‘Analysing the deviation of CDS from its reference bond spread and its potential relationship with anticipating systemic risk’

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Table of Abbreviations/Acronyms

AIG - AMERICAN INTERNATIONAL GROUP
BIS - BANK OF INTERNATIONAL SETTLMENTS
BNY - BANK OF NEW YORK
BOA - BANK OF AMERICA
BOC - BANK OF CANADA
BS - BOND SPREAD
CCP - CENTRAL COUNTERPARTY CLEARING
CDO - COLLATERALIZED DEBT OBLIGATION
CDS - CREDIT DEFAULT SWAP
CEO - CHIEF EXECUTIVE OFFICER
CFA - CHARTERED FINANCIAL ANALYST
CFTC - COMMODITY FUTURES TRADING COMMISSION
ECB - EUROPEAN CENTRAL BANK
FED - FEDERAL RESERVE
GBP - GREAT BRITISH POUND
HSBC - HONGKONG AND SHANGHAI BANKING CORPORATION
IMF - INTERNATIONAL MONETARY FUND
ISDA - INTERNATIONAL SWAPS AND DERIVATIVES ASSOCIATION
JPM - JP MORGAN CHASE
MS - MORGAN STANLEY
MUFJ - MITSUBISHI FINANCIAL GROUP JAPAN
OTC - OVER THE COUNTER
RBS - ROYAL BANK OF SCOTLAND
RF - RISK FREE RATE
SS - STATE STREET
USD - UNITED STATES DOLLAR
WF - WELLS FARGO

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Abstract:

In 1994, J.P. Morgan alongside Deutsche bank developed the Credit Default Swap (CDS), an innovation of its time but a product that has only created consistent controversy ever since. Although there is nothing ground breaking about the product itself, as it is a version of an insurance contract designed to offload credit risk to a third party. Much of the blame for the financial crisis has been attributed to its role. This was due mainly to financial institutions leveraging up their books and using CDS as a get out of jail card so that they couldn't be held responsible in the case of default. Since the turn of the century, there has been a huge growth in the research of credit derivatives and the correlated relationship between CDS and bond spreads specifically known CDS-Bond basis. In this paper we propose an analysis of the deviation of CDS from their respective bond spreads and its potential relationship in predicting systemic risk. The author proposes that using two time-frames, one defined as economically sound and the other with high levels of volatility will be able to determine the answer to this analysis. The first aspect of the paper will be reviewing the current literature that exists in the scope CDS, CDS and bond spreads and its association with systemic risk and the models used to determine this. The statistical tests, the data used and the methodology it is based upon are then outlined. Finally, the analysis is presented through a discussion where the results of the two-time frames are compared and critically evaluated where we come to the conclusion that yes there is a statistical significance to suggest that the deviation of a CDS from the associated bond spread could potentially be used a metric in predicting systemic risk.

1.1 Introduction:

Warren Buffet, coined the Oracle of Omaha and CEO and founder of conglomerate Berkshire Hathaway described Credit Default Swaps as 'Weapons of Mass Destruction' and 'potential timebombs' (Buffet, 2003). This negative depiction wasn't the only one though as in 2016, the Journal of Financial Economics blasted CDS for their continued controversy nearly a decade after the financial crisis. They argued that in a frictionless world CDS would never have grown to what it became throughout the 2000's. On the other side of the coin however, Robert F. Engle, notable Nobel Prize winner, states that CDS could take the place of credit rating agencies who he believes are conflicted in the way they are paid for by the issuer of a bond and now that CDS are traded through clearing houses, they are going to be a very good measure of credit worthiness of different firms going into the future (Engle, R.F., 2011).

A credit default swap is defined in one sentence as 'an insurance contract that protects against losses arising from some kind of pre-defined credit event involving a reference entity such as a bond' (Bystrom 2005). To add to this definition, CDS are third party contracts between a party that requires protection and a party that provides protection against a form of credit risk or default. The protection buyer makes periodic payments to the protection seller in return for this said service or transfer of risk (Narayanan and Uzmanoglu, 2018). Credit derivatives such as CDS allow companies to trade credit risks in much the same manner that they trade market risks, historically speaking banks have been the biggest buyer of CDS protection and insurance companies have been biggest seller of protection (Hull, J.C, 2018).

The opinion of such products is open to wide interpretation and it is argued that CDS has taken a lot of blame for the global financial crisis as they were an easy scapegoat in an era vast regulatory failure. However, in response to the Journal of Financial Economics, no such frictionless world exists and still continue to exist, although at a smaller scale, notionally speaking anyways. ISDA, the international swaps and derivatives association who now act as the main clearing house worldwide for over the counter derivative (OTC) transactions have put a figure to this contracting market. They confirm that between 2011 and 2015, the notional value of all CDS contracts has fallen by a massive 61 percent, from $15.4 trillion to $6 trillion respectively. (Culp, C.L et al, 2016). One would think this means that they are gradually being phased out but the Bank of International Settlements argues that although the notional value of CDS has reduced, this has not reduced the size of the market, it has just meant a compression of contracts in an aim to reduce exposures. This was mainly due to post crisis reforms such as standardisation of contracts, expanded reporting requirements, mandatory central clearing and margin requirements for a wide range of derivatives (BIS, 2018). One thing can be confirmed however though, is that although it may seem that CDS are no longer a desired derivative product, this is far from the truth. From the perspective of the author, it is evident that there is a stigma attached to CDS and one such question to ask is can CDS be used for any other purpose other than for hedging risk. A number of papers have discussed this and focused on using CDS spreads as method of price discovery. This theory known as CDS-Bond basis (CDS basis) is defined as the difference between the CDS premium minus the yield spread of a fixed coupon bond of similar maturity over a risk-free benchmark rate (Fontana et al, 2015). Essentially it measures how the movement of the CDS spread fluctuates from the underlying bond spread in different market conditions. Generally speaking, there is an established long run equilibrium between CDS and bond spread of the same entity and only in times of large changes in liquidity and financial turmoil do these spreads deviate (Alexopoulou, I. et al, 2009).

The aim of this paper will be to conduct a comparative study that will specifically focus on two key time frames, one of market/financial turmoil and one of market confidence, between 2008-2010 and 2016-2018 respectively. The purpose of this is to use CDS and bond spread data to test if there is an association between the decoupling of these spreads due to changing market conditions and whether the movement of these spreads across these timeframes could potentially be used in predicting or determining systemic risk. Used in the study are fourteen firms that have issued debt in both these timeframes that have underlying CDS contracts associated with them.

For the purposes of the study, the bonds used in the study must be within the final cycle before maturity to match the maturity of the CDS and must have a fixed rate and a fixed maturity. Zero coupon bonds, floating rate bonds and bonds with perpetual maturities will be excluded. The paper will add to existing literature in the two ways; firstly, there has been no study, to the authors knowledge, conducted to date that focuses on the deviation of CDS spreads from bonds spreads over different time periods that could possibly act as a model for premeditating financial distress and therefore systemic risk. Secondly, if it transpires that positive and negative movements in CDS bond basis could be used as a metric for predicting systemic. How reliable and useful could this metric become particularly with the reputational damage that CDS has taken since the financial crisis. For the purposes of this paper, the risk-free rate will be assumed as the 5-yr US treasury rate. In current papers, the empirical tests to date suggest there is a possible relationship between these variables.

