WHAT DRIVES CORPORATE CDS SPREADS?

COMPARISON ACROSS US, UK AND EUROZONE MARKETS

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Abstract

This study examines the determinants of quarterly corporate CDS spreads in US, UK and Eurozone (EU17) during the recent financial crisis and across all GICS sectors. Based on the findings of Das et al. (2009), we regress CDS spread against both accounting and market-based variables; jointly they provide a better fit for our data. Our analysis reveals that accounting and market-based variables are more significant predictors of CDS spreads during periods of financial distress than at other times. We note that the significance of the variables and their spread prediction power varies considerably across each period of analysis and across each market. We also note a substantial portion of CDS spreads that cannot be accounted for especially in the post-crisis period across the three markets even after accounting for CDS market liquidity dynamics. We also study the characteristics of the default and non-default components of yield spreads before, during and after the financial crisis and note that they follow a similar trend across each market. For US, UK and EU17 default risk only partially explains the movement in yield spreads and non-default component is a key driver of bond yield spreads more so in the crisis and post-crisis era. By regressing the non-default component of yield spreads against liquidity proxies, we find a significant effect of liquidity on the non-default component not only during the crisis period but also in the post-crisis period for the three markets. We suggest that high level of yield spreads coupled with greater liquidity effect may be pushing CDS spreads which may not necessarily be an indication of higher risk of corporate default in the post-crisis era.

Keywords: *CDS spreads, financial crisis, default, counterparty risk, non-default, liquidity, panel data.*

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

1. Introduction

The 2008 financial crisis which originated in the US spread rapidly across the globe. Major financial institutions went bankrupt (e.g. Lehman Brothers, Washington Mutual, Wachovia), were acquired/nationalised (e.g. Bear Stearns, Northern Rock, Lloyds, RBS) or had to be rescued (e.g. AIG, Citigroup). The developed economies including US, UK and Eurozone were the worst hit. These developed economies could be characterised by excessive amount of personal debt, an overinflated housing market, sizeable corporate bond market and a colossal financial sector. Previous studies concurred that financial institutions play a vital role within the economy by acting as nodes and lending to corporate and businesses. As such the 'flow of funds' is associated with the 'flow of risk' arising from the uncertainty in borrower's debt servicing capability (Ho, Palacios and Stoll, 2013). This collectively implies that the crisis which started in the financial sector had a dominos effect in the market for credit risk. This coupled with extensive level of debt in the corporate sector, made the prospect of major corporate defaults in these economies a realistic possibility. This study examines the behaviour of corporate Credit Default Swap (CDS) spreads before, during and after the financial crisis to assess the impact of the financial turmoil on these economies. US, UK and Eurozone countries are also the biggest markets for corporate CDS contracts globally. Consequently, a comparative evaluation of the corporate credit risk dynamics will provide fascinating insights into the corporate CDS market for these developed economies.

Credit Default Swap is a contractual agreement that transfers the risk of one or more referenced entity from one party (usually a lender of credit) to another (the insurer). There are three parties involved in a typical CDS contract referred to as the protection buyer, protection seller and the referenced entity. The protection buyer pays a periodic fee (usually of semi-annually or quarterly periodicity) to the protection seller till the maturity date of the CDS contract or until the referenced entity defaults, declares bankruptcy or faces other predefined credit events whichever occurs sooner. Following a credit event the protection seller is obligated to compensate the protection buyer for the loss (possibly hypothetically) incurred, as a result of the credit event[1] and is equal to the difference between the par value of bond and its market value post credit event or post default value (typically determined using a simple auction mechanism) by means of specialised settlement procedure (either by cash or physical settlement) for a specified face value called the notional amount of the referenced entity's debt obligation (ISDA, 2014) .

The underlying referenced entity could be a corporate or a sovereign/municipal entity and in either case the cost of insurance on debt is positively related to the underlying risk of default on obligation (usually a bond) of the referenced entity. CDS contracts for varying maturity ranging from 0.5 to 30 years exist, however 5 years maturity contracts are considered to be the most frequently traded. As noted in Blanco, Brenan & Marsh (2005), 5 years CDS contract are the most liquid credit derivatives traded in the financial market and form the basic building block for

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[1] Following are the major credit events as noted in ISDA framework,
Bankruptcy: relevant only for corporate entities.
Obligation acceleration: obligation becomes due and payable before its normal expiration date.
Obligation default: refers to a technical default, such as violation of a bond covenant.
Failure to pay: failure of the reference entity to make any due payments.
Repudiation/Moratorium: provides for compensation after specified actions of a government (e.g. delay in payment).
Restructuring: reduction and renegotiation of delinquent debts in order to improve or restore liquidity, in 2009, US contracts eliminated restructuring as a potential trigger event. (source: www2.isda.org)

more complex structured credit products[2]. CDS contracts act as financial instruments used to hedge against credit default, as such should incorporate increased possibility of default in its relative pricing. In essence, CDS can be seen as a form of insurance against credit default. For a regular premium, the purchaser of the CDS contract is able to sell his debt to the CDS seller in case of a pre-defined credit event.

CDS market is part of the larger Over-The-Counter (OTC) derivative market[3] comprising of interest rate contracts (81.0%), foreign-exchange contracts (10.6%), equity linked contracts (1.0%), commodity contract (0.4%) etc. Although CDS represents only 3.5% of the OTC market the sheer notional amount of all contracts outstanding, is more than double that of the GDP of 17 Eurozone countries combined[4]. The first CDS contract was created in 1994 by JP Morgan to extend lines of credit for Exxon to cover potential damages resulting from the Exxon Valdez oil spill disaster of 1989 (Linkins, 2010). JP Morgan contracted with European Bank of Reconstruction and Development (EBRD) on a $4.8 billion credit line for Exxon, where EBRD would cover for potential default by Exxon in exchange for a periodic fee (Tang & Yan 2010). By 1997, the gradual growth in market resulted in the notional open interest in CDS being in the order of $200billions (Avellaneda & Cont, 2010). Development of an active secondary market propelled the growth in the market by early 2000. Subsequently, the market for CDS grew

[2] Other credit derivatives products include 1) Total return Swap – where return from one asset or a group of asset is swapped for the return on another asset or group of assets and 2) Credit spread option- which is an option on the spread between the yield earned on two assets Blanco *et al.* (2005)
[3] The total notional amount outstanding for the OTC market was reported over $692.91 trillion as of June 2013 (BIS Statistics, 2014) Refer to Fig – 1 Composition of the OTC derivatives market. Data as of June 2013 in trillion USD (www.bis.org) and Fig – 2 Composition of the Credit derivatives market (www.occ.gov)
[4] GDP as of last quarter 2012 for the 17 Eurozone countries was at $12.19 trillion USD (www.worldbank.org)

exponentially until the financial crisis of 2008 where the total notional amount outstanding[5] was reported as close to $58.24 trillion at its peak. Following the credit crisis of 2008, the volume of CDS contracts has reduced significantly mainly due to industry level ‘portfolio compression’[6] efforts spurred by regulator. The total notional amount outstanding as of June 2013 was reported at $24.35 trillion[7] (BIS statistics, 2014) evenly divided between bought and sold protection. Although the financial crisis of 2008-2009 is often quoted as the reason for reduction in CDS outstanding contract, it is rather believed that the CDS market has been stable since 2008 supported by a relatively stable outstanding notional of Equity-linked, Interest rate and Currency derivatives over the same time span (Jarrow, 2010).

[Figure 1 about here]

[Figure 2 about here]

[Figure 3 about here]

As argued by Hull, Predescu and White (2004), both CDS spreads and yield spreads based on bond prices should be close to each other under a special set of circumstances. Past few years have also witnessed a wealth of literature advocating CDS spreads as a better proxy for credit risk compared to bond yield, some of the distinct advantages are detailed as follows, 1) CDS

[5] Notional amount refers to the par amount of credit protection bought or sold and is used to calculate the premium payment for each payment period as well as the recovery amount in an event of default

[6] Portfolio compression mechanism has been introduced since 2007 whereby large simultaneous long and short CDS positions referencing the same underlying borrower are cancelled out. This helps reduce the unnecessary exposure to counterparties that created no material economic benefit.

[7] Within the CDS market single name instrument comprises of $15.57 trillion and multiple name instruments accounting for $11.36 trillion measured in terms of notional amount outstanding as of June 2012. Refer to Fig. 3 - Credit Default Swap – Notional amount outstanding trends. Data as of Jun 2012 (BIS statistics, 2013)

spreads are directly observables for a given underlying bond and hence does not require any adjustment or assumption on risk free benchmark rate whereas bond spread has to be computed using a riskless benchmark which is often difficult to ascertain (Longstaff Mithal & Neis, 2005; Blanco *et al*., 2005). 2) CDS spread data consist of bid and ask quotes which once made makes the dealer committed to trade a minimum principle of $10 million at the quoted price. On the contrary bond yield spread data requires no commitment from dealer to trade on the prices (Hull *et al.*, 2004). 3) CDS contracts are directly written on credit event of the underlying bond and so are not distorted by embedded options, features like call options and covenants unlike bond yields (Duffie, 1998). 4) Unlike other credit risk instruments like bonds and swaps, CDS are not interest rate based instruments which ensures minimal effect of interest rate movement on spread estimation. 5) Studies have also shown that CDS spreads react more rapidly to changes regarding the credit quality of the underlying reference entity compared to the bond market (Hull *et al.*, 2004; Blanco *et al.*, 2005; Zhu, 2006). Especially during period of financial distress CDS market is found to dominate the information transmission process between the CDS and bond market (Delatte, Gex & Lopez, 2012).

Apart from these studies, as noted in Annaert, Ceuster, Roy & Vespro (2012) the credit premium in bond spreads is driven by liquidity factors (Sarig & Warg, 1989 and Chen, Lesmond & Wei, 2007), tax effects and risk premia (Elton, Gruber, Agarwal & Mann, 2004) and various market micro-structure effects like maturity effect, coupon effect etc. which makes it an inferior measure of credit risk compared to CDS spreads. CDS also have a more pronounced liquidity relative to bonds which ensures that credit sensitive relevant information are quickly processed, as such CDS provides an excellent laboratory for studying the mechanism of the credit market

(Breitenfellner & Wagner, 2012). Additionally, CDS market are considered to be better than bond market due to the bond market relative illiquidity and high barriers to shorting bonds which impedes the price discovery process (Blanco *et al.*, 2005). Thus, the increasingly popular CDS provides an alternative, more reliable, cross-sectional and time-series indicator of corporate credit risk. Consequently, a wide range of studies have employed CDS spreads as a pure measure of corporate credit risk. These coupled with the existence of large amount of CDS data, have yielded a number of studies that have attempted to determine firstly; the factors that drive the CDS spreads and secondly the impact of CDS spreads on the wider market as a whole. One of the earliest studies in this area was by Longstaff *et al.* (2005) who used CDS spreads to obtain direct measures of the size of both the default and non-default component of bond yield spreads. Later studies include those by Becchetti, Carpentieri and Hasan (2012), Calice, Chen and Williams (2012), Kunt and Huizing (2013) amongst others.

Majority of these studies have focused on credit indices or used small samples particularly focussing on a sector or a particular economy. Studies by Becchetti *et al.*, (2012) extend their analysis to US, UK and Eurozone, with very few spread predictor variables. Moreover, their sample is limited from 1997-2003 and use option-adjusted credit spread index. Study by Tang and Yan (2012) focuses on predicting CDS spreads using both fundamental and liquidity driven variables, their research was limited to North American CDS contracts from 2002-2009 and does not measure the effect post-crisis. Annaert *et al.*, (2012) have undertaken a research on estimating the determinants of CDS spreads from 2004-2010. However their study was limited to financial sector firms specific to 32 listed Euro area banks. Svec & Maurice (2010) provided the first study to investigate the factors driving the CDS spreads of Australian companies. However, this research was specific to the investment grade Australian companies and compared spread determinant market and economy wide risk factors like volatility and liquidity with market-based structural form variables. A similar study on variables affecting CDS spreads was undertaken by Cossin & Hricko (2001) and Aunon-Nerin, Cossin, Hricko & Huang (2002), their study used a number of firm specific variables including credit rating, 3 month treasury constant maturity interest rate, slope of the yield curve (measured as the difference between the short term and long term interest rate), time to maturity, volatility of firms assets, leverage, Index returns, stock price as well as idiosyncratic factors for explaining CDS spreads for 323 corporate underlying across different geographies. However similar to other studies, the sample used in these studies are either too restrictive for the period of analysis or are highly biased towards US corporate. We follow Das, Hanouna and Sarin (2009) and incorporate accounting variables as well as market variables to examine the behaviour of the CDS spread before, during and after the crisis across all GICS sectors (excluding Government) for the US, UK and the Eurozone (17 countries)[8] markets. This research explores a wider sample domain and is more comprehensive. We undertakes a comparative exploration where CDS spreads predictor variables are compared and contrasted across US, UK and EU17 economies, industry sectors and across period of analysis including pre-crisis, crisis and post-crisis periods.

The remainder of this paper is as follows. Section 2 introduces CDS spreads descriptive for US, UK and EU17 markets, whereas Section 3 introduces the independent variables that determine the credit spread used in this study and the descriptive statistics. Section 4 presents the empirical results for the fixed-effect panel data regression for the three samples across

[8] EU17 henceforth; includes Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovak Republic, Slovenia and Spain.

different sub-periods of analysis. Section 5 carries out a series of robustness checks to validate our research findings. Section 6 discusses the policy implications of our findings and Section 7 concludes.

2. US, UK and EU17 CDS Spreads

For US, UK and EU17 markets 5 year constant maturity quarterly CDS spreads (CBGN database collected from Bloomberg) belonging to the senior debt type are used. 5 years tenure contracts are considered the most liquid of all the CDS contracts of varying maturities that trade in the market. We find that overall CDS spreads in both US (Fig. 4A) and UK (Fig. 4B) markets follow a similar trajectory before, during and after the financial crisis. However, CDS spreads for the EU17 (Fig. 4C) increases during the crisis period and is comparatively higher even in the post-crisis period.

[Figure 4A about here]

[Figure 4B about here]

[Figure 4C about here]

Fig. 4A, Fig. 4B and Fig. 4C also displays the median, 10th and 90th percentile corporate CDS spread from 1st January 2005 to 31st December 2012 on a quarterly basis. For US and UK, the figures show CDS spread increasing dramatically from third quarter of 2007 reaching its peak in 2009. During the height of the crisis, the interdecile spread between 10% and the 90%

quartiles for US at annual and quarterly level was in excess of 822 bp and 1453 bp respectively. For UK, this was in excess of 572 bp annually and 926 bp quarterly respectively. After the crisis period, CDS spreads declined for both US and UK, where the decline starts effectively from first quarter of 2009. For EU17, the CDS spreads increases during the crisis period but peaks during the post-crisis period; where the interdecile range was in excess of 654 bp annually and 1051 bp quarterly respectively.

To examine the broad statistics, we turn to table 1, where CDS spreads data are taken from 1st January 2005 to 31st December 2012. For US sample, our dataset consists of 13,857 quarterly spread observations, 3,338 observations for the UK and 5,979 observations for the EU17 sample. Panel A of table 1 splits the CDS spreads on an annual basis for US, UK and EU17 market. For US, we observe a minimum spread of 4.83 bp and the maximum spread to be 13,091.41 bp. Similarly, the minimum and maximum spreads are 3.67 bp and 8,344.94 bp for UK and 3.38 bp and 16,102.98 bp for EU17 respectively. Though there is an overall decline in the spread from 2009 onwards, the median spread has remained stubbornly high both for US and UK, indicating that for certain firms at least the CDS spread has decreased whilst for other it has not. For EU17, the spread reduced following the financial crisis but again rose sharply in the post-crisis period, which could be attributed to the turmoil caused by the sovereign credit default crisis in the Eurozone.

Panel B of table 1, provides the breakdown of CDS spreads by GICS sectors for the US, UK and EU17 across three periods namely; pre-crisis, crisis and post-crisis. In defining these three periods, we follow Breitenfelner and Wagner (2012). More specifically, we define the pre-crisis period as from 1st January 2005 to 30th June 2007; crisis period from 1st July, 2007 to 30th June

2009 and post-crisis period from 1st July 2009 to 31st December 2012. We observe that both the mean and the median spread increases between the pre-crisis period and the crisis period for all three samples. Mean (median) increases from 80.56 bp (35.00 bp) to 371.08 bp (144.39 bp) for the US, whereas for the UK it increased from 60.25 bp (32.72 bp) to 240.40 bp (118.17 bp) respectively. For EU17 mean (median) spreads increases from 59.99 bp (26.14 bp) to 266.40 bp (119.57 bp) in the crisis period. Moving on from the crisis period to the post-crisis period, we find an overall decline in CDS spreads for both US and UK sample. However, the spreads are nowhere comparable to the pre-crisis level. Specifically for the US, the mean (median) declines to 256.97 bp (125.51 bp) and for the UK it declines to 167.02 bp (118.38 bp) respectively. However, mean (median) spread for EU17 in the post-crisis period is at 278.19 bp (154.14 bp) higher than the crisis period. Of all the GICS sectors, 'Financial' and 'Consumer cyclical' sectors have higher (median) spreads in the crisis and post-crisis period across the three markets. Panel C of table 1, provides breakdown of CDS spreads by issuing country of the underlying firm. We notice for US and UK the median spreads follow more of less a similar trend across each sub-period of analysis. However for the EU17 countries there is lot of variations in median spreads across the crisis and post-crisis period. Median spreads for Germany, France and Netherlands and lower than US and UK, however those for Greece, Portugal and Ireland are much higher in the post-crisis period. This also highlights the variable effect of Eurozone crisis on the corporates spreads for firms in different economies.

[Table 1 about here]

Following Gorton and Metrick (2010), we use the difference between the LIBOR (for unsecured interbank borrowing)[9] and overnight interest swap (OIS for risk free rate)[10] as a proxy for counterparty risk. Table 2, provides a breakdown of the counterparty risk during each sub-period of analysis. For US, we see that from the pre-crisis period mean of 9 bp, the counterparty risk jumps to 90 bp during the crisis, subsequently declining to 21 bp in the post-crisis period. A similar scenario emerges for the UK market, where there is a jump from 11 bp to 101 bp followed by a decline to 30 bp in the post-crisis period. For EU17, the pre-crisis mean of 6 bp increases to 78 bp in the crisis period before declining back to 37 bp in the post-crisis era. Figures 5 provides a graphical comparison of the counterparty risk across US, UK and EU17 markets, indicating despite the decline in market turmoil, there is still significant counterparty risk in all three markets compared to pre-crisis period. Furthermore, we find a strong positive correlation between the CDS spread and counterparty risk for the three markets and well as between the three markets.

[Table 2 about here]

[Figure 5 about here]

[9] Libor is the rate paid on unsecured interbank loans, cash loans where the borrower receives an agreed amount of money either at call or for a given period of time at an agree interest rate. These loans are not traded and can be expressed as the interest rate at which banks are willing to lend to other Financial Institutions (Gorton and Metrick, 2010)

[10] OIS is a fixed to floating interest rate swap that ties the floating leg of a contract to a daily overnight reference rate. The floating rate of the swap is a geometric average of the overnight index over every day of the payment period (Gorton and Metrick, 2010)

3. Explanatory variables driving CDS spreads

We draws from the wealth of literature on credit risk modelling that studies the effect of various firm-level, market-level and macro-economic proxies that are used to infer credit risk dynamics of a firm. A bulk of these variables used to extract credit risk information can be classified under two major headings 1) Intrinsic - firm-level variables and 2) Extrinsic- macro-economic variable. Few credit risk forecasting models propose the use of these variables as supplementary in understanding credit risk rather than their use in isolation. Following section provides a review of the major category of variables used to study variations in corporate credit risk in the past literature;

3.1. Intrinsic firm level variables

Firm level variables can be categorized into further two types 1) Accounting-based ad-hoc measures drawn from company financial statement that provide indication of firm level credit risk and 2) Market-based theoretical measures that draw from information in company financial statement along with stock trading data.

