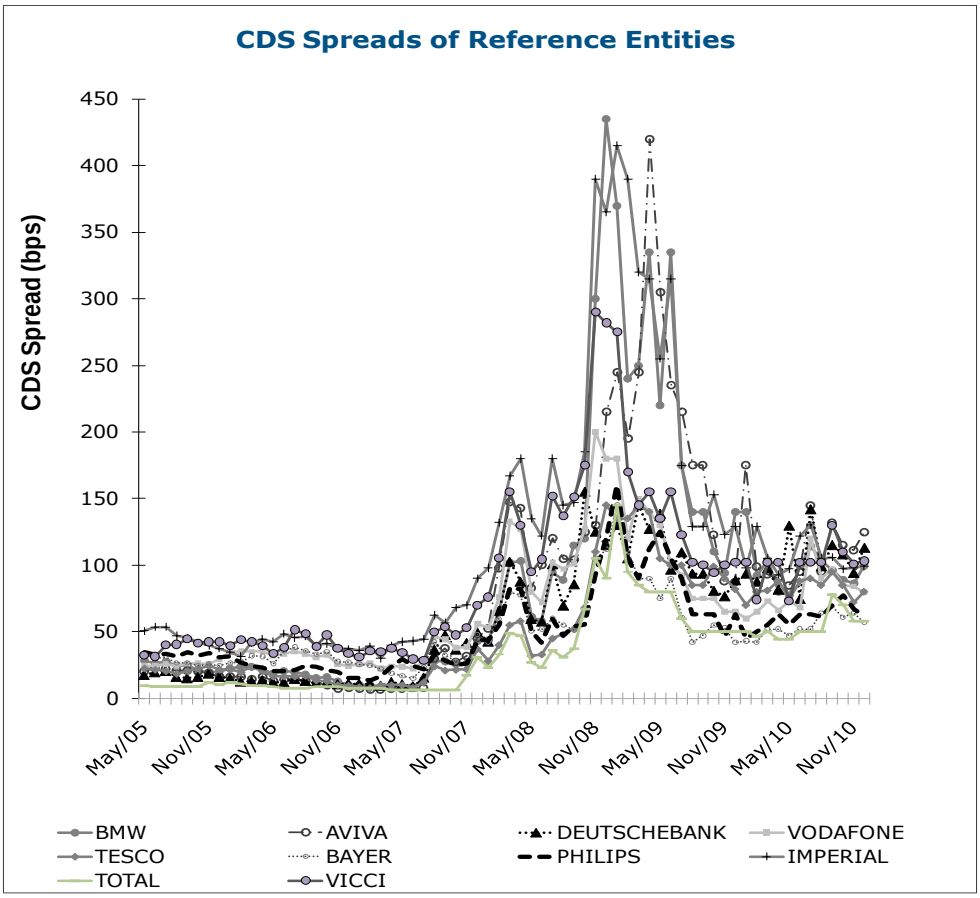


Figure 1 presents CDS spread levels of the contracts from April 2005 to November 2010 chosen for this study. All CDS spreads began to rise sharply due to the signals of the sub-prime mortgage crisis in the second half of 2007. At the end of 2008 and beginning of 2009 they made peaks when many collapses and bailouts in financial markets took place. At the end of 2010, CDS spreads are much lower than at their peak values but still vulnerable to financial shocks.

Table 2

Descriptive Statistics of CDS Spreads of Reference Entities

	AVIVA	BAYER	BMW	DEUTSCHE BANK	IMPERIAL	PHILIPS	TESCO	TOTAL	VICCI	VODAFONE
CDS Spread Level										
Mean	86	48	88	61	115	51	52	35	89	67
Standard Deviation	85	26	95	46	97	31	40	31	60	44
Range	7 to 420	15 to 145	9 to 435	9 to 155	30 to 415	14 to 160	8 to 145	7 to 145	29 to 290	23 to 200
CDS Spread Change										
Mean	1.57	0.37	1.05	1.42	0.72	0.41	0.86	0.72	1.05	0.83
Standard Deviation	39	12	47	22	38	14	11	13	25	19
Range	-115 to 175	-35 to 43	-160 to 180	-55 to 70	-140 to 205	-55 to 40	-35 to 42	-50 to 55	-105 to 115	-60 to 73

As observed in Table 2, cross-sectional variation in CDS spreads over the period is also remarkably high. Although the minimum spread is only 7 basis points (bps) for Aviva and Total, the maximum spread level recorded is 435 bps (BMW). The average spread ranges from a low of 35 bps for Total to a high of 115 bps for Imperial. An indicator of volatility, standard deviation, is varying between 26 bps (Bayer) and 97 bps (Imperial). The descriptive statistics of CDS spreads also reveal that Imperial and BMW are relatively riskier than other reference entities since they have the highest mean and standard deviation. The reasons behind this conclusion are that a higher spread is viewed as higher credit risk of the underlying entity, and high standard deviation is an indicator of high volatility and hence of high default risk.

B. Explanatory Variables and Their Relationship with CDS Spread

Credit Default Swaps are usually priced using two different approaches. For reduced form models default is the outcome of a random jump process and is regarded as an unpredictable event. For structural form models, the asset value of a company is assumed to be consisting of equity and a zero coupon bond; default occurs if the value of the firm's asset is less than the promised debt payment at the maturity of the debt. Risk free rate, leverage and volatility of the

asset are the main empirically tested determinants of structural form models. However, as documented in many papers, their explanatory power is empirically weak. We believe that the structural model needs adding more explanatory variables that reflect the features of CDS contracts and of general market conditions. In particular, we are interested in two sets of variables classified as market and firm-specific variables. In the next section, we will explain the variables and their theoretical relationship to CDS spreads.

Firm-specific Variables

The set of variables that we use in this group are volatility, stock price, liquidity of the contract and credit risk of the counterparty. In a similar study that investigates the effect of bond liquidity on CDS-bond basis, Nashikkar et al. (2010) use instead leverage, tangible assets and current ratio (the ratio of current assets to current liabilities) as firm-specific variables. The variables for our study are motivated as follows.

