Accepted Manuscript

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PII: S1042-4431(16)30213-X
DOI: https://doi.org/10.1016/j.intfin.2018.02.002
Reference: INTFIN 1016

To appear in: *Journal of International Financial Markets, Institutions & Money*

Received Date: 6 December 2016
Revised Date: 11 October 2017
Accepted Date: 13 February 2018

WHAT DRIVES CORPORATE CDS SPREADS? A COMPARISON ACROSS US, UK AND EU FIRMS

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ABSTRACT: We investigate the determinants of corporate credit default swap spreads for US, UK and EU firms and decompose the predictive power of accounting- and market-based variables for spreads in pre-crisis, crisis and post-crisis periods. We find that the predictive power of accounting risk measures decreases during and following the crisis, and the growing relevance of market-based variables highlights the growing significance of forward-looking risk measures for modeling spreads. By decomposing bond yield spreads into default and non-default components, we find a significant non-zero basis in the post-crisis period, highlighting the mispricing between the two markets. We find that mispricing between the two markets has significant predictive power in forecasting subsequent price movement in the CDS market in the post-crisis period.

***Keywords*: CDS, spread prediction, CDS-bond basis**

***JEL Classification*: C33, G01, G13, G15, G23**

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This research did not receive any specific grant from funding agencies in the public, commercial, or not for profit sectors.

Introduction

Credit Default Swap (CDS) spreads has increasingly been used to gauge the financial health of corporations in both commercial applications (Moody's and Bloomberg's CDS implied default probability) and academia. In spite of their popularity, there is widespread disagreement on the information relevance of CDS spreads. Understanding what drives CDS spreads is vital and beneficial for investors, analysts and policy makers and represents an important research question, given the central role that the CDS market plays in assessing the credit worthiness of firms and their ability to lead other markets. The growing importance of the CDS market has resulted in the extant literature analyzing CDS spreads.

The earliest studies using CDS spreads (i.e., Hull et al., 2004; Blanco et al., 2005; Longstaff et al., 2005) analyze the relationship between CDS spreads and bond yields. Das et al. (2009) and Trujillo-Ponce et al. (2014) use CDS spreads as a proxy to analyze models for measuring corporate credit risk. Fabozzi et al. (2007) and Baum and Wan (2010) test the influence of fundamental variables on CDS pricing, whereas Ericsson et al. (2009) investigate the relationship between theoretical determinants of default risk and CDS spreads. Other studies exploring CDS spread determinants include those by Norden and Weber (2012), Becchetti et al. (2012), Eichengreen et al. (2012), and Annaert et al. (2013), among others. Overall, CDS spread determinants have been investigated before but not sufficiently analyzed, and the literature lacks a comprehensive comparative analysis. This, coupled with the existence of few studies that investigate the determinants of non-financial firms' CDS spreads across different economic conditions, provides the motivation for this study.

Our study is developed in two parts. First, we conduct a panel data analysis to study the relationship between firm-specific accounting- and market-based variables on corporate CDS spreads, while controlling for non-default spread drivers. Further, we decompose the spread prediction ability of accounting and market variables and observe how they evolve for US, UK and EU firms across sub-periods of analysis. Second, using the methodology developed in Longstaff et al. (2005), we decompose bond yield spreads into default and non-default components, using CDS spreads as a proxy for default risk to explain the dynamics of the non-default element of bond yield spreads. This non-zero CDS-bond basis is then used to explain subsequent changes in CDS spreads, highlighting the existence of mispricing between the CDS and bond markets and the subsequent price correction in the CDS market.

This paper contributes to the existing literature in the following ways. First, we provide a comparative analysis of accounting- and market-based variables, thereby addressing the debate (see Das et al., 2009; Galil et al., 2014) on the relative importance of these variables in modeling CDS spreads. We document the changing nature of spread predictor variables across different markets and sub-periods and decompose the model's explanatory power, emphasizing their relative importance. Second, we employ CDS market illiquidity measures to explain CDS spreads and document the growing relevance of non-default spread drivers. Third, we provide a comparative evaluation across US, UK and EU, which are the largest markets for corporate CDS contracts globally, providing fascinating insights into CDS drivers across different markets. Finally, we complement the previous literature (Kim et al., 2016) by investigating the predictive power of the basis to study future price movements in the CDS market. Our findings validate that the CDS market dominates the information transmission process between the CDS and bond market, which is more prominent in the post-crisis period, and we find the mispricing between the two markets has significant predictive power in forecasting subsequent price movement in the CDS market.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature on CDS spreads and spread prediction models. Section 3 presents the data, empirical method and the main results. Section 4 discusses the policy implications and concludes.

1. Literature Review

2.1 CDS spreads as proxy for corporate credit risk

Previous studies have focused on various competing measures for estimating corporate credit risk dynamics, including the credit rating, bond yields spreads and CDS spreads. CDS spreads are considered a better proxy for credit risk compared to bond yields for various reasons (see Ericsson et al., 2009). In addition, CDSs also have a more pronounced liquidity relative to bonds and as such provide an excellent laboratory for studying the mechanism of the credit market (Breitenfellner and Wagner, 2012). Thus, the increasingly popular CDS is considered to provide an alternative, more reliable, cross-sectional and time-series indicator of corporate credit risk. This, coupled with the existence of a large amount of CDS data, has yielded a wide range of studies that have employed CDS spreads as a pure measure of corporate credit risk.

2.2 Accounting and Market-based measures

Previous studies on default prediction models have found a significant association between credit risk and firm financials. The usefulness of accounting information for credit risk estimation is supported by Das et al. (2009), who found that accounting-based information explains nearly two-third of the variation in CDS spreads and has comparable estimation power to market-based variables. This is further corroborated by Batta (2011), Hasan et al. (2016) among others. Although accounting variables are believed to have some degree of financial distress prediction ability, their use in estimating corporate credit risk can be challenged on various grounds. Indeed, accounting variables lack a theoretical basis for their use in default prediction models, are a 'backward looking' model input that is updated with a rather low frequency and released with a time lag, suffer from possible accounting manipulations, are sample specific and prone to conservatism due to historical cost accounting (Bystorm, 2006). Additionally, accounting variables are considered to be of limited utility in predicting defaults because they are prepared on a 'going-concern' basis (Hillegiest et al., 2004). Overall, despite its limited theoretical rationale, accounting information is found to provide a good indication of the financial health of the company and hence cannot be ignored.

The literature on credit risk modeling using market-based measures suggests two competing paradigms for modeling credit risk, namely a structural form that uses option pricing theory and a reduced form using term structure theory to explain credit spread behavior. The structural form (Merton, 1974) assumes that the firm has a simple capital structure comprised of just debt and equity and interprets the equity of the firm as a call option on the firm's asset with debt as the strike price. The alternative approach to Merton's model is the use of the reduced-form model developed by Jarrow and Turnbull (1995). Unlike Merton's model, the reduced-form approach does not provide an explicit link between default and firm specific variables (Duffie and Singleton, 1999; Switzer and Wang, 2013). Hence, the structural model is preferred over the reduced-form approach because it offers an economically intuitive framework for credit risk pricing and is widely used to analyze corporate credit spreads (Ericsson et al., 2009; Hasan et al., 2016).

2.3 CDS liquidity

Liquidity is one of the major concerns in the CDS market especially due to the non-continuous nature of trades, which relies heavily on the degree of confidence between counterparties. Liquidity in the CDS market could dry up quickly, especially during a crisis period, and could take a long time to recover. All CDS trades have certain costs, including search costs, broker commissions and asymmetric information costs and the higher the costs the greater the illiquidity associated with the corresponding CDS contract (Acharya and Johnson, 2007). Until recently, CDS market liquidity has been sparsely studied. Recent studies (e.g., Bongaerts et al., 2011; Arakelyan and Serrano, 2012; Lesplingart et al., 2012) have focused on CDS market liquidity and found it to be a crucial factor driving CDS spreads.