2.1 Literature Review:

2.1.1 Credit Derivatives:

Credit Derivatives are a type of over-the-counter (OTC) derivative instrument that mainly trace their origins to the mid-1990s. The term OTC involves the engagement in a contract between two parties (that is privately agreed) with no involvement of an exchange or intermediary. Credit Derivatives gained notoriety when firms needed a way to hedge risk on their corporate debt but also at a time when there was a need to boost returns. They are financial contracts that transfer the (credit) risk of an underlying asset from one counterparty to another without actually transferring the underlying asset. Although they may seem new, contracts similar to credit derivatives, such as letters of credit and credit guarantees have been around for centuries but credit derivatives are different in the sense that they are traded separately from the underlying assets and you do not need to own the underlying asset (Bystrom, 2004).

One other unique feature of credit derivatives is that credit risk is transferred without any funding actually changing hands. Only in the case where a credit event occurs does the buyer of credit risk provide funds ex post to the seller. Bystrom argues that CDS are used as a method of exploiting arbitrage by financial services firms on top of their ability to transfer credit risk from the balance sheet which makes them a quite attractive product to hedge funds also. Credit derivatives are categorized into two types known as 'single name' and 'multi name'. Single name credit derivatives include credit default swaps (CDS), total-rate of-return swaps, and credit-spread options. The main multi name credit derivative is a collateralized debt obligation (CDO) which is a portfolio of specified debt instruments such as mortgage back securities with a complex structure where the cash flows from the portfolio are channelled to different categories of investors based upon some sort of pre-determined seniority (Hull, 2018). For the purposes of this paper, the focus will be solely on single name credit derivatives, specifically the largest of all single name credit derivatives, Credit Default Swaps.

2.1.2 What are Credit Default Swaps?

As outlined in the introduction, CDS are bilateral OTC insurance contracts that promise compensation in the event of a corporate default. Protection buyers purchase CDS protection on a company, the referenced entity, and if that company fails to meet its debt obligations, then the ensuing credit event triggers a pay-out from protection sellers (Du, L.

et al, 2018). It is therefore a protection taken out in the form of insurance against the risk of a default by a company on its debt obligations. The buyer of the CDS makes periodic payments to the seller until either the end of the agreement, predominately five years, or until said credit event occurs (Hull, J.C. 2018). According to ISDA, there are five main types of credit events that trigger the CDS:

1. Acceleration of debt
2. Failure to meet payment obligations
3. Bankruptcy
4. Moratorium
5. Restructuring

(Ericsson, J. et al, 2005)

What is quite interesting about CDS is that although they are an OTC swap, they do not incorporate many of the features of standard swap contracts. These include the exchange of cash flows or interest rates as in circumstances of currency and interest rate swaps. Surprisingly CDS do have quite a number of similarities to insurance policies. Firstly, like insurance policies, CDS only pay out if a credit event occurs similar to the situation that occurs with standard insurance policies. If a motorist crashes the car, then and only then is there a pay out to cover the loss. Secondly, CDS have a premium that is paid so to provide the service. It is usually monthly or quarterly instalments payable until such a time that the credit event occurs or the contract runs its course. However, in a standard insurance contract the insured party must typically have direct economic or monetary exposure to said product so as to obtain insurance, this differentiates from a CDS contract as you do not have to own the bonds to take out a CDS contract (Stulz, R.M., 2010). Although since 2011, the legislation in the EU has changed with respect to sovereign issued bonds in so far as no CDS can be taken out on any sovereign EU bond without owning the bond at the same time.

A key difference between CDS and insurance policies though is that those buying a CDS have the ability to trade in and out of their contracts in a way that is not possible with insurance policies. CDS can also be used to hedge the credit risk of on-balance sheet transactions by acquiring CDS protection. Such protection provides capital relief while also protecting against credit losses (Terzi et al, 2011). Table 1.1 one below gives a graphical description of how a CDS contract works.

Table 2.1: How a CDS contract works.

As the above description outlines, in response to purchasing a bond the protection buyer seeks out a CDS which they pay a premium for to the seller who provides CDS insurance in the event that the reference entity defaults on their $10,000,000 bond. If this does occur, the pay-out will be as follows,

Protection buyer payoff = Bond par value – Bond market value.

It is quite common for CDS contracts to settle in cash and usually have maturities ranging from 5 to 10 years but more commonly 5 years. The reference entity is usually unrelated to the parties taking out the CDS contract (McDonald, 2014).

2.1.3 History & Evolution of Credit Default Swaps:

CDS were engineered in 1994 by J.P. Morgan Inc. and Deutsche Bank to transfer credit risk from their balance sheets to protection sellers. The main reasoning for this was to offset their risk exposure and protect themselves against the large leveraging activities they were involved in. At that time, hardly anyone could have imagined the extent to which CDS would occupy the daily lives of traders, regulators, and financial economists alike in the twenty-first century (Augustin, P. et al, 2016). To put this into perspective, between the 1994 and 2011 the total notional value of CDS grew from zero to $28 trillion (Wilson, 2011). It is interesting to note that from a comparative point of view, the gross notional amount outstanding in OTC interest rate contracts totalled $563.293 trillion in December 2014, compared to $19.462 trillion of credit derivatives (Augustin et al, 2016). As we can see the value of credit derivatives only make up 3.45% of the value of interest rate contracts.

In reviewing the development of the CDS market, one must look at the regulatory and market changes that aided in the growth of CDS. As outlined by Hull, the interesting part about swaps is that they are only limited to the imagination of financial engineers and the desire of corporate treasurers and portfolio managers for exotic structures (Hull, J.C, 2004). The first swap was engineered by Solomon Brothers in the 1980s in the form of an interest rate swap, since then there has been a huge growth in the market making activities of these products. But the question here is, what have interest rate swaps got to do with CDS? Outside of the fact that CDS were just a development off the back of previous financial engineering, there isn't much comparison. Critically speaking the majority of swaps encompass an exchange in cash flows by both parties but in regards to CDS, this isn't the case. As outlined previously, CDS incorporate many of the underlying assumptions of an insurance contract but are only regulated by the legislation covering swaps. This essentially makes a CDS an evolution of a swap that aims to mitigate credit risk.