It is an empirical fact that an increase in *volatility* leads to an increase in CDS spread. The intuition for this is that since default depends on the movement of the firm value, the latter is more likely to default if its value oscillates more. As discussed before, there are mainly two types of volatility measures in the literature: historical and option-implied volatility. Whereas option-implied volatility reflects market expectation of future volatility, historical volatility shows how volatile the asset was in the past. Benkert (2004) and Cao et al. (2006) analyze and compare the effect of these two volatility measures on CDS spread and conclude that although both have a positive relationship with CDS spreads, the effect of option-implied volatility is stronger than historical volatility. Based on previous studies and the forward-looking characteristics of option-implied volatility, we only give place to this volatility measure in our study.

Stock price of the firm reflects the business and financial condition of the underlying company. Thus, any negative news about the company is observed in stock prices faster than in any other variable such as rating. Further, as documented in Welch (2004), stock price is the best proxy for capturing variation in leverage. Ideally, leverage should be computed as the ratio of the book value of debt divided by the market value of equity. However, book values of debt are reported on a quarterly basis making difficult to obtain monthly measures of leverage. Instead, a valid proxy for leverage used in the literature is the stock return. A higher stock return leads to smaller leverage and an improvement on the financial condition, and hence smaller credit risk.

Another firm-specific variable is *liquidity*. Literature regarding the impact of this variable on CDS spreads is contradictory. On the one hand, since it is a derivative contract, not an asset, it is argued that CDS spreads cannot contain a liquidity premium. On the other hand, the occurrence of a large bid-ask spread is interpreted as existence of illiquidity risk. In this study, to minimize the presence of illiquidity effects, we only analyze five year contracts as they represent the most liquid segment of the market. Nevertheless, in order to accommodate any illiquidity effect in this market we consider the spread between bid-ask CDS levels as a proxy for illiquidity, see also Tang and Yan (2006). Our expectation is that an increase in illiquidity will trigger an upward movement in CDS spreads.

Another very relevant factor in our analysis is *counterparty risk.* As experienced during the financial crisis with the collapse of Lehman Brothers and the bailout of Bear Sterns, the sellers of CDS contracts are not default-free. Furthermore, it is a stylized fact that different CDS contracts written on the same reference entity have a different price, finding that we attribute to the risk of the sellers. Thus, if the seller of the contract has a higher credit rating compared to the other sellers, the corresponding CDS contract will be more expensive. Arora et al. (2010) use the

spread of CDS written on the default risk of the protection seller as a proxy for counterparty risk. We believe, however, that the CDS spread of the counterparty cannot be an indicator of pure counterparty risk as it also reflects general market conditions. Considering this fact, we subtract the change in the iTraxx index from the change in CDS spread of the counterparty (HSBC Bank for our data) and use this "premium" variable as a proxy for counterparty risk. The idea is similar to standard capital asset pricing formulations based on excess returns. We expect a negative relationship between the proxy for counterparty risk and CDS spreads, that is, when credit risk of the counterparty deteriorates, investors are not willing to pay a higher premium for the contracts offered by the counterparty.

Market Variables

In the second group, consisting of market variables, we consider the risk free rate, S&P 500, iTraxx Europe and VIX indices.

The structural approach predicts a negative relationship between the interest rate and credit spreads. Collin-Dufresne et al. (2001) note that a higher interest rate should increase the risk-neutral drift of the value process which reduces the probability of default and decreases spreads. In this study, we use one year Euro swap rate as a proxy for interest rate. We prefer to use swap rates instead of government bond rates, as government bonds are not regarded as benchmark for the risk free rate any more by financial markets due to illiquidity, short sale and tax considerations.

The *stock market* sentiment is also very relevant to our analysis. We include this variable as a market variable because we believe that the stock market return is one of the most relevant proxies for the overall business climate. As general market condition affects expected recovery rates, CDS spread will narrow when economic activity is high and widen when economic

activity is low. Avramov et al. (2007), Collin-Dufresne et al. (2001), Greatrex (2009) and Aunon-Nerin et al. (2002) confirm a negative relationship between S&P 500 index and credit risk. In this study, we also give place to S&P 500 index as a proxy for general market conditions as it is known as the leading stock market index in financial markets. A related measure of asset markets' sentiment more relevant for our analysis of credit risk is the *CDS Market Index*. We believe that an index constructed from CDS contracts can reflect the market condition especially in the CDS market better than an equity market index. Consequently, we use the iTraxx Europe index as a proxy for CDS Market Index; this index is made up of 125 equally-weighted European names selected by a dealer poll based on CDS volume traded over the previous six months. We expect a strong positive relationship between iTraxx Europe index and CDS spread.

Besides firm-specific volatility, we also consider the *Volatility index (VIX)* which is a measure of implied volatility of the S&P 500 index options that accounts for overall market volatility. Greatrex (2009) documents a positive relationship between VIX index and CDS spreads. Collin-Dufresne et al. (2001) conclude that an increase in VIX index raises credit spread, yet a decrease does not have an effect on credit spreads. As our dataset contains information from a very volatile period, we expect a positive relationship between CDS spreads and VIX index.

III. METHODOLOGY AND EMPIRICAL RESULTS

In this study we prefer to use monthly frequency data since some CDS spreads do not change on a daily basis and can have extreme values on some days. From a technical point of view daily data are exposed to autocorrelation problems which can lead to unreliable empirical results using standard econometric methods.

We begin with an overview of CDS spreads in the period we examine. Figure 2 exhibits time series plots of monthly CDS spreads of two contracts versus explanatory variables. We select two contracts as representatives of the data sample. One contract from the non-financial group is BMW, and the other one from the financial group is Deutsche Bank. Figure 2 in the Appendix (Panels A, B and C) plots monthly CDS spreads in levels against iTraxx, VIX and S&P 500 indices, respectively. Until the beginning of 2008, the tranquil period, the plots make apparent the positive relationship between CDS spreads and iTraxx and VIX indices and the negative relationship between CDS spreads and S&P 500 index. However, after 2008 due to the effects of the financial crisis, we observe that CDS spreads generally move independently from aggregate market sentiment. Figure 2, Panel D, plots the relationship between CDS spreads and the risk free rate. Until April 2007, in line with theory, CDS spreads move inversely to the risk free rate. Figure 2, Panel E and F exhibit the plot of CDS spread levels versus implied volatility and stock price, respectively. As expected, we generally observe a positive relationship between implied volatility and CDS spread and a negative relationship between stock price and CDS spreads.