Overall, the literature on modeling spreads using accounting, market-based, and non-default measures provides conflicting evidence on the usefulness of these variables in explaining CDS spread. On one hand, some studies (e.g., Das et al., 2009; Batta, 2011; Hasan et al., 2016) find accounting measures to be more informative, whereas other studies (e.g., Galil et al., 2014) find market-based variables substantially add to the model's power of explaining CDS spreads. Moreover, the growing field of research on non-default drivers of CDS spreads (e.g., Tang and Yan, 2007; Bongaerts et al., 2011) has compelled further investigation on CDS spread modeling.

2. Sample and research design

3.1 Sample selection: CDS spreads

Five-year constant maturity quarterly CDS spreads belonging to the senior debt type with a modified restructuring clause are downloaded from the Bloomberg database. We use five-year CDS spreads because five-year contracts account for nearly 85% of the CDS market and have the best liquidity. First, CDS contracts are screened for their underlying firm issuer country and observations are limited to those belonging to the US, UK and EU. Second, we exclude CDS contracts belonging to the Financial GICS[4] sector in line with previous studies that exclude banks from empirical investigations due to their special business models, asset-liability structures, regulatory requirements on capital adequacy and higher leverage ratios (Hasan et al., 2016). Finally, we exclude CDS contracts for firms that have defaulted over the period of investigation to ensure our sample is not biased due to non-random attrition. For the EU sample, we start with the 17 EU countries. However, due to the unavailability of CDS spread data following from the sample selection criteria (as discussed above), the final EU sample contains CDS spreads data for firms in 12 EU countries[5].

The combined sample consists of 17,845 quarterly spreads belonging to 704 firms over the sample period of 01/01/2005 to 31/12/2012. The unbalanced nature of the sample is consistent with other studies (e.g., Das et al., 2009; Galil et al., 2014) because not all CDS contracts trade in a given quarter; hence CDS spreads are missing for certain contracts over the period of

[4] The Global Industry Classification Standard (GICS) was jointly developed by Standard & Poor's and MSCI/Barra to establish a global standard for categorizing companies into main sectors and industries.
[5] The 12 EU countries include Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain.

investigation. Further, the sample period is subdivided into three sub-period of analysis around the Global Financial Crisis (GFC): pre-GFC (01/01/05 – 30/06/07); GFC (01/07/07 – 30/06/09) and post-GFC (01/07/09 – 31/12/12), as in Breitenfelner and Wagner (2012). The GFC period for the US and UK are closely linked. For the EU, the GFC was transformed into a sovereign debt crisis, although in our study it is denoted as the post-GFC period for the EU sample. We aim to test the effect of GFC on US, UK and EU corporations and this drives our choice of selecting a standard period of analysis across the three samples. We rationalize that the credit risk dynamic of listed firms will not only be a function of the economic condition for the national boundary but also likely be influenced by global economic conditions because financial markets are global and interconnected. Other studies propose a modified version of the period of analysis further splitting the crisis period. However, our choice of period is based on the ease of comparing corporate credit risk dynamics across the economic conditions and the need to have a sufficient number of observations in each period to draw statistically significant inferences. We specifically end our sample in Q4 2012 considering the relevant rules for non-financial companies under the Dodd-Frank Act (Title VII) passed in 2010, which became final and effective after September 2012, with the first expected clearing mandate set in Q4 2012 and compliance deadlines set throughout 2013 (Ernest and Young, 2012). The sample end date ensures our analysis is not affected by the regulatory changes in the CDS market.

Table 1 provides the descriptive statistics for CDS spreads aggregated across year for the three markets in Panel A[6]. Although there is an overall decline in spreads from 2009 onwards,

[6] We undertake a Kruskal-Wallis rank test of the equality of the population on CDS spreads to confirm the statistical significant difference across the three samples, across the whole period as well as each sub-period of analysis, the results (not reported here) indicate the difference between the samples is statistically significant.

the median spread has remained stubbornly high for both the US and UK, indicating that for certain firms, at least the CDS spread has decreased whereas for other it has not. However, the spreads are nowhere comparable to the pre-GFC level. For the EU, median spreads reduced following the GFC but again rose sharply in the post-GFC period, indicating the turmoil caused by the sovereign credit crisis. Panel B breaks down spreads by the issuing country of the underlying firm. We notice huge variations in the EU median spread across the GFC and post-GFC periods. Median spreads for Germany and the Netherlands are lower than those for the US and UK; in contrast, those for Portugal, Italy, Greece and Spain are much higher in the post-GFC period, highlighting the variable effect of the Eurozone crisis on corporate credit risk.

Table 1: Descriptive statistics of credit default swap spreads

Descriptive statistics of credit default swap spreads (in basis points) from 01/01/05 to 31/12/12, for the US, UK and EU broken down by year in Panel A, by country in Panel B, and by GICS industry sector in Panel C. N is the number of quarterly CDS spread observations available across each year, country and GICS sector. The pre-GFC period is defined as 01/01/05 to 30/06/07; the GFC period is defined as 01/07/07 to 30/06/09 and the post-GFC period is defined as 01/07/ 09 to 31/12/12.

Panel A: Summary of variables: Spread by year						
US						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	883	92.36	42.72	5.00	2,696.86	168.30
2006	921	96.17	39.37	5.00	2,670.00	196.22
2007	1,091	116.36	43.13	4.83	1,731.20	178.78
2008	1,698	355.04	148.29	19.39	9,110.67	643.27
2009	1,654	325.71	123.61	17.25	9,108.99	683.43
2010	1,689	205.76	112.01	17.31	2,443.19	270.50
2011	1,641	261.34	120.87	15.22	7,199.96	563.21
2012	1,559	243.25	118.86	12.77	13,080.11	524.90
Total	**11,136**	**232.96**	**97.26**	**4.83**	**13,080.11**	**495.54**

UK Year	N	Mean	Median	Min	Max	Std dev.
2005	259	78.36	42.14	9.00	641.25	105.25
2006	263	64.22	36.38	3.67	419.38	75.60
2007	291	82.43	39.17	4.44	590.45	103.41
2008	338	245.64	124.55	21.27	4,575.94	381.60
2009	343	243.50	106.37	16.25	8,344.94	550.73
2010	359	157.51	96.05	17.44	1,212.10	168.35
2011	356	177.12	106.67	19.72	1,208.55	189.97
2012	346	153.80	100.58	24.36	857.74	151.02
Total	**2,555**	**156.76**	**84.73**	**3.67**	**8,344.94**	**281.19**

EU Year	N	Mean	Median	Min	Max	Std dev.
2005	425	78.84	37.42	8.95	810.00	114.68
2006	467	77.67	36.21	5.65	698.33	110.20
2007	513	87.86	40.23	5.46	870.32	128.13
2008	545	294.21	136.72	14.00	3,551.34	405.58
2009	554	386.32	129.30	13.12	10,271.69	831.56
2010	548	252.12	112.35	18.47	16,102.98	740.17
2011	564	279.90	148.97	18.52	3,497.36	382.14
2012	547	263.92	143.99	23.15	2,597.74	316.93
Total	**4,163**	**223.30**	**94.69**	**5.46**	**16,102.98**	**484.52**

Panel B: Summary of variables: Spread by Country

	Pre-GFC			GFC			Post-GFC		
Country	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
US	**2,041**	**92.50**	**40.55**	**3,390**	**320.85**	**122.74**	**5,705**	**230.99**	**113.85**
UK	**590**	**70.77**	**38.00**	**735**	**216.05**	**98.33**	**1,230**	**162.59**	**98.53**
EU	**1,017**	**76.82**	**36.17**	**1,210**	**277.23**	**108.23**	**1,936**	**266.55**	**131.42**
FRANCE	351	65.10	36.08	382	208.05	104.68	590	211.22	132.63
GERMANY	265	78.41	36.52	327	276.24	110.66	552	178.87	98.10
ITALY	92	102.36	49.90	99	301.65	170.00	150	477.68	258.29
NETHERLANDS	90	51.76	30.88	132	233.69	73.02	203	160.48	77.52
SPAIN	74	46.03	30.26	83	410.11	126.48	133	419.87	257.29
FINLAND	59	90.08	43.33	63	425.46	137.72	98	282.65	233.46
BELGIUM	22	54.98	26.29	34	520.85	98.92	48	729.70	72.12
PORTUGAL	21	51.88	30.00	19	98.00	79.17	29	425.79	337.44
IRELAND	15	247.03	185.50	18	327.51	232.29	26	534.10	285.48
LUXEMBOURG	14	363.78	443.46	34	476.36	360.87	79	381.97	312.06
GREECE	9	44.70	44.32	9	89.35	88.13	14	846.87	510.31
AUSTRIA	5	40.64	43.38	10	161.75	88.06	14	115.39	105.96