With references to changes in key regulatory legislation, it was the repeal of the Glass-Steagall Act in 1999 that had the largest effect on the growth of swap transactions. This act was introduced in 1933 in response to the Great Depression of the late 1920's which caused the collapse of twenty percent of all financial institutions. The aim of the act was to separate investment banking activity from commercial banking activity with a goal of stopping commercial banks becoming involved in any activity that potentially be risky to their depositor's money. It essentially defined what investment banking activity and commercial activity were and detailed what activities commercial banks could not get involved in, specifically ringfencing the activities from each other.
Throughout the 1980s however, a lot of lobbyist activity occurred against the act which led to its complete repeal in 1999. By the time this occurred, commercial banks were already permitted to earn 25% of net revenue from securities activities (Crawford, C. 2011). As early as 1987 and in response to the growth of swaps activity, the CFTC (Commodity Futures Trading Commission) attempted to regulate the industry but the major swaps dealers at the time threatened to move their business overseas if the CFTC did so. The CFTC dropped their case for regulating swaps activity and amended the requirements of a swap transaction. They were required to have "individually tailored terms," could not be traded on or connected to "a clearing organization or a margin system," and could not be "marketed to the general public" (Wimarth Jr, A.E. 2017). Without these regulations, the growth of CDS and other hedging strategies was inevitable as investment banks looked for more opportunistic ways of upping their returns. In assessing these developments, it is hard to

ignore that without extensive reduction and repeal of key regulation, CDS and other relatable products would never have gained such notoriety. As discussed in the introduction, CDS were scapegoated in the aftermath for their role in the financial crisis but it is very evident and quite concerning that the regulation in place, or lack of, aided and abetted in the crisis in a more substantial way than any single product such as CDS could ever have. In conclusion, it is clear that CDS and related products were developed out of opportunity, such opportunity that only arrived from poor regulatory oversight and the repeal of key legislation.

2.1.4 Why use CDS and Who are the main market participants in the CDS market?

As is to be expected there are generally only a limited number of parties in the CDS market and rarely do we see these firms lie outside of financial services. Banks and other lenders are natural buyers of CDS protection for such purposes as transfer and hedging of risk, while highly rated dealers, insurance companies, financial guarantors and credit derivative product companies were the typical protection sellers prior to the financial crisis (Terzi, N. et al, 2011). According the CFA institute, most CDS protection sellers set premium rates at 1% per annum for investment grade debt and 5% per annum for high yield debt (CFA Institute, 2019). Analysing the statistics related to CDS, it is quite clear who the major players in the market are. The bank of international settlements provides statistical data each quarter on the breakdown of the CDS market, table 1.2 below illustrates the evidence of the main participants associated with CDS.

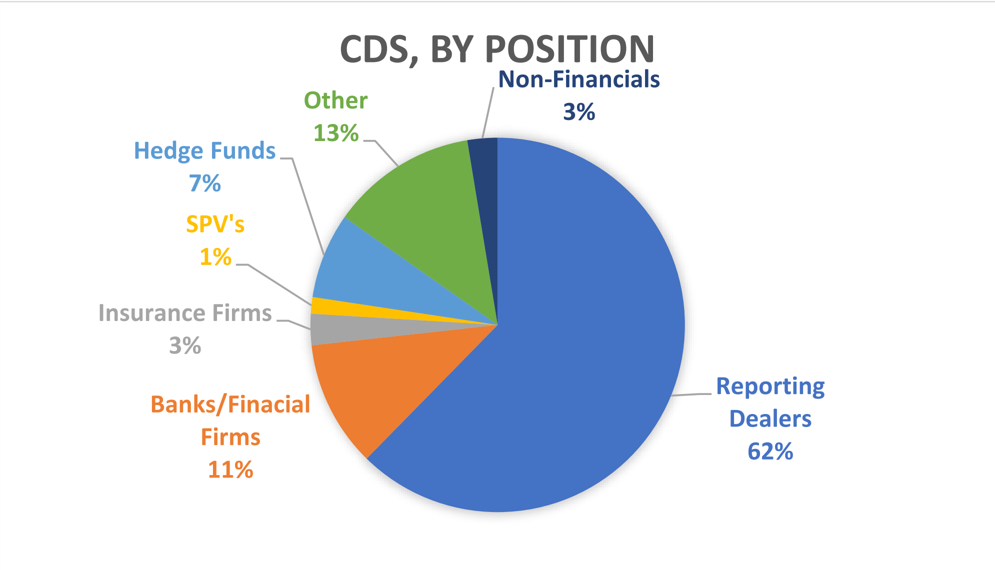

Table 2.2: CDS, by position.

(BIS, 2018).

As can be seen from above, reporting dealers make up a large percentage of the CDS markets which incorporates financial institutions that participate in the compilation of OTC derivatives or a triennial central bank survey (BIS, 2018). Reporting dealers can therefore be defined as financial institutions who take part in both OTC derivative transactions and direct transactions between buyer and seller. As the diagram outlines, financial institutions take up a large of percentage of market share but it is worth mentioning the presence that hedge funds also play in the market, at 7.37% respectively. For the purposes of the pie chart above, the central counterparty share (CCP) in the CDS market was removed as this is a make-up of all counterparties that overlap with one another and has no requirement to be included.

So why would a firm attempt to use CDS in the first place? According to Bloomberg, it has to do with efficiency as described below,

"Consider a corporate bond, which represents a bundle of risks, including perhaps duration, convexity, callability, and credit risk. If the only way to adjust credit risk is to buy or sell that bond, and consequently affect positioning across the entire bundle of risks, there is a clear inefficiency. Fixed income derivatives introduced the ability to manage duration, convexity, and callability but credit derivatives complete the process by allowing the independent management of default or credit spread risk" (Bloomberg, 2015).

Yes, CDS may have the features of a product developed from inefficiency but the reality is it was engineered out of opportunity in a time of lesser regulation. Although when assessing the main uses for CDS, there are a few primary motivations;

1. Capital Structure Arbitrage – With respect to realising arbitrage, an investor/institution purchases an asset in the aim of securing an imbalance in the price of said asset and therefore earning a profit. This is quite a popular strategy with FX traders who look to profit from discrepancies in the difference between highly liquid currencies such as GBP & USD. However, it is a little more difficult to realise arbitrage in the bond market as bonds can generally be less liquid. The use of CDS can be used to realise this arbitrage as generally the spread on a CDS should move in line with the underlying bond spread. However, as CDS move quite rapidly with

market forces due to their sensitivity and highly liquid nature, a difference in these spreads can determine discrepancies and therefore arbitrage. This practise is known CDS bond basis or capital structure arbitrage which will be discussed in length later in this paper.

2. Risk Management – the basic aim of investing in financial security is to realise potential profit while also mitigating the risk of loss on the asset. CDS offers this opportunity in so far as you purchase a CDS on the security so that if a credit event/default occurs, you are compensated for your losses. It allows institutions/investors to transfer the risk from their balance sheet freeing up potential capital for other investments that might not be possible if they were unable to purchase the CDS on the financial asset.
3. Investment opportunity – although CDS resemble insurance contracts as they look replace the risk of loss on an asset with a monetary pay-out. They are also quite useful in producing their own investment opportunities. They provide an investor with more options than would normally be the case, such as if an investor believes a company will default but the circumstances do not suit to initiate a short position. They could use CDS to short by taking a long position in said firm and then purchasing CDS on that long position. A long position is purchasing an asset believing it is undervalued and when the value is realised, you sell the asset for a profit. But by taking out a CDS on the long position the investor has entered a long/short position, so when the firm actually defaults, they gain from their long position in the company by having taken out CDS contracts to eliminate any loss. As outlined above, CDS provides investors/institutions more exotic ways of performing financial strategies and therefore investment opportunities.