Previous studies on bond pricing and default prediction have well established the importance of financial accounting information as an important estimator of default risk. Studies using bond yield (Yu, 2005) as estimator of credit risk and bankruptcy prediction (Altman, 1968; Ohlson, 1980 among others) find a significant association between measures of credit risk and information contained in financial reports. The traditional approach of predicting default risk which relied on usage of scoring model like Altman's Z-score[11] (Altman, 1968) and Ohlson's O-score[12] (Ohlson, 1980) typically attempts to discriminate defaulting and non-defaulting firms using accounting information. These models use the information contained in the financial statements of the company to provide an adequate assessment of the financial distress risk and classifies a company as sound or financially distressed based on some predefined benchmarks. Apart from using default forecasting models powered by accounting variables, later studies have employed the direct use of accounting variables in estimation of CDS spread and found a significant spread predictive power. Studies by Callen, Livnat & Segal (2007), support this by finding a significant effect of credit relevant accounting information especially earning announcement on short-term maturity CDS prices, indicating accounting information could be employed to estimate a firm's short-term credit risk dynamics. The usefulness of accounting information for credit risk estimation is further supported by Das *et al.*, (2009) who find; accounting based information explains nearly two-third of the variation in CDS spreads and have comparable estimation power than market-based variables. Also, as detailed in Batta (2011), accounting information has a direct effect on corporate credit risk as well as provides an indirect effect through security prices and credit rating. This is supported by Ahmed, Billing, Morton & Stamford-Harris (2002) who affirms the key role of accounting information in credit rating assessment process. Batta (2011) argues that the indirect role of accounting information on credit ratings implies that models which fail to consider accounting information in

[11] Z-score is based on a statistical technique of Multivariate Discriminant Analysis (MDA) which has been widely adopted to identify potential insolvent companies. The solvency profile is represented as a single index score and is a linear combination of variables with an aim to provide distinction between a solvent and insolvent firm (Mason and Harris, 1979).
[12] Ohlson's O-score uses an econometric technique based on logistic transformation (Logit model) to assign a score that forecasts the probability of default for a firm (Ohlson, 1980)

conjunction with credit rating miss a crucial channel for interpreting and disseminating credit relevant information derived from firm's financial reports.

Although accounting based models uses variables[13] that are believed to have some degree of financial distress prediction ability their use in estimating corporate credit risk can be challenged on various grounds; 1) There is no theoretical basis for the use of specific accounting variables in default prediction models. 2) Accounting variables are considered to be 'backward looking' as it relies on historical information rather than market's assessment of the future (Bystorm, 2006), hence the information on basis of which these models are built cast doubts on the validity and reliability front. 3) Accounting measures are updated with a rather low frequency, are released with a time lag as well as suffer from possible accounting manipulations[14] (Bystorm, 2006). 4) Accounting variables are sample-specific, as the accounting ratios and ratio weights are estimations drawn from the sample. Therefore a change in these ratios over time necessitates a re-development of the model on a periodic basis. 5) Moreover, accounting variables are prone to conservatism as they are subject to historical cost accounting, which substantially alters the book value from the true asset value and by doing so reduces its default predicting power (Agarwal & Taffler, 2008). 6) Additionally these variables are by design of limited utility in predicting defaults as accounting data are prepared on 'going-concern'[15] basis (Hillegiest, Keating, Cram & Lundstedt, 2004). Although, there is limited theoretical rationale for use of ad-hoc accounting information; these variables are found to provide good indication of the financial

[13] Z-score and O-Score is calculated using accounting variables like total assets, total liabilities, market value of equity, retained earnings, working capital etc.

[14] The most well know example is the case of Enron during the years leading up to its eventual default and chapter 11 bankruptcy filing in December 2001, where manipulated accounting information led to an incorrect estimation of Enron's credit risk

[15] The going-concern concept directs accountants to prepare financial statement with an assumption that business will remain in existence for an indefinite period

health of the company and hence cannot be ignored. We rationalizes that, if information from company operation and management are an indication of the company's financial strength, these measures can help understand company's credit risk dynamics and hence could prove to be an important driver of corporate credit risk and simultaneously help in understanding CDS spread behavior.

3.2. Accounting based variables

Following Das *et al.* (2009), we use 10 accounting based variables to proxy for (1) firm size, (2) profitability, (3) financial liquidity, (4) trading account activity, (5) sales growth and (6) capital structure. We list these variables below:

(i) *Firm size (ln_size)*: We use the log value of total assets divided by the Consumer Price Index.

(ii) *Three ratios that gauge profitability*: They are return on assets *(ROA),* Net income growth *(incgrowth)* and interest coverage *(c).* ROA is calculated using net income divided by total assets. Further Net income growth is calculated as net income minus previous quarter's net income divided by total assets. Interest coverage is calculated as pretax income plus interest expense divided by interest expense.

(iii) *Financial liquidity*: The quick ratio *(quick)* and cash to asset ratio *(cash)* is used. The quick ratio is calculated as current assets minus inventories over current liabilities and the cash to asset ratio is cash and equivalents over total assets.

(iv) *Trading account activity (trade)*: The ratio of inventories to cost of goods sold.

(v) *Quarterly sales growth (salesgrowth)*: Sales divided by the previous quarter sales minus one.

(vi) *Capital structure*: The ratio of total liabilities to total assets *(booklev)* and the ratio of retained earnings to total assets *(retained)*.

3.3. *Market based variables*

The literature on credit risk modelling using market-based measures suggest two competing paradigms for modelling credit risk namely; the structural-form that uses option pricing theory to evaluate corporate credit risk and the reduced-form approach using term structure theory to explain credit spread behavior.

To estimate default risk, this research employs Merton (1974) model based on the assumption that the firm has a simple capital structure comprising of just debt and equity. Merton interprets the equity of the firm as a call option on the firm's asset and the debt as the strike price of that call option. The alternative approach to the Merton model is the use the reduced-form model developed by Jarrow and Turnbull (1995). However, unlike the Merton structural model, the reduced-form approach does not provide an explicit link between default and firm specific variables on credit risk (Duffie and Singleton, 1999; Switzer and Wang, 2013). Hence, the Merton model is preferred over the reduced-form approach.

The starting point of the Merton model is the assumption that the total value of the firm V follows geometric Brownian motion;

$$dV = \mu_v V dt + \sigma_v dW$$

Where μ_V is the expected return on V, σ_V is the volatility of the firm value V and W is the standard Wiener process.

We let X be the book value of the debt at time t, with maturity of duration T. The market value of equity E based on the Black-Scholes-Merton (BSM) model is then:

$$E = VN(d_1) - Xe^{-rT}N(d_2)$$

$$\text{where:}$$

$$d_1 = \frac{\ln\left(\frac{V}{X}\right) + \left(r + \frac{1}{2}\sigma_V^2\right)T}{\sigma_V^2\sqrt{T}},$$

$$d_2 = d_1 - \sigma_V\sqrt{T}$$

r is the risk-free interest rate and N is the cumulative density function of the standard normal distribution.

This research uses "distance to default" (DD) in the Merton model as a measure of credit risk. The key to estimating DD is the estimation of V and σ_V in the BSM model. To estimate these two variables this research follows the approach as detailed in Vassalou and Xing (2004). Assuming a forecasting horizon of 1 year, i.e. (T = 1) or 250 trading days in a year, firstly σ_V and μ_V are estimated iteratively using the estimated equity volatility from the past year as a starting value. Using BSM and for each trading day, V is computed using E as the market value of equity for that day. The estimation procedure is repeated for the remaining 249 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 is discontinued and the values are inserted in the BSM equation to obtain V. The resulting values of *V*, σ_V and μ_V are then used to calculate the firm-specific *DD* over a horizon *T* as,

$$DD = \frac{\ln\left(\frac{V}{X}\right) + \left(\mu_V - \frac{1}{2}\sigma_V^2\right)T}{\sigma_V^2\sqrt{T}}$$

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 is set as book value of short term liabilities plus one half of the long term liability and is similar to the one used by KMV CreditMonitor™ and considered to be relatively more realistic. The *DD* measures the number of standard deviation this ratio needs to deviate from its mean for default to occur. The probability of default is then simply *N* (-*DD*).

Average annualised equity return (*ret)* is estimated using the last 250 trading day market capitalization value of the equity, a negative relationship between equity return and CDS spreads is expected as better market performance indicates a lower credit risk. As volatility is a measure of market uncertainty, it may proxy for market strains that limit capital mobility across different market segments or the investor's risk aversion (Pan and Singleton, 2008) and thus increase in volatility should lead to an increase in credit spread. In this study we use the volatility *(σret)* as the annualized standard deviation estimated from prior 250 trading days daily stock price return.

For the risk-free rate, we use the 3-month US-LIBOR for US, 3-month UK-LIBOR for UK sample and 3 months EURIBOR for EU17. This rate is same across all firms in the same period and thus acts as a time dummy variable accounting for the time clustering in our dataset.

As periods of low interest rates are normally related to periods of economic downturns, we expect a negative relationship between the risk-free rate *(r)* and CDS spread.

We include the prior year i.e. 12 months return *(index)* on the S&P500 index for the US, FTSE100 index for UK, and EUROSTOXX 50 Index for EU17 sample. The prior year return on the respective index GICS sector *(rgics)* provides sector return. As periods of low market/sector returns are normally related to periods of economic downturns, we expect a negative relationship between the index/sector return on CDS spread. Alternatively, improvement in the business environment should lessen firm's chances of default and thus increase their default recovery rates. Duffee (1998), Collin-Dufresne, Goldstein and Spencer-Martin (2001) and Bharath and Shumway (2008) have found a similar negative relationship between changes in interest rates and firm default risk. Thus following Collin-Dufresne *et al.* (2001), Ericsson, Jacobs and Ovieda (2009), Duffie, Saita and Wang (2007), Campbell and Taksler (2003), Cremers, Driessen, Maenhaut and Weinbaum (2008), Avramov, Jostavo and Philipov (2007), Boss and Scheicher (2005) and Dullmann and Sosinka (2007), we use the market wide stock index as a measure of the business environment, GICS sector return as measure of sector performance and risk-free rate as a measure of economic activity. All these variables act as time dummies and are firm invariant for our dataset.

3.3. Descriptive Statistics

In table 3, we present summary statistics for the predictor variables used in this study for the US (Panel A), UK (Panel B) and EU17 (Panel C) markets. In general the calculated average value of the explanatory variables used is much smaller than their corresponding standard deviation.

The Jarque-Bera Test (not reported here), rejects normality in all cases due to high kurtosis and skewness values in all three sample sets. We also find (again not reported here) that the variables during each of the three separate periods are significantly different from each other. The fact that the variables change over time leads to high kurtosis coefficient which in turn leads to rejection of normality across all three sub-periods.

[Table 3 about here]

4. Empirical Results

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

$$
\begin{aligned}
\log(CS_{it}) = {} & \alpha_i + \beta_{1i} size_{it} + \beta_{2i} ROA_{it} + \beta_{3i} incgrowth_{it} + \beta_{4i} c_{it} \\
& + \beta_{5i} quick_{it} + \beta_{6i} cash_{it} + \beta_{7i} trade_{it} + \beta_{8i} salesgrowth_{it} \\
& + \beta_{9i} booklev_{it} + \beta_{10i} retained_{it} + \beta_{11i} DTD_{it} + \beta_{12i} ret_{it} \\
& + \beta_{13i} \sigma ret_{it} + \beta_{14i} r_t + \beta_{15i} Index^{-1year}{}_t + \beta_{16i} rgics_t + \varepsilon_{it}
\end{aligned}
$$

The model assumes correlation (clustering) over time for a given firm, with independence over firms, i.e. the credit risk for a given firm is correlated over time but is independent across other firms in our sample. We use fixed-effect panel data regression due to the following reasons, Firstly, the OLS pooled regression model is too restrictive as it considers the coefficients to be constant across each firm in the sample and thus does not explain the full richness of our panel data dynamics. Moreover, as the true model of our dataset is fixed-effect, the pooled OLS regression is bound to provide inconsistent estimates. This is tested using the Breusch-Pagan Langrage multiplier test and found to be significant at 95% level of significance and thus does not support the use of pooled OLS regression for the models. Secondly, the study assumes the individual-specific effect i.e. unobserved heterogeneity α_i in the model are correlated with the regressors, this is tested with the random-effect model using the Haussmann statistics (not reported here). We find that the Haussmann test is significant at 95% level of significant which further substantiates our choice of using fixed-effect regression. Finally, our model consists of regressors that are both time and firm variant *(ln_size, ROA, incgrowth, c, quick, cash, trade, salesgrowth, booklev, retained, ret, σret and DTD)* and well as those that are time-variant but firm-invariant *(r, index, rgics)* and act as time dummies in our model. Fixed-effect regression is better equipped to handle both types of regressors in one single regression model.

Table 4 provides the regression results for the US (Panel A), UK (Panel B) and EU17 (Panel C) markets over four separate period of analysis as defined earlier. Due to missing firm-level data, the number of quarterly observation drops substantially across the three markets. For the US market, our sample consist of 6393 quarter-firm with 1256, 1778 and 3359 quarter-firm observations for pre-crisis, crisis and post-crisis period respectively. For the UK sample there is only 578 quarter-firm observations for the whole period with 129, 146 and 303 quarter-firm observations in each of the sub-periods. Similarly, for the EU17 market the sample consists of

590 quarter-firm observations, with 135, 211 and 244 quarter-firm observations in pre-crisis, crisis and post-crisis period respectively.

[Table 4 about here]

Across the three samples, size of firm (*ln_size)* does not have a bearing on the CDS spreads except for a weak relation (at 10% level) for the UK market in crisis period. For the US market, there is a statistically significant negative relationship between the CDS spread and firm ROA. This is expected and is true across all sub-periods. However, in case of UK and EU17, for all the sub-periods the relationship between CDS spread and ROA is negative but not significant. Similar to Das *et al.* (2009), we find a negative and significant relationship between interest coverage ratio *(c)* and CDS spreads for the whole period and post-crisis period for UK sample, but this relationship is not significant across the US and EU17. Contrary to expectation, the net income growth *(incgrowth)* is positive and significant across all sub-periods for the US sample indicating faster growing firms have more credit risk. However, the relationship does not hold and is not significant in the UK and EU17 sample. Unlike Das *et al.*, (2009), we find the quick ratio *(quick)* is positive and significant in the post-crisis period for US and for crisis and post-crisis period for UK markets, this relationship is not significant for EU17 market. The book value of leverage *(booklev)* is positive and significant for the whole period across both US and UK sample indicating leverage increases firm's credit risk i.e. CDS spreads. However this relationship becomes insignificant during the crisis period for both samples and for EU17 market.

For the remaining accounting variables the results are mixed with the significance of each parameter changing for each sub- period and across the US, UK and EU17 markets.

With regard to market-based variables, we find that for the US market there is a significant positive relationship between the CDS spread and volatility of returns *(σret)* as expected. For the UK and EU17 market, we find a similar relationship but the results are not significant for the pre-crisis period. Turning now to distance to default *(DTD)* coefficient for the US market, we find that as expected the relationship is negative and significant for the whole period and each sub-periods. However, this relationship is not significant during the pre-crisis period for the UK and EU17 and for the crisis period in the EU17. We find that most of the market-based variables are significant across all periods (with some exceptions) in the US sample, whereas all market-based variables become significant during the crisis period for UK and during the post-crisis period for EU17. The overall R^2 for the model varies across each sub period and is characterised by low R^2 during the pre-crisis period, higher R^2 values during the crisis period and reduction in model's explanatory power in the post-crisis period. The model has a good overall fit with closer R^2 and *Adj.* R^2 values across each sub-period of analysis.

Overall, CDS spreads explanatory power of the predictor variables in our model changes significantly based on the period of analysis. This is evident in the US, UK and EU17 samples. Overall the accounting and market-based variables jointly explain about 61.97%, 55.85% and 64.07% of the variation in CDS spreads in the whole period across US, UK and EU17 markets respectively. However the spread prediction power is low during the pre-crisis period i.e. 24.14%, 16.85% and 45.79% (for US, UK and EU17 respectively) increases significantly during the crisis period with *Adj.* R^2 value of 74.90%, 61.32% and 63.91% for the US, UK and EU17 markets. In the post-crisis period the model's explanatory power drops to 27.42%, 33.68% and 40.05% for the US, UK and EU17 samples respectively. This indicates that the accounting and market-based variables are more significant predictors of CDS spreads during crisis periods than at other times.

Our model uses both accounting and market based variables, which make our results susceptible to distortion due to presence of multi-collinearity effect. We undertake a multi-collinearity diagnostic test (not reported here) using tolerance and VIF scores. The results are found to be less than the threshold value (not reported here) across all samples and sub-period of analysis indicating absence of multi-collinearity effect. Overall, the above observations illustrates that the accounting and market-based variables together do a good job in explaining the variance in CDS spreads across the markets especially more during the crisis period.

To find if the effect of adding each block of predictor variables i.e. accounting and market-based variables are consistent over each sub-periods, we run a hierarchical fixed-effect regression using block of predictor variables across each sub-period of analysis. Table 5 provides the result for the model R^2 firstly, by using only accounting variables and then by adding market-based variables to obtain the change in model's explanatory power across each sub-period. We report the model *Adj.* R^2 and change in *Adj*. R^2 for US, UK and EU17 sample in Panel A, Panel B and Panel C respectively. We find that, across US, and UK markets there is a substantial increase in model's explanatory power when the market-based variables are included (Block 1) and more so during crisis period. The increase in models R^2 over and above the accounting variables is at 6.30% (3.93%) in the pre-crisis period, 3.54% (6.71%) in the crisis period and 5.66% (6.43%) in the post-crisis period for the US (UK) sample. The effect size[16] estimates the magnitude of difference between the *Adj.* R^2 values and we find the effect of adding market-based variables is mostly small (< 0.1) for all sub-period in the US and UK sample. For EU17, the increase in model's *Adj.* R^2 over and above the accounting variables is at 22.74% in the whole period, indicating a large effect size. The increase in *Adj.* R^2 is 1.48% (small effect size) in the pre-crisis period, 0.81% (small effect size) in the crisis period and 24.18% (large effect size) in the post-crisis period. This confirms that market-based variables have significant explanatory power in determining CDS spreads across each sub-period of analysis although their incremental explanatory power is different across each sub-period and sample.

[Table 5 about here]

Considering our estimates could be biased on the order of entering the block of explanatory variables used to explain CDS spreads. We re-run the regression model, this time by entering market-based variables first and estimating model's R^2 and then adding the accounting variables to re-estimate models *Adj.* R^2 and change in *Adj.* R^2 value (Block 2). For UK sample, we observe the model change in R^2 is negative for the whole period and the crisis period and for EU17 the model change in R^2 is negative for the whole period and the post-crisis period. This indicates that adding accounting variables to the model increases noise and then reduces the model's explanatory power. However, it is important to note that these changes in *Adj.* R^2 value are very small. For the US sample, we find that adding accounting variables increases the

[16] Effect size of less than 0.1 indicates a small effect, effect size between 0.1 and 0.3 indicates a medium effect and effect size larger than 0.3 indicates a large effect (Cohen, 1988)

model's *Adj.* R^2 value (small effect size) across each sub-period. Moreover, there is increment in model's *Adj.* R^2 value for pre-crisis and post-crisis period for the UK sample and in the pre-crisis and crisis period for the EU17 sample. This indicates accounting variables may have some incremental explanatory power although not as much as the market-based variables. Based on these observations, we can conclude that although market-based variables which are available real-time and not subject to accounting adjustments and manipulations provide a better explanation of the variance in CDS spreads, the use of accounting variables further enhances the model's explanatory power. However, combination of both type of variables perform better than each of them individually. Moreover, even by adding both set of predictor variables along with macroeconomic indicators there is still a substantial portion of CDS spreads that cannot be accounted for especially in the post-crisis period for all the three markets.