3.2 Spread prediction model

Following Aunon-Nerin et al. (2002), who find the use of the logarithm of spreads provides a better fit than their direct use in a regression, and Das et al. (2009), who claim that the inclusion of accounting variables improves the overall fit of the model, we estimate the following panel data fixed-effect regression function for each firm *i* and quarter *t*:

$$ln(CS_{it}) = \alpha + \sum_1^j \beta_j AC_{it} + \sum_1^k \gamma_k MB_{it} + \sum_1^m \delta_m \, CONTROL_t + \chi LIQ_{it} + \varepsilon_{it} \qquad (1)$$

The model assumes correlation clustering over time for a given firm with independence over firms. We use a fixed-effect panel data regression for the following reasons. First, the OLS pooled regression model is too restrictive and does not explain the full richness of our panel dataset. Moreover, because the true model is a fixed-effect regression, the pooled OLS regression is bound to provide an inconsistent estimate[7]. Second, we assume that the individual-specific effect, i.e., the unobserved heterogeneity α_i in the model, is correlated with the regressor[8], which further substantiates our choice of using a fixed-effect regression. Finally, our model consists of regressors that are both firm and time variant and those that are time variant but firm invariant to act as time dummies in our model. The fixed-effect regression is better equipped to handle both types of regressor in one single regression model.

In Eqn. 1, β_j is a vector of six accounting variables (AC_{it}) for each firm *i* in quarter *t*, Following Das et al. (2009), we use *(SIZE)* as a measure of firm size estimated as the log of total assets divided by the Consumer Price Index with 2005 as the base. The measure of firm

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[7] This is tested using the Breusch-Pagan Langrage multiplier test which is found to be significant at 95% level and thus does not support the use of pooled OLS regression.
[8] This is tested using the Hausman statistics which is found to be significant at 95% level

profitability, return on assets *(ROA)*, is estimated as the net income divided by total assets. Financial liquidity is measured by the quick ratio *(QUICK)*, estimated as current assets minus inventories over current liabilities. The measure of a firm's trading account activity *(TRADE)* is estimated as the ratio of inventories to the cost of goods sold. Quarterly sales growth *(SALES)* is estimated as sales divided by the previous quarter sales minus one. The measure of the capital structure *(LEVERAGE)* is estimated as the ratio of total liabilities to total assets.

In Eqn. 1, γ_k is a vector of three market-based variables (MB_{it}) for each firm *i* in quarter *t*. We use the distance to default (*DTD*) in the Merton model as the primary market measure of credit risk. The key to estimating *DTD* is the estimation of firm value (*V*) and standard deviation of firm value (σ_V) in the Black-Scholes-Merton (BSM) model. To estimate these two variables, we follow the approach as detailed in Vassalou and Xing (2004). Assuming a forecasting horizon of 1 year (*T*), i.e., 250 trading days in a year, first σ_V is estimated iteratively using the estimated equity volatility from the past year as a starting value. Using BSM, for each trading day, *V* is computed using the market value of equity (*E*) for that day. The estimation procedure is repeated for the remaining 250 trading days in that year. The standard deviation of the return in *V* during that period becomes the new starting value for σ_V for the next iteration. If the difference in σ_V between two successive iterations is less that 10^{-4}, the iteration procedure will be discontinued and the values will be inserted in the BSM equation to obtain V. The resulting values of *V* and σ_V are then used to calculate the firm-specific *DTD* over a horizon *T* as in Eqn. 2,

$$DTD = \frac{\ln\left(\frac{V}{X}\right) + \left(\mu_v - \frac{1}{2}\sigma_v^2\right)T}{\sigma_v^2\sqrt{T}} \tag{2}$$

A default occurs when the ratio of the value of assets to debt is less than one (i.e., its log is negative). The exogenous default boundary (*X*) is set as the book value of short-term liabilities plus one half of the long-term liability. It is similar to the one used by KMV CreditMonitor™ and considered to be relatively more realistic. The *DTD* measures the number of standard deviations this ratio needs to deviate from its mean for default to occur.

Average annualized equity return (μ_V) is estimated using the last 250 trading day market capitalization value of equity. A negative relationship between equity return (*AER)* and CDS spreads is expected because better market performance indicates a lower credit risk. Because volatility is a measure of market uncertainty, it proxies for market strains that limit capital mobility across different market segments or investors' risk aversion (Pan and Singleton, 2008); thus, an increase in volatility should lead to an increase in credit spreads. Volatility measured using the annualized standard deviation of equity returns *(STDEV)* is estimated from the past 250 trading days' daily stock price return.

Apart from firm-specific variables, we also control for a variety of macroeconomic indicators that are firm invariant but time variant in our model and act as time dummies accounting for time clustering in our dataset. In Eqn. 1, δ_m represents a vector of three macroeconomic indicators. The risk-free rate (*RATE*) is proxied by the three-month US-LIBOR for the US, three-month UK-LIBOR for the UK and three month EURIBOR[9] for the EU. Because periods of low interest rates are normally associated with periods of economic downturn, we expect a negative relationship. We include the prior year, i.e., the 12-month index return *(INDEX)* using the S&P500 index for the US, the FTSE100 index for the UK, and the

[9] The authors acknowledge that these risk-free rate proxies rose sharply in the crisis period, partly due to a lack of liquidity in the market. However, these also represent the best available proxy for risk free rate.

EURO STOXX 50 Index for the EU. An improvement in the business environment should lessen a firm's chances of default and thus increase their default recovery rates, lowering CDS spreads. The prior year return on the respective GICS index sector *(GICS_R)* provides the sector return. Because periods of low market/sector returns are normally related to periods of economic downturn, we expect a negative relationship between *INDEX*, *GICS_R* and spreads. Thus, following Bharath and Shumway (2008) and Ericsson et al. (2009), among others, we use the market-wide equity index as a measure of the business environment, the GICS return as measure of sector performance and the risk-free rate as measure of economic activity.

Finally, to control for CDS market illiquidity, we use the absolute quoted bid-ask spread (*ABS*) following Arakelyan and Serrano (2012) as a liquidity measure (LIQ_{it}) for each firm i at quarter t in Eqn. 1. Lower values point towards higher liquidity in the CDS market, and the value is estimated as the absolute difference between the highest bid and the lowest ask quote for the underlying CDS contract in the given quarter. As liquidity dries up, the size of the bid-ask spread increases, indicating greater divergence of opinion or information asymmetry (Tang and Yan, 2007). Arakelyan and Serrano (2012) claim that the bid-ask spread reflects order processing, inventory holding and asymmetric information costs and is an important factor driving CDS spreads

Table 2 provides the regression output for US, UK and EU samples over whole period and sub-periods of analysis. Across the three samples, the size of the firm (*SIZE)* does not have a bearing on the CDS spreads except for a positive relationship for whole period in the US and UK. As expected, a significant negative relationship between spread and firm profitability (*ROA)* is observed similar to Das et al. (2009); however, this relationship does not hold in the GFC period across samples. The quick ratio *(QUICK)*, trading account activity (*TRADE*) and sales growth (*SALES*) exhibit a weak relationship with spreads, which switches signs based on the sample and sub-period of analysis. The firm capital structure (*LEVERAGE*) is found to be mostly positive wherever significant, indicating more levered firm has higher credit risk.

Overall for the accounting variables, the significance of each variable changes for each sub-period and across the three markets. Our findings above corroborate Kanagaretnam et al. (2016), who do not find a statistically significant and consistent association between CDS spreads and traditional accounting-based risk measures. This could be attributed to CDS spreads being forward-looking risk measure, whereas accounting variables are more likely to capture current and past risks.