Aunon-Nerin et al. (2002), Blanco et al. (2005), Benkert (2004) and other related papers use panel data analysis to study the relation between the variables. These panel data models assume that all the contracts in the data sample have the same relationship with the explanatory variables. For example, these models expect that every CDS contract has the same relationship with the variable gauging counterparty risk. For this reason, we believe that the results from panel data analysis can be misleading. Similarly, papers such as Greatrex (2009), Collin-Dufresne et al. (2001) and Ericsson et al. (2009) run the regressions for each contract separately, and report the average of coefficients which can also lead to invalid inferences if the actual relation between variables varies with the CDS contract. Instead, we select a sample of ten CDS

contracts, each representing a different economic sector, and present the results separately for each firm in our dataset.

In order to analyze CDS spreads in levels and changes, we need different econometric methods. Initially, we analyze CDS spreads using a co-integration analysis. Second, we analyze changes in CDS spreads in a stationary dynamic regression framework for two separate periods, namely tranquil and volatile periods.

A. Co-integration Analysis

The empirical literature concerned with CDS spreads is surprisingly successful in explaining the determinants of this variable. For example, Aunon-Nerin et al. (2002), Ericsson et al. (2009) and Benkert (2004) find R^2 values close to 90% that indicate an extraordinary fit of the regressors used by the authors. Unfortunately, CDS spreads usually follow unit root processes implying non-stationary dynamic regression models and yielding, in turn, residual series that are also non-stationary unless the regressors are co-integrated to the CDS spread. The unit root character of the residuals implies that its variance grows over time, yielding an R^2 that approaches one as the sample size increases, and invalidating any conclusion based on this goodness of fit measure. To avoid spurious regression inferences, see Granger and Newbold (1974), we will analyze CDS spreads in a co-integration framework.

For instance, for the relation between CDS spread and iTraxx, the long run regression equation is given by

(1) $$CDS_t = \mu + \alpha * iTraxx_t + \varepsilon_t$$

where ε_t is the stationary error variable under the null hypothesis of co-integration. This equation captures the long run relationship between these variables, but it does not take into account any possible change in the long run relationship due to potential structural breaks in the data. This implies that the results of the analysis can be misleading under the presence of a break in the data due to the financial crisis. Hence, we will use Gregory and Hansen Co-integration test (1996) which accounts for a change in the long run relationship by considering the presence of a potential structural break. Gregory and Hansen propose an Augmented Dickey-Fuller type test designed to test the null of no co-integration against the alternative of co-integration in the presence of a shift in the relationship. In particular, we consider the cases where the intercept and/or slope coefficients have a single break at an unknown time.

In order to incorporate the occurrence of a break at an unknown time, we include a dummy variable defined as

$$\varphi_{t\tau} = \begin{cases} 0 \; if \; t \leq [n\tau] \\ 1 \; if \; t > [n\tau] \end{cases}$$

where the unknown parameter $\tau \in$ (0, 1) denotes the (relative) timing of the change point, and [.] denotes the integer part. Thus, the model with a shift in the intercept is

(2) $$CDS_t = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha iTraxx_t + \varepsilon_t$$

with μ_1 the intercept before the shift and μ_2 the change in the intercept at the time of the shift. The model with shift in the intercept and slope is

(3) $$CDS_t = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha_1 iTraxx_t + \alpha_2 \varphi_{t\tau} iTraxx_t + \varepsilon_t$$

with $\alpha_1$denoting the co-integrating slope coefficients before the regime shift and α_2 the change in the slope coefficients due to the shift.

In order to choose whether to use a co-integration test or not, we apply Zivot and Andrews (1992) unit root test that makes allowance for a structural break at an unknown time. This test indicates that liquidity of each contract, counterparty risk and risk free rate are stationary variables.[2] Hence, for simplicity in the analysis, we only consider iTraxx Europe and VIX index from market variables and stock price and implied volatility from firm-specific variables in the co-integration analyses.

In Table 3, we present our findings for Models (2) and (3). The results indicate that CDS spreads of all reference entities are co-integrated with iTraxx Europe, VIX index, implied volatility and stock price. From the statistical analysis of the model coefficients, Model (3) seems to be suited for Aviva, Philips, Imperial Tobacco, Total and Vinci; this model depicts a regime shift in the long run relationship which indicates that the relationship between CDS spreads and explanatory variables changes due to a structural break. For the rest of firms we only observe a level shift in the intercept but not in the slope coefficients. The relationship with the explanatory variables is in line with the expectations outlined in the previous section. All CDS levels depict a positive and strong relationship with iTraxx Europe index implying that changes in iTraxx Europe index are quickly incorporated into CDS spreads. Regarding the effect of volatility measures, we observe that for the VIX index our data do not provide strong statistical evidence that supports the existence of a positive relationship with CDS spreads. On the contrary, we observe that the firm-specific implied volatility exhibits a positive relation with some CDS spreads such as Bayer, Imperial Tobacco, Tesco, Total, Vinci and Vodafone. Regarding the

[2] Results on Zivot and Andrews Test are available from the authors upon request.

relation between stock price and CDS spreads, our dataset reveals that only BMW, Philips Electronics and Tesco's stock price have a statistical negative influence on the CDS spreads.

B. Dynamic Stationary Regressions

For the CDS spread change analysis we follow a different strategy. First, we detect the break dates to differentiate the tranquil and volatile periods. Then, we analyze CDS spreads in changes considering all explanatory variables in two periods. As observed in Figure 1, all individual CDS contracts depict a tranquil and a volatile period highlighting the existence of structural breaks in the dataset. Annaert et al. (2010) consider April 2007 and Cesare and Guazzarotti (2010) assume July 2007 as structural break dates for all the contracts in their dataset. These authors take these break dates as given for every contract in their sample. The choice of the same break date for every contract in their study can be misleading, as the idiosyncratic properties of each contract are different.

For the stationary regressions in our analysis, we apply different techniques to detect the existence of structural breaks in the sample. In particular, we use the supremum of a family of likelihood ratio tests as suggested by Andrews and Ploberger (1994). To confirm our results we also apply a generalized fluctuation test, called OLS-CUSUM test, which tests for a structural change using cumulative sums of the common OLS residuals; see Ploberger and Kramer (1992).