2.1.5 CDS Bond basis – Bond spreads, CDS spreads and Systemic Risk:

The aim of this chapter is to understand what systemic risk is, how and where it happens, CDS - bond basis in the form of CDS and bond spreads and how these two variables overlap. In describing where and when systemic risk occurs, the author will look at potential situations where such circumstances could have occurred.

Systemic risk is the risk that a default of one financial institution will create a ripple or domino effect that leads to defaults by other institutions which threatens the stability of the whole financial system (Hull, J.C., 2018). There are not many examples of this as generally a contagion such as systemic risk is mitigated by sovereign governments or practises are put in place by central banks and institutions like the World Bank and International Monetary Fund (IMF) to curb this. Each decade on record over the last forty years has had a period of large uncertainty or recession, they usually occur in cycles, boom and busts per say. The 1970s saw a period of large oil price increases due to lack of supply and high inflation rates known as stagflation, the 1980s was an era of Black Monday where in one day the value of the market dropped by almost 25%, the 1990s and early 2000s saw the Asian crisis and the Dotcom bubble. However, these are all forms idiosyncratic risk where only one type of asset or a limited number of industries were affected each time.

The Great Financial Crisis (GFC) in 2008 differed from the previous occurrences as during the market turmoil, many large financial institutions were bailed out by governments rather than being allowed to fail because of the threat of systemic risk (Hull, J.C., 2018). Examples include financial institutions such as AIG in the US, RBS in the UK and AIB in Ireland. If these institutions were allowed to fail, the chances of systemic risk snowballing were much greater. However, this bail out didn't apply to all institutions as was the case with Lehman Brothers and Anglo-Irish Bank respectively.

CDS - bond basis (CDS basis) is essentially defined as the difference between the CDS premium and the spread of the yield on a fixed coupon bond of similar maturity over a risk-free benchmark rate (Fontana et al, 2015). The aforementioned premium as discussed by Fontana is the regular obligation the protection buyer must pay for the CDS similar to that of insurance policy. In previous studies such Blanco et al, Alexopoulou, I. et al and Buhler & Trapp the risk-free rate has been outlined as the US 5-year treasury rate, LIBOR (the London Interbank Offered Rate) or the 5-year corporate bond mid yield spread. The mid yield spread is defined as the average between the bid and ask spread of a financial security. Although academics have criticized the US treasury rate as a viable benchmark risk-free rate as it is unreliable. CDS basis, unlike standard corporate bond spread comparisons, is the difference between the CDS spread and bond spread over a risk-free rate which can also be referred to as the reference entity. CDS basis changes quite quickly with market forces, widening can be broadly explained by changes to liquidity, liquidity preference and concentration and increased funding costs tied to balance sheet constraints (Boyachenko et al, 2018). What makes CDS spreads an interested topic for this study is that similar to corporate bond spreads, they capture a firm’s default risk but the empirical results suggest that even though both spreads can capture a firm’s default risk. CDS spreads are to be preferred over corporate bond spreads when measuring said firm-specific credit risk. (Alexopoulou, I. et al, 2009).

Financial market theory suggests that CDS and corporate bond spreads are bound by no arbitrage conditions and by ignoring differences in liquidity and firm specific fundamentals this should in fact hold. Therefore, under the assumption of no arbitrage theory an investor who invests in CDS against the default of a specific firm should in theory purchase a CDS equal to the observed corporate bond yield spread. The issue here is that arbitrage does exist in this market and it has been exploited by market participants in the past and there are two reasons attributing to this. Firstly, it is relatively easy to short credit by buying credit protection in the CDS markets which would in theory push CDS spreads higher if everything else held equal, in comparison it is very difficult to short corporate or treasury bonds as the liquidity is just not there. Secondly if an investor had the choice in the wake of adverse market conditions to hold onto credit protection in the form of CDS or keep an investment in bonds, they would sell their position in the corporate bonds to minimise losses (Alexopoulou, I. et al, 2009). Focusing on the second assumption, in the wake of adverse market conditions, as investors begin to sell the bonds as quick as possible on the market due to the risk of default. Other special purpose vehicles will look to take up CDS protection against the default of these bonds. As the price of the bond drops due to the lack lustre demand, the spread on the CDS will spiral upwards due to the demand causing the CDS spread and bond to move in completely different directions. This therefore causes the decoupling or deviation as discussed exposing the opportunity of arbitrage as the liquidity in both markets are now worlds apart. It also provides sufficient evidence to conduct a study on the relationship between these two variables.

Assuming this theory holds which Blanco et al (2003), Longstaff et al (2003) and Alexopoulou et al (2009) have confirmed in previous literature, the next step is to focus on what benefits or drawbacks the movement of these CDS spreads provide. For example, CDS spreads offer a great deal of information that can be profitably used by asset managers and if properly used, the data on CDS spreads could potentially alert regulators to problems at individual banks, securities firms and insurance companies (Terzi et al, 2011). Breaking this down from the perspective of an asset manager, when the CDS basis is positive, the CDS spread is greater than the bond spread, an asset manager could short the bond and sell the CDS protection to capture the basis or arbitrage. If the basis was negative, they could buy the bond and the protection which would lock in a risk-free annuity equal to the basis (Bai et al, 2011).

Focusing upon how regulators could implement legislation for CDS spreads, they offer a lot of information regarding the liquidity and credit quality of firms and can potentially act as a contagion of the market if obligations on them are not paid out. Take for example a CDS seller such as AIG in the mid-2000's, at the time they were underwriting and selling CDS protection for double and triple A rated bonds and other multi-name derivatives and were taking a huge market share in doing so. However, they didn't have the necessary reserves to pay out if a credit event occurred on a huge proportion of these assets which ended up occurring in 2008. If the US government had not bailed AIG out, they would have collapsed and would have been unable to honour their payment of the CDS in the case of a credit event. This could in turn cause the collapse of other institutions in the process when they don't receive the agreed pay-out as per the CDS contract. As discussed, the CDS can act as a contagion which could attribute to systemic risk, regulators could input conditions that a CDS seller must have sufficient reserves to cover default before they can sell CDS protection. It provides further information for regulators to act upon, when the CDS spreads no longer move in parallel with the bond spread, it may be time to stress test that specific institution for possible default. In concluding remarks and as outlined by the Financial Times, 'Credit Default Swaps reflect the credit quality of a firms' assets that trade the derivative and widen over Treasury yields during periods of banking stress' (Financial Times, 2011). If the credit quality of a bank's financial assets is poor, it usually means the credit quality of the system isn't far behind it. Therefore, it is worth mentioning the ability that CDS basis and CDS spreads have to play in assisting in the analysis of a firm's credit quality and long-term sustainability.

2.1.6 Previous/Related Literature:

In the decade since the financial crisis, quite a lot more literature in the scope of CDS spread and CDS – bond basis has been published. However, the most evident and ground breaking material had already been published prior to this, that being said its relation to what actually occurred in the lead up to and the aftermath of the financial crisis did actually occur.