With regard to market-based variables, we find a significant positive relationship between the spread and volatility of returns *(STDEV)*, as expected, for the US. For the UK and EU, a similar relationship, although not consistent across sub-period, indicates that higher volatility drives up credit risk. Annualized equity return *(AER)* does not exhibit a consistent relationship with spreads and is significant only for the US sample in the post-GFC period and for the EU sample in the GFC period, but with opposite signs. The coefficient of distance to default *(DTD)* is negative and significant across all sub-periods for the US and EU samples, indicating that a greater distance to theoretical default lowers the credit risk of firm. Although this relationship is not significant across the sub-periods for the UK sample, the coefficient is mostly negative. Overall, the majority of the market-based variables are significant across the samples and most sub-periods.

The control variables (*INDEX* and *GICS_R*) exhibit a significant negative relationship with spreads indicating that the credit risk of firm is influenced by the business environment and corresponding sector performance. The risk-free rate (*RATE*) is mostly negative and significant, indicating that when the business environment deteriorates, it has a negative effect on firm credit risk. It is worth noting that the risk-free rate in the post-GFC period has been kept artificially low to ease the business environment in the US and UK. This has not really helped reduce firm risk, evident from the positive and significant relationship in the post-GFC period for the US and UK samples.

The measure of CDS illiquidity (*ABS*) has a positive and significant association with spreads in the whole period, indicating that higher illiquidity increases credit risk for the US and UK samples. Interestingly, the relationship in the EU sample is negative wherever significant, indicating firms that have illiquid CDS contracts have lower credit risk, which points towards higher trading on European CDSs in the sovereign crisis period, driving up a firm's credit risk.

The overall explanatory power of the model varies across each sub-period and is characterized by a low R^2 in the pre-GFC period, an increase in R^2 during the GFC period followed by a reduction in the model's explanatory power in the post-GFC period. This indicates that accounting- and market-based variables are more significant predictors of spreads during the crisis period than at other times, which is consistent with Annaert et al. (2013) and Tang and Yan (2015). Overall, the spread explanatory power of the predictor variables in our model changes significantly based on the period of analysis[10].

[10] We also undertake a multi-collinearity diagnostic test (not reported here to save space), and the estimated VIF (Variance Inflated Factor) score is less than the threshold, indicating the absence of multicollinearity.

Table 2: Fixed effect panel data regression

Panel data fixed effect regression (with robust standard errors) of the log of CDS spreads to accounting- and market-based variables. The variables are estimated on a quarterly frequency from the period of 01/01/2005 to 31/12/2012. The R^2 reported is the fixed effect within regression values. Periods are as defined in Table 1.

	US				UK				EU			
	Whole Period	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
SIZE	0.117*	0.044	0.02	0.015	0.401**	-0.191	0.771*	0.309	0.25	0.254	-0.533	-0.615
ROA	-1.08***	-0.961*	-0.267	-1.614***	-0.379	0.453	-0.458	-2.442**	-1.795*	-0.59***	-0.176	-3.49**
QUICK	-0.051	-0.066	-0.17***	-0.024	-0.022	-0.139	0.187*	0.086	0.041	-0.326*	-0.105	0.025
TRADE	0.006*	-0.018	0.003	0.006	-0.259*	0.219	-0.272	-0.406*	0.046	-0.1	0.05	0.092
SALES	-0.001	-0.001	-0.001	-0.001	0.001*	0.001**	-0.001	0.003*	-0.001	-0.002*	-0.004**	-0.001
LEVERAGE	0.852***	1.53***	0.379	1.104***	1.653**	0.908	1.701**	-0.721*	0.144	-1.511	0.095	2.486**
AER	-0.002	0.006	-0.004	-0.002***	0.019*	0.053	-0.001	-0.004	0.001	-0.008	0.12**	-0.002
STDEV	0.995***	1.75***	0.735***	0.65***	0.215	-0.148	0.888	1.337**	2.033***	0.996	0.815	2.129***
DTD	-0.03***	-0.01***	-0.02***	-0.015***	-0.03***	-0.004	-0.016	0.004	-0.03***	0.005	-0.05**	-0.013**
RATE	-15.9***	-5.09***	-8.2***	45.775***	-12.42***	-7.132	2.591	31.407**	-11.5***	-31.8***	-9.22**	-1.31
INDEX	-0.133*	-1.38***	-1.12***	0.038	-0.583***	1.376***	-1.29***	-0.215*	-1.65***	0.036	-2.08***	-1.34***
GICS_R	-0.94***	0.272**	-0.69***	-0.693***	-1.076***	-0.512	-0.684**	-0.67***	-0.207	-0.217	0.174	-0.32
ABS	0.001***	0.001	0.004	-0.002	0.018***	0.022	0.014***	0.009	-0.002***	0.025	-0.001	-0.01***
_cons	3.893***	2.858***	4.474***	3.935***	1.854*	3.794***	-1.046	3.026*	2.985***	4.478***	7.951***	5.991***
N	6,169	1,234	1,754	3,181	962	230	241	491	722	213	239	270
R^2	62.69%	23.25%	74.06%	25.56%	54.43%	19.42%	63.71%	26.32%	61.59%	43.71%	62.83%	41.65%
F statistics	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*Notes: ***, **, and * indicate rejection of the null hypothesis at 1%, 5% and 10%, respectively.*

Das et al. (2009) claim that accounting variables are better predictors of CDS spreads than market-based variables; whereas Galil et al. (2014) claim that market-based variables have a higher prediction power of spreads. The accounting- and market-based variables in Table 2 provide mixed results that change based on the sample and sub-period in consideration, pointing to the need to further investigate the relative importance of these variables in a spread prediction model. We undertake further analysis by decomposing the models' explanatory power into the subset of explanatory variables used in the regression model (Eqn. 1). The Pratt index (Pratt, 1987; Thomas et al., 1998) is a useful statistical measure that orders independent variables based on their relative importance, and we use the pratt index to decompose the model's explanatory power to the subset of predictor variable categories in the regression model, i.e., AC_{it} (*SIZE*, *ROA*, *QUICK*, *TRADE*, *SALES*, *LEVERAGE*), MB_{it} (*AER*, *STDEV*, *DTD*), LIQ_{it} (*ABS_L*) and $CONTROLS_t$ (*RATE*, *INDEX*, *GICS_R*).

Table 3 provides the output for the Pratt index applied on the regression model in Eqn. 1. The Pratt index helps to decompose the explanatory power of the models and attributes it to the variable categories (*AC*, *MB*, *LIQ* and *CONTROL*). Because the model's explanatory power varies across sample and the sub-period, the Pratt index provides a useful gauge of the relative importance of these variable categories in modeling CDS spreads.

Table 3: Relative importance of CDS spread predictor variables

Pratt Index estimated for each sample (US, UK and EU) across each sub-period for predictor variable category AC (*SIZE*, *ROA*, *QUICK*, *TRADE*, *SALES*, *LEVERAGE*), MB (*AER*, *STDEV*, *DTD*), LIQ *(ABS)* and CONTROLS *(RATE*, *INDEX*, *GICS_R)*. In Panel A, the absolute bid-ask spread *(ABS)* is used as proxy for CDS market illiquidity, whereas the proportional quoted bid-ask spread *(PROP)* and Amihud's measure *(AMH)* are used in Panel B and Panel C, respectively. The Pratt index is estimated for each variable category with a quarterly frequency from the period of 01/01/2005 to 31/12/2012. Sub-periods are as defined in Table 1.