4.1. The Default and Non-default components

For firms analysed in the previous section, we estimate monthly corporate bond yield spread based on the 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 obtained monthly bond yield for 294 firms in US, 50 firms in UK and 95 firms in EU17 sample. The bracketing set procedure uses 3894, 1089 and 2715 individual bonds (for US, UK and EU17 respectively) to draw bond yield estimates from Jan-2005 till Dec-2012 on a monthly basis. To estimate the standard benchmark risk free rate we use treasury curve and interpolate the yield on a riskless bond with the same maturity and coupon using standard cubic spline algorithm. The estimated risk free rate is subtracted from the bond yield to obtain monthly bond yield spreads for each CDS contract in our sample. In order to obtain the five year yield spreads for the firm, we regress the yield spreads for the individual bonds in the bracketing set on their respective maturities. The fitted value of the regression at the 5 years horizon is used to estimate the corporate yield spreads for the firm. In total we are able to estimate 15,658 monthly bond yield spread for US, 3,035 for UK and 6,283 bond yield spreads for EU17 sample. We further take the monthly credit default swap spread as the estimate of the default component of the monthly corporate bond yield spread. The difference between the two gives the non-default component of the spread. Panel A of table 6A, table 6B and table 6C reports the corporate yield spreads averaged across each GICS sector for the US, UK and EU17 sample respectively across each sub-period.

For the US market, we find that the median bond yield spread increases across all the sectors during the crisis period with a subsequent decline during the post-crisis period. This is reflected by the median spread across all GICS sectors which increase from 113.31 bp in the pre-crisis period to 330.42 bp during the crisis period before dropping back to 203.29 bp in the post-crisis period. A similar trend can be observed for the UK market, where the mean yield spread increases from 91.86 bp in the pre-crisis period to 313.79 bp in the crisis period before declining to 220.78 bp in the post-crisis period. However, for both the US and UK markets the post-crisis spread is much higher than the pre-crisis level. For the EU17 sample, the median bond yield spreads increased from 98.34 bp in the pre-crisis period to 205.95 bp in the post-crisis era

However, contrary to US and UK markets the bond yield spreads further peaks to 224.25 bp in the post-crisis period.

Panel B of tables 6A, table 6B and table 6C provides the median default component, the non-default component, and ratio of the default component to the total corporate yield spread across firms in the US, UK and EU17 markets respectively. The non-default component for firms is obtained by subtracting the default component (CDS spreads) from the corresponding corporate bond yield spread. Similarly, the ratio of default component is obtained by dividing the default component to the bond yield spread for the GICS sectors across each sub-periods. Overall, we find that the default ratio varies widely across the GICS sector and for each sub-period. For the US sample, we find that default component to bond yield spread represents about 25%, escalating to 30% and 50% of the bond yield spreads for pre-crisis, crisis and post-crisis period. Similarly, for the UK market the default ratio to bond yield spreads is at 20% in the pre-crisis period, increasing to 32% in the crisis and 53% in the post-crisis period. The EU17 sample follows a similar trend with the ratio of 19%, 47% and 66% in the pre-crisis, crisis and post-crisis period respectively. Across all the 3 samples the ‘financial’ GICS sector shows the highest escalation in the default component, highlighting the stress in the financial sector observed since the financial crisis of 2008-2009. Table 6D provides a similar breakdown of default, non-default component and default ratio across each country for each sub-period indicating the variation in default ratio within each member country of EU17 sample.

[Table 6A about here]

[Table 6B about here]

[Table 6C about here]

[Table 6D about here]

Panel B of table 6A, table 6B and table 6C, also shows that default risk only partially explains the corporate yield spread and the non-default component of the spread is a key additional explanatory factor. Figure 6 plots the aggregate time-series variation in the median non-default component of bond yield spreads for the three markets. All three markets in aggregation follow a similar trend over the period of analysis. The plot shows a considerable increase in non-default component of yield spreads during the crisis period across the three markets and comparably higher non-default component in post-crisis period than the pre-crisis era. For EU17 sample, although the non-default component tends to move below zero, it merely indicates that the default proportion of bond yield spread has increased tremendously which is causing the median non-default element to go negative. Figure 7A, figure 7B and figure 7C plots the non-default component of all the firms across all GICS sectors in our sample for which data is available for US, UK and EU17 markets respectively. As illustrated by the histograms there is considerable cross-sectional variation in the non-default components of yield spreads. Moreover, the non-default frequency peaks at around 90bp for the US and EU17 sample whereas the peak is higher at around 130-150bp for the UK sample. These results together indicate that default component represents more than 50% of the total bond yield spreads in the post-crisis era and the presence of a significant amount of non-default component in bond yield spreads across the three markets. This also highlights that although the bond markets have stabilized, there is still fear in the market of the possibility of default which is still significant even in the post-crisis period.

Moreover, this result is more prominent during the crisis period and holds true in the post-crisis period across the three markets; irrespective of the type of firm. Our observations are unlike the finding by Longstaff *et al.* (2005) who drew these observations only for high-rated investment grade US firms.

[Figure 6 about here]

[Figure 7A about here]

[Figure 7B about here]

[Figure 7C about here]

Earlier studies have documented the existence of the non-default components in corporate yield spreads. Examples of such studies include Elton *et al.*, (2001), Huang and Huang (2003), Han and Zhou (2007) amongst others. These studies typically find that liquidity is a crucial variable in explaining the behavior of the non-default component. However, these studies have relied on intra-day or daily observations in contrast to our study where the observations are on a monthly basis. The OTC nature of the bond market itself renders studying the effect of liquidity on bond spreads difficult. Given the monthly frequency of our observations, we are unable to estimate the traditional measures of liquidity such as the Amihud measure (Amihud, 2002). We therefore rely on the bond characteristics and an adjusted measure of the bid-ask spread, the interquartile range to proxy for liquidity.

All of those earlier studies have not examined the behavior of the non-default component during times of crisis or the impact of liquidity on the non-default component during the crisis period. A recent study by Friewald, Jankowitsch and Subrahmanyam (2012) examines the impact of liquidity on the corporate bond spread during times of financial crisis and concludes that liquidity becomes more pronounced during the financial crisis. Friewald *et al.* (2012) restrict their study only to the bond market and hence only to the corporate spread. In this study we extend their analysis to the non-default component and to before, during and after the financial crisis. However, where their analysis included a wide range of liquidity measures and bond characteristics, ours due to monthly observations are restricted (with the exception of the interquartile range) to bond characteristics.

We now focus on the cross-sectional variation in the time series average of the non-default component of yield spreads to examine the impact of liquidity. The first proxy is the coupon as a percentage par value of the bond; we expect bonds issued with larger coupons to be less liquid as they are mostly held in the portfolio of investors who prefer the coupon payments (Tang and Yan, 2006). The second proxy is the principal amount issued; we expect bonds with larger amounts issued to be more liquid as it measures the availability of bond to the investors. The third proxy is the age of bond; we expect recently issued (on-the-run) bonds to be more liquid as they attract more investors and are mostly held in portfolio of investors who may choose not to trade the bond (Boa, Pan & Wang, 2011). The fourth proxy is the maturity of the bond. Bonds with shorter maturity are considered to be more liquid as investors for long bonds may prefer the cash flow and hence may choose not to trade the bond. Bonds with longer maturities, typically over 10 years are assumed to be less liquid as they are purchased by buy and hold investors who trade infrequently. The final proxy is the interquartile range and is an indirect measure of the bid-ask spread, defined as the difference between the 75th percentile and 25th percentile of daily price observations. This measure captures the inter-period volatility. We expect bonds with more volatility to be less liquid indicating risk-averse investor's preference for stable returns. Although most of the liquidity variables used in this study are either constant across bonds (i.e. *coupon, amount issued*) or change linearly over time (e.g. *age*, *maturity*) and could be considered a crude liquidity proxies. However their use makes intuitive sense and have been found to be widely used in studies including Edward, Harris & Piwowar (2004), Tang and Yang (2008) among others. For descriptive statistics of liquidity variables please refer to table 3.

[Table 7A about here]

[Table 7B about here]

[Table 7C about here]

Panel A of table 7A, table 7B and table 7C provides the result of regressing (between-effect panel data regression) the log of corporate yield spread against the liquidity proxies for the US, UK and EU17 samples respectively. Most of the liquidity proxies are significant for the US, UK and EU17 sample. The coupon *(coupon)* coefficient is positive and significant across all sub-periods. Similarly, as expected the coefficient for principal amount issued *(ln_principal_amt)* and age *(Age_Y)* is negative and significant across all sub-periods for all three samples. The coefficient of maturity is negative and significant across all sub-periods for the US and EU17 sample. However, for the UK sample maturity is negative and significant only for the crisis period whereas it is positive and significant for the whole period and post-crisis period. The interquartile range is positive and significant for all sub-periods in the US and EU17 sample, while this relationship only hold true during the crisis period for the UK sample and is not significant in the pre-crisis period for the EU17 sample. The interquartile range is not significant for other sub-periods in the UK sample.

For the US sample, the liquidity proxies collectively explain about 48.53% of the variation in bond yield spreads for the whole period. However the *Adj.* R^2 value varies across each sub-period. *Adj.* R^2 decreases from 44.72% in the pre-crisis period to 33.70% during the crisis period and increases to 47.28% during the post-crisis period. For the UK sample, the liquidity proxies collectively explain about 45.98% of the variance in bond yield spreads for the whole period. The *Adj.* R^2 value increases from 39.09% in the pre-crisis period to 49.31% in the crisis period and is at 43.53% in the post-crisis period. However for the EU17 sample we notice that liquidity proxies collectively explain about 44.07% of the variance in bond yield spreads for the whole period, where the *Adj.* R^2 value decreases from 59.16% in the pre-crisis period to 48.60% in the crisis period and further drops to 38.50% in the post-crisis period. This is expected as default component account for 66% of the bond yield spreads. The higher *adj.* R^2 value in the crisis period is in agreement to Friewald *et al.*, (2012) who find that liquidity effect becomes more pronounced during crisis period when capital constraints become binding and the inventory holding cost and search cost rises dramatically. However, it is interesting to note that liquidity effect has is more pronounced for the US sample during the post-crisis period contrary to popular belief in the bond market.

Panel B of table 7A, table 7B and table 7C provides the result of regressing (between-effect panel data regression) the log of non-default component of corporate yield spread against the liquidity proxies for the US, UK and EU17 samples respectively. The coupon *(Coupon)* coefficient is positive and significant as expected, principal amount *(ln_principle_amt)* is negative and significant across all sub-periods for US, UK and EU17 sample (except for crisis period for EU17 sample). Age *(Age_Y)* coefficient is negative and significant across all period for both UK and EU17, whereas it is only significant in pre-crisis and crisis period for the US sample. The maturity *(Maturity_Y)* coefficient is negative and significant across each sub-period for US and EU17 sample while it is negative and significant only in the crisis periods for the UK sample. Collectively, the results from UK sample are inconsistent with the view that longer-maturity bonds are less liquid than shorter-maturity bonds. The interquartile range *(IQR)* coefficients are positive and significant only for the crisis period across the three samples However, for other sub-periods this relationship is inconclusive.

Overall, the bond liquidity proxies explain about 38.30%, 37.49% and 39.10% of the variation in the non-default component of bond yield spreads in the whole period for US, UK and EU17 samples respectively. The model explanatory power *Adj.* R^2 remains more or less stable from 33.85% in the pre-crisis period to 23.97% during the crisis period and to 38.08% in the post-crisis period for the US sample. For the UK sample *Adj.* R^2 increases from 31.92% during the pre-crisis period to 37.11% in the crisis period and to 34.15% in the post-crisis period. However for the EU17 sample the liquidity proxies explain higher variation of 66.04% in the pre-crisis period which falls to 44.29% in the crisis period and further 31.38% in the post-crisis period.

In summary Panel A and Panel B for table 7A, table 7B and table 7C illustrates that bond market liquidity plays an important role in both explaining the corporate yield spread and the non-default component of the yield spread. Furthermore, the liquidity proxies that are significant predictors for the yield spread may not be equally significant for the non-default component.

The liquidity proxies explain about 45% of the variation on bond yield spreads for the whole period and about 38% of the variation in non-default component of yield spreads which is significantly high. The effect of liquidity varies from period to period and become more pronounced during the crisis period for the UK markets whereas for the US and EU17 market, bond liquidity is still a significant factor influencing the non-default component of yield spreads especially in the post-crisis period. An explanation of the increase in liquidity effect for the UK sample during the crisis could be the risk-averse nature of investors who choose to move their portfolio from illiquid to liquid assets. Higher liquidity effect during the post-crisis period also indicates investor's skepticism even in the post-crisis period thereby increasing the gap between liquid and illiquid bonds and the tendency for 'flight to quality' effect during the crisis and post-crisis period. There is also a possibility of yield spreads and specifically the non-default component of yield spreads to be influenced by the liquidity dynamics in other capital markets (including CDS and Equity market). Although, it will be interesting to study the effect of liquidity and liquidity spillover from CDS and equity market, that is not the focus of this study. In short our finding reinforces the results obtained from earlier studies in this area.

Earlier studies including Tang and Yan (2006) have indicated that illiquidity in the bond market can affect dealer's hedging capabilities and hence increase the premium embedded in CDS spreads. Accordingly, when an underlying bond has poor liquidity *ceretis paribus* the corresponding CDS spreads is higher for those contracts. Our result suggests a significant effect of bond liquidity during the crisis period which is still high in the post-crisis period (more than 30% for post-crisis period across each of the three markets). Based on the liquidity spillover effect from bond market to the CDS market, the higher CDS spreads during the crisis and the post-crisis period may not be necessarily due to the higher risk of default but may points towards a larger component of illiquidity effect driving the CDS spreads especially for the US and UK market. Likewise, the liquidity dynamics of the CDS market could also affect the CDS spreads for the firms in our sample. We proceed to test the liquidity dynamics of the CDS market and its effect on CDS spreads in the following section,

4.2. CDS liquidity and effect on CDS spreads

Lesplingart, Majois and Petitjean (2012) considers CDS market as being rather illiquid compared to the equity market, evident from the higher CDS bid-ask spreads. The OTC nature of the CDS market also makes it a non-continuous market where traders have to wait for the next trader to successfully close out a deal. The heavy dependence on the degree of confidence between the counterparties causes liquidity to dry up quickly in the CDS market especially during the crisis period and could take a long time to recover as evident during the recent financial crisis.

The first comprehensive study on the CDS market liquidity was carried out by Tang & Yang (2006), latter studies by Lesplingart *et al.*, (2012) among other has contributed to the growing interest in the CDS market liquidity dynamics, which until recently had been sparsely studies. Previous studies have utilized a number of liquidity measures instead of relying on a single summary measure to access the liquidity in the CDS market. As stated in Tang & Yang (2006), the multiple measures serves to enhance the robustness of the findings especially with liquidity, which in itself is an elusive concept and can have several distinct dimensions. Accordingly, Tang & Yang (2006) used three measures of liquidity namely; number of quotes and trades within a given month (NQT)[17], order imbalance[18] and bid–ask spreads[19]. We follow Lesplingart *et al.*, (2012) and use absolute quoted bid-ask spread[20] and proportionally quoted bid-ask spread as the two proxies for CDS market liquidity. Bid–ask spread represents the cost a trader needs to pay to unwind a position. Higher the bid ask spread greater the divergence of opinion or information asymmetry of the market and hence lower liquidity (Tang & Yang, 2006). Proportionally quoted bid-ask spread is calculated as,

$$Prop_{spread} = \frac{Ask_{quote} - Bid_{quote}}{\frac{Ask_{quote} + Bid_{quote}}{2}}$$

Due to limited nature of the data available on the OTC market (in Bloomberg) we are unable to obtain volume related estimates to calculate advanced liquidity measures like Amihud and Roll impact etc. (Das, Kalimipalli & Nayak, 2014). Figure 8A and Figure 8B reports the time-series aggregate trend of the two CDS liquidity variables from Q1 2005 till Q4 2012 for US, UK and EU17 markets. Absolute bid-ask spread *(abs_bidask)* is an indicator of the CDS market illiquidity and hence lower values in the pre-crisis period points lower higher liquidity in the CDS market. Similarly, proportional bid–ask spread *(pro_bidask)* is a measure of CDS market liquidity. These graphs collectively indicate that, Liquidity dried up in the crisis period and the CDS market is still very illiquid in the post-crisis period.

[17] NQT serves as a measure of trading activity and is expected that a CDS contract will have more quotes and trade as the demand for credit protection increases. Hence active trading may be linked to less liquidity.
[18] Tang & Yang (2006) claim that order imbalance is related to less liquidity and is correlated with NQT (r = 0.57)
[19] Bid –Ask spread is estimated in percentage (bid-ask spread divided by mid bid-ask spread) and higher value is associated with low liquidity.
[20] Difference between ask quote and bid quote for a CDS contract

[Figure 8A about here]

[Figure 8B about here]

We conduct fixed-effect panel data regression due to the panel characteristics of our dataset which consist of quarterly observations. In addition we use issuer-clustered standard errors (white standard errors) to account for possible correlations within the CDS issuer cluster. We consider 2 specifications using each of the two CDS liquidity proxies *(abs_bidask and pro_bidask)* individually in the regression model. We analyze the results across each sub-period namely; pre-crisis, crisis and post-crisis. The descriptive statistics of the two CDS liquidity proxies are reported in table 3.

The main focus of this section is to estimate the effect of CDS market liquidity on CDS spreads. Hence, we control for other fundamental determinants of spreads by controlling for credit risk predictor variables. In total, we use 16 independent variables from our comprehensive set including accounting-based, market-based and macro-economic variables. The outputs of the regression are provided in table 8. We note that the, CDS spread explanatory power (R^2) of the model changes based on the period of analysis and the sample under consideration. For specification 1, CDS liquidity proxy; absolute bid-ask spread *(abs_bidask)* is positive and significant across the whole period, crisis and post-crisis period for all the three markets whereas *abs_bidask* is not significant in the pre-crisis period for UK and EU17. For specification 2, proportional bid-ask spread *(pro_bidask)* is negative and significant across all sub-periods and markets (except for crisis period in EU17 sample).

[Table 8 about here]

[Table 9 about here]

Table 9 provides the *Adj.* R^2 and the incremental R^2 value (change) under each of the two specifications using the two liquidity proxies used in this study for US (Panel A), UK (panel B) and EU17 (Panel C). From table 9, we note by adding the liquidity proxy i.e. a*bs_bidask* (Specification-1) model's explanatory power increases from 61.97% to 64.09% for the whole period, where the increase is from 24.14% to 25.09% in the pre-crisis period, from 74.90% to 77.29% in the crisis period and from 27.42% to 43.76% in the post-crisis period for the US sample. Similarly for the UK (EU17) sample, the *Adj.* R^2 increases from 55.85% to 61.05% (63.07% to 64.07%) in the whole period, and the increase is from 16.85% to 16.81% (45.79% to 49.16%) in the pre-crisis period, from 61.32% to 74.41% (63.91% to 70.76%) in the crisis period and from 33.68% to 41.93% (40.05% to 51.58%) in the post-crisis period. The effect size is small (except for medium size effect for UK sample in the crisis period) across each sub-period and across the three samples.

Under Specification 2 *(pro_bidask)*, model's R^2 increases from 61.97% to 72.99% (medium effect size) for the whole period. The increase is from 24.14% to 61.41% (large effect size) in the pre-crisis period, from 74.90% to 80.24% (small effect size) in the crisis period and from 27.42% to 45.28% (medium effect size) in the post-crisis period for the US sample. Similarly for the UK (EU17) sample, the *Adj.* R^2 increases from 55.85% to 75.25% (63.07% to 72.22%) in the whole period, and the increase is from 16.85% to 45.75% (45.79% to 69.10%) in the pre-crisis period, from 61.32% to 66.66% (63.91% to 65.46%) in the crisis period and from

33.68% to 43.50% (40.05% to 58.67%) in the post-crisis period. The effect size is mostly medium (except for small effect size in the crisis period) across each sub-period and across the three samples.