Blanco et al (2005) conducted a study in a time period between 2001-2002 and studied the dynamic relation between investment grade bonds and Credit Default Swaps (CDS). By focusing on 33 entities (13 financial, 20 non-financial), it was concluded that the CDS market leads the bond market in determining the price of credit risk. Buhler & Trapp (2009) completed one of the first major studies completed on CDS premia and bond yields. Their study took in 119 euro denominated CDS contracts encompassing 1548 trading days between 2001 & 2007. This study was much larger than any other taken to date and provided a lot of interesting results. In these results they found on average the CDS basis was 48.75 basis points higher across all firms. One of the first studies completed on solely euro area firm's mid crisis was Alexopoulou et al (2009) who published a study in an ECB working paper series with the aim of comparing the price of credit risk in CDS and corporate bonds markets. Their study took in 29 firms (15 non-financial & 14 non-financial) that were included on the iTraxx index between 2004 & 2008. The bonds and CDS were all euro denominated. Finally, Flannery et al (2010) compared the movement in CDS spreads against the changes in credit ratings on corresponding bonds or references entities. The study focused on 302 CDS spreads of North American financial institutions between 2006 and 2009. The firm level analysis was a little more narrow than previous studies as it studied 15 major US financial institutions specifically investment banks. In reviewing the above literature, it is quite clear a substantial depth of research has been completed, nonetheless this research was all completed either before or shortly after the financial crisis leaving 10 years' worth of now valuable information currently untouched which could reveal some very valuable and interesting insights into CDS-Bond basis.

In comparing the results of the previous literature, what does it tell us going forward?

Instantly what is profound across all the studies is how useful CDS spreads or CDS basis is in price discovery and also predicting large changes in the financial landscape. Take for example Blanco et al, in 27 out of the 33 firms studied, 80% of the price discovery was found in the CDS market rather than the bond market. However, when examining the determinants of changes in the pricing of credit risk in the two markets. It was found that the macro variables i.e. interest rates, term structure, equity market returns have a larger immediate impact on credit spreads than on CDS spreads. In critiquing the paper, it is odd why Blanco et al decided to focus on such a small time-frame. Regardless of the volatility of the market between Jan, 2001 & July, 2002, an 18-month time span can lead to results that may not be as desirable as expected. Secondly, the paper decided to ignore the two fundamental approaches to pricing risk which were prevalent in most other papers of this nature, this makes it difficult to hold its relevance in the vast amount of literature currently out there. Lastly, only investment grade corporate bonds were used in the study which sometimes lack a lot of liquidity in comparison to lesser graded bonds. However, the reasoning for using only investment grade bonds is justified in this case as the issue with speculative graded bonds is that they typically trade below par which makes the study of these spreads much more difficult.

Although the study conducted by Flannery et al differed hugely from that of Blanco, the results still do contain some fascinating comparisons. It was found that CDS spreads increased quite quickly as information became available of possible defaults on bonds but at the same time credit ratings didn't respond and still remained predominately triple A. What is worrying about such a study however is how little regulators put pressure on credit rating agencies to keep up to date with rating these so-called investment grades bonds and not amending their triple A rating. However, when reviewing the paper, the issue with the study conducted by Flannery at al was that no previous research in this area had been conducted and none has been done since. This singles it out as the only relevant material comparing movements in CDS spreads and changes in credit ratings. Secondly, it is known that credit agencies are normally quite slow in changing the credit ratings on financial securities so to avoid causing huge volatility in the market and also to make sure the research is in fact substantiated before downgrading or a upgrading the grade on a security.

Alexopoulou et al (2009) found that in the European markets, CDS spreads tend to be more sensitive to changes in systemic risk compared with corporate bonds spread. Instead corporate bond spreads seem to change in price more regarding firm specific factors. What was also very interesting was the apparent 'no-arbitrage' relationship between CDS and bond does in the long term, however when arbitrage does begin to exist the information normally is found in the CDS market as they absorb information much quicker than the bond markets. Finally, it was discovered that CDS markets price discovery abilities strengthened following the financial crisis. In the largest study completed in this topic area, Buhler & Trapp provided quite ground breaking results, they found that the low liquidity in the bond market and the high liquidity in the CDS market was the main cause for these spreads to deviate. However, when the spreads began to converge, the research confirmed that this was due lower interest rates, a higher bond index and lower market liquidity factors. The interesting part about this study was liquidity plays a huge role in the movements of CDS and bond spreads, the CDS-Bond basis has a tendency become more positive in the wake of less liquidity in the bond market and more liquidity in the CDS market. The fact that the converging of these spreads has been due to a lowering of interest rates, usually a stimulant used by central banks to help the growth of an economy is also intriguing as although central banks do not want any part in the CDS market they still realise their importance in the price discovery landscape.

In conclusion, it is quite clear a large body of research has been completed on both CDS and the relationship between the CDS and bond spreads. The aim of the methodology and data analysis of this paper is to add to this body of literature by conducting a variety of tests and aim to add to the existing work. Alexopoulou et al (2009) paper was quite fundamental in the research of this paper and the aim will be to resemble keys area of this paper but instead focus on US denominated bonds and specifically only financial firms.

3.1 Data and Methodology:

The data gathered was for financial firms that had issued fixed rate coupon bonds with underlying CDS contract associations. As the most popular form of CDS contract encompasses a 5-year maturity, the aim was to find corporate bonds for these specific financial firms that had similar maturity dates i.e. they either matured at the same time as the CDS or in a short space of time afterwards, normally within two years. Financial securities were gathered in two different time frames for each firm; firstly between 2008-2010 where the bond and CDS matured no later than 2012 and secondly financial securities between 2016-2018 where the bond and CDS matured no later than 2020. For the firm to be considered for the study, the bond must be dollar denominated with a fixed rate coupon that has maturity date similar to that of the CDS contract i.e. in its last cycle before maturity. The purpose of the bonds being fixed rate is to make sure a guaranteed coupon is paid each month.

3.2 Data:

3.2.1 Data Retrieval:

In order to be able to carry out accurate testing and the predicative power of CDS as a method of anticipating systemic risk, we collated all data from Bloomberg. Thankfully this was provided through the authors employers who volunteered their access to the platform for research, extraction and read only purposes. Initially, the aim was to gather data for fifty firms that had associated CDS contracts on their debt securities, this was to include twenty-five financial firms and like-wise twenty-five non-financial firms. In aiming to gather data for all fifty firms, a number of issues arose:

Firstly, quite a large number of non-financial firms have very limited debt issuance which are either tagged with perpetual maturity or have already matured. Secondly, for quite a lot of these firms there were no associated CDS contracts on the securities. Thirdly, quite a majority of the bonds issued by non-financial firms were floating rate and zero-coupon bonds. Fourthly, many of the non-financial firms’ bonds were not dollar denominated and finally for many of these firms there was large gaps in the data related to either their risk adjusted CDS spread or bond prices.

Predictably, many of these issues did not arise with financial firms apart from in some cases the historical data was very difficult to find because either the risk adjusted CDS spread/bond data had missing information at key timeframes or there was no data available at all. In the majority of the cases, all CDS spread and bond price data were available for current outstanding bonds but these particular issues arose only with many already matured bonds. To curb this issue, any firms with missing or no data were excluded from the study, however this left no non-financial firms so the study as discussed in the literature review will focus around financial related firms only. The list of the firms used in the study can be found in appendices.