Pratt Index	**US**				**UK**				**EU**			
Panel A	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
AC	0.22	0.42	0.12	0.36	0.11	0.47	0.06	0.15	0.17	0.38	0.21	0.25
MB	0.67	0.54	0.84	0.61	0.28	0.41	0.23	0.14	0.64	0.32	0.73	0.68
LIQ (ABS)	0.00	0.00	0.00	0.00	0.32	0.08	0.53	0.58	0.01	0.21	0.03	0.01
CONTROL	0.10	0.04	0.04	0.03	0.29	0.04	0.17	0.13	0.19	0.10	0.03	0.06

	US				**UK**				**EU**			
Panel B	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
AC	0.22	0.42	0.13	0.36	0.12	0.33	0.11	0.23	0.19	0.50	0.23	0.25
MB	0.66	0.54	0.81	0.61	0.41	0.33	0.71	0.31	0.56	0.33	0.65	0.65
LIQ (PROP)	0.01	0.00	0.03	0.00	0.31	0.30	0.11	0.28	0.08	0.07	0.12	0.03
CONTROL	0.11	0.04	0.02	0.03	0.16	0.03	0.07	0.18	0.17	0.10	0.00	0.06

	US				**UK**				**EU**			
Panel C	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
AC	0.22	0.41	0.13	0.35	0.17	0.50	0.14	0.34	0.20	0.50	0.24	0.26
MB	0.67	0.54	0.82	0.61	0.52	0.45	0.75	0.40	0.64	0.42	0.75	0.69
LIQ (AMH)	0.01	0.02	0.01	0.01	0.31	0.05	0.10	0.24	0.01	0.05	0.01	0.01
CONTROL	0.10	0.03	0.04	0.03	0.00	0.00	0.01	0.02	0.16	0.03	0.01	0.05

From Table 3 Panel A, we note that the *AC* and *MB* variable categories are comparative and at times *AC* variables have higher explanatory power in the pre-GFC period for UK and EU samples which is in line with Das et al. (2009). However, for the US sample, *MB* variables (54%) have higher explanatory power compared to *AC* variables (42%) in the pre-GFC period. Consequently, across the three samples, the results are inconclusive in the pre-GFC period. Collectively, *AC* variables explain on average 42% of R^2 for the models in the pre-GFC period across the three samples. However, during the GFC period, there is a considerable shift in spread prediction ability of *MB* variables, which increases to 84% and 73% for the US and EU samples. In contrast, the proportion of variability explained by *AC* variables drops to 12% and 21%, respectively. In the post-GFC period the *MB* variables retain relatively higher explanatory power for the US and EU samples. Interestingly for the UK sample, in both the GFC and post-GFC period, *LIQ* is a significant contributor to the model's explanatory power, whereas it is negligible for the other sub-period and samples (except for pre-GFC in EU sample), indicating that the higher illiquidity of CDS contracts plays a larger role in increasing credit risk for UK firms. The *CONTROL* variables do not contribute much to the model R^2 except when the whole period is taken into consideration.

Because liquidity is not directly observed in the market and previous studies have employed competing measures to capture CDS illiquidity, we use alternative specifications of the liquidity measure as a robustness check[11]. The proportionally quoted bid-ask spread (*PROP*), estimated as the difference between the bid-ask spread divided by the mean bid-ask spread (Lesplingart et al.,

[11] We also conduct other robustness checks namely; (1) We include 1 quarter lag of independent variables in the regression model to control for endogeneity and (2) We re-run the models using only Q2 and Q4 observations. Overall, the findings are consistent. The robustness checks are not reported here and are available on request.

2012), is used, and the models are re-estimated. The results are reported in Panel B. Similarly, Amihud (2002) proposes a measure of liquidity *(AMH)* that is more suitable for low-frequency data, estimated as the quarterly average absolute return over the trading volume (Tang and Yan, 2007). The results are reported in Panel C. Across the three panels in Table 3, the findings are consistent and robust to the alternative specifications of the liquidity measure used in this study.

From the results in Table 2 and Table 3, we conclude that *MB* variables are more important predictors of CDS spreads than *AC* variables and point towards the growing importance of illiquidity in the CDS market as an important driver of CDS spreads, especially in the post-GFC period. Moreover, even by adding both the set of predictor variables along with liquidity and macroeconomic controls, there is still a substantial portion of spreads that cannot be accounted for, especially in the post-GFC period, for all the three markets. Previous studies claims that CDS spreads provide a clean measure of default risk. However, the lower explanatory power of the models in the post-GFC era may be highlighting the presence of noise in the CDS spreads itself, which requires further investigation.

3.3 Default and non-default component of bond yield spread

For firms analyzed in the previous section, we estimate the monthly corporate bond yield spread based on bracketing procedure as detailed in Longstaff et al. (2005). We use SEC-registered, fixed rate, senior, unsecured bonds with no embedded options and with maturity bracketing the horizon of CDS spread observations in our dataset. Moreover, each firm needs to have at least two bonds to be included in the bracketing set. We are able to obtain the monthly bond yield for 294 firms in the US, 50 firms in the UK and 95 firms in the EU. The bracketing set procedure uses 3894, 1089 and 2715 individual bonds (for the US, UK and EU, respectively) to draw bond yield estimates from 01/01/2005 to 31/12/2012. To estimate the standard benchmark risk-free rate, we use treasury curve and interpolate yield on a riskless bond with the same maturity and coupon using standard cubic spline algorithm. This estimated risk free rate is subtracted from the bond yield to obtain monthly bond yield spreads for each CDS contract. To obtain five year yield spreads, we regress yield spreads for individual bonds in the bracketing set on their respective maturities. The fitted value of the regression at a 5 year horizon is used to estimate the corporate yield spreads for the firm. In total, we are able to estimate 15745, 3034 and 6283 monthly bond yield spreads for the US, UK and EU, respectively. We further take the monthly CDS spread as an estimate of the default component of the monthly bond yield spread. The difference between the two gives the non-default component of bond yield spreads, also referred to as the CDS-bond basis (basis henceforth) and is a well-known no-arbitrage relationship.

Table 4 provides the median yield spreads for each of the sample across the three sub-periods in Panel A. For the US and the UK, we note that median bond yield spread increases during the GFC period with a subsequent decline in the post-GFC period. However, for both the US and UK, the median post-GFC spread is much higher than the pre-GFC level. In line with the observations for the CDS market, bond yield spreads for the EU are higher in the post-GFC period highlighting the effects of the sovereign debt crisis. Panel B provides the median default component, the non-default component and the ratio of the median default component to the median bond yield spread across firms in the US, UK and EU, respectively. For the US, the default component to the yield spread is approximately 25%, escalating to 30% and 50% of the bond yield spreads for the pre-GFC, GFC and post-GFC periods. Similarly, the UK and EU samples follow a similar trend with default ratios of 20%, 32% and 53% and 19%, 47% and 66% in the pre-GFC, GFC and post-GFC periods, respectively. Table 4 also shows that default risk only partially explains the bond yield spread, and the non-default component is a key additional explanatory factor[12]. Although default component represents more than 50% of the total bond yield spreads in the post-GFC era, the presence of a significant non-default component in yield spreads across the three markets can be witnessed. Thus, although the bond markets have stabilized, there is still fear in the market of the possibility of a default, which is still significant in the post-crisis period. Moreover, these results are more prominent in the post-GFC period across the three markets, irrespective of the type of firm. Longstaff et al. (2005) drew similar inferences, but their study argued this effect to be true for only high-rated investment grade US firms. Our observations extend this inference across all types of firms and across the three samples.

[12] We also undertake a Kruskal-Wallis rank test of the equality of the population on bond yield spreads across the whole period as well as each sub-period of analysis; the results (not reported here) indicate that the difference between the samples is statistically significant.

Table 4: Ratio of default component to bond yield spread

The sample is based on the monthly corporate bond yield spread estimated based on the bracketing approach of Longstaff et al. (2005) from 01/01/2005 to 31/12/2012. *Dflt* is median default component, *Ndflt* is the median non-default component, Spread is the average yield spread over the benchmark 3 month Interbank Offer Rate, and *Ratio* is the default component divided by the yield spread. Ratios denoted by an asterisk are significantly different at the 5% level. N^B is the number of monthly bond yield spreads in the bracketing set.