The coefficient for *abs_bidask* is positive and significant, indicating if bid-ask spread widens (i.e. liquidity decreases) the CDS spread increases. However, we also note that the coefficient for *pro_bidask* is negative and significant. This is in contrast to the observations by Tang & Yang (2006) and Lesplingart *et al.*, (2012). However, it can be rationalized that the denominator for *pro_bidask* is the dependent variables (mid value of CDS spreads) in the regression model. Hence the negative relationship between *pro_bidask* and CDS spreads can be justified. Liquidity proxy *pro_bidask* (specification 2) provides the highest increment in the model's R^2 value across all period. The results above collectively signify that CDS liquidity has a significant effect on CDS spreads across all sub-periods which cannot be ignored when studying the dynamics of CDS spreads.

5. Robustness tests

We undertake a variety of robustness checks to ensure validity and reliability of our research findings,

As indicates in Das *et al.*, (2009) most of the accounting data may not be actually known at the end of the quarter instead reported at some subsequent time. Furthermore Sengupta (2004) suggest the delay to be on an average around 40 days. Consequently, we take a lag of one quarter on accounting variables and re-run the regression models. The results are reported in table 10.

For US (Panel A), UK (Panel B) and EU17 (Panel C), there are no major changes in the significance of the accounting variables and most of the market-based variables retain their significance. Moreover, the model's explanatory power across each sub-period is consistent for the three samples. Table 11 reports the changes in *Adj.* R^2 value and the effect size by using 1 quarter lag of accounting variables in the regression model. For US (Panel A), UK (Panel B) and EU17 (Panel C) sample the effect size is mostly small across all sub-periods. This indicates that *Adj.* R^2 trends remains consistent and robust even after using lagged accounting variables in the regression model.

[Table 10 about here]

Considering not all firms in our sample publish accounting data on a quarterly basis, we check if the regression results change on using only Q2 and Q4 observations i.e. excluding observations from Q1 and Q3 which are mostly carry over from previous quarter values in case of missing values. Most of the accounting based variables in our sample are published either annually or semi-annually with observations repeated across each quarter wherever missing. Excluding Q1 and Q3 observations i.e. taking out the repetitive observations in accounting variables (wherever missing), the sample size drops from 6393 to 3240 quarter-firm observations in the US (Panel A) sample. The model's *Adj.* R^2 increases from 61.97% to 63.73% (small effect size) for the whole period. For the US sample, the model now explain about 35.24% of the variation in CDS spreads in the pre-crisis period, 75.91 % in the crisis and 31.24% in the post-crisis period. For the UK (Panel B), sample size drops from 578 to 101 quarter-firm observations in the whole period. The overall model *Adj.* R^2 increases from 55.85% to 69.71% (small effect size) for the whole period. The observations for the sub-periods in UK sample are too low to generate valid and consistent *Adj.* R^2 values. A similar outcome can be observed for the EU17 (Panel C) the sample size drops from 590 to 267 quarter-firm observations and the model's *Adj.* R^2 increases from 63.07% to 64.80% (small effect size) for the whole period. For the EU17 sample, the model now explain about 72.96% of the variation in CDS spreads in the crisis period and 54.23 % in the post-crisis period. The sample size is very small to draw valid inference for the pre-crisis period. Overall, *Adj.* R^2 values show a similar trend across all sub-periods, denoting stability and robustness of our regression estimates.

Most of the studies in this field consider financial sector separately when analyzing spread prediction models (Das *et al*, 2009). Most firms in the financial sector act as counterparties to the CDS insurance contracts. Hence, the relationship between the accounting variables and CDS spreads for firm belonging to the financial sector may not be hold true as with other sectors. We test if our results vary when excluding the observations from the financial GICS sector. The results are reported in table 11 for US (Panel A), UK (Panel B) and EU17 (Panel C). Overall we notice for the US and UK sample there are about 214 and 28 quarter-firm observations respectively in the whole period belonging to the Financial GICS sector. For the EU17 sample there are no observations for firms belonging to Financial GICS sector. Consequently, by removing these observations the *Adj.* R^2 trend remains the same and the resulting effect size is small across all sub-periods for US (Panel A) , UK (Panel B) and EU17 (Panel C). These results collectively indicate that our results are not driven or affected by observations from firms belonging to financial GICS sector pointing towards consistency and reliability of the model estimates.

[Table 11 about here]

Furthermore, studies by Tan and Yang (2006) and Erickson and Renault (2006) claims that liquidity effect may interact with credit risk. Consequently, liquidity effect may be more pronounced for bonds with lower credit risk. To explore whether the effect of liquidity on yield spreads is a function of the credit risk (measured using CDS spreads), we control for credit risk associated with the bonds and re-run our regression function. Results are reported in table 12 for US (Panel A), UK (Panel B) and EU17 (Panel C). We notice that CDS spreads have a positive coefficient and are significant across all sub-periods for the three samples. Moreover most of the coefficients retain their significance and sign. *Adj.* R^2 increases (albeit slightly) across all sub-periods. However, the *Adj.* R^2 trend remains the same for each sub-period and across the three markets. This indicates that after controlling for credit risk the effect of bond liquidity on yield spreads is still significant across each sub-period of analysis.

[Table 12 about here]

6. Policy Recommendations

We have examined the extent to which the credit default swap spreads are sensitive to both accounting and financial market variables in the US, UK and EU17 economy before, during and after the financial crisis. We also explored, how the parameters behave during the crisis, and we have seen the rapid increase in the CDS spreads during the financial crisis. By splitting the bond spread into the default component and the non-default component, we have been able to isolate to show that during a financial crisis, the non-default component of yield spread has decreased. However, the overall bond spread is not only driven by the credit spread but also by the liquidity and underlying bond characteristics such as the coupon, age and maturity of the bonds etc.

Given the explosion in the use of CDS contracts by market participants, our findings have a number of implications for policy makers.

First we find the variables driving the CDS spreads change over time. This is consistent with studies for bond yield spreads. Our results thus imply that policy makers need to be aware of the period and the context in which the estimates are made and that if the context changes or estimation period is long, then they need to re-estimate the model.

Second, given the changing nature of the CDS spread during the crisis, it is possible that the CDS spreads have overreacted to the prevailing market conditions. Thus relying on the CDS spreads alone as an estimate of market signalling may be inaccurate. In such circumstances policy holders should examine other market indicators such as the equity market etc. in conjunction with CDS market signals.

Third, the non-default component of the bond yield spreads increased during the crisis and the post-crisis period across US, UK and EU17 markets. Given that this is driven by amongst other things, bond characteristics, policy holders may wish to create an environment, where companies issues bonds with characteristics that increases the overall market liquidity especially during periods of financial stress.

Fourth liquidity is an important component driving yield spreads and the non-default component of bond yields. Similarly, the liquidity in the CDS market is also a major driver of

CDS spreads more so during the crisis and the post-crisis period. Furthermore, consistent with earlier studies liquidity effects varies across different period of analysis. Thus, policy holders should consider the impact of bond liquidity on yield spreads and CDS liquidity of CDS spreads. With the possibility of a possible liquidity spillover effect, the lack of liquidity in a specific market during a specific period may mean there are issues that need to be quickly understood and dealt with considering the association between the other capital markets and corporate credit markets.

Fifth counterparty risk increases significantly during times of crisis and is correlated with the increase in CDS spreads. Policy makers must ensure that appropriate legislation is in place in the event of systemic market failure and ensure sufficient market wide liquidity to deal effectively with such crisis in future.

7. Conclusion

This paper empirically tests the explanatory variables that drive the characteristics of corporate CDS spread in the US, UK and EU17 from 2005 to 2012 and includes the crisis period in the financial markets. We find that CDS spread in US, UK and EU17 where they are actively traded has increased significantly. We fit both accounting and market-based variables to the CDS spread and like Das *et al.*, (2009), we find that this provides a good fit to the spread. The combination of accounting-based and market-based variables perform better than each of them individually. However, we find that majority of the accounting variables are not significant in explaining the CDS spread and that most of the market-based variables are significant in explaining the CDS spread during the whole period and more so especially during the crisis period. The CDS spread provides markets with a direct rather than the traditional indirect measure to corporate credit risk. As such it provides useful indicator to market participants and regulators on the market's view of risk. We also find that CDS spread explanatory variables change significantly over time, particularly the combination of accounting and market-based independent variables used in this study do a good job in explaining variance in CDS spreads especially during the crisis period when it matters the most. We also note that the spread prediction power has dropped significantly in the post-crisis period across US, UK and EU17 markets even with the same set of explanatory variables. This suggests variables driving spreads have to be re-estimated on a regular basis, or it might lead to wrong conclusions drawn by policy makers and supervisors. Moreover, there is still a substantial portion of CDS spreads across the three markets that cannot be accounted for using the set of explanatory variables explored in this study. In line with previous studies we also find that liquidity effect became more pronounced during crisis period across the markets. However, contrary to popular belief the liquidity effect is found to be substantial even in the post-crisis period. All these point towards investor's skepticism and preference for quality which has not plunged even in the post-crisis period. Furthermore, high level of yield spreads coupled with greater liquidity effect may be pushing CDS spreads which may not necessarily be indicating higher risk of credit default in the post-crisis period. We have also seen that the counterparty risk increased during the crisis period and is still high in the post-crisis period for US, UK and EU17. The variables driving the counterparty risk and economic events triggering an upsurge in counterparty risk has not been explored in this study and remains an avenue of future research.

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Table 1: Descriptive statistics of credit default swap spreads

Descriptive statistics of credit default swap spreads (in basis points) from January 1, 2005 to December 31, 2012, for US, UK and EU17 markets broken down by year in Panel A and by GICS (Global Industry Standard Classification) sector industry classification in Panel B and by country in Panel C. N is the number of quarterly CDS spread observations available across each year, specific GICS sector and country. The pre-crisis period is defined as from Jan 1, 2005 to Jun 30, 2007; crisis period from July 1, 2007 to June 30, 2009 and post-crisis period from July 1, 2009 to Dec 31, 2012.

Panel A: Summary of variables: Spread by year

US						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	1,149	83.01	38.69	5.00	2,696.86	153.77
2006	1,183	82.67	32.79	5.00	2,670.00	177.13
2007	1,374	111.90	42.42	4.83	1,954.58	182.58
2008	2,083	390.90	159.93	11.50	9,110.67	698.77
2009	2,048	377.30	145.87	17.25	9,108.99	730.09
2010	2,072	245.12	125.94	17.31	13,091.41	567.86
2011	2,021	278.77	132.51	15.22	7,199.96	579.93
2012	1,927	254.06	127.87	12.77	13,080.11	532.29
Total	**13,857**	**252.20**	**104.00**	**4.83**	**13,091.41**	**555.66**
UK						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	317	67.30	35.00	7.58	641.25	98.04
2006	322	54.79	30.70	3.67	419.38	71.25
2007	363	75.09	37.83	4.44	655.85	100.68
2008	448	252.92	136.66	21.27	4,575.94	366.48
2009	472	260.25	125.32	16.25	8,344.94	531.03
2010	485	158.54	114.22	17.44	1,212.10	150.03
2011	471	179.33	135.24	19.72	1,208.55	168.83
2012	460	157.50	123.20	24.36	857.74	134.41
Total	**3,338**	**160.63**	**92.85**	**3.67**	**8,344.94**	**274.51**
EU17						
Year	**N**	**Mean**	**Median**	**Min**	**Max**	**Std dev.**
2005	588	62.12	29.63	7.70	810.00	101.37
2006	625	61.23	26.50	3.38	698.33	99.42
2007	691	73.75	35.34	3.94	870.32	114.30
2008	789	263.68	134.70	14.00	3,551.34	361.06
2009	821	325.03	129.74	13.12	10,271.69	697.25
2010	829	247.87	137.60	18.47	16,102.98	627.66
2011	829	320.93	184.67	18.52	3,497.36	413.18
2012	807	292.76	179.12	23.15	2,597.74	318.62
Total	**5,979**	**218.84**	**104.87**	**3.38**	**16,102.98**	**436.90**

Panel B: Summary of variables: Spread by GICS Industry classification									
US		**Pre-crisis**			**Crisis**			**Post-crisis**	
GICS sector	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Basic Materials	215	110.90	56.26	298	441.14	165.82	461	181.15	123.91
Consumer, Non-cyclical	390	67.68	28.85	642	235.09	88.94	1,266	172.93	88.46
Financial	654	42.49	25.98	742	517.51	208.00	1,325	368.80	169.10
Utilities	201	48.43	39.17	345	226.47	128.35	616	288.06	116.13
Industrial	376	55.91	29.93	470	194.22	96.79	849	220.37	87.44
Energy	229	41.48	30.25	349	174.97	115.39	648	143.70	113.05
Technology	93	56.71	50.05	153	396.01	106.66	304	243.09	128.43
Consumer, Cyclical	487	186.04	73.88	542	637.64	275.68	943	382.62	189.91
Communications	264	76.53	44.25	375	401.69	194.52	606	201.60	114.59
Diversified	-	-	-	2	102.47	102.47	12	69.62	65.25
Total	**2,909**	**80.56**	**35.00**	**3,918**	**371.08**	**144.39**	**7,030**	**256.97**	**125.51**

UK		**Pre-crisis**			**Crisis**			**Post-crisis**	
GICS sector[1]	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Basic Materials	44	93.84	35.00	69	570.93	179.80	128	236.42	119.10
Consumer, Non-cyclical	160	36.53	34.97	144	112.02	74.65	253	79.06	68.24
Financial	147	14.55	10.44	216	268.09	153.34	420	180.01	159.15
Utilities	100	40.96	20.88	125	112.90	73.67	246	136.14	88.11
Industrial	114	73.71	38.68	96	221.29	130.83	177	121.38	106.65
Energy	10	6.93	6.35	8	45.66	45.17	14	124.69	88.71
Consumer, Cyclical	98	110.22	91.56	88	377.76	295.63	153	298.35	211.76
Communications	123	104.33	42.42	120	228.23	140.75	231	197.04	135.09
Diversified	10	24.72	23.66	16	140.76	84.02	28	65.57	62.86
Total	**806**	**60.25**	**32.72**	**882**	**240.40**	**118.17**	**1,650**	**167.02**	**118.38**

EU17	Pre-crisis			Crisis			Post-crisis		
GICS sector	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
Basic Materials	164	104.07	42.81	142	364.89	145.48	258	191.93	119.12
Consumer, Non-cyclical	162	43.68	27.04	154	119.17	86.69	294	128.90	86.70
Financial	402	14.94	12.00	474	187.29	120.63	940	302.18	189.72
Utilities	177	20.85	20.50	157	86.57	63.77	274	131.64	87.16
Industrial	178	74.92	27.83	164	259.10	112.77	316	195.34	133.51
Energy	40	20.02	16.79	40	90.91	62.68	69	109.27	90.58
Technology	19	177.35	134.00	24	1,105.98	422.50	35	404.72	252.39
Consumer, Cyclical	183	86.31	56.74	164	393.93	219.49	291	378.15	223.84
Communications	207	116.92	54.00	226	437.00	164.35	373	498.87	228.75
Diversified	10	115.80	88.08	16	455.02	444.69	26	499.81	462.42
Total	**1,542**	**59.99**	**26.14**	**1,561**	**266.40**	**119.57**	**2,876**	**278.19**	**154.14**

Note: (1) No quarterly CDS spread data available for Technology GICS sector for the UK sample.

Panel C: Summary of variables: Spread by Country									
		Pre-crisis			**Crisis**			**Post-crisis**	
Country	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**	**N**	**Mean**	**Median**
US	**2,909**	**80.56**	**35.00**	**3,918**	**371.08**	**144.39**	**7,030**	**256.97**	**125.51**
UK	**806**	**60.25**	**32.72**	**882**	**240.40**	**118.17**	**1,650**	**167.02**	**118.38**
EU17[2]	**1,542**	**59.99**	**26.14**	**1,561**	**266.40**	**119.57**	**2,876**	**278.19**	**154.14**
France	456	56.84	30.91	426	222.35	118.05	748	207.53	136.76
Germany	360	67.94	26.41	385	261.83	115.00	745	175.09	110.94
Netherlands	152	41.13	23.94	173	243.85	88.33	334	173.69	103.43
Italy	180	64.26	19.79	165	243.52	118.46	303	372.10	242.34
Spain	147	32.50	18.31	135	339.24	150.00	228	384.40	279.26
Finland	66	89.46	43.04	56	468.12	180.49	98	282.65	233.46
Ireland	50	91.74	30.64	56	311.36	235.68	91	697.57	394.96
Portugal	45	31.77	16.21	41	104.80	108.15	73	529.57	469.61
Belgium	34	41.66	20.46	45	437.01	107.11	76	528.54	97.11
Luxembourg	16	322.60	345.39	32	503.99	454.00	79	381.97	312.06
Austria	26	23.04	18.75	35	180.48	130.83	61	183.63	164.02
Greece	10	43.06	44.16	12	175.86	126.45	40	1115.40	978.56

Note: (2) No quarterly CDS spread data available for EU countries; Cyprus, Estonia, Malta, Slovakia and Slovenia.

Table 2: Descriptive statistics of Counterparty risk

Descriptive statistics of counterparty risk, defined as the difference between LIBOR and OIS starting from 1st January 2005 till 31st December 2012. Observations are on monthly basis and periods as defined in Table 1. For US sample: Libor (BB code: US0003M Index) and OIS (BB code: USSOC Curncy), UK sample: Libor (BB code: BP0003M Index) and OIS (BB code: BPSWSC Curncy) and for EU17 sample: Libor (BB code: EUR003M Index) and OIS (BB code: EUSWEC Curncy)

	US			**UK**			**EU17**		
	Mean	**Median**	**Stdev**	**Mean**	**Median**	**Stdev**	**Mean**	**Median**	**Stdev**
				Whole period					
LIBOR	2.33	1.34	2.08	3.08	2.47	2.28	2.27	2.10	1.52
OIS	1.99	0.26	2.12	2.66	0.94	2.28	1.89	1.54	1.48
LIBOR - OIS	0.34	0.15	0.43	0.42	0.23	0.46	0.37	0.29	0.36
				Pre-crisis					
LIBOR	4.62	5.07	0.91	4.99	4.87	0.42	2.93	2.83	0.73
OIS	4.53	4.99	0.91	4.89	4.75	0.42	2.87	2.77	0.73
LIBOR - OIS	0.09	0.08	0.02	0.11	0.11	0.02	0.06	0.06	0.01
				Crisis					
LIBOR	2.93	2.80	1.58	4.71	5.81	2.00	3.83	4.64	1.44
OIS	2.03	1.99	1.71	3.70	5.03	2.23	3.05	4.01	1.47
LIBOR - OIS	0.90	0.75	0.55	1.01	0.82	0.55	0.78	0.69	0.38
				Post-crisis					
LIBOR	0.36	0.31	0.10	0.78	0.74	0.16	0.90	0.85	0.41
OIS	0.15	0.15	0.04	0.47	0.49	0.06	0.53	0.43	0.34
LIBOR - OIS	0.21	0.17	0.11	0.30	0.24	0.15	0.37	0.31	0.22

Table 3: Descriptive statistics of explanatory variables

size is the log of value of total assets divided by the consumer price index (with 2005 as the base), *ROA* is the net income divided by total assets, *incgrowth* is the net income minus the previous quarter's net income dived by total assets, *c* is calculated as pre-tax income plus interest expense divided by interest expense, *quick* is current assets minus inventories over current liabilities, *cash* is cash and equivalents over total assets, t*rade* is inventories to cost of goods sold ratio, *salesgrowth* is sale growth, *booklev* is total liabilities to total assets, *retained* is retained earnings to total assets, *ret* is annualised prior 250-trading day equity return, *σret* is annualised prior 250-trading day equity volatility, *DTD* is distance to default (bounded between +20 and -20), *r* is the 3 month Interbank Offer Rate taken from Bloomberg, *index* prior year return in the S&P500 index for the US, FTSE100 index for the UK and EUROSTOXX 50 index for EU17, *rgics* is prior-year GICS industry return for the respective indexes, *Coupon* of corporate bonds is in percentage terms, *Amount* is principal amount outstanding in billions of USD, GBP and EUR for US, UK and EU17 respectively, *Age* is age of bonds in years, *Maturity* is time to maturity of bonds in years, *IQR* is the interquartile range and is a proxy for the bid-ask spread.