Table 4

Structural Break Dates

Reference Entity	Group	Structural Break Dates
Aviva PLC	Financial	December 2007
Bayer AG	Non-Financial	December 2007
BMW AG	Non-Financial	July 2008
Deutsche Bank	Financial	December 2007
Imperial Tobacco Group PLC	Non-Financial	May 2008
Philips Electronics N.V.	Non-Financial	December 2007
Tesco PLC	Non-Financial	August 2008
Total S.A.	Non-Financial	August 2008
Vinci PLC	Non-Financial	December 2007
Vodafone Group PLC	Non-Financial	December 2007

Table 4 shows that for most of the firms in the study the break occurs at the end of 2007 when the subprime mortgage crisis deepened, liquidity diminished and some hedge funds collapsed. For BMW, Imperial Tobacco, Tesco and Total, the break occurred nearly 7-8 months later, in the next wave of bankruptcies when the main dealers collapsed and fears of systematic defaults triggered in financial markets.

Under CDS spread change analysis, we first explore the individual relationship between CDS spread and iTraxx, S&P 500 and the counterparty risk proxy. With this analysis we are aiming to answer two research questions. Is iTraxx index better than S&P 500 to explain individual CDS spreads? Is counterparty risk reflected in CDS spreads? In the second stage, we apply multivariate regression methods both for firm-specific and market variables to observe which group of variables is more successful at explaining CDS spread changes before and after the break. With these analyses, we are aiming to find whether the pricing of credit risk has changed due to shocks in financial markets. The models here considered are presented below.

Univariate Models for iTraxx, VIX and S&P 500 Indices

(4) $$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta \text{iTraxx}_t + \varepsilon_t$$

(5) $$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta \text{VIX}_t + \varepsilon_t$$

(6) $$\Delta CDS_t = \alpha_0 + \alpha_1 r_t^{S\&P} + \varepsilon_t$$

with $\Delta CDS_t = CDS_t - CDS_{t-1}$ and $r_t^{S\&P}$ the log return on S&P500.

We use univariate regression models to compare the explanatory power of iTraxx Europe and S&P 500 indices. The results of this analysis (see Table 5) support our hypothesis. Individual CDS contracts are more sensitive to aggregate movements in their own market than in the stock market. Moreover, all CDS contracts have a positive and very strong relation with iTraxx Europe index before the break. Nevertheless, the influence of iTraxx Europe index on individual CDS contracts is remarkably smaller after the break compared to the tranquil period. This finding points out that individual contracts break away from aggregate market movements during the turmoil period. As a by-product of this analysis we observe that iTraxx Europe and S&P 500 are correlated. In order to avoid potential multi-collinearity problems, we just consider iTraxx Europe index as a market sentiment variable in the following multivariate regression analyses.

Multivariate Regression Models for Firm-specific and Market Variables

(7) $$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta ImpVol_t + \alpha_2 StockRet_t + \alpha_3 Liq_t + \alpha_4 CountRisk_t + \alpha_5 \Delta CDS_{t-1} + \varepsilon_t$$

(8) $$\Delta CDS_t = \alpha_0 + \alpha_1 \Delta iTraxx_t + \alpha_2 \Delta VIX_t + \alpha_3 \Delta InterestRate_t + \alpha_4 \Delta CDS_{t-1} + \varepsilon_t$$

with *ImpVol* standing for implied volatility; *StockRet* representing the log return of the stock price on the reference entity, *Liq* is the liquidity of each contract that is measured by bid-ask

spread, $CountRisk_t = \Delta CDS_t^{HSBC} - \Delta iTraxx_t$ and $\Delta InterestRate$ is the change in one year Euro Swap Rate.

Multivariate analyses on CDS spread changes presented in Table 6 propose two intuitive conclusions. First, in the pre-crisis period, all CDS spreads are mainly dominated by common market factors. However during the crisis, the outlook completely changes and even iTraxx Europe index loses its predictive power to explain credit risk. Second, during the crisis, firm-specific regressions imply different inferences for financial and non-financial firms. For non-financial ones, CDS spreads become more sensitive to firm-specific variables than to common market factors. However, for financial firms such as Aviva operating as an insurance company and Deutsche Bank operating as a bank, both market and firm-specific variables fail to explain most of the variation in CDS spreads. Therefore, during the crisis, there is a remarkable difference in the sensitivity of the financial and non-financial CDS spreads on the firm-specific and market variables.

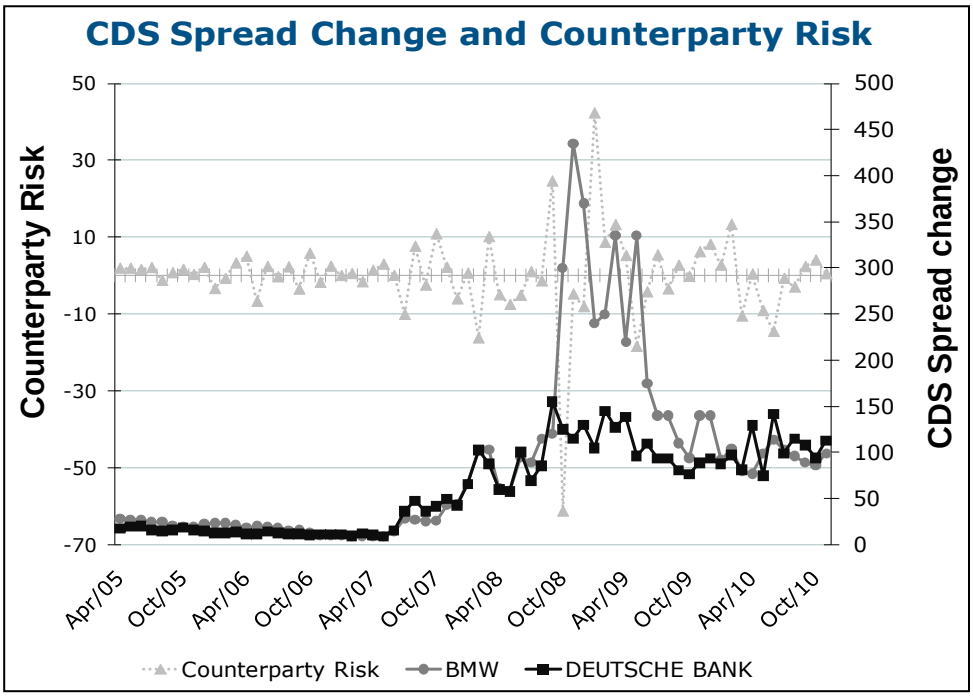
It is important to notice that the explanatory power of multivariate models in this study is very high compared to previous studies based on stationary regression models such as Greatrex (2009) and Ericsson et al. (2009). Macro variables explain up to 91 % and 67% of variation in CDS spread changes before and after the break, respectively. On the other hand, the variables related to firm characteristics can explain the variation in CDS spread change up to 56% and 77% before and after the break, respectively. These results provide empirical evidence that reveals that incorporating iTraxx index and counterparty risk into the regressions enhance the explanatory power of empirical models for describing the variation in CDS spreads.