Panel A: Median yield spread across each sub-period

	Whole period		Pre-GFC		GFC		Post- GFC	
Sample	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**
US	15,745	197.78	4,474	113.31	4,038	330.42	7,233	203.29
UK	3,034	203.48	998	91.86	819	313.79	1,217	220.78
EU	6,283	176.11	1,767	98.34	1,681	205.95	2,835	224.25

Panel B: Median default and non-default component of yield spread across each sub-period

	Whole period			Pre-GFC			GFC			Post- GFC		
Country	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**
US	**77.58**	**101.36**	**0.39***	**28.50**	**72.40**	**0.25***	**98.99**	**186.97**	**0.30***	**102.03**	**88.94**	**0.50***
UK	**87.60**	**117.85**	**0.43***	**18.70**	**68.29**	**0.20***	**100.16**	**179.53**	**0.32***	**116.51**	**114.74**	**0.53***
EU[1]	**90.60**	**85.54**	**0.51***	**18.67**	**76.16**	**0.19***	**96.07**	**110.55**	**0.47***	**146.96**	**81.79**	**0.66***
FRANCE	89.76	87.28	0.55*	27.83	72.28	0.26*	102.24	125.93	0.45*	133.26	86.45	0.67*
GERMANY	112.50	50.26	0.76*	14.19	96.61	0.15*	96.68	79.26	0.60*	142.97	28.78	0.83*
ITALY	88.12	96.90	0.41*	14.51	86.63	0.15*	80.04	126.44	0.37*	192.10	88.12	0.73*
NETHERLANDS	70.86	107.16	0.41*	21.63	104.13	0.19*	79.53	131.14	0.37*	100.18	98.07	0.47*
SPAIN	150.39	36.04	0.71*	10.80	32.97	0.25*	128.99	31.53	0.67*	281.98	45.84	0.81*
FINLAND	90.31	125.44	0.43*	38.76	73.08	0.34*	118.24	129.04	0.37*	145.20	149.94	0.41*
BELGIUM	70.69	109.57	0.38*	21.67	61.30	0.24*	75.84	136.72	0.37*	84.56	123.33	0.36*
PORTUGAL	116.56	83.12	0.35*	12.11	.	.	91.50	92.77	0.53*	591.15	82.40	1.06
IRELAND	156.38	167.44	0.31*	8.58	.	.	138.34	.	.	616.68	167.44	1.22
LUXEMBOURG	78.56	140.76	0.41*	.	.	.	121.53	139.90	0.55*	76.91	140.76	0.38*
AUSTRIA	141.65	54.39	0.70*	14.25	36.15	0.43*	140.02	53.11	0.90	188.58	65.67	0.69*

Note: No Dflt and Ndflt data available for Greece

3.4 Predictive power of basis

Because CDS is essentially an insurance contract against the default of a firm's bond, the CDS and corporate bond markets should theoretically move in tandem, closely interacting with each other (Kim et al., 2016). Consequently, the basis should be closer to zero after ignoring some technical issues, such as market friction, and any violation of this relationship would represent a mispricing between the two markets. CDS spreads are also documented to react more rapidly to changes in the credit quality of the underlying firm compared to bond yield spreads (Hull et al., 2004; Blanco et al., 2005). Moreover, during periods of financial distress, the CDS market is found to dominate the information transmission process between the CDS and bond market (Delatte et al., 2012). The ability of the CDS market to rapidly adjust to new information compared to the bond market suggests that greater mispricing between the two markets would lead to rapid adjustment of spreads in CDS market. Consequently the non-zero basis could have some spread predictive power and could be used to predict the subsequent movement in the CDS market. Most studies (e.g., Longstaff et al., 2005; Bai and Collin-Dufresne, 2014) have focused on the cause of the non-zero basis, whereas Kim et al. (2016) is the first to focus on the implication of the basis for future price movement in a related market. We extend this investigation by using the basis to study future spread changes in the CDS market. Our study is different from Kim et al. (2016) in the sense that they investigate the predictive power of basis for future returns in corporate bonds. We compliment this by focusing on the predictive power of the basis on changes in spreads in the CDS market.

However, the basis and CDS spreads occur simultaneously and the information transmission mechanism means the mispricing between the two markets could drive subsequent spreads in either of the two financial markets, leading to endogeneity issues. To test the direction of causality and the effect of one over the other, i.e., between the basis and CDS spread changes, we undertake a granger type causality test.

We test for the direction of causality between the basis and change in CDS spreads. To account for the possibility of reverse causality, we develop Eqn. (3) and (4) in line with previous studies (Qui et al., 2016) that have applied granger causality tests. Eqn. (3) specifically tests the hypothesis that the basis drives changes in CDS spreads, whereas Eqn. (4) tests for the possibility of reverse causality.

$$\Delta CDS_{it} = \alpha + \tau_1 L.\Delta CDS_{it-1} + \tau_2 BASIS_{it} + \tau_3 L.BASIS_{it-1} + \sum_1^j \beta_j AC_{it} + \sum_1^k \gamma_k MB_{it} + \sum_1^m \delta_m CONTROL_t + \chi LIQ_{it} + \varepsilon_{it} \tag{3}$$

$$BASIS_{it} = \alpha + \tau_1 L.BASIS_{it-1} + \tau_2 \Delta CDS_{it} + \tau_3 L.\Delta CDS_{it-1} + \sum_1^j \beta_j AC_{it} + \sum_1^k \gamma_k MB_{it} + \sum_1^m \delta_m CONTROL_t + \chi LIQ_{it} + \varepsilon_{it} \tag{4}$$

In Eqn. (3), the absolute change in CDS spreads (Δ*CDS*) is a function of lagged change in CDS spreads (*L.*Δ*CDS*), current basis (*BASIS*) and lagged basis (*L.BASIS*), whereas in Eqn. (4), the basis (*BASIS*) is a function of the lagged basis (*L.BASIS*), current change in CDS spreads (Δ*CDS*) and lagged changed in CDS spreads (*L.*Δ*CDS*). Firm-level and macroeconomic controls in the models are as detailed in Section 3.2. As a robustness check, we repeat the analysis for the percentage change in CDS spreads (*%*Δ*CDS*) for Eqn. (3) and Eqn. (4).

Table 5: Effect of Basis on change in CDS spreads

Panel data fixed effect regression (with robust standard errors) of the absolute change in CDS spreads (ΔCDS) as a function of the lagged change in CDS spreads (*L.ΔCDS*), current basis (*BASIS*) and lagged basis (*L.BASIS*) while controlling for accounting- and market-based variables. Firm-level and macroeconomic controls in the models are as detailed in Section 3.2. The variables are estimated from the period of 01/01/2005 to 31/12/2012. The R^2 reported is the fixed effect within regression values. Sub-periods are as defined in Table 1. In Panel B, as a robustness check, we repeat the analysis for the percentage change in CDS spreads *(%ΔCDS)*