We select the data for the period between 2008-2010 for the following reason. The aim is to assess the movement of CDS spreads in comparison to the underlying corporate bond spread throughout the stages of the financial crisis. We ended the study in 2010 as the majority of CDS matured in 2011/2012 and although a sovereign debt crisis ensued in the EU, the same circumstances did not occur in the US where all the firms we have chosen have their debt denominated. The period of 2016-2018 was chosen to allow a comparative study to be completed against the 2008-2010 data. This period 2016-2018 respectively has been confirmed as a time of continued economic growth for many nations and most of the developed world. This is stark contrast to the years between 2008-2010 where we saw vast shrinking of economies, huge illiquidity in bond markets, spiral losses in the equity market and large corporate default.

3.2.2 Data Description:

As discussed previously, when accessing the data, the bonds must have a fixed rate and a fixed maturity. Therefore, zero coupon bonds or floating rate notes were excluded as were bonds with no fixed maturity or any bond that has a convertible or perpetual option. As the most commonly used CDS contract has a maturity of 5 years and to conduct a valid study the maturity of these bonds must be in line with the maturity on the CDS. This will no doubt be the most difficult part of the quantitative research as bonds range in all maturities whereas the most common credit default swap maturity is 5 years (Berman, 2006). To combat this the author will look at bonds within the final cycle before their maturity. When exporting the data, it was noted that many of the bonds that were being used had no 5yr CDS spread listed so to combat this issue the CDS spread used was the Bloomberg risk adjusted CDS spread on all securities. The Bloomberg risk adjusted spread is Bloomberg's generated CDS spread for a given security over a risk-free rate. This is available on all valid fixed rate bonds with a CDS contract. Overall there were fourteen firms used in the study, all financial entities as each firm needed to have issued debt in the timeframes being studied that also included a CDS contract. The bond data used for this study were all spreads with no options embedded; the data is the bond spread over predetermined risk-free rate to calculate a bond credit spread which was determined by both previous literature and what is relevant to this study. This risk-free rate will be discussed in further detail later in the paper.

3.2.3 Data Example:

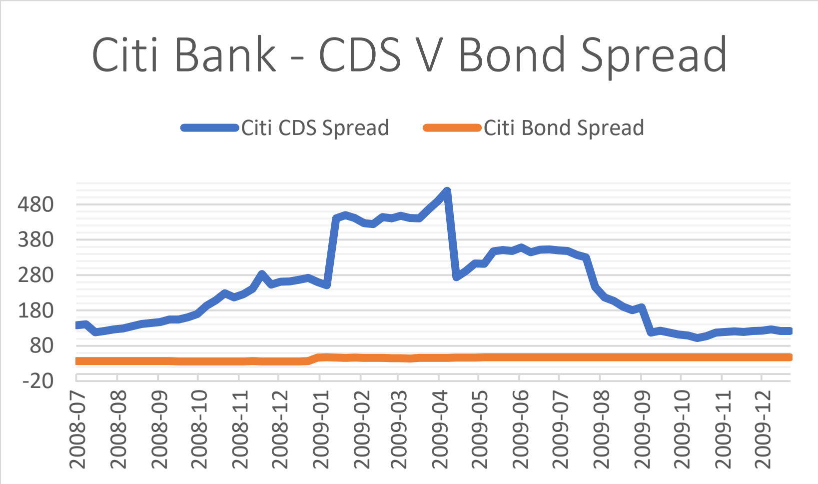

Table 3.1: Citi CDS V Bond spread 2008-2009

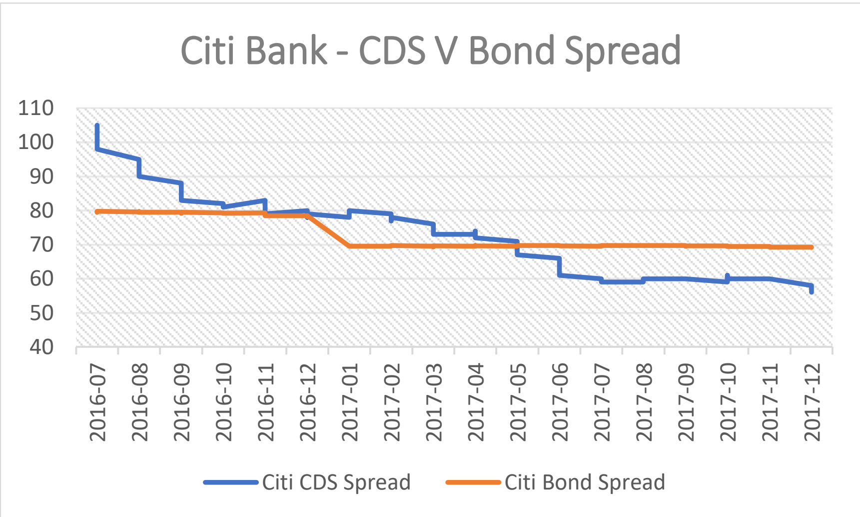

Table 3.2: Citi CDS V Bond spread 2016-2017

As it can be seen above, there are vast differences in the spreads between the time frames. Between mid-2008 and the end of 2009, the bond spread remains relatively stable but the CDS deviates largely describing the huge volatility in the market and growing worry on Citi debt. To give a bit of context to this situation, when a bond is issued, the spread should remain constant as the coupon payments are made by the issuer, this should be the same for the CDS as the value of CDS should correspond with the bond. However, when poor market conditions begin to appear and the possibility of default emerges, the CDS spread will deviate quite heavily from the bond spread as the premium for the CDS largely increases, this is due mainly to the greater demand for CDS protection, ensuing large fluctuations in the CDS spread. It is worth mentioning the CDS spread began to drastically rise around the collapse of Lehman Brothers in September 2008 where the market began to see large negative returns on almost all assets. On the other hand, however, between mid-2016 and the end of 2017, both the CDS spread and bond spread move a lot more in line with no mass fluctuation as seen between 2008-2009. This can be mostly associated the calmer market conditions where the contribution of less volatility and favourable macro-economic conditions allow for the CDS spread to align itself with the bond spread, suggesting that in favourable market conditions the no arbitrage theory between CDS and bond spread does hold weight.

3.2.4 Risk Free Rate:

In the literature review three versions of a risk-free rate were briefly discussed, firstly the use of LIBOR as the risk-free rate, secondly versions of the US Treasury rate and finally the corporate bond mid-yield spread. For the purposes of this paper, the risk-free rate used was US 5-yr treasury rate which was used to calculate the bond credit spread. In narrowing down this decision, LIBOR was eliminated as it is currently being phased out completely by the major financial markets which makes it no longer viable. The corporate bond mid-yield spread was excluded due to accessibility reasons. The accurate spread was calculated by computing the bond spread over the associated risk-free rate as the below computation illustrates, the aforementioned bond spread is the bid-ask spread of the bond i.e. the difference between the bid price and ask price of the bond assigned by Bloomberg.

$$\text{RABS} = \text{BS} / r_f$$

RABS = Risk-Adjusted Bond spread,

BS = Bond Spread

r_f = risk-free rate

These treasury rates can be extracted from the Department of Treasury website, freely accessible worldwide and are computed daily. Although, as the CDS and bond spread data were collected on a weekly basis and the treasury rate data is released daily, the treasury rates needed to be computed into a weekly average. From here the CDS basis was calculated, this is the difference between the Bloomberg risk adjusted CDS spread and the calculated bond spread.