C. Analysis of Counterparty Risk

One of the aims of this study is to investigate whether counterparty risk is incorporated in the pricing of CDS spreads or CDS market is still only pricing default risk of reference entity. Figure 3 plots the evolution of CDS spread changes versus counterparty risk.

Figure 3

CDS Spread Change and Counterparty Risk



As mentioned before, the proxy for counterparty risk is calculated by subtracting the change in iTraxx index from the change in counterparty CDS spread. Figure 3 shows that BMW spread changes, as a representative of non-financial contracts, do not react to changes in counterparty risk until July 2007. However, after this date changes in CDS spread start to move inversely to changes in counterparty risk. For Deutsche Bank, as a representative of financial contracts, changes in CDS spread are not affected by counterparty risk for all sample period. We use the

following univariate regression model to analyze the effect of counterparty risk on CDS spread change:

(9) $$\Delta CDS_t = \alpha_0 + \alpha_1 CountRisk_t + \varepsilon_t$$

The results of this analysis presented in Table 5 suggest different consequences for financial and non-financial contracts. We find that non-financial contracts started pricing counterparty risk after the break produced by the financial crisis. One possible explanation for this result is that in the period preceding the crisis the market assesses CDS dealers as risk-free entities, since no major counterparties have experienced bankruptcy, bail-out or default before. Also, collateralization could have been considered as a sufficient measure to mitigate counterparty risk. However, during the financial crisis, due to the fear of systematic defaults, counterparty risk has started to be reflected in CDS prices. Our empirical analysis also suggests that counterparty risk is not priced for CDS on financial contracts. This finding is particularly surprising for the second period under analysis. The observed increase on default correlation between reference entities and the major CDS counterparties in this period should lead to a decrease on the corresponding spread that is not observed empirically. A possible explanation for this phenomenon is offered by Arora et al. (2010). These authors suggest that the market expects large CDS dealers to be treated as too large to fail when other major financial firms begin to default. A similar result is observed by Nashikkar et al. (2010) in the analysis of liquidity effects on bond spreads; these authors note that for financial firms there is an implicit obligation by regulators to step in when a financial crisis unfolds in order to prevent financial contagion.

IV. CONCLUSIONS

This article explores the ability of firm-specific and market variables to explain variation in credit default swap spreads in levels and changes. We analyze monthly data of ten firms covering the main economic sectors in Europe from April 2005 to November 2010.

One of the most remarkable results of this study is that the relation between credit spreads and their determinants depends very much on the market circumstances prevailing at the time period analyzed. In other words, the relation between CDS spread and their determinants is regime dependent. Moreover, we find some evidence that CDS spreads of financial firms behave quite differently from CDS spreads of non-financial firms, especially during the financial crisis. For non-financial firms, CDS spreads are mainly determined by market variables during the tranquil period, but by firm-specific variables during the volatile period. However, for non-financial firms, both firm-specific and market variables are more informative in the tranquil period and both lose their explanatory power during the financial crisis.

The analysis also finds that the iTraxx Europe CDS index is the variable with the strongest predictive ability to describe variation in CDS spreads. This finding can be interpreted in a similar way to capital asset pricing models for equity markets. However, it is important to notice that iTraxx Europe index also loses its predictive power on single CDS contracts during the financial crisis period. Hence CDS spreads seem to decouple from the underlying market risk in CDS contracts and are mainly driven by idiosyncratic factors.

Finally, our analysis of counterparty risk offers some of the first insights in the literature on the pricing dynamics of counterparty risk in the CDS market. The empirical results indicate that counterparty risk has started to be priced in the CDS contracts on non-financial firms after the occurrence of the structural break corresponding to the financial crisis period. This is informative

for policy makers in that the market does not regard counterparties as risky entities during the tranquil period. However, after the collapse of the main CDS market dealers, the market starts pricing counterparty risk and CDS contracts written on the same reference entity are sold at different prices depending on the creditworthiness of the seller. Contrary to non-financial contracts, we cannot find any counterparty risk effect on financial contracts. The higher correlation between financial firms and the major counterparties on the CDS market, also belonging to the financial sector, is not priced on the CDS spreads of financial firms. This finding leads us to think that after the financial crisis investors expect that the implementation of regulatory measures and government intervention with the aim of avoiding systemic risk, are sufficient to guarantee the fulfillment of the credit derivative contract even under default of the counterparty.