Panel A:	**US**				**UK**				**EU**			
ΔCDS	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
L.ΔCDS	-0.058	-0.015	-0.146*	-0.082*	0.084*	0.191**	0.029	-0.026	0.285***	-0.288	0.199	-0.066
BASIS	-0.028	-0.004	-0.041	-0.076	0.007	0.024**	0.025	-0.054	-0.24**	-0.052*	-0.217	-0.268
L.BASIS	0.012	0.021	-0.025	0.115**	0.001	-0.04	-0.012	0.093**	0.243*	0.036	0.303*	0.296*
SIZE	2.988	-3.514	-12.024	-4.643	8.846*	16.191	30.74	1.519	19.442*	20.529	74.744*	245.567
ROA	-208.4***	67.202	-227.354*	-122.8**	2.265	-21.32*	-66.1	15.62	-99.276	28.898	-398.64	148.168
QUICK	-2.631	4.171	-13.321	-1.026	1.556	7.54*	-15.01	6.766**	1.367	-13***	26.469	10.32
TRADE	-0.829	0.371	-9.61	-0.402**	8.039	50.556	12.145	18.584	-28.822	-1.252	140.1**	-233.829
SALES	0.09**	0.059	-0.007	0.059*	0.104*	-0.068	0.03	0.214**	-0.02**	-0.084	0.214	0.007
LEVERAGE	2.317	-53.615	87.602	-12.033	20.2***	17.377	-29.668	2.629	65.357	18.195	-20.878	11.519
AER	-1.046*	2.865**	-1.688	-0.094	-0.96***	0.571	-6.5**	-1.16***	1.917	-7.719	-47.9**	3.938
STDEV	-3.723	1.638	-1.692	-89.3***	-5.116	17.494	54.196	-10.063	-142.974**	18.335	-146.3	-156.08*
DTD	-0.557*	-0.742*	0.459	-1.05***	-0.074	-0.119	0.648	-0.2	-1.698*	0.248	1.234	-3.632**
RATE	-35.007	-347.4*	-607.7**	-275.302	31.155	190.465	127.75	339.486	-6.75	-19.211	1103.19	5936.8**
INDEX	7.832	-4.806	45.911	1.744	3.708	-6.504	9.592	6.518*	-97.271**	-27.7**	77.414	21.964
GICS_R	-114.6***	-9.478	-176.4***	-70.6***	-25.81**	-8.195	-8.354	-39.088*	38.567	50.6**	52.49	-56.021*
ABS	0.059	-0.005	3.228**	0.678*	-1.55***	-0.897	-2.013	-0.962	1.903	-0.452	5.866	10.126
_cons	4.792	74.883*	65.35	69.4***	-53.75**	-105.57	-167.03	-13.995	-77.439	-107.8*	-521.3*	-1316.245
N	5,415	962	1,387	3,066	492	124	144	224	287	84	104	99
R^2	8.15%	3.60%	10.00%	16.48%	21.34%	13.96%	12.04%	48.57%	42.24%	19.11%	52.09%	50.16%
F statistics	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B	US				UK				EU			
%ΔCDS	Whole Period	Pre-GFC	GFC	Post-GFC	Whole Period	Pre-GFC	GFC	Post-GFC	Whole Period	Pre-GFC	GFC	Post-GFC
L.%ΔCDS	-0.04***	-0.039	-0.08***	-0.12***	0.044	0.143	-0.059	-0.012	-0.044	-0.2	-0.091	-0.193*
BASIS	0.003	-0.004	0.009**	-0.07***	0.013	0.038*	0.021	-0.068	-0.1***	-0.13**	-0.068	-0.12*
L.BASIS	0.005	0.004	0.01***	0.07***	-0.001	-0.08	-0.018	0.13***	0.091***	0.12	0.09**	0.171***
SIZE	-1.232	-10.2**	-11.1*	-1.01	16.032***	43.369	28.449	0.238	4.06	39.75	21.832	62.805
ROA	-49.5***	-26.272	-40.891*	-59.3***	-10.476	-46.693	-18.11	9.542	-106.011	44.133	-185.7	-60.683
QUICK	0.13	5.67*	-4.758	0.127	5.155*	20.173	-2.764	8.01**	1.397	-37.7***	22.092	11.589**
TRADE	-0.503**	-0.083	1.469	-0.5***	19.578	112.291	149.1*	12.332	-9.4	-11.678	38.594	-78.483
SALES	0.044***	0.05*	0.013	0.048***	0.026	-0.218	-0.014	0.208*	-0.022***	-0.178	0.017	-0.001
LEVERAGE	-1.821	-15.47	29.084	-7.099	19.958	81.592	-97.5	-3.75	-21.931	92.439	-119.7	6.221
AER	-0.192	2.8***	-0.454**	-0.103	-0.826**	2.763	-1.965	-0.076	2.067**	-32.9**	-18.05	3.694***
STDEV	-9.97***	26.645	-14.419	-20.3***	18.627	26.388	90.905	-29.502	-77.32***	129.813	-34.86	-74.55**
DTD	-0.28***	-0.199	-0.095	-0.25***	0.339	-0.213	0.754	-0.332	-0.963**	1.484	3.21	-2.54***
RATE	38.84***	-313***	-312***	465.072*	146.12***	50.23	213.1	605.607	89.089	179.297	430.7	550.648
INDEX	7.925***	8.234	56.4**	8.354***	9.508**	-19.501	-9.285	10.9**	-71.42***	-119***	-30.95	-42.1***
GICS_R	-57.3***	-26.5**	-67.6***	-48.9***	-31.21**	-11.687	-26.23	-42.812*	18.797	208***	-12.02	1.447
ABS	-0.022	-0.034	2.39***	-0.109	-0.984*	-2.912	-3.827	-1.183	1.181***	-0.962	2.138*	3.826**
_cons	15.8*	75.05**	67.166	18.095	-111.8***	-271.7	-142.5	0.007	22.031	-261.4	-116.6	-313.823
N	5,415	962	1,387	3,066	492	124	144	224	287	84	104	99
R^2	12.64%	4.85%	18.20%	23.25%	8.00%	10.36%	10.8%	31.78%	28.07%	19.35%	35.9%	38.03%
F Statistics	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*Notes: ***, **, and * indicate rejection of the null hypothesis at 1%, 5% and 10%, respectively, based on t statistics.*

Table 6: Effect of change in CDS spreads on Basis – Reverse Causality test

Panel data fixed effect regression (with robust standard errors) of the current basis (*BASIS*) as a function of the lagged basis *(L.BASIS)*, absolute change in CDS spreads (Δ*CDS*) and lagged absolute change in CDS spreads *(L.ΔCDS)* while controlling for accounting- and market-based variables. Firm-level and macroeconomic controls in the models are as detailed in Section 3.2. The variables are estimated from the period of 01/01/2005 to 31/12/2012. The R^2 reported is the fixed effect within regression values. Sub-periods are as defined in Table 1. In Panel B, as a robustness check, we repeat the analysis using the percentage change in CDS spreads *(%ΔCDS)*.

Panel A:	**US**				**UK**				**EU**			
BASIS	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
L.BASIS	0.464***	0.49***	0.152	0.491***	0.527***	0.37***	0.2**	0.48***	0.654***	0.40***	0.43***	0.474***
ΔCDS	-0.162**	-0.066	-0.217**	-0.255	0.05	0.669**	0.099	-0.691*	-0.48***	-1.073**	-0.413*	-0.42***
L.ΔCDS	-0.036	0.067	-0.146	0.002	0.116	1.11*	0.16	-0.042	-0.071	-0.079	-0.17	-0.136
SIZE	-20.072	4.271	-104.149	-15.559	23.682	-71.443	143.5**	90.079*	30.862	38.565	137.758	-53.228
ROA	-575.852	-81.833	-974.341	93.64	-104.841	239.59*	-550***	-55.332	-487.335**	-50.919	-1796**	-160.911
QUICK	11.61	-5.508	84.493	-6.918	16.43***	-20.383	-19.49	-5.408	15.75**	74.8**	7.811	5.23
TRADE	0.634	7.492**	-39.96*	2.144***	32.493	-134.54	95.333	-147.087	-44.043*	-19.765	6.498	111.811
SALES	0.151	0.034	1.196	-0.004	0.248	0.314	-0.97	-0.764*	-0.058***	-0.925	0.025	-0.021
LEVERAGE	-34.611	-81.267	612.444	-122***	-134.613**	-72.588	-966**	-23.707	47.114**	81.341	-688.5	-23.368
AER	-0.308	1.745	2.27	0.705	-1.338***	-7.706	-7.801	-1.09	2.833**	6.303	49.585	2.237
STDEV	184.13***	-178.5*	218.97*	108.9**	129.818	195.373	653.5**	189.7**	-11.286	-634.264	-396.9	57.196
DTD	2.26**	0.156	10.9***	0.939**	0.36	2.11	18.0***	0.392	-2.55***	-6.662	-16.3**	-1.536
RATE	275.042*	-48.459	-2112.7*	603.345	78.633	-1877.1	1847**	3185*	-61.342	-1665*	-1168.3	3161.24
INDEX	-103.6***	-68.19	-79.63	-46.5***	-61.074***	43.849	-613***	-24.911	-162.28***	88.268	-196.1*	-188***
GICS_R	-169.1***	-5.429	-351***	-64.4***	-28.486	-95.695	89.921	-83.5***	102.518*	-213*	251.858	91.504*
ABS	0.165	0.086	5.703	1.012	0.264	6.438	-3.538	-2.764	-0.11	1.425	1.703	1.741
_cons	128.438	122.278	200.241	175**	-37.702	476***	-565.04	-439.689	-102.492	33.157	51.139	285.867
N	5,415	962	1,387	3,066	492	124	144	224	287	84	104	99
R^2	36.54%	22.47%	23.06%	37.18%	65.22%	34.28%	56.72%	49.51%	69.93%	49.93%	65.88%	50.99%
F statistics	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B:	US				UK				EU			
BASIS	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**	**Whole Period**	**Pre-GFC**	**GFC**	**Post-GFC**
L.BASIS	0.46***	0.49***	0.17	0.50***	0.526***	0.38***	0.211**	0.49***	0.639***	0.407***	0.40***	0.473***
%ΔCDS	0.097	-0.128	0.463	-0.9***	0.061	0.167*	0.067	-0.604*	-0.64***	-0.408**	-0.489	-0.536**
L.%ΔCDS	-0.079	0.243	-0.33*	-0.098	0.199	0.529***	0.11	-0.04	-0.092	-0.04	0.008	-0.399
SIZE	-20.63	4.656	-101.17	-14.76	20.591	-65.251	151.1**	88.98*	25.66	33.015	127.57	-145.053
ROA	-539.22	-87.775	-909.96	63.264	-98.317	240.54*	-575.5***	-60.82	-516.9**	-60.65	-1729**	-287.762*
QUICK	12.14	-5.453	90.27	-6.282	15.65***	-17.515	-26.29	-5.11	18.40*	73.5**	9.624	6.886
TRADE	0.80	7.468**	-37.01*	1.702***	30.866	-108.14	67.01	-152.6	-32.01*	-23.559	-57.988	197.12*
SALES	0.13	0.037	1.20	0.028	0.25	0.35	-0.94	-0.78**	-0.06***	-0.892	-0.187	-0.027
LEVERAGE	-35.31	-77.229	577.7	-121***	-134.7**	-83.695	-964.9**	-28.1	4.85	99.487	-728.05	-39.57
AER	-0.10	1.689	3.098	0.615	-1.421**	-7.89	-10.91**	-0.302	2.74**	1.49	76.61**	3.09
STDEV	185.7***	-175.5*	224.4**	106.9***	124.736	188.68	653.5**	177.6*	45.37*	-597.874	-275.34	85.98
DTD	2.381**	0.141	10.6***	0.913**	0.274	1.929	18.03***	0.325	-2.12***	-6.269	-15.2**	-1.46
RATE	280.962*	-41.017	-1873.8*	1069.451	53.179	-1674.7	1828**	3331.8*	72.26	-1584*	-1228.2	652.78
INDEX	-105.9***	-61.793	-96.895	-37.6***	-62.05***	47.316	-601.2***	-22.3	-148.9**	71.631	-248.7**	-239.9***
GICS_R	-147.3***	-10.312	-290.9***	-89.2***	-25.106	-108.18	95.20	-82.28***	102.8*	-186.75	210.754	121.3**
ABS	0.155	0.093	4.54	0.725	0.371	4.746	-3.44	-2.821	-1.08	1.376	-1.823	-1.27
_cons	127.685*	116.579	185.146	168.898**	-18.18	446***	-601.8*	-428.88	-75.1	40.702	146.644	799.24
N	5,415	962	1,387	3,066	492	124	144	224	287	84	104	99
R^2	36.27%	22.61%	22.66%	39.88%	65.40%	34.24%	56.25%	49.73%	67.19%	49.80%	62.19%	49.05%
F statistics	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