Panel A				**US**			
Variables	**Mean**	**Median**	**Min.**	**Max.**	**Std. Dev.**	**Skew.**	**Kurt.**
ln_size	5.202	5.095	-0.002	10.062	1.415	0.802	3.995
ROA	0.013	0.014	-8.941	0.984	0.087	-85.820	8,840.729
incgrowth	-0.001	0.000	-8.454	0.981	0.086	-75.848	7,467.961
c	-145.741	3.992	$-18*10^{-5}$	10,799.0	16,952.3	-109.11	11,906.83
quick	0.922	0.780	0.018	8.781	0.661	3.105	20.500
cash	0.064	0.042	0.000	0.668	0.066	2.065	9.564
trade	1.403	0.693	0.020	160.630	5.933	15.455	293.817
salesgrowth	9.716	4.017	-98.812	8,500.561	141.956	51.656	3,021.159
booklev	0.678	0.661	0.062	6.159	0.216	5.942	134.960
retained	0.073	0.099	-51.118	0.721	0.566	-58.719	5,193.152
ret	0.915	0.091	-1.000	1,312.857	18.696	60.391	4,044.626
σret	0.317	0.253	0.001	3.707	0.227	3.214	20.706
DTD	9.800	9.242	-20.000	20.000	6.462	-0.189	3.181
r	0.019	0.006	0.002	0.055	0.020	0.717	1.815
index	0.033	0.066	-0.397	0.466	0.196	-0.460	3.240
rgics	0.023	0.038	-0.340	0.416	0.124	-0.330	3.895
Coupon	4.907	4.950	0.420	16.750	1.835	0.253	4.431
Amount	76.2×10^{6}	27.4×10^{6}	30,000	16×10^{10}	44.4×10^{7}	22	627
Age	5.590	4.839	0.000	26.958	4.049	1.160	4.619
Maturity	5.066	4.625	0.003	30.375	3.444	1.242	6.931
IQR	0.926	0.513	0.000	41.393	1.394	6.289	84.115
abs_bidask	15.091	7.500	-1,452.99	682.513	33.089	0.219	368.184
pro_bidask	0.093	0.076	-0.354	0.720	0.063	2.463	12.297

Panel B				UK			
Variables	**Mean**	**Median**	**Min.**	**Max.**	**Std. Dev.**	**Skew.**	**Kurt.**
ln_size	5.136	4.937	1.376	9.993	1.799	0.652	2.943
ROA	0.022	0.017	-0.369	0.942	0.073	5.868	80.315
incgrowth	0.002	0.000	-0.610	0.939	0.062	2.076	58.688
c	5.687	3.725	-107.191	278.667	11.962	10.550	225.115
quick	0.445	0.395	0.000	7.565	0.507	4.829	51.825
cash	0.065	0.048	-0.057	0.535	0.062	2.122	10.098
trade	0.626	0.359	0.003	4.659	0.761	2.040	7.565
salesgrowth	6.206	0.000	-91.804	539.758	33.050	8.041	99.040
booklev	0.747	0.740	0.236	1.875	0.217	0.745	5.917
retained	0.092	0.109	-3.706	0.962	0.326	-4.475	39.012
ret	0.555	0.139	-0.998	278.734	5.771	40.383	1,883.251
σret	0.276	0.229	0.026	1.339	0.159	2.440	11.765
DTD	10.216	10.798	-20.000	20.000	7.158	-0.777	4.391
r	0.028	0.012	0.005	0.063	0.023	0.398	1.347
index	0.035	0.058	-0.313	0.447	0.171	-0.288	3.148
rgics	0.024	0.031	-0.341	0.363	0.107	-0.125	3.772
Coupon	3.693	3.375	0.250	20.000	1.912	1.571	9.749
Amount	41.2×10^{7}	18.5×10^{5}	35,000	65.8×10^{7}	78×10^{7}	3.008	15.205
Age	6.494	6.392	0.003	29.958	3.027	0.599	5.297
Maturity	3.899	2.358	0.000	24.550	3.989	1.550	5.294
IQR	0.934	0.443	0.000	4941.154	32.533	151.698	23,036.48
abs_bidask	11.517	7.012	0.000	242.119	13.881	5.761	64.343
pro_bidask	0.104	0.079	0.000	0.827	0.081	3.090	15.372

Panel C				EU17			
Variables	**Mean**	**Median**	**Min.**	**Max.**	**Std. Dev.**	**Skew.**	**Kurt.**
ln_size	5.852	5.722	2.589	9.810	1.512	0.442	2.767
ROA	0.008	0.006	-1.180	0.489	0.044	-13.436	431.874
incgrowth	0.000	0.000	-1.307	1.662	0.045	5.977	649.823
c	6.875	3.981	-137.368	1,631.00	41.539	34.802	1,352.294
quick	0.658	0.620	0.004	15.214	0.523	12.518	308.721
cash	0.051	0.038	0.001	0.385	0.046	1.909	8.710
trade	0.753	0.606	0.001	3.728	0.659	1.637	5.525
salesgrowth	8.030	4.526	-97.993	1,843.75	50.682	17.657	507.636
booklev	0.765	0.763	0.034	1.908	0.177	0.699	6.791
retained	0.110	0.088	-1.473	0.800	0.193	-1.508	11.410
ret	55.432	-0.005	-1.000	151,268.7	2,773.637	54.146	2,950.750
σret	0.347	0.292	0.053	2.904	0.202	3.105	21.622
DTD	7.016	6.817	-20.000	20.000	8.441	-0.787	4.431
r	0.022	0.015	0.002	0.050	0.015	0.593	1.942
index	-0.007	0.032	-0.268	0.179	0.106	-0.764	2.976
rgics	-0.004	0.007	-0.394	0.287	0.127	-0.584	3.883
Coupon	4.053	4.000	0.100	20.000	1.620	1.724	12.589
Amount	37.9×10^6	10.4×10^6	5,000	50×10^8	57.8×10^6	2.712	13.334
Age	3.523	2.783	0.000	19.639	2.840	1.105	3.994
Maturity	5.424	5.228	0.000	15.875	2.580	0.318	2.671
IQR	0.659	0.406	0.005	60.102	0.943	10.584	343.504
abs_bidask	14.042	7.447	-467.500	1,483.097	31.517	21.997	911.525
pro_bidask	0.051	0.037	-0.256	0.533	0.041	2.887	16.221

Table 4: 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. Independent variables are as described in Table 3. The sample is based on CDS spreads from Q1 2005 to Q4 2012 on a quarterly basis. (R^2 reported is the fixed effect within regression values) Periods are as defined in Table 1.

Panel A - US	**Regression of log of CDS spread**			
Variables	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
Intercept	4.532***	3.374***	4.728***	4.237***
ln_size	-0.065	0.018	-0.057	-0.082
ROA	-2.05***	-2.079**	-0.928**	-2.475***
incgrowth	1.218***	1.149**	0.662***	0.849**
c	0.001***	-0.001	-0.001	0.001***
quick	-0.03	-0.104	-0.155***	0.095**
cash	0.259	0.623	0.437	-1.246***
trade	0.008**	-0.012	0.003	0.006
salesgrowth	-0.001	-0.001	-0.001	-0.001
booklev	1.085***	1.078***	0.385	1.254***
retained	0.327*	-0.495**	0.222	0.098
ret	-0.002	-0.002	-0.005	-0.002***
σret	0.998***	1.684***	0.778***	0.655***
DTD	-0.027***	-0.013***	-0.016***	-0.013***
r	-15.986***	-5.417***	-7.794***	48.646***
index	-0.141*	-1.366***	-1.208***	0.027
rgics	-0.967***	0.198	-0.695***	-0.705***
N	6,393	1,256	1,778	3,359
R^2	62.07%	25.11%	75.13%	27.77%
Adjusted R^2	61.97%	24.14%	74.90%	27.42%

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

Panel B - UK	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
Intercept	1.318	4.997***	-0.453	2.094
ln_size	0.336	-0.455	0.885*	0.272
ROA	0.377	-0.073	-2.041	-0.851
incgrowth	-0.068	0.556	1.015	0.997
c	-0.013***	-0.002	0.007	-0.011***
quick	0.035	-0.096	0.218*	0.149*
cash	0.325	-0.304	-2.77**	0.384
trade	-0.187	0.42	-1.088***	-0.131
salesgrowth	0.001	0.002	-0.003	0.003
booklev	2.817***	2.161**	1.48	0.447
retained	0.982	1.215	0.388	0.531
ret	0.021	0.245	0.066***	-0.009
σret	0.351	-0.486	1.033*	1.794***
DTD	-0.025**	-0.038	-0.053**	0.013*
r	-13.54***	-14.299	1.767	28.059**
index	-0.69***	0.345	-0.384	-0.376***
rgics	-0.889***	-0.034	-0.125	-0.844***
N	578	129	146	303
R^2	57.07%	27.24%	65.59%	37.19%
Adjusted R^2	55.85%	16.85%	61.32%	33.68%

Panel C – EU17	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
Intercept	3.318***	5.058***	5.468**	6.662***
ln_size	0.204	0.217	-0.119	-0.649
ROA	-2.062	-0.07	-0.212	-5.197
incgrowth	0.712	-0.487*	0.011	2.5
c	-0.005	0.004	-0.001	-0.003
quick	0.057	0.063	-0.093	0.007
cash	-1.757**	-1.153	-0.675	0.558
trade	0.111	-0.107***	0.137	0.037
salesgrowth	-0.001	-0.003***	-0.002	-0.001
booklev	-0.051	-2.592*	-0.942	1.687
retained	-0.44	-0.131	-0.067	-0.49
ret	0.001	-0.012	0.073	-0.003**
σret	2.37***	0.684	2.149***	2.401***
DTD	-0.028***	0.015	-0.03	-0.012*
r	-10.903***	-29.026***	-3.066	-3.584
index	-1.677***	0.008	-1.913***	-1.556**
rgics	-0.169	-0.297	0.199	-0.25
N	590	135	211	244
R^2	64.07%	52.26%	66.66%	44.00%
Adjusted R^2	63.07%	45.79%	63.91%	40.05%

Table 5: Hierarchical fixed effect regression

Hierarchical fixed effect (within) regression (with robust standard errors) using block of predictor variables in the regression model. The accounting variables (AC) block consists of a set of 10 predictor variables (*size, ROA, incgrowth, c, quick, cash, trade, salesgrowth, booklev, retained*). Market-based variables (MB) block consist of 3 predictor variables (*ret, σret, DTD*). Variables (*r, index, rgics)* act as a time-dummy variables accounting for the time clustering in our datasets. The values for time dummy variables are same across all firms in the same period in the regression model. Change represents the change in Adjusted R^2 value by adding a block of predictor variables in the regression model.

Panel A	**US**							
	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
Block 1	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
AC	54.98%	-	17.84%	-	71.36%	-	21.78%	-
AC + MB	61.97%	6.99%	24.14%	6.30%	74.90%	3.54%	27.43%	5.66%
Effect size	0.18		0.08		0.14		0.08	
Block 2	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
MB	61.42%	-	21.48%	-	69.31%	-	23.28%	-
MB + AC	61.97%	0.55%	24.14%	2.66%	74.90%	5.60%	27.42%	4.15%
Effect size	0.01		0.04		0.22		0.06	

Panel B	**UK**							
	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
Block 1	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
AC	53.61%	-	12.92%	-	54.61%	-	27.25%	-
AC + MB	55.85%	2.24%	16.85%	3.93%	61.32%	6.71%	33.68%	6.43%
Effect size	0.05		0.05		0.17		0.10	
Block 2	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
MB	57.83%	-	15.90%	-	66.20%	-	27.26%	-
MB + AC	55.85%	-1.98%	16.85%	0.94%	61.32%	-4.88%	33.68%	6.41%
Effect size	-0.04		0.01		-0.13		0.10	

Panel C	**EU17**							
	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
Block 1	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
AC	40.33%	-	44.31%	-	63.10%	-	15.87%	-
AC + MB	63.07%	22.74%	45.79%	1.48%	63.91%	0.81%	40.05%	24.18%
Effect size	0.62		0.03		0.02		0.40	
Block 2	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**	**Adj. R^2**	**Change**
MB	65.90%	-	36.83%	-	58.31%	-	49.54%	-
MB + AC	63.07%	-2.84%	45.79%	8.96%	63.91%	5.60%	40.05%	-9.49%
Effect size	-0.08		0.17		0.16		-0.16	

Table 6A: US - Ratio of default component to bond yield spread.

The sample is based on monthly corporate bond yield spread estimated based on the bracketing approach of Longstaff *et al.* (2005) from Jan 2005 to Dec 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, Ratio is the default component divided by the yield spread. Ratios denoted by asterisk are significantly different from 1 at 5% level. N^B is the number of monthly bond yield spreads in the bracketing set.

Panel A: Median yield spread for US across each sub-period

	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
GICS sector	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**
Basic Material	978	214.32	269	132.68	262	326.86	447	212.35
Consumer, non-cyclic	3,303	154.81	817	103.75	820	268.97	1,666	141.84
Financial	4,308	225.80	1,432	95.88	1,140	385.03	1,736	283.10
Utilities	1,116	201.81	235	110.05	288	332.19	593	197.55
Industrial	1,853	175.85	486	121.13	454	282.81	913	168.62
Energy	851	219.87	175	107.84	223	315.60	453	223.81
Technology	495	149.84	106	70.35	128	256.92	261	134.50
Consumer, cyclic	1491	243.00	484	191.45	378	478.12	629	226.40
Communication	1350	232.81	470	149.47	345	439.99	535	257.88
Total	**15,745**	**197.78**	**4,474**	**113.31**	**4,038**	**330.42**	**7,233**	**203.29**

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

	Whole period			**Pre-crisis**			**Crisis**			**Post-crisis**		
GICS sector	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**
Basic Material	86.66	101.12	0.40*	30.25	78.77	0.23*	105.70	179.22	0.32*	118.56	80.36	0.56*
Consumer, non-cyclic	57.38	93.53	0.37*	28.50	80.24	0.27*	62.96	189.07	0.23*	66.27	71.34	0.47*
Financial	122.50	98.52	0.54*	23.50	66.27	0.25*	176.52	171.44	0.46*	165.60	98.92	0.58*
Utilities	83.65	108.99	0.41*	34.38	75.08	0.31*	99.59	195.74	0.30*	104.26	94.86	0.53*
Industrial	56.79	108.02	0.32*	24.88	85.52	0.21*	76.83	195.47	0.27*	72.45	94.61	0.43*
Energy	75.63	102.33	0.34*	31.30	49.24	0.29*	91.03	192.17	0.29*	110.99	93.64	0.50*
Technology	50.01	66.04	0.33*	25.30	35.12	0.36*	59.80	179.00	0.23*	49.65	56.12	0.37*
Consumer, cyclic	114.06	105.59	0.47*	44.00	86.97	0.23*	163.68	163.00	0.34*	137.05	95.74	0.61*
Communication	92.55	128.13	0.40*	51.35	69.95	0.34*	171.81	229.67	0.39*	101.86	132.66	0.39*
Median	**77.58**	**101.36**	**0.39***	**28.50**	**72.40**	**0.25***	**98.99**	**186.97**	**0.30***	**102.03**	**88.94**	**0.50***

Table 6B: UK - Ratio of default component to bond yield spread.
Specifications of the table are similar to as reported in table 6A

Panel A: median yield spread for UK across each sub-period

	Whole period		Pre-crisis		Crisis		Post-crisis	
GICS sector[1]	***N^B***	**Spread**	***N^B***	**Spread**	***N^B***	**Spread**	***N^B***	**Spread**
Basic Material	92	274.00	30	184.11	21	424.93	41	262.46
Consumer, non-cyclic	258	153.60	106	233.32	64	221.45	88	8.22
Financial	1,390	232.55	387	49.04	349	358.74	654	273.81
Utilities	694	80.48	245	65.18	202	231.85	247	-28.15
Industrial	87	169.56	30	-46.06	27	315.46	30	253.87
Energy	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.
Consumer, cyclic	130	244.76	57	158.89	48	361.59	25	216.21
Communication	383	331.22	143	131.47	108	333.25	132	545.97
Total	**3,034**	**203.48**	**998**	**91.86**	**819**	**313.79**	**1,217**	**220.78**

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

	Whole period			Pre-crisis			Crisis			Post-crisis		
GICS sector[1]	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**
Basic Material	90.91	192.39	0.33*	.	.	.	276.32	408.79	0.65*	86.34	168.57	0.33*
Consumer, non-cyclic	63.27	87.41	0.41*	40.92	56.61	0.18*	67.30	180.00	0.30*	80.08	62.71	9.74*
Financial	141.53	104.48	0.61*	9.69	39.73	0.20*	149.00	161.70	0.42*	162.02	109.90	0.59*
Utilities	70.00	130.92	0.87*	19.00	85.16	0.29*	66.86	175.63	0.29*	81.61	132.13	-2.90
Industrial	89.13	129.91	0.53*	.	.	.	315.00	267.61	1.00	83.98	116.82	0.33*
Energy	.	.	.	.	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.	.	.	.	.
Consumer Cyclic	55.09	130.68	0.23*	50.11	104.21	0.32*	56.27	253.11	0.16*	55.01	85.41	0.25*
Communication	73.52	135.07	0.22*	36.65	124.84	0.28*	100.59	175.49	0.30*	93.43	122.21	0.17*
Median	**87.60**	**117.85**	**0.43***	**18.70**	**68.29**	**0.20***	**100.16**	**179.53**	**0.32***	**116.51**	**114.74**	**0.53***

Note: (1) No monthly bond yield spread data exist for Energy and Technology GICS sector for the UK sample.

Table 6C: EU17 - Ratio of default component to bond yield spread.
Specifications of the table are similar to as reported in table 6A

Panel A: Median yield spread for EU17 across each sub-period								
	Whole period		**Pre-crisis**		**Crisis**		**Post-crisis**	
GICS sector[2]	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**	N^B	**Spread**
Basic Material	306	194.24	120	107.39	87	310.10	99	297.55
Consumer, non-cyclic	591	156.62	136	108.31	164	188.78	291	176.20
Financial	3371	187.65	847	86.44	877	198.97	1647	245.17
Utilities	592	127.82	193	66.07	168	155.41	231	156.54
Industrial	555	175.79	180	119.84	134	243.35	241	207.63
Energy	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.
Consumer, cyclic	331	190.88	121	119.57	86	224.12	124	282.98
Communication	450	189.14	140	123.13	141	244.79	169	217.24
Diversified	87	434.78	30	110.05	24	619.16	33	547.64
Total	**6283**	**176.11**	**1767**	**98.34**	**1681**	**205.95**	**2835**	**224.25**

Panel B: Median default and non-default component of yield spread across each sub-period												
	Whole period			**Pre-crisis**			**Crisis**			**Post-crisis**		
GICS sector[2]	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**	**Dflt**	**Ndflt**	**Ratio**
Basic Material	80.03	113.23	0.41*	33.48	71.05	0.31*	119.77	129.76	0.39*	198.21	161.14	0.67*
Consumer, non-cyclic	62.69	90.03	0.40*	18.35	89.61	0.17*	64.24	129.54	0.34*	83.28	77.01	0.47*
Financial	119.57	73.67	0.64*	11.75	76.95	0.14*	104.23	97.87	0.52*	188.23	62.92	0.77*
Utilities	58.23	72.27	0.46*	17.41	51.50	0.26*	57.08	101.39	0.37*	79.69	75.18	0.51*
Industrial	90.19	101.96	0.51*	31.37	91.79	0.26*	105.00	147.51	0.43*	120.23	97.73	0.58*
Energy	.	.	.	.	.	.	.	.	.	.	.	.
Technology	.	.	.	.	.	.	.	.	.	.	.	.
Consumer Cyclic	134.77	74.89	0.71*	47.75	55.29	0.40*	176.81	40.31	0.79*	179.69	102.48	0.63*
Communication	72.90	119.39	0.39*	42.33	82.10	0.34*	86.49	149.93	0.35*	87.24	135.91	0.40*
Diversified	427.90	128.72	0.98*	.	.	.	446.65	149.18	0.72*	420.26	120.23	0.77*
Median	**90.60**	**85.54**	**0.51***	**18.67**	**76.16**	**0.19***	**96.07**	**110.55**	**0.47***	**146.96**	**81.79**	**0.66***

Note: (2) No monthly bond yield spread data exist for Energy and Technology GICS sector for the EU17 sample.