3.2.5 Data Criticism:

When assessing the data used, the validity of the data must be mentioned. As the CDS spreads were not always available for many of the already matured bonds, the paper relied solely on the Bloomberg risk-adjusted CDS spread. Although very reliable in its robust valuation methods, there is no way of comparing this data for any possible inadequacies. The same issue arises with missing bond price data, many of the firms originally chosen had to be discarded due to either no data or large gaps at key time frames. In other related papers, Thomas Reuters DataStream was used to access the relevant data but unfortunately this is not something we had access to for the purposes of this paper.

3.3 Methodology:

The purpose of this paper is to add to the existing literature focusing on the theory of a linear relationship between CDS spreads and bond spreads. This paper will add to the existing literature by studying two-time frames, 2008-10 and 2016-18 with the aim of suggesting that there is correlation between the deviation of CDS spreads from the bond spread and the threat of systemic risk.

'Much of the data we collect will be collected over time, this gives a record of past performance and understanding of trends, if we can understand these past changes and trends over time, we can consider ways of projecting these forward for making forecasts about the future' (Curwin, J. & Slater, R. 2004). The purpose of carrying out such a comparative study is to identify trends and from these trends, actions can be taken to both mitigate future economic shocks and also prepare investors and regulators for any circumstances unforeseen previously. According Davis & Pecar (2013), regression analysis is used review the relationship between a dependant variable and one or more independent variables. In the case of this study, the two variables are the CDS spread and the bond spread and the author will look to find if the no arbitrage theory holds and if not, could it be a method used to predict systemic risk. Theoretically, the CDS spread should move in correlation with that of the bond spread. However, as the example above suggests, it is clear to see that market conditions can have quite an important role in rejecting the no arbitrage theory associated CDS and bonds. Below outlines the hypothesis of the paper and secondly the tests ran to test the theory.

3.3.1 Hypothesis:

A comparative study of CDS bond basis between 2008-10 & 2016-18 by analysing the correlation between large positive and negative movements of CDS and Bond spread and if this correlation could potentially be used a precursor for systemic risk.

- A study will be undertaken comparing the relationship between fourteen corporate bonds over a fixed maturity against a CDS on the same fourteen entities over a similar maturity.

As this hypothesis outlines that either the results will suggest CDS-Bond basis can or cannot be used as a determinant for predicting systemic risk, then there must be an alternative hypothesis to confirm. For the purposes of this study 'H_0' is outlined as the null hypothesis and 'Ha' is the alternative hypothesis.

H_0 – Yes, with reasonable level of confidence it can argued that both positive and negative CDS-Bond basis can be used as a further measurement of predicting systemic risk.

Ha – No, with strong level of confidence there is no basis to suggest CDS and bond spreads can determine systemic risk confirming the movements in these spreads are purely by chance.

3.3.2 Testing:

There is currently a large volume of literature on CDS and bond spreads that focuses heavily on the scope of pricing credit risk, through this existing literature there are two models for doing so. Firstly, the structural model assumes that default occurs when the process of describing the value of a firm hits a given boundary and is quite an extensive method of pricing credit derivatives. On the other and secondly there is the reduced-form approach or intensity-based models which assumes that the time of default or the price of default is specified or determined by a specific hazard rate. In comparing these methods, Alexopoulou, I. et al, Longstaff, et al. and Bystrom focused on the structural model of credit risk which appears to be the most robust method of pricing credit risk. However, this paper will not go into any more detail regarding credit risk and will not further contribute to any of this existing literature or any of these methods of pricing credit risk. Instead it will be structured similar to that of Blanco et all who published a paper analysing the dynamic relationship between investment grade bonds and credit default swaps. In following such a study, pricing methods of credit risk such as structural models and intensity-based models will be shelved and the aforementioned focus will be on the movements of the CDS spread from the bond spread. The following tests are outlined and critiqued for the purposes of studying CDS Bond-Basis and its theoretical association with systemic risk.

3.3.3 Mean and Standard Deviation:

Put simply, the mean of a set of quantitative data is the sum of the measurements, divided by the number of measurements contained in the data set i.e. if there are there is twenty results as part of a particular study, these are all added up and divided by the total number of results (n). This is the most basic form of the mean and is usually defined as the arithmetic mean. The arithmetic mean is essentially the average of all results and gives the person studying the data one result for the data set rather than a series of different values (McClave, J. & Sincich, T., 2014).

The formula for the mean is,

$$x = \sum x/n$$

∑x = sum of values in a dataset
n = total number of observations

Standard Deviation or otherwise known as variance on the other hand is the difference in the values of a dataset from the mean. Generally, the lower the standard deviation the closer the dataset is to the average. It is computed simply as the square root of the sum of squared deviations from the mean divided by n-1 where n is the number of observations (Waters, D. 2008). The standard deviation is quite useful in determining the validity of the average of the mean i.e. if a set values in a data set have large fluctuations, high and low. The higher values will skew the dataset average upwards; the purpose of the standard deviation will determine a more accurate assumption of how close the observations are to the average.

The formula for standard deviation is,

$$x = \sqrt{\sum(xi - \mu)}/n\text{-}1$$

xi = each of the values in a dataset

μ = mean of x values

n = number of observations

But in using the mean and standard deviation, the question is what purpose or additional value will these formulas or statistical results provide when analysing CDS and bond spreads. As discussed in the literature review, under normal financial market theory, the CDS is a product developed from the bond as it is essentially in its purest form an insurance contract issued in case of default on the aforementioned debt security. Therefore, in theory it can be assumed that there is a no arbitrage theory between CDS and bond spreads. The purpose of using the mean and standard deviation is to test this theory at its simplest form, if the mean of the CDS and the bond are the same or relatively similar we assume no arbitrage theory exists and if not then we can assume that there is very little relationship between the variables. Under scrutiny, the mean and standard deviation of the CDS and bond spread should be similar in periods of calm market conditions and show huge differences in periods where there is high volatility in the markets such as in 2016-19 and 2008-10 respectively. The issue with the mean and standard deviation is that they are restricted to confirming averages and variances which do not provide sufficient data to suggest any correlation between variables, therefore it is a good method of finding if there is a basic relationship but they need to be used together with models and other statistical calculations to prove their validity.

3.3.4 Pearson's Correlation of Coefficients:

There are many occasions in business and finance when changes in one variable appear to be related in some way to movements in one or several other variables. Certain questions do arise such as are the movements of these variables occurring in the same or opposite direction such as in the situation of the prices and the yield on a bond, or is there a causal relationship involved where by one variable changes another or are these changes or movements purely by chance (Lucey, T. 2002).