*Notes: ***, **, and * indicate rejection of the null hypothesis at 1%, 5% and 10%, respectively, based on t statistics.*

Table 5 reports the result of testing Eqn. (3), i.e., the effect of *BASIS* on Δ*CDS*, and Table 6 reports the results of Eqn. (4), i.e., the reverse causality test, the effect of Δ*CDS* on *BASIS*. From Table 6, we do not find any evidence of causality running from Δ*CDS* to *BASIS* for both absolute change (Panel A) and percentage change in CDS spreads (Panel B). From Table 5, we note some evidence of causality from lagged *BASIS* to Δ*CDS* in the post-GFC period. This finding suggests that when there is higher mispricing between the CDS and the bond market, the CDS spreads in the subsequent period converge to reflect the new credit dynamics of the firm. This effect is more pronounced in the post-GFC period and cannot be attributed for other periods across the three samples.

These findings extend the literature (Shleifer and Vishny, 1997; Kim et al., 2016) on the limit to arbitrage by documenting the existence of mispricing between the CDS and the bond markets, leading to subsequent price correction in the CDS market. The effect on the CDS market following the mispricing between the CDS and bond markets contributes to the importance of financial market in improving the efficiency and quality of related markets. Our findings that the price adjustment in the CDS market is more pronounced following the mispricing between the two markets, in the post-GFC period, highlight that CDS markets in the post-GFC era maybe driven by other non-default drivers and may not be reflective of the true default dynamic of a firm.

3. Conclusion

Using an extensive sample that covers firms in the US, UK and EU as well as a wider timeline of analysis covering different economic conditions, we provide a comparative evaluation of corporate CDS spread dynamics. Our model incorporates firm-specific accounting, market-based and liquidity measures to examine the extent to which corporate CDS spreads are sensitive to various determinants of firm credit risk. Given the explosion in the use of CDS contracts by market participants, our findings have a number of implications for policy makers.

Consistent with Annaert et al. (2013) and Tang and Yan (2015), we find that spread predictor variables are better in explaining CDS spreads during periods of financial distress than at other times across the three samples. This suggests that during dire economic conditions, CDS spreads provide a better representation of corporate credit risk and may be subject to greater noise during other periods. Additionally, a substantial portion of CDS spreads in the post-crisis period that could not be explained by the comprehensive model points towards the growing influence of non-default drivers of CDS spreads. This finding implies that policy makers should ensure that they do not relying solely on the CDS market as an estimate of the credit risk signal at all times but rather consider other market (equity and bond markets) indicators in conjunction with CDS market signals. This finding has implications for the use of CDS spreads for regulation and estimation of systemic risk (e.g., Flannery et al., 2010; Giglio, 2011), advocating caution on the implementation of rules based on CDS spreads. Moreover, we find the variables driving CDS spreads change over time, for the UK and EU samples over the sample periods consistent with studies for bond yield spreads. Thus, our results imply that policy makers need to be aware of the period and context in which estimates are made and, if the context changes or the estimation period is long, prioritize re-estimation of the model.

By decomposing the spread prediction ability of accounting- and market-based variables, our findings (for 10 out of 12 cases) corroborate Galil et al. (2014), who claim that market based variables have higher predictive power of spreads.. Especially, during and following the financial crisis, market-based variables turn out to be more important predictors of CDS spreads, and the growing importance of CDS market liquidity is evident, specifically in the UK sample. This considerable spread prediction ability of market-based variables points towards the benefits of using forward-looking measures such as *DTD* compared to backward-looking accounting variables; thus, our findings support and extend the observations drawn by Galil et al. (2014). This has major implications for financial accounting regulators, who need to ensure corporate reporting, which represents an essential means by which companies communicate with their stakeholders, provide a true, fair and timely representation of the firm credit risk.

By splitting the bond yield spread into default and non-default components, we are able to isolate and show that default risk, proxied by CDS spreads, only partially explains bond yield spreads and that the presence of a significant proportion of non-default components points towards a greater mispricing between the bond and CDS markets, both during and following the global financial crisis. This mispricing, which is represented by the significant non-zero basis, could either reflect the divergence in opinions between the financial markets or presence of non-default driven market constraints that hinder the asset pricing process. Although the previous literature has ventured into the causes of mispricing, few have tried to investigate the predictive power of this mispricing to study price movement in the related market. We find a positive relationship between the CDS-bond basis and subsequent changes in CDS spreads, indicating that higher mispricing causes a rapid adjustment of CDS spreads in the post-crisis period. This finding has a number of implications. First, CDS spreads in the post-crisis period seem to respond more rapidly to mispricing than at other times. Second, mispricing could be a potential driver of CDS spreads in the aftermath of the financial crisis, which needs to be understood to enable speculative arbitrage opportunities. Third, the spillover of pricing information between the bond and CDS markets points towards the limit of arbitrage between the two financial markets. Our findings, which document the existence of mispricing between CDS and bond markets, leading to a subsequent price correction in the CDS market in the post-crisis era, contributes to the importance of the corporate bond market in improving the efficiency and quality of the corporate CDS market.

Acknowledgments

The authors would like to thank the editor and two other anonymous referees for their constructive and helpful comments and suggestions.

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WHAT DRIVES CORPORATE CDS SPREADS?

A COMPARISON ACROSS US, UK AND EU FIRMS

INTFIN_2016_93

Highlights:

1. A comparative analysis of accounting- and market-based spread predictor variables.
2. We report the results for three samples: US, UK and EU firms.
3. The variables driving CDS spreads change over time for UK and EU firms.
4. We report the existence of mispricing between CDS and bond markets.
5. CDS-Bond basis can help predict future CDS spread changes.