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Appendix

Figure 2

Time Series Graphs

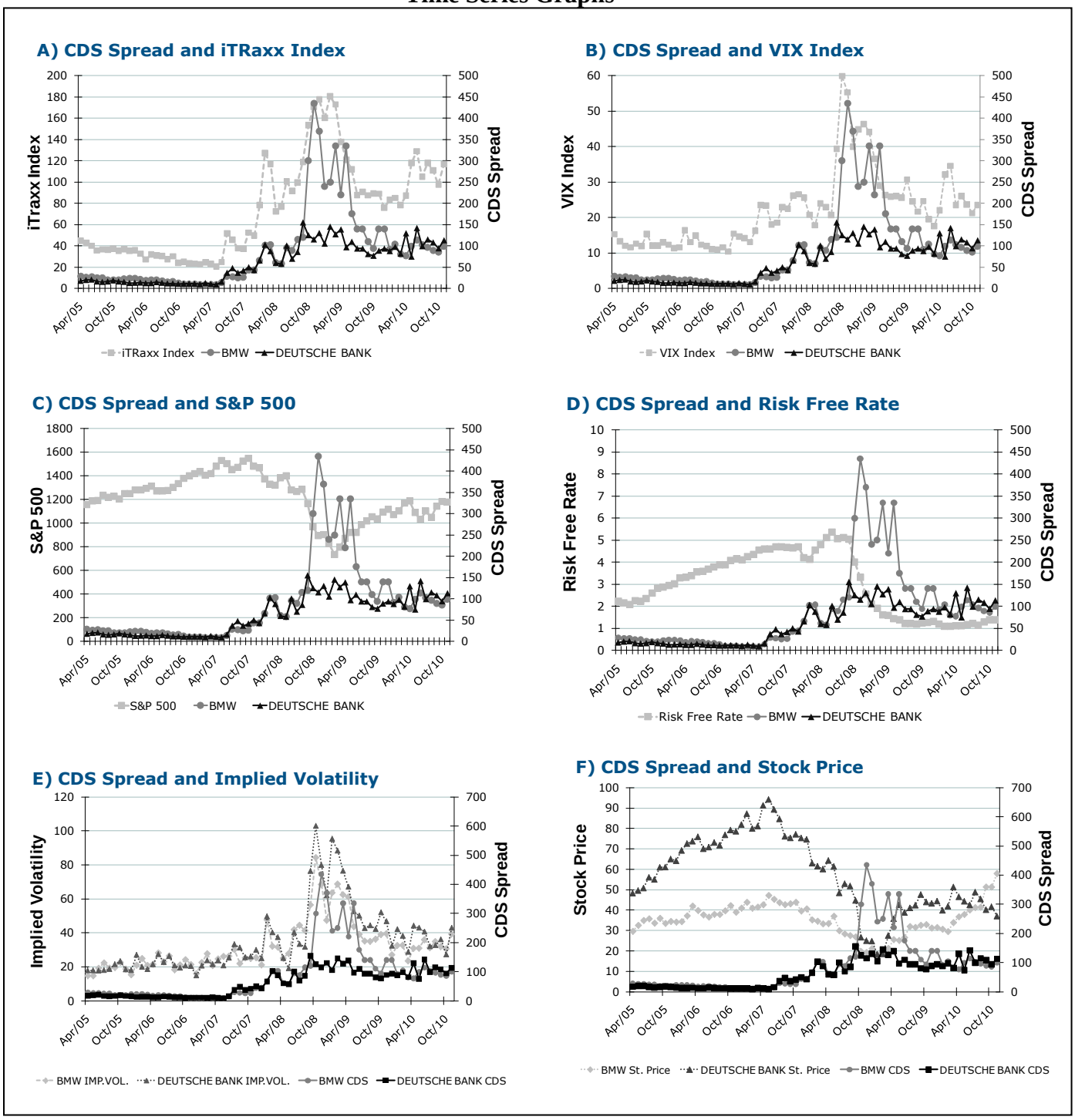

Table 3

Co-integration Analyses Results with Structural Break

Reference Entity	Aviva		Bayer		BMW		Deutsche Bank		Imperial Tobacco		Philips Electronics		Tesco		Total		Vinci		Vodafone	
Model	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**	**Model 2**	**Model 3**
Break Date	**Mar-09**	**Feb-07**	**Mar-09**	**May-08**	**Oct-08**	**Nov-08**	**Apr-09**	**Jul-08**	**Dec-09**	**Oct-08**	**Mar-08**	**Mar-08**	**Dec-08**	**Dec-08**	**Sep-08**	**Sep-08**	**Nov-07**	**Jan-09**	**Dec-07**	**Nov-08**
Intercept	-66.6	-68.9 **	8.70	8.66	67.9*	24.9	-35.7**	-35.8**	-56.9**	-47.8*	31.5**	16.2	7.90	9.47	-12.9	-1.57	-28.7	-34.8**	-27.5**	-24.6**
	(-1.36)	(-2.00)	(1.62)	(1.49)	(1.91)	(0.42)	(-2.11)	(-2.27)	(-2.41)	(-1.90)	(2.69)	(0.96)	(1.37)	(1.52)	(-0.78)	(-0.10)	(-1.49)	(-2.83)	(-3.40)	(-2.59)
Dummy	54.2**	-38.1	-9.00**	45.9	36.3**	64.8	27.5**	11.9	-54.3**	-14.0	-8.87*	34.7	49.4**	63.5*	17.9**	-45.0	17.03	257.9**	-9.54**	9.69
	(4.45)	(-0.38)	(-3.17)	(1.40)	(2.71)	(0.81)	(6.15)	(0.28)	(-4.20)	(-0.13)	(-1.86)	(1.44)	(11.8)	(1.94)	(4.62)	(-0.84)	(1.53)	(2.40)	(-2.14)	(0.42)
iTraxx Index	1.41**	1.81**	0.58**	0.54**	0.56**	0.40	0.86**	0.74**	1.52**	1.08**	0.72**	0.57**	0.22**	0.23	0.47**	0.33**	0.71**	1.21**	0.94**	0.98**
	(5.93)	(10.06)	(9.02)	(6.76)	(2.05)	(1.14)	(7.37)	(4.51)	(7.60)	(4.25)	(7.93)	(3.65)	(3.94)	(0.00)	(7.20)	(4.42)	(3.35)	(9.89)	(13.9)	(12.6)
VIX Index	-5.43**	-1.13	-0.42	-0.06	2.26*	2.07	-0.24	1.55*	1.57	2.54**	-0.51	0.33	0.81**	1.00**	-0.69	0.60	-0.74	-0.26	-0.69*	-0.5
	(-4.72)	(-1.10)	(-1.20)	(-0.12)	(1.71)	(1.33)	(-0.39)	(1.64)	(1.56)	(1.97)	(-1.17)	(0.41)	(3.80)	(4.10)	(-1.57)	(1.25)	(-0.80)	(-0.36)	(-1.65)	(-0.93)
Implied Volatility	2.76**	0.07	0.41*	0.21	0.82	0.99	0.32	-0.03	1.86**	1.6	0.07	-0.19	0.90**	0.70**	0.93**	0.07	2.25**	1.43**	1.16**	1.11**
	(6.40)	(1.35)	(1.91)	(0.74)	(0.98)	(1.03)	(1.13)	(-0.7)	(2.14)	(1.25)	(0.23)	(-0.31)	(3.62)	(2.35)	(2.76)	(0.17)	(4.59)	(3.54)	(4.40)	(3.44)
Stock Price	0.09	-0.00	-0.09	-0.06	-3.15**	-1.81	0.32	0.1	0	0	-1.02**	-0.39	-0.08**	-0.08**	-0.06	-0.24	-0.06	0.05	0.08	0.01
	(1.18)	(-0.01)	(-0.72)	(-0.47)	(-4.35)	(-1.35)	(1.61)	(0.50)	(-0.44)	(-0.43)	(-2.60)	(-0.59)	(-5.11)	(-4.68)	(-0.17)	(-0.68)	(-0.14)	(-0.20)	(1.34)	(-0.24)
Dummy*iTraxx Index		-1.08**		0.09		1.27**		-0.08		0.08		0.26		0.01		0.45**		-0.65**		-0.14
		(-2.75)		(0.53)		(-2.05)		(-0.36)		(0.17)		(1.35)		(0.12)		(3.24)		(-2.27)		(-0.94)
Dummy*VIX Index		-2.32		-1.41*		-1.67		-2.48**		-5.24**		-1.53		-0.81		-3.71**		-2.02		-0.28
		(-1.24)		(-1.68)		(-0.62)		(-2.13)		(-2.18)		(-1.60)		(-1.43)		(-4.50)		(-1.43)		(-0.31)
Dummy*Implied Volatility		4.32**		0.23		-0.82		0.71		9.3**		0.28		0.54		2.34**		-0.99		0.03
		(6.64)		(0.41)		(-0.49)		(1.14)		(-3.47)		(-0.38)		(0.74)		(3.55)		(-0.79)		(-0.06)
Dummy*Stock Price		0.14		-0.76		-2.29		1.11*		-0.03		-1.75**		-0.02		1.32		-3.68		0
		(-0.74)		(-1.61)		(-1.40)		(-1.81)		(-0.72)		(-2.03)		(-0.34)		(-1.05)		(-1.74)		(-0.00)