Table 6D: Ratio of default component to bond yield spread.
Specifications of the table are similar to as reported in table 6A

Panel B: Median default and non-default component of yield spread across each sub-period												
	Whole period			**Pre-crisis**			**Crisis**			**Post-crisis**		
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***
EU17[3]	**90.60**	**85.54**	**0.51***	**18.67**	**76.16**	**0.19***	**96.07**	**110.55**	**0.47***	**146.96**	**81.79**	**0.66***
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*
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*
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*
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*
Portugal	116.56	83.12	0.35*	12.11	.	0.12*	91.50	92.77	0.53*	591.15	82.40	1.06
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*
Ireland	156.38	167.44	0.31*	8.58	.	.	138.34	.	.	616.68	167.44	1.22
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*
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*
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*
Luxembourg	78.56	140.76	0.41*	.	.	.	121.53	139.90	0.55*	76.91	140.76	0.38*

Note: (3) No Dflt and Ndflt data available for EU countries; Cyprus, Estonia, Greece, Malta, Slovakia and Slovenia.

Table 7A - US: Between-effect regressions

This table reports the results from regressing the log of the corporate yield spread in basis points (Panel A) and log of the non-default component in basis points (Panel B) against a number of liquidity proxies for the US sample during four separate periods as defined in Table 1. The yield spread is defined as the difference between the yields on the 5 year corporate bond obtained by using the bond bracketing procedure as described by Longstaff et al. (2005). The non-default component is the difference between the yield spread and the CDS spread. *Coupon* is expressed in percentage terms, *Ln_principal_amt* is natural log of the principal amount issued in millions, *Age_Y* is age of bond in years, *Maturity_Y* is the time to maturity in years and *IQR* is inter-quartile range in basis points.

Panel A	**Log of Corporate Yield Spread**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	4.969***	4.085***	5.342***	6.052***
Coupon	0.213***	0.361***	0.187***	0.208***
Ln_principal_amt	-0.05***	-0.067***	-0.03***	-0.102***
Age_Y	-0.03***	-0.026***	-0.014***	-0.026***
Maturity_Y	-0.053***	-0.056***	-0.038***	-0.05***
IQR	0.493***	0.405***	0.164***	0.518***
N	76,506	23,935	20,748	31,823
R^2	48.53%	44.73%	33.72%	47.29%
Adjusted R^2	48.53%	44.72%	33.70%	47.28%

Panel B	**Log of Non-default component**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	4.109***	3.837***	4.697***	3.986***
Coupon	0.303***	0.34***	0.209***	0.336***
Ln_principal_amt	-0.061***	-0.068***	-0.028***	-0.073***
Age_Y	-0.006	-0.024***	-0.009*	-0.008
Maturity_Y	-0.044***	-0.02**	-0.033***	-0.031**
IQR	0.184***	-0.001	0.034**	0.197***
N	62,230	19,510	17,723	24,997
R^2	38.30%	33.87%	23.99%	38.09%
Adjusted R^2	38.30%	33.85%	23.97%	38.08%

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

Table 7B - UK: Between-effect regressions
The specifications are similar to as detailed in tables 7A.

Panel A	**Log of Corporate Yield Spread**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	5.701***	9.417***	5.723***	5.502***
Coupon	0.23***	0.469***	0.241***	0.246***
Ln_principal_amt	-0.078***	-0.37***	-0.078***	-0.077***
Age_Y	-0.098***	-0.094**	-0.034***	-0.059***
Maturity_Y	0.047***	-0.002	-0.025**	0.073***
IQR	0.001	-0.238	0.129***	-0.001
N	15,937	2,138	2,791	11,008
R^2	46.00%	39.23%	49.40%	43.56%
Adjusted R^2	45.98%	39.09%	49.31%	43.53%

Panel B	**Log of Non-default component**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	3.169***	8.108***	5.248***	3.149***
Coupon	0.38***	0.429***	0.268***	0.402***
Ln_principal_amt	-0.025*	-0.3**	-0.08**	-0.038**
Age_Y	-0.043***	-0.08*	-0.024*	-0.035**
Maturity_Y	0.009	0.006	-0.026*	0.045**
IQR	-0.001	-0.331	0.059*	-0.001
N	12,372	2,023	2,400	7,949
R^2	37.52%	32.09%	37.24%	34.19%
Adjusted R^2	37.49%	31.92%	37.11%	34.15%

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

Table 7C – EU17: Between-effect regressions

The specifications are similar to as detailed in tables 7A.

Panel A	Log of Corporate Yield Spread			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	5.479***	4.606***	4.77***	5.109***
Coupon	0.239***	0.369***	0.279***	0.239***
Ln_principal_amt	-0.058***	-0.076***	-0.027***	-0.045***
Age_Y	-0.093***	-0.061***	-0.035***	-0.064***
Maturity_Y	-0.051***	-0.075***	-0.094***	-0.016*
IQR	0.3***	0.174	0.233***	0.283***
N	46,365	5,860	9,980	30,525
R^2	44.08%	59.19%	48.63%	38.51%
Adjusted R^2	44.07%	59.16%	48.60%	38.50%

Panel B	Log of Non-default component			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	3.438***	4.819***	2.323***	3.833***
Coupon	0.425***	0.405***	0.399***	0.409***
Ln_principal_amt	-0.029**	-0.113***	0.053***	-0.059***
Age_Y	-0.031***	-0.046**	-0.021*	-0.07***
Maturity_Y	-0.182***	-0.05**	-0.187***	-0.137***
IQR	0.305***	-0.02	0.238***	0.354***
N	30,795	4,694	7,558	18,543
R^2	39.11%	66.08%	44.33%	31.40%
Adjusted R^2	39.10%	66.04%	44.29%	31.38%

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

Table 8: Fixed-effect panel data regression using CDS liquidity variables

Panel data fixed effect regression (with robust standard errors) of the log of CDS spreads to accounting, market-based variables and CDS liquidity proxies. Independent variables are as described in table 4 and period are as defined in table 1..

Panel A - US	***Spec 1: Abs_bidask***				***Spec 2: Prop_bidask***			
Variables	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	4.589	3.145	4.856	4.481	5.343	4.472	5.574	4.808
size	-0.076	0.025	-0.059	-0.08	-0.132***	-0.013	-0.136	-0.032
ROA	-2.148***	-2.38***	-1.254***	-1.517**	-2.641***	-1.456***	-1.185***	-2.202***
incgrowth	1.027***	1.361**	0.69***	0.446	1.31***	0.612*	0.674***	0.818**
c	0.001***	-0.001	-0.001	0.001***	0.001***	0.001**	-0.001	0.001**
quick	-0.018	-0.083	-0.138**	0.08*	-0.022	-0.03	-0.122**	0.07*
cash	0.256	0.584	0.458	-0.975***	0.034	0.058	0.373	-0.976***
trade	0.008**	-0.011	0.006**	0.005	0.005	-0.003	0.005**	0.005
salesgrowth	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.001	-0.001
booklev	1.103***	0.998***	0.224	0.68***	0.637***	0.333	0.211	0.952***
retained	0.372**	-0.53**	0.316	0.065	0.141	-0.509***	0.097	0.04
ret	-0.002	-0.008	-0.002	-0.001	-0.004***	-0.004	-0.005	-0.002***
σret	0.624***	2.015***	0.538***	-0.011	1.199***	1.681***	1.013***	0.747***
DTD	-0.026***	-0.012***	-0.015***	-0.011***	-0.019***	-0.007***	-0.009	-0.013***
r	-15.986***	-5.188***	-8.592***	48.211***	-9.139***	-5.943***	-6.145***	32.717***
index	-0.2***	-1.196***	-1.189***	-0.028	0.001	-0.735***	-0.854***	-0.002
rgics	-0.959***	0.187	-0.774***	-0.627***	-0.799***	0.181*	-0.706***	-0.475***
abs_bidask	0.007***	0.023**	0.004***	0.024***	-	-	-	-
pro_bidask	-	-	-	-	-4.579***	-4.003***	-6.025***	-7.828***
N	6,191	1,224	1,678	3,289	6,191	1,224	1,678	3,289
R^2	64.19%	26.13%	77.52%	44.05%	73.06%	61.95%	80.44%	45.56%
Adjusted R^2	64.09%	25.09%	77.29%	43.76%	72.99%	61.41%	80.24%	45.28%

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

Panel B - UK	*Spec 1: Abs_bidask*				*Spec 2: Prop_bidask*			
Variables	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	0.733	4.731	1.682	2.475	4.286	5.912	0.09	2.067
size	0.393	-0.453	0.321	0.219	-0.112	-0.289	0.859*	0.311
ROA	0.629	-0.223	-0.653	-0.827	-0.49	0.221	-2.93**	-0.791
incgrowth	-0.16	0.739	0.081	0.707	0.099	0.321	1.338***	0.785
c	-0.014***	-0.002	0.005	-0.011***	-0.005	0.002	0.008	-0.01***
quick	0.006	-0.082	0.105	0.147*	0.111*	-0.168*	0.224**	0.197**
cash	0.469	-0.243	-1.538*	0.224	-0.408	-0.414	-2.951***	-0.171
trade	-0.232	0.38	-0.793***	-0.25**	-0.214**	0.163	-1.019***	-0.023
salesgrowth	0.002	0.002*	-0.002	0.002	0.001	0.002**	-0.003	0.002
booklev	2.928***	2.195*	1.507	0.454	1.808***	1.064*	1.711	0.599
retained	1.04	1.272	0.804	0.547	1.304***	0.794	1.202	0.541
ret	0.012	0.235*	0.034	-0.006	0.013	0.157	0.068***	-0.013*
σret	-0.244	-0.334	-0.121	0.779	0.729*	-0.502	1.189**	2.006***
DTD	-0.02**	-0.036	-0.023	0.012	-0.016*	-0.031	-0.043**	0.01
r	-12.581***	-12.785	0.71	30.059**	-8.048***	-18.747	1.184	19.913*
index	-0.753***	0.319	-1.495***	-0.401***	-0.368**	-0.215	0.337	-0.273**
rgics	-0.813***	-0.072	-0.375	-0.625***	-0.672***	-0.136	0.015	-0.827***
abs_bidask	0.036***	0.015	0.049***	0.02**	-	-	-	-
pro_bidask	-	-	-	-	-4.228***	-2.444***	-6.847***	-3.088**
N	565	126	140	299	565	126	140	299
R^2	62.22%	28.12%	77.54%	45.24%	76.00%	53.13%	70.74%	46.72%
Adjusted R^2	61.05%	16.81%	74.41%	41.93%	75.25%	45.75%	66.66%	43.50%

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

Panel C- EU17	Spec 1: Abs_bidask				Spec 2: Prop_bidask			
Variables	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	2.451	0.022	4.46	4.769	3.519	1.188	5.757	6.527
size	0.356*	0.027	0.132	-0.347	0.254	-0.009	-0.164	-0.462
ROA	-1.531**	-2.862	0.147	-2.272	-1.972***	-5.349	-0.391	-1.521
incgrowth	0.188	-1.144	0.463	2.259	0.081	-1.33***	-0.077	0.184
c	-0.004	-0.021*	-0.002	-0.008	-0.003	-0.014*	-0.001	-0.004
quick	0.082	0.407***	-0.274	-0.117	0.207**	0.193*	-0.011	0.03
cash	-1.418	-0.608	-1.213	1.646	-1.735**	0.215	-0.588	-0.057
trade	0.074	-0.492***	0.155	-0.109	0.127	-0.305***	0.139	0.087
salesgrowth	-0.001	-0.01***	-0.001	-0.001	-0.001	-0.007***	-0.002	-0.001
booklev	-0.008	5.951	-0.918	2.232*	-0.117	5.817***	-0.794	1.286
retained	-0.201	2.649	0.493*	0.395	-0.692*	3.553*	-0.029	-0.576
ret	0.003	-0.059	0.076	-0.001	-0.003**	-0.029	0.061	-0.004***
σret	1.801***	0.647	1.545***	0.351	2.065***	0.348	2.151***	2.029***
DTD	-0.022***	0.043	-0.031	-0.006	-0.01**	0.032	-0.023	-0.006
r	-6.395**	-34.914	-5.159	26.502*	-3.913	-43.168***	-2.147	4.163
index	-1.398***	-1.956	-1.528***	-0.804	-1.48***	-1.489	-1.876***	-1.377*
rgics	-0.038	0.188	0.043	-0.068	0.141	-0.569	0.146	0.065
abs_bidask	0.01**	0.012	0.01***	0.029*	-	-	-	-
pro_bidask	-	-	-	-	-16.431***	-12.22***	-7.531	-18.07***
N	427	50	207	170	427	50	207	170
R^2	65.50%	66.80%	73.17%	56.45%	73.33%	79.82%	68.31%	62.83%
Adjusted R^2	64.07%	49.16%	70.76%	51.58%	72.22%	69.10%	65.46%	58.67%

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

Table 9 – Effect of CDS liquidity variable in the spread prediction model

The table compares the change in Adj. R^2 value for the regression model by adding the CDS liquidity variables. Specification 1 uses absolute bid ask spreads *(abs_bidask)* calculated as the difference between ask and bid quote, whereas specification 2 using proportional bid ask quote *(pro_bidask)* calculated as difference between ask and bid quote divided by mid bid-ask spread.

Panel A - US	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
	Original Sample			
N	6,393	1,256	1,778	3,359
R^2	62.07%	25.11%	75.13%	27.77%
Adjusted R^2	61.97%	24.14%	74.90%	27.42%
	Specification 1 : Absolute bid-ask spreads			
N	6,191	1,224	1,678	3,289
R^2	64.19%	26.13%	77.52%	44.05%
Adjusted R^2	64.09%	25.09%	77.29%	43.76%
Change	2.12%	0.95%	2.39%	16.34%
Effect size	0.06	0.01	0.11	0.29
	Specification 2 : Proportional bid-ask spreads			
N	6,191	1,224	1,678	3,289
R^2	73.06%	61.95%	80.44%	45.56%
Adjusted R^2	72.99%	61.41%	80.24%	45.28%
Change	11.01%	37.27%	5.34%	17.85%
Effect size	0.41	0.97	0.27	0.33

Panel B - UK	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
	Original Sample			
N	578	129	146	303
R^2	57.07%	27.24%	65.59%	37.19%
Adjusted R^2	55.85%	16.85%	61.32%	33.68%
	Specification 1 : Absolute bid-ask spreads			
N	565	126	140	299
R^2	62.22%	28.12%	77.54%	45.24%
Adjusted R^2	61.05%	16.81%	74.41%	41.93%
Change	5.20%	-0.04%	13.09%	8.25%
Effect size	0.13	0.00	0.51	0.14
	Specification 2 : Proportional bid-ask spreads			
N	565	126	140	299
R^2	76.00%	53.13%	70.74%	46.72%
Adjusted R^2	75.25%	45.75%	66.66%	43.50%
Change	19.41%	28.91%	5.34%	9.82%
Effect size	0.78	0.53	0.16	0.17

Panel C– EU17	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
	Original Sample			
N	590	135	211	244
R^2	64.07%	52.26%	66.66%	44.00%
Adjusted R^2	63.07%	45.79%	63.91%	40.05%
	Specification 1 : Absolute bid-ask spreads			
N	427	50	207	170
R^2	65.50%	66.80%	73.17%	56.45%
Adjusted R^2	64.07%	49.16%	70.76%	51.58%
Change	1.00%	3.38%	6.85%	11.53%
Effect size	0.03	0.07	0.23	0.24
	Specification 2 : Proportional bid-ask spreads			
N	427	50	207	170
R^2	73.33%	79.82%	68.31%	62.83%
Adjusted R^2	72.22%	69.10%	65.46%	58.67%
Change	9.15%	23.31%	1.55%	18.62%
Effect size	0.33	0.75	0.04	0.45

Table 10: Robustness test using 1 quarter lag of accounting variables

Panel data fixed effect regression of the log of CDS spreads to 1 quarter lag of accounting measures and market-based measures. The sample is based on quarterly CDS spreads from Q1 2005 to Q4 2012. The variables are as described in Table 3. Periods are as defined in Table 1.

Panel A - US	**Log of CDS spreads**			
Variables	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	4.508***	4.003***	5.35***	3.969***
L1. ln_size	-0.047	0.018	-0.118	-0.002
L1.ROA	-2.065***	-1.808	-0.682*	-1.769***
L1.incgrowth	0.846***	1.048*	0.212	0.507
L1.c	0.001	-0.001***	-0.001	0.001***
L1.quick	-0.008	-0.097	-0.255***	0.116**
L1.cash	0.034	0.084	0.868*	-1.224***
L1.trade	0.004	-0.016	0.002	0.002
L1.salesgrowth	0.001	-0.001	0.001	0.001
L1.booklev	1.011***	0.742*	0.003	1.037***
L1.retained	0.337*	-0.347	-0.087	0.091
ret	-0.002	-0.01	-0.007	-0.002***
σret	0.964***	1.6***	0.78***	0.691***
DTD	-0.026***	-0.011***	-0.015**	-0.015***
r	-16.015***	-14.097***	-7.377***	47.765***
index	-0.192***	-1.061***	-1.169***	0.041
rgics	-1.044***	-0.031	-0.755***	-0.704***
N	5,992	1,100	1,592	3,300
R^2	61.80%	29.09%	73.44%	25.44%
Adjusted R^2	61.70%	28.04%	73.17%	25.08%

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

Panel B - UK	Log of CDS spreads			
Variables	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	1.336	2.641**	-4.342*	4.993***
L1. ln_size	0.387	-0.026	1.068**	-0.141
L1.ROA	0.537	0.407	-1.137	-0.063
L1.incgrowth	-0.202	0.163	0.782**	-0.756
L1.c	-0.011***	-0.006***	-0.006**	-0.002
L1.quick	0.046	-0.173	0.484***	-0.092
L1.cash	0.072	0.126	-1.111	0.56
L1.trade	-0.17	0.229*	-0.576***	0.014
L1.salesgrowth	0.002*	0.001*	0.002	0.005*
L1.booklev	2.535**	0.672	3.966***	-0.612
L1.retained	0.937	-0.236	1.075	0.726
ret	0.058*	0.068	-0.006	-0.003
σret	0.195	0.134	1.164*	1.788***
DTD	-0.031**	-0.007	-0.007	-0.008
r	-13.787***	-3.526	5.651**	30.388**
index	-0.748***	4.661***	-1.317**	-0.156
rgics	-1.419***	0.207	-0.555*	-0.715**
N	563	124	140	299
R^2	56.92%	44.45%	74.17%	35.75%
Adjusted R^2	55.66%	36.14%	70.81%	32.10%

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

Panel C – EU17	**Log of CDS spreads**			
Variables	**Whole Period**	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	3.548***	6.138***	2.617	5.954***
L1. ln_size	0.124	0.119	0.172	-0.563
L1.ROA	-1.803	1.853**	0.541	-6.016
L1.incgrowth	0.857	-0.528*	0.386	2.94
L1.c	0.001	-0.002	0.002	-0.001
L1.quick	0.063	0.143	-0.292***	0.169
L1.cash	-2.134**	0.538	-0.516	-0.865
L1.trade	0.198*	-0.033	0.583***	0.174
L1.salesgrowth	-0.003**	-0.002*	-0.001	0.001
L1.booklev	0.017	-3.712***	0.22	1.724
L1.retained	-0.219	0.266	0.11	-0.293
ret	0.001	-0.016	0.018	-0.005**
σret	2.482***	0.702	2.363***	2.624***
DTD	-0.028***	0.014*	0.003	-0.014*
r	-11.253***	-33.251***	-3.732	-9.195
index	-1.811***	-0.463	-2.05***	-1.274**
rgics	-0.219	0.109	-0.01	-0.509
N	566	123	201	242
R^2	64.83%	58.09%	69.21%	41.59%
Adjusted R^2	63.81%	51.76%	66.53%	37.44%

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

Table 11: Robustness test - Panel data fixed effect regression of the log of CDS spreads to accounting and market based measures under different specifications

Panel data fixed effect regression of the log of CDS spreads to accounting and market based measures. The sample is based on quarterly CDS spreads from Q1 2005 to Q4 2012. The variables are as described in Table 3 and periods are as defined in Table 1. The change in R^2 and Adj. R^2 are reported firstly, for the original sample, secondly using 1 quarter lag of accounting variables, thirdly excluding Q1 and Q3 observations and lastly excluding all observations from firms belonging to Financial GICS sector for the US (Panel A), UK (Panel B) and EU17 (Panel C). Change in Adj. R^2 is the difference in Adj. R^2 compared to the original sample and effect size estimates the magnitude of effect between the adjusted R^2 values.