Model 2 Shift in the Intercept of the Cointegrating Relationship
Model 3 Shift in the Intercept and Slope of the Cointegrating Relationship
*,** indicates t statistics that are significant at the 10% and 5 % percent level respectively.

Table 5

Univariate Analyses Results on CDS Spread Change

Reference Entity	Aviva		Bayer		BMW		Deutsche Bank		Imperial		Philips		Tesco		Total		Vinci		Vodafone	
Break Date	**December 07**		**December 07**		**July 08**		**December 07**		**May 08**		**December 07**		**August 08**		**August 08**		**December 07**		**December 07**	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Counterparty Risk	-0.29	-0.08	-0.73**	-0.60**	-0.73	-2.28**	-0.02	0.27	-0.74	-2.00**	-0.21	-0.62**	0.06	-0.45**	0.44	-0.71**	-0.63	-1.56**	-0.43	-0.88**
	(-0.71)	(-0.16)	(-2.20)	(-4.82)	(-1.48)	(-4.06)	(-0.06)	(0.74)	(-1.30)	(-2.33)	(-0.96)	(-3.14)	(0.22)	(-2.43)	(1.14)	(-4.80)	(-1.64)	(-4.40)	(-1.31)	(-2.96)
R^2	15%	0%	17%	36%	8%	29%	0%	2%	6%	35%	3%	25%	0%	21%	14%	41%	9%	50%	7%	28%
iTraxx Index	1**	1.27**	0.8**	0.42**	0.83**	2.04**	0.69**	0.63**	0.92**	1.64**	0.46**	0.55**	0.45**	0.68**	0.4**	0.45**	0.86**	1.05**	0.76**	1**
	(4.30)	(3.80)	(6.96)	(3.41)	(9.65)	(2.51)	(8.92)	(2.18)	(5.88)	(2.04)	(5.39)	(3.64)	(6.67)	(4.90)	(5.39)	(2.16)	(10.42)	(3.62)	(14.66)	(5.35)
R^2	74%	22%	80%	28%	82%	22%	70%	17%	66%	24%	55%	28%	77%	56%	57%	17%	66%	36%	88%	56%
S&P 500 Index	-2.55**	-1.89	-2.13**	-0.6	-2.96**	-2.73	-1.70**	-1.06	-3.91**	-3.09	-1.3**	-0.41	-1.63**	-1.65**	-1.58**	-0.31	-2.32**	-1.66	-1.78**	-2.08**
	(-2.61)	(-1.16)	(-5.15)	(-1.06)	(-4.82)	(-1.06)	(-3.38)	(-1.04)	(-4.64)	(-1.26)	(-3.41)	(-0.62)	(-5.79)	(-4.84)	(-4.00)	(-0.45)	(-4.20)	(-1.16)	(-3.50)	(-2.71)
R^2	47%	5%	56%	6%	47%	7%	42%	5%	54%	14%	42%	2%	56%	55%	47%	1%	47%	10%	48%	27%

The *t* -statistics (in parantheses) are based on the White (1980) heteroskedastic-consistent estimate of the covariance matrix.

*,** indicates t statistics that are significant at the 10% and 5 % percent level respectively.

Before indicates Before Break Date and After indicates After Break Date.