Panel A	**US**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
	Original Sample			
N	6,393	1,256	1,778	3,359
R^2	62.07%	25.11%	75.13%	27.77%
Adjusted R^2	61.97%	24.14%	74.90%	27.42%
	Using 1 quarter lag of accounting variables			
N	5,992	1,100	1,592	3,300
R^2	61.80%	29.09%	73.44%	25.44%
Adjusted R^2	61.70%	28.04%	73.17%	25.08%
Change	-0.28%	3.90%	-1.73%	-2.35%
Effect size	0.00	0.16	-0.02	-0.09
	Excluding Q1 and Q3 observations			
N	3,240	621	949	1,670
R^2	63.91%	36.91%	76.32%	31.90%
Adjusted R^2	63.73%	35.24%	75.91%	31.24%
Change	1.76%	11.10%	1.01%	3.82%
Effect size	0.03	0.46	0.01	0.14
	Excluding Financial GICS Sector			
N	6,179	1,197	1,722	3,260
R^2	61.76%	25.31%	75.38%	27.30%
Adjusted R^2	61.66%	24.30%	75.15%	26.94%
Change	-0.31%	0.15%	0.24%	-0.48%
Effect size	-0.01	0.01	0.00	-0.02

Panel B	**UK**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
	Original Sample			
N	578	129	146	303
R^2	57.07%	27.24%	65.59%	37.19%
Adjusted R^2	55.85%	16.85%	61.32%	33.68%
	Using 1 quarter lag of accounting variables			
N	563	124	140	299
R^2	56.92%	44.45%	74.17%	35.75%
Adjusted R^2	55.66%	36.14%	70.81%	32.10%
Change	-0.19%	19.30%	9.49%	-1.57%
Effect size	0.00	1.15	0.15	-0.05
	Excluding Q1 and Q3 observations			
N	101	22	29	50
R^2	74.56%	*NA*	*NA*	*NA*
Adjusted R^2	69.71%	*NA*	*NA*	*NA*
Change	13.87%	*NA*	*NA*	*NA*
Effect size	0.25	*NA*	*NA*	*NA*
	Excluding Financial GICS Sector			
N	550	129	140	281
R^2	57.86%	27.24%	65.56%	38.61%
Adjusted R^2	56.60%	16.85%	61.08%	34.89%
Change	0.75%	0.00%	-0.24%	1.21%
Effect size	0.01	0.00	0.00	0.04

Notes: (1) *NA* denotes insufficient observations and so inconsistent and unreliable coefficient of determinant R^2 for the regression model.

Panel C	EU17			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
	Original Sample			
N	590	135	211	244
R^2	64.07%	52.26%	66.66%	44.00%
Adjusted R^2	63.07%	45.79%	63.91%	40.05%
	Using 1 quarter lag of accounting variables			
N	566	123	201	242
R^2	64.83%	58.09%	69.21%	41.59%
Adjusted R^2	63.81%	51.76%	66.53%	37.44%
Change	0.74%	5.98%	2.62%	-2.62%
Effect size	0.01	0.13	0.04	-0.07
	Excluding Q1 and Q3 observations			
N	267	58	112	97
R^2	66.92%	*NA*	76.86%	61.86%
Adjusted R^2	64.80%	*NA*	72.96%	54.23%
Change	1.74%	*NA*	9.05%	14.18%
Effect size	0.03	*NA*	0.14	0.35
	Excluding Financial GICS Sector			
N	590	135	211	244
R^2	64.07%	52.26%	66.66%	44.00%
Adjusted R^2	63.07%	45.79%	63.91%	40.05%
Change	0.00%	0.00%	0.00%	0.00%
Effect size	0.00	0.00	0.00	0.00

Notes: (1) *NA* denotes insufficient observations and so inconsistent and unreliable coefficient of determinant R^2 for the regression model.

Table 12: Robustness test - Regressing the yield spread against liquidity proxies while controlling for bond specific credit risk.

This table reports the result for regressing the log of corporate yield spread against liquidity proxies while controlling for bond specific credit risk. Log of CDS spreads is taken as the direct measure of the credit risk for the bond. The table below presents the regression output for US (Panel A), UK (Panel B) and EU17 (Panel C) market across each sub-period. Periods are as given in Table 1.

Panel A	**US**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	3.382***	3.206***	4.088***	2.771***
Coupon	0.224***	0.317***	0.184***	0.188***
Ln_principal_amt	-0.055***	-0.061***	-0.047***	-0.073***
Age_Y	-0.016***	-0.031***	-0.007*	-0.015***
Maturity_Y	-0.018***	-0.036***	-0.026***	0.021***
IQR	0.138***	0.162***	0.069***	0.15***
ln_CDS	0.397***	0.316***	0.34***	0.577***
N	70,171	20,610	19,257	30,304
R^2	67.04%	55.21%	56.58%	66.01%
Adjusted R^2	67.04%	55.20%	56.57%	66.00%
Panel B	**UK**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	3.441***	7.926***	3.809***	3.093***
Coupon	0.242***	0.312***	0.241***	0.244***
Ln_principal_amt	-0.061***	-0.328**	-0.047**	-0.064***
Age_Y	-0.041***	-0.033	-0.015	-0.042***
Maturity_Y	0.035***	-0.002	-0.018	0.073***
IQR	-0.001	-0.349	0.073*	-0.001
ln_CDS	0.382***	0.471***	0.284***	0.427***
N	14,042	1,227	2,171	10,644
R^2	49.90%	38.83%	49.45%	49.33%
Adjusted R^2	49.88%	38.53%	49.31%	49.30%
Panel C	**EU17**			
	Whole Period	**Pre-crisis**	**Crisis**	**Post-crisis**
Intercept	3.144***	4.537***	3.02***	2.602***
Coupon	0.277***	0.371***	0.302***	0.26***
Ln_principal_amt	-0.04***	-0.109***	-0.013*	-0.046***
Age_Y	-0.056***	-0.062***	-0.02***	-0.054***
Maturity_Y	-0.042***	-0.052**	-0.088***	-0.013*
IQR	0.194***	0.162	0.164***	0.182***
ln_CDS	0.377***	0.228***	0.299***	0.496***
N	42,958	4,818	9,202	28,938
R^2	53.04%	65.32%	52.45%	48.42%
Adjusted R^2	53.03%	65.28%	52.42%	48.41%

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

Figure 1 - Composition of the OTC market – Notional amount outstanding, data as of June 2013 (Sources: www.bis.org)

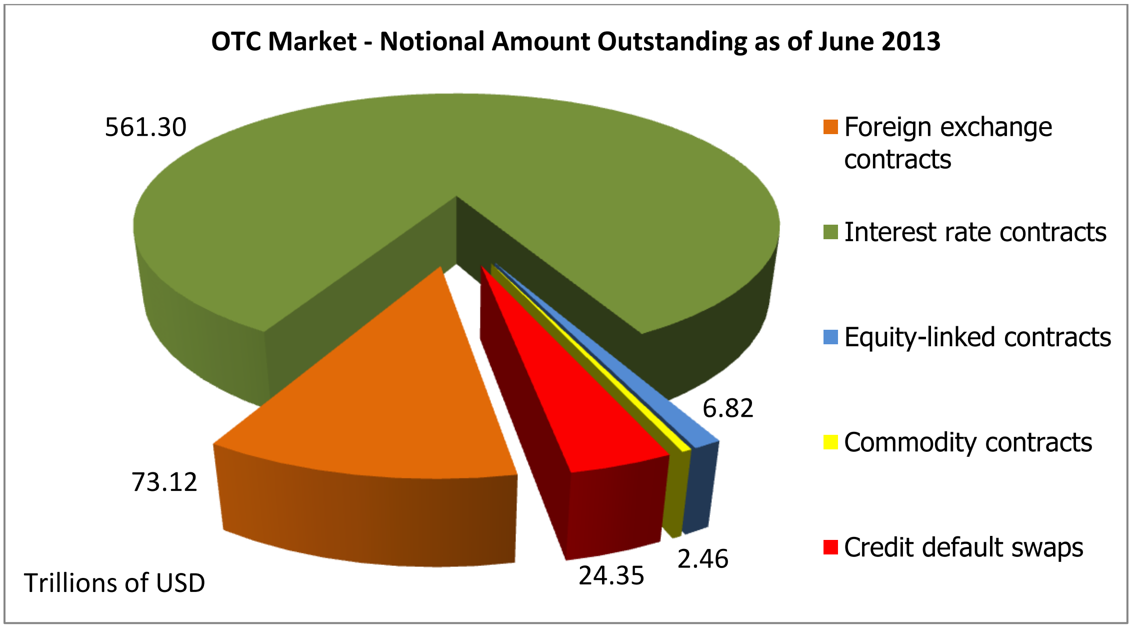

Figure 2: Composition of the OTC credit derivative market measured on the basis of notional amount outstanding as of December 2012 (Source: www.occ.gov)

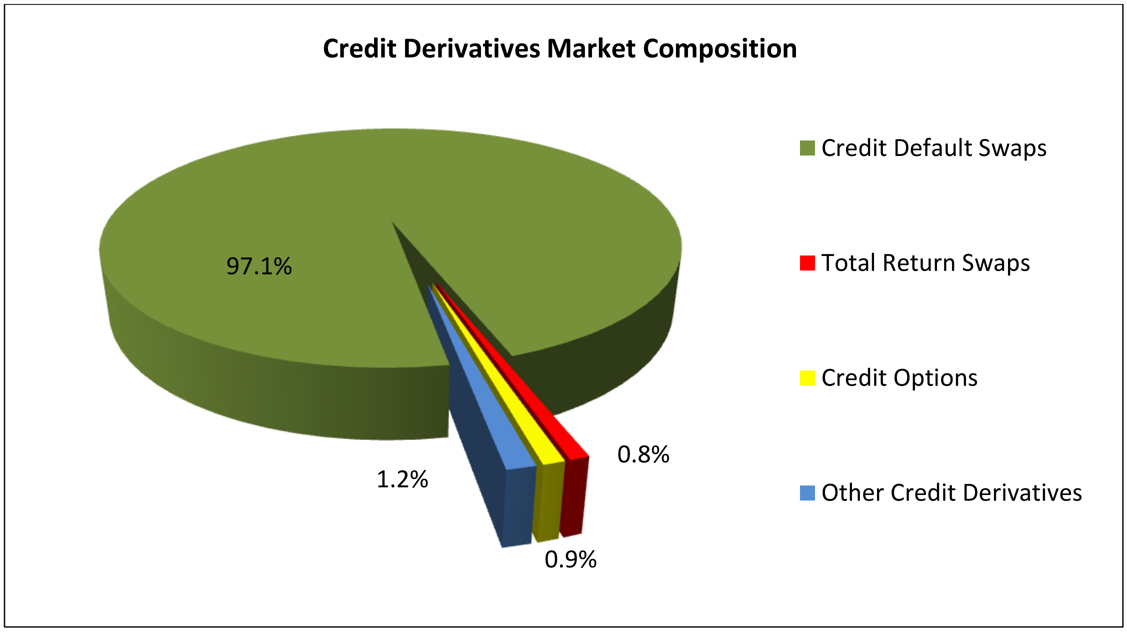

Figure 3: Corporate CDS contracts notional amount outstanding global trends from June 2005 till June 2013 (Source: www.bis.org)

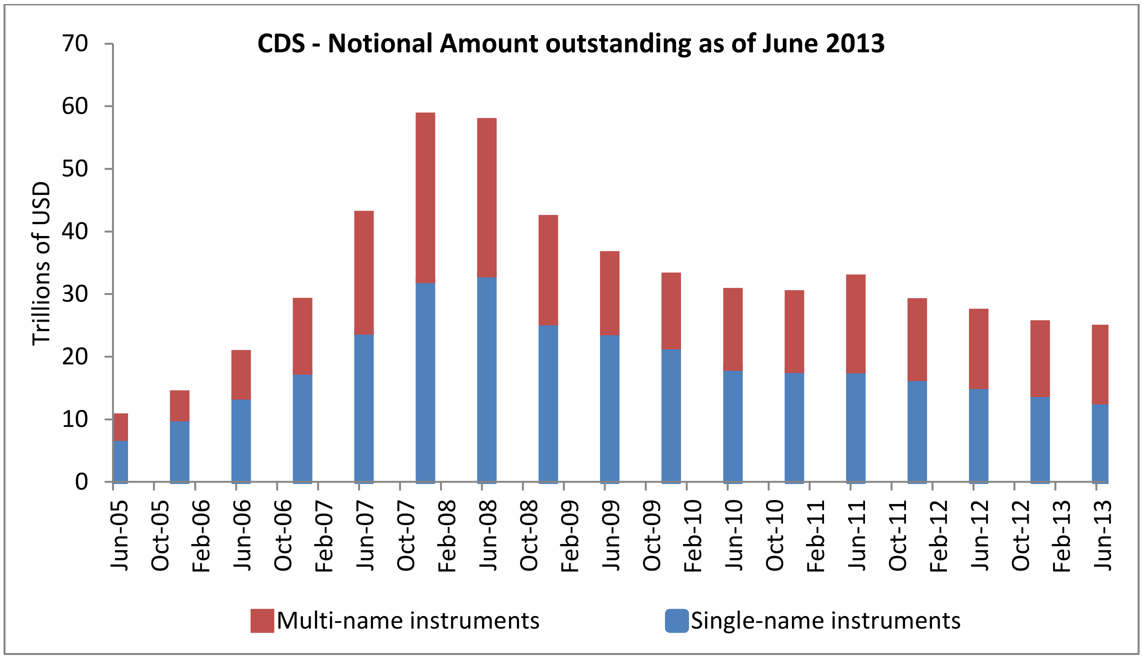

Figure 4A: US CDS spreads (level in basis points) from Q1 2005 till Q4 2012. Graph contains observations on a quarterly basis. The median spreads along with 10th and 90th percentiles are plotted across each sub-periods i.e. pre-crisis, crisis and post-crisis period. The Pre-Crisis period is from Jan 1, 2005 to Jun 30, 2007; Crisis period is from July 1, 2007 to June 30, 2009 and Post-Crisis period is from July 1, 2009 to Dec 31, 2012.

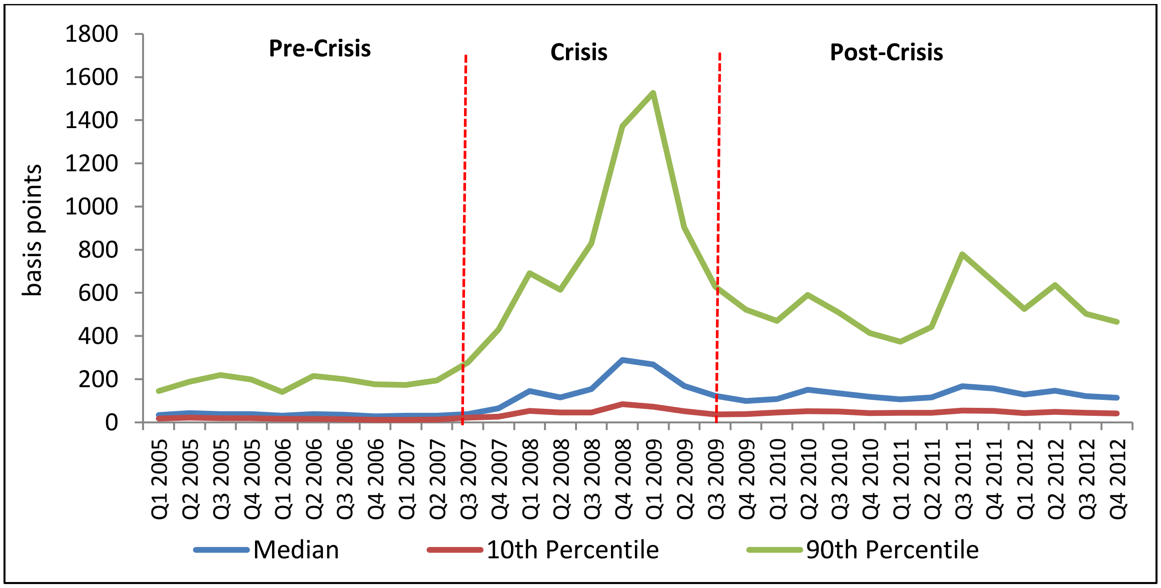

Figure 4B: UK CDS spreads (level in basis points) from Q1 2005 till Q4 2012. Graph contains observations on a quarterly basis. The median spreads along with 10th and 90th percentiles are plotted across each sub periods i.e. pre-crisis, crisis and post-crisis period. Periods are as defined in Figure 4A.