Table 6

Multivariate Analyses Results on CDS Spread Change

Reference Entity	Aviva		Bayer		BMW		Deutsche Bank		Imperial		Philips		Tesco		Total		Vinci		Vodafone	
Break Dates	December 07		December 07		July 08		December 07		May 08		December 07		August 08		August 08		December 07		December 07	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Intercept	1.99*	-2.17	-0.74	-1.86	0.32	-11.72	0.61	2.96	0.67	-16.6**	0.22	-1.82	0.3	-2.07	0.38	-3.59	1.63	-1.47	0.46	-0.73
	(1.87)	(-0.27)	(-1.34)	(-0.78)	(0.39)	(-1.19)	(0.65)	(0.73)	(0.32)	(-2.08)	(0.38)	(-0.78)	(0.44)	(-1.00)	(0.52)	(-1.43)	(1.35)	(-0.37)	(1.12)	(-0.25)
iTraxx	0.91**	1.5**	0.88**	0.46**	0.87**	2.15*	0.68**	0.57**	0.91**	1.00	0.40**	0.74**	0.38**	0.51**	0.29**	0.50	0.93**	0.96**	0.93**	0.91**
	(6.92)	(4.59)	(7.27)	(3.19)	(6.92)	(1.83)	(5.77)	(2.31)	(4.12)	(1.53)	(3.35)	(3.93)	(5.51)	(3.58)	(4.91)	(1.74)	(5.71)	(2.51)	(10.38)	(3.70)
VIX Index	-0.22	-1.63**	0.05	-0.45	-0.07	-1.43	0.09	0.62	0.49	1.63	0.22	-1.15**	0.39**	0.3	0.74**	-0.72	-0.50	0.35	-0.52**	0.49
	(-0.61)	(-2.17)	(0.20)	(-1.16)	(-0.13)	(-0.49)	(0.25)	(0.65)	(0.45)	(1.35)	(0.89)	(-2.16)	(3.12)	(0.62)	(2.00)	(-0.80)	(-1.03)	(0.28)	(-3.17)	(0.75)
Interest Rate	-15.7*	-15.4	11.04**	-15.5	7.03	-71.2	-1.41	16.05	10.39	-95.01**	-1.60	-12.6	-1.72	-20.04**	-0.22	-21.90	-6.28	-3.94	4.14	0.87
	(-1.74)	(-0.67)	(2.20)	(-1.42)	(1.09)	(-1.05)	(-0.22)	(1.17)	(0.52)	(-2.56)	(-0.35)	(-1.01)	(-0.36)	(-2.45)	(-0.07)	(-1.28)	(-0.82)	(-0.12)	(1.20)	(0.05)
ΔCDS_{t-1}	0.42**	-0.07	-0.16**	-0.08	0.1	-0.24	0.15	-0.56**	0.14	-0.33*	0.11	0.07	0	-0.07	0.05	-0.29	0.18	0.01	0.05	-0.07
	(2.71)	(-0.39)	(-2.46)	(-0.55)	(1.38)	(-0.99)	(0.50)	(-3.87)	(0.79)	(-1.84)	(0.95)	(0.38)	(-0.02)	(-0.59)	(0.53)	(-0.93)	(1.32)	(0.07)	(0.77)	(-0.80)
R^2	**86%**	**25%**	**84%**	**38%**	**84%**	**32%**	**72%**	**53%**	**68%**	**49%**	**57%**	**47%**	**81%**	**67%**	**69%**	**38%**	**71%**	**36%**	**91%**	**58%**

Reference Entity	Aviva		Bayer		BMW		Deutsche Bank		Imperial		Philips		Tesco		Total		Vinci		Vodafone	
Break Dates	December 07		December 07		July 08		December 07		May 08		December 07		August 08		August 08		December 07		December 07	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Intercept	-5.12*	32.95	-1.7	-4.24	-4.76	-12.14	0.23	-3.36	-4.24	-32.2	-0.42	0.71	-1	-4.57	7.25	-3.01	-7.35**	-3.49	-11.21*	-1.92
	(-1.84)	(0.94)	(-0.35)	(-0.76)	(-0.56)	(-0.59)	(0.10)	(-0.54)	(-0.60)	(-0.80)	(-0.08)	(0.07)	(-0.40)	(-0.87)	(1.29)	(-0.78)	(-3.27)	(-0.53)	(-1.69)	(-0.24)
Implied Volatility	0.86*	-1.13	0.28	0.05	0.34	-1.49 *	0.57**	1.06**	0.29	5.37**	0.44	0.48	0.86**	0.91	-0.03	-0.27	0.81**	-0.06	0.3	0.82
	(1.85)	(-1.18)	(1.37)	(0.24)	(0.93)	(-1.93)	(3.36)	(2.24)	(0.39)	(3.49)	(1.50)	(1.43)	(2.37)	(1.48)	(-0.11)	(-0.48)	(2.41)	(-0.15)	(1.22)	(1.28)
Stock Return	-0.51*	-2.64*	-0.35**	-0.3	-0.61**	-2.36**	-0.36**	0.31	-1.38	2.41*	-0.18	0.00	-0.26	-0.51	-0.54**	-0.74	-0.11	-0.74	-0.27	-0.47
	(-1.80)	(-1.77)	(-2.03)	(-0.79)	(-3.02)	(-2.50)	(-2.21)	(0.78)	(-1.55)	(1.89)	(-1.20)	(0.02)	(-1.14)	(-0.77)	(-2.09)	(-0.77)	(-0.47)	(-1.27)	(-1.41)	(-0.49)
Liquidity	2.55*	-4.39	1.12	1.17	2.21	6.24	0.29	1.1	2.37	3.19	0.32	-0.33	0.57	0.83	-2.09	0.63	2.31**	0.45	4.11*	0.56
	(1.86)	(-1.08)	(0.68)	(0.82)	(0.63)	(1.04)	(0.33)	(0.99)	(1.00)	(0.75)	(0.24)	(-0.13)	(0.63)	(0.98)	(-1.22)	(0.70)	(3.65)	(0.46)	(1.84)	(0.29)
Counterparty Risk	0.23	0.06	-0.63**	-0.56**	-0.46	-1.00*	0.15	-0.12	-0.33	-1.52**	-0.12	-0.67**	0.06	-0.25**	0.26	-0.82**	-0.75**	-1.55**	-0.28	-0.59*
	(0.69)	(0.09)	(-2.58)	(-3.45)	(-1.05)	(-1.93)	(0.41)	(-0.31)	(-0.61)	(-3.16)	(-0.44)	(-2.34)	(0.19)	(-2.74)	(0.88)	(-3.58)	(-2.64)	(-3.53)	(-0.96)	(-1.60)
ΔCDS_{t-1}	0.22	-0.06	-0.13	-0.06	-0.01	-0.18	0.05	-0.66**	0.18	-0.03	0.11	0.16	0.05	0.21	-0.03	-0.24*	-0.05	-0.05	-0.3	-0.24*
	(0.99)	(-0.31)	(-0.56)	(-0.40)	(-0.09)	(-1.66)	(0.29)	(-5.03)	(0.59)	(-0.19)	(0.57)	(0.97)	(0.32)	(1.51)	(-0.13)	(-1.81)	(-0.38)	(-0.52)	(-1.29)	(-1.86)
Imp. Volatility(-1)					0.41	4.53**													0.24	0.88*
					(1.27)	(5.53)													(0.59)	(1.71)
Stock Return(-1)				-0.61*																
				(-1.75)																
R^2	**55%**	**22%**	**44%**	**47%**	**34%**	**77%**	**56%**	**49%**	**28%**	**58%**	**25%**	**31%**	**45%**	**59%**	**34%**	**53%**	**49%**	**55%**	**42%**	**48%**

The *t* -statistics (in parantheses) are based on the White (1980) heteroskedastic-consistent estimate of the covariance matrix.
*,** indicates t statistics that are significant at the 10% and 5 % percent level respectively.
Before indicates Before Break Date and After indicates After Break Date.