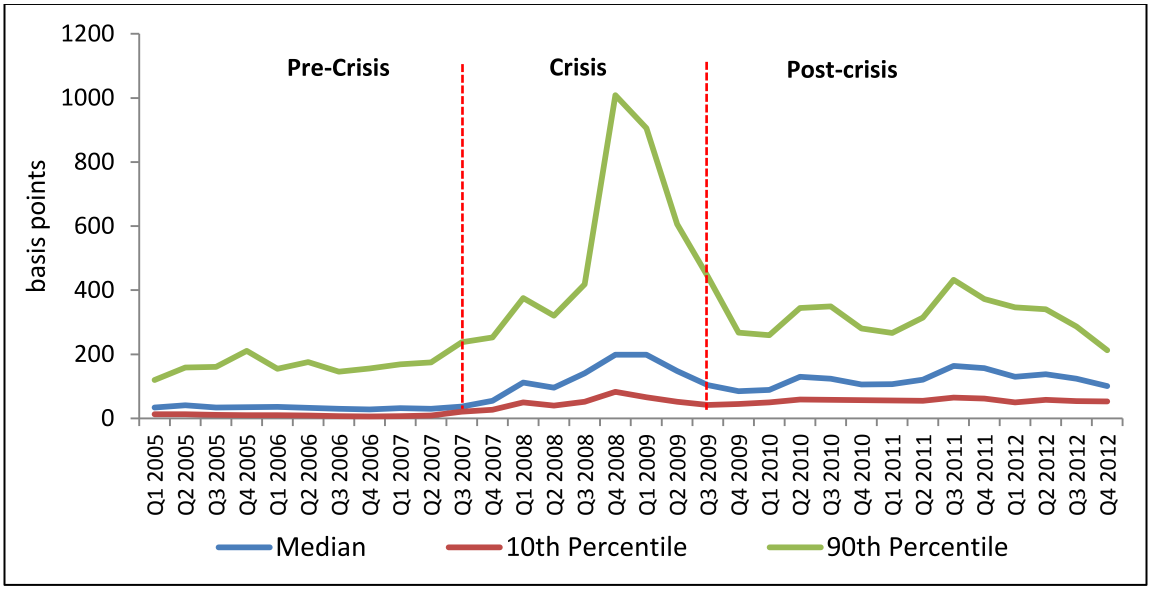

Figure 4C: EU17 CDS spreads (level in basis points) from Q1 2005 till Q4 2012. Graph contains observations on a quarterly basis. The median spreads along with 10th and 90th percentiles are plotted across each sub periods i.e. pre-crisis, crisis and post-crisis period. Periods are as defined in Figure 4A.

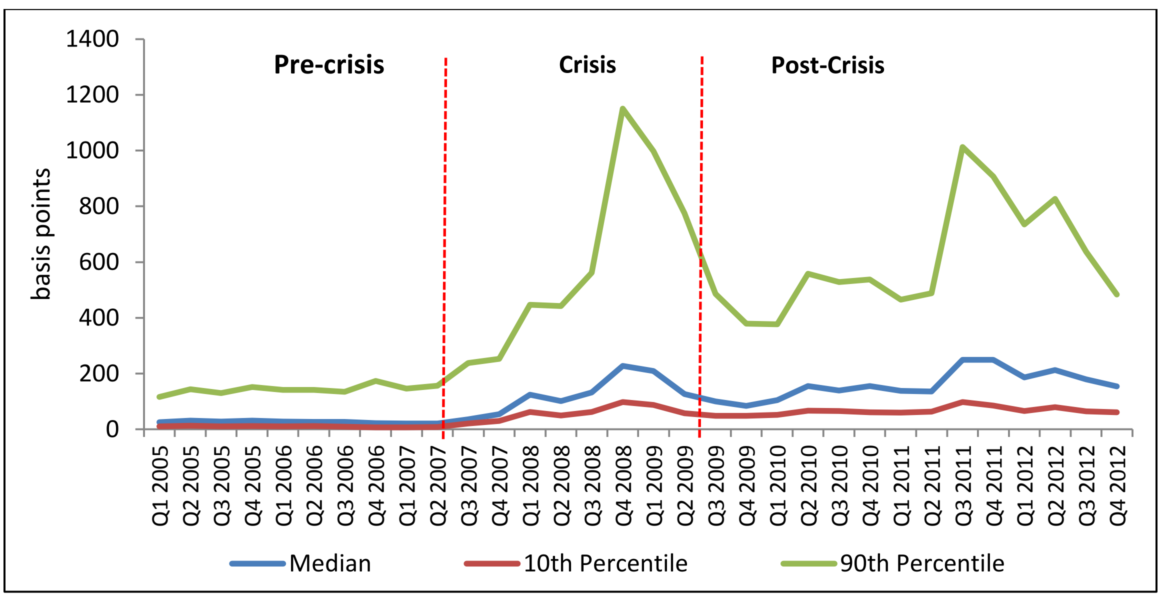

Figure 5: Monthly counterpart risk, defined as the difference between LIBOR and OIS starting from 1st January 2005 to 31st December 2012. Observations are on monthly basis and periods as defined in Figure 4A.

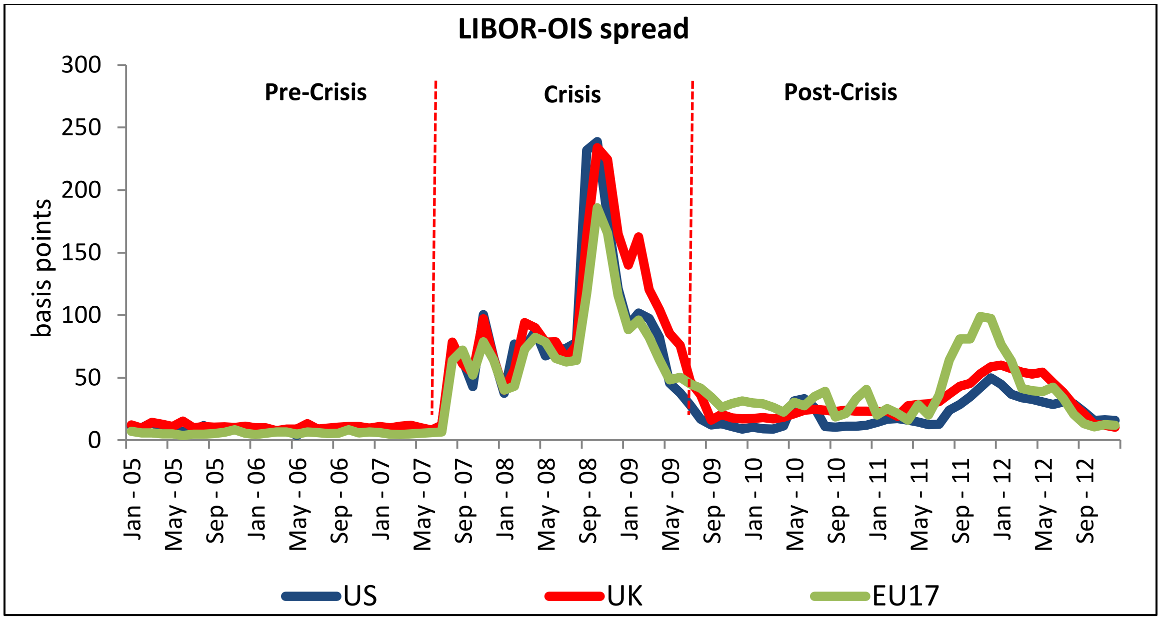

Figure 6: Time-series plot of the median non-default component across US, UK and EU17. The plot shows the time series of the median non-default (Ndflt) component in basis points across the US, UK and EU17 for the period January 1st 2005 to December 31st 2012. Observations are on monthly basis and periods as defined in Figure 4A.

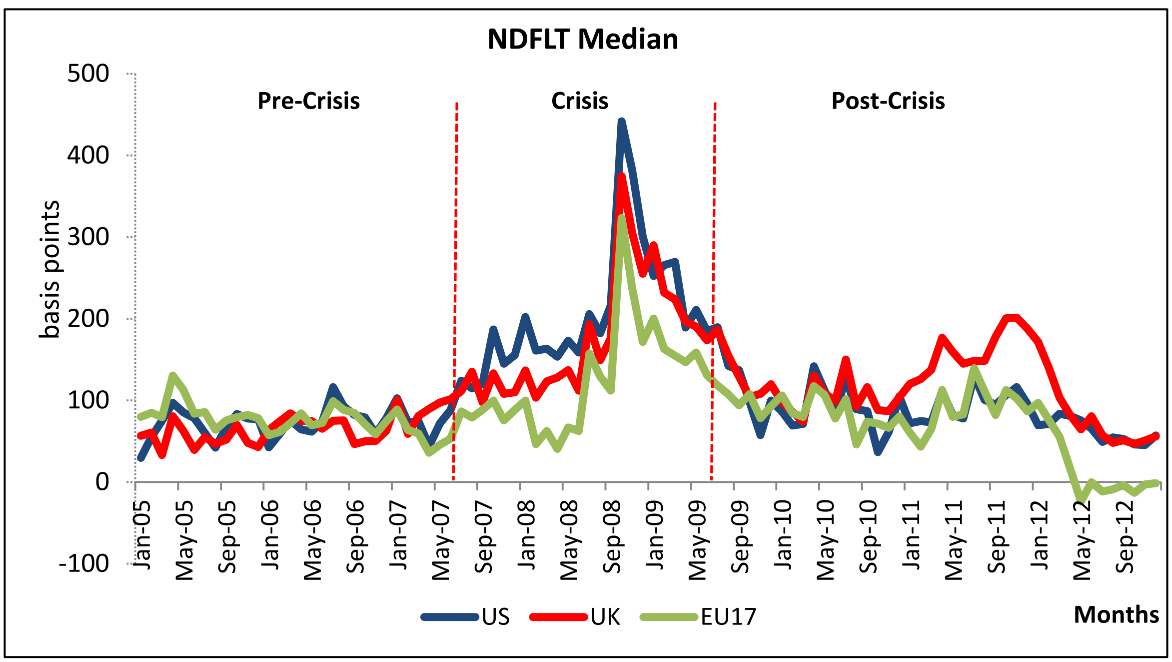

Figure 7A: Distribution of non-default components for the US sample
The plots show the distribution of non-default component of yield spread for the period January 1st 2005 to December 31st 2012 for the US sample.

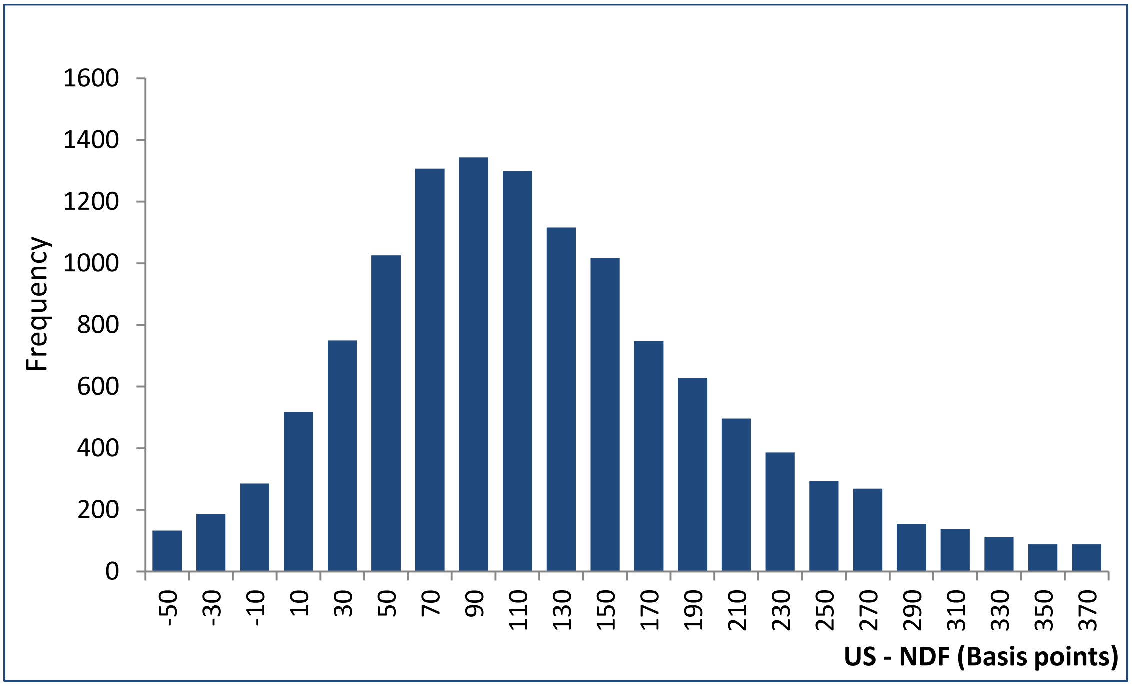

Figure 7B: Distribution of non-default components for the UK sample
The plots show the distribution of non-default component of yield spread for the period January 1st 2005 to December 31st 2012 for the UK sample.

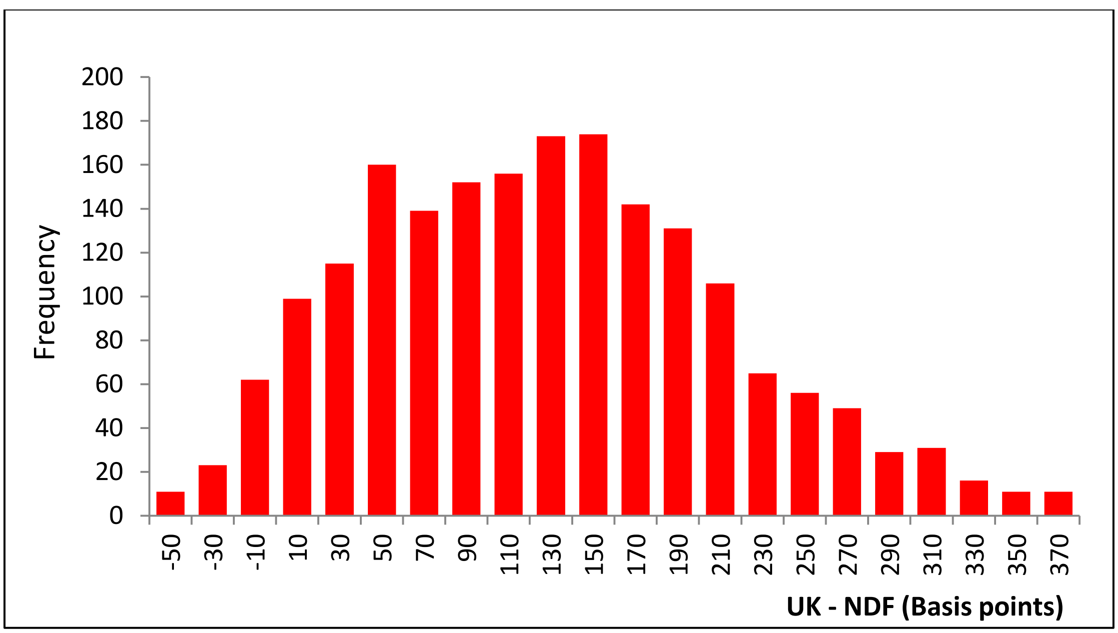

Figure 7C: Distribution of non-default components for the EU17 sample
The plots show the distribution of non-default component of yield spread for the period January 1st 2005 to December 31st 2012 for the EU17 sample.

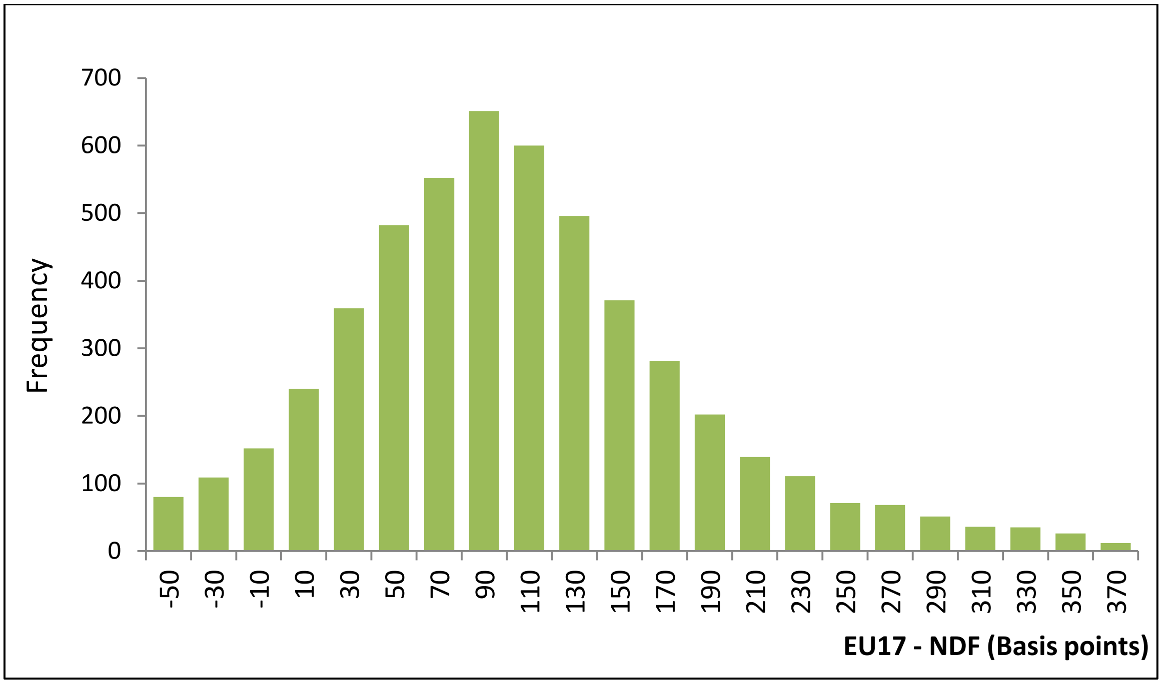

Figure: 8A – CDS liquidity variables - Absolute bid–ask spread aggregate trend
Median value of CDS liquidity variable, Absolute bid-ask spread calculated on a quarterly basis from Q1 2005 till Q4 2012. *Abs_bidask* is estimated as the difference between ask and bid quotes. Periods are as defined in table 1.

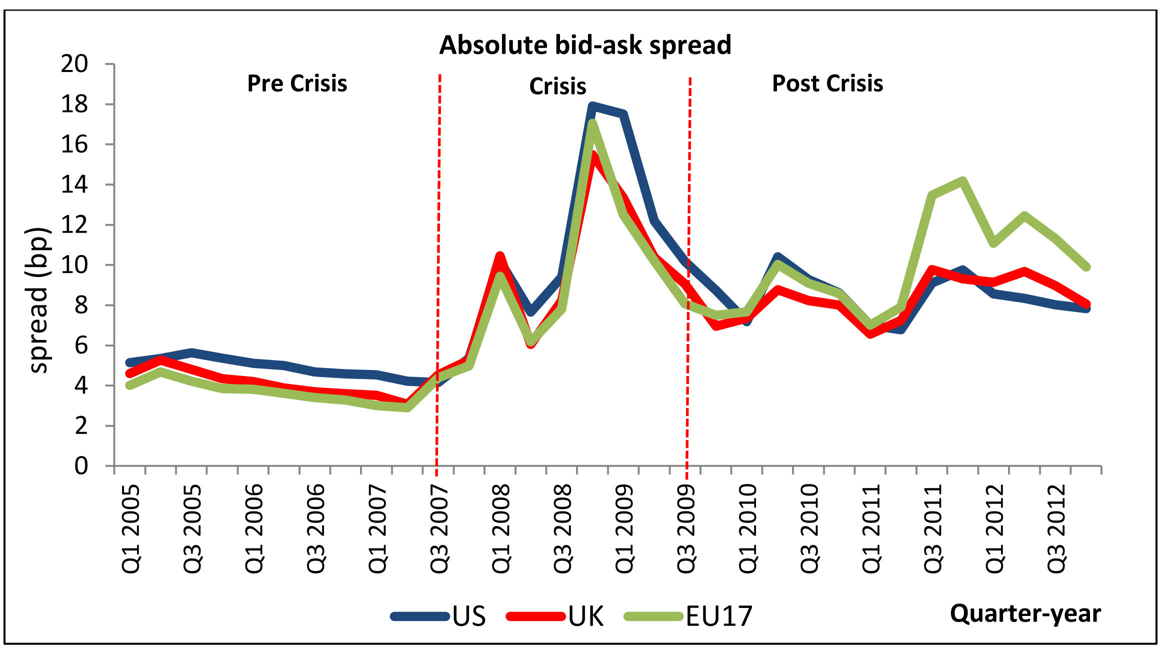

Figure: 8B – CDS liquidity variables - Proportional bid–ask spread aggregate trend
Median value of CDS liquidity variable, proportional bid-ask spread calculated on a quarterly basis from Q1 2005 till Q4 2012. *Pro_bidask* is estimated as the ratio of spread between the ask and bid quotes and the average of bid and ask quote. Periods are as defined in table 1.