Covariance is defined as the directional relationship between the movements in different assets, it measures the strength of a relationship between two variances but is limited to this and does not go as far as proving the cause of or the effect of the relationship. Taken as example, there may be a relationship between the movements of two variables but this does not necessarily mean they have legitimate association with each other. For the purposes of this paper, covariance alone would not provide sufficient evidence that there is relationship between CDS spreads and bond spreads. The correlation statistical method not only focuses upon similar movements between variables but also calculates whether these variables are somehow associated with one another. The correlation measure calculates this association using either positive or negative values in the same or different directions and is confirmed between the numbers -1 and 1. A result greater than 1 or less than -1 suggests an error in the correlation measure whereas a measurement of exactly -1 or 1 is defined as perfect positive or negative correlation. Finally, a result of 0 in a correlation coefficient test confirms there is no statistical relationship between the variables. The closer these results come to 1 or -1, the stronger the relationship between them (Davis, G. & Pecar, B. 2013). The correlation coefficient method is outlined as below,

$$rxy = \sum(xi - \bar{x}) (yi - \bar{y}) /\sqrt{\sum(xi - \bar{x})^2 \sum(yi - \bar{y})^2}$$

$\mathbf{r_{xy}}$ – the correlation coefficient of the linear relationship between the variables x and y

$\mathbf{x_i}$ – the values of the x-variable in a sample

$\bar{\mathbf{x}}$ – the mean of the values of the x-variable

$\mathbf{y_i}$ – the values of the y-variable in a sample

$\bar{\mathbf{y}}$ – the mean of the values of the y-variable

The Pearson correlation coefficient is the statistical method used to see if there is a correlation between two continuous variables, it is quite robust as it is based on the method of covariance which is outlined above. In this case the variables are CDS spreads and bond spreads (Davis, G. & Pecar, B. 2013). The purpose of using this study is to compare both time series, 2008-10 and 2016-18 respectively to see if there is a strong Pearson correlation coefficient between the variables. What the author is suggesting here is that if there is positive/negative correlation between the variables in 2016-18 and less of such a relationship between 2008-10 then it can be assumed that adverse market conditions effect the relationship between CDS spreads and bond spreads and therefore the deviation of these variables could potentially be used as a way of predicting adverse market conditions and therefore be used to potentially predict systemic risk (Curwin, J. & Slater, R. 2004).

3.3.5 Linear/Logistic Regression:

Regression analysis is a statistical and predictive method of modelling that focuses on the relationship between a dependent and independent variable where by the independent variable is the predictor and the dependent variable is the target (Lucey, T. 2002). The regression analysis model can be used in most situations where there are two variables in which one variable is dependent on another and if such independent variable should change then we can assume the dependent should follow in a similar fashion.

Linear regression provides the foundation for many of the statistical regression models as it attempts to determine the best fit line between the X and Y variables or the independent and dependent variables. Linear regression is normally modelled as below,

$$Y = a + b*X + e$$

Y = Dependent Variable

X = Independent Variable

a = intercept between the variables

b = slope of the line

e = the error term

The interesting aspect of linear regression is that it provides quite a lot of rigorous results for such a simple test such as correlation details which was discussed earlier in this paper. There is also a heavy focus put upon the descriptive statistical aspect of the data in linear regression which outlines the means, standard deviations and the overall relationship between the tested variables. Finally, linear regression outlines the strength of a relationship the independent variable studied has upon the movement of the dependent variable through its r_2 function.

The biggest issue that appears to exist with linear regression however is that it is very sensitive to outliers. Outliers are the values that exist in the scatter plot but do not coexist with other results that make up the best fit line of regression, they however exist with a large variation from other results that then skew the outcome of the linear regression model. For example, if linear regression is being undertaken to test if income is affected by age and the sample of individuals studied are between the ages of 20-65 and the income varies between $25000-$85000, then an individual that is 85 will cause an outlier which can in turn skews the best placed regression line which therefore can make the results unreliable.

Logistic regression on the other hand is a type of regression that attempts to find the probability of success or failure on a given set of variables i.e. true/false, yes/no and 0/1. The purposes of using such a model is when one variable i.e. the dependent variable is directly affected by the change in another variable.
Logistic regression is modelled as below,

$$\text{Odds} = p / (1 - p)$$

Where p = is the probability of an event occurring.

(Ray, S. 2015)

Generally speaking, in this model $p / (1 - p)$ is defined as the probability of an event occurring over the probability of the same event not occurring. The issue with logistic regression is that it can only be used successfully if each variable used in the statistical analysis has ten samples or more, this is simply due to the fact that the results cannot be reliable if the sample size is to small and therefore a minimum number of samples per variable is required.

For the purposes of this paper though, linear regression will be used as opposed to logistic regression. The aim of the paper is to analyse if the relationship between CDS spreads and bond spreads can be a method of determining systemic risk and the decoupling/deviation of the CDS spreads from the bond spreads over separate time periods is the test subject. Logistic regression determines the result into a yes/no or true/false characterization which is not what the results of testing these variables will do. CDS spreads and bond spreads didn't or will not cause systemic risk and therefore logistic regression is an unreliable test. Linear regression on the other hand, will provide in-depth analysis of the relationship between the variables which when compared against the timeframes that the data was drawn from, will allow the author to make assumptions of whether the deviation of CDS spreads from bond spreads is a valid method for potentially predicting systemic risk.

3.6 Comparative Measures

3.6.1 Inverted Yield Curve:

The yield curve is a line that plots the interest rates of a specific bond over a set period of time graphically and compares these yield curves over different maturities. The most relevant and frequently reported yield curves are the ones associated with US treasury debt i.e. US government debt. US treasury debt has multiple different maturities ranging from 3-months to thirty years, the most used treasury yield curves are the 3 month, 2yr, 5yr, 10yr and 30yr yield curves. The US treasury department issues these bonds and as the bonds with longer maturities usually carry higher risk, such bonds demand higher yields than those of shorter maturities. On this basis, the 30-yr US treasury bond should yield higher than the 10yr bond which then should yield higher than the 3-month treasury note and so on. As discussed, the logic is based upon risk, without providing a higher yield to take on 30yr government debt, there is no incentive from a risk and return perspective and an investor would only ever invest in 3month treasury debt in a risk averse measure (Yahoo Finance, 2019). The interesting aspect about treasury yields is that they are often used as a leading indicator of both investor and economic confidence i.e. when the yields correspond how the market would like them to perceived such as long term debt yielding higher than short term debt then it is a sign of good economic conditions (Wright, J.H. 2007). The aspect of the treasury yield that is quite interesting is the inversion of these curves and its relationship with recessions.

The inverted yield curve is phenomenon that occurs when shorter-term bond yields climb above longer-term bond yields over the course of a number of months and usually tends to occur before a recession. Yet the interesting part about the inverted yield curve is that although it is a key market barometer of the risk of future recessions, economic growth generally remains steady and the labour market strength persists which potentially asks the question if the inverted yield is actually a valid predictor of an coming recession (Kruger, D & Santilli, P. 2019). Taking a look at the yield curves over the two periods discussed throughout this paper, we can see the evidence of where the yield curve has both inverted and where long-term treasury bonds and medium-term treasury bonds yield the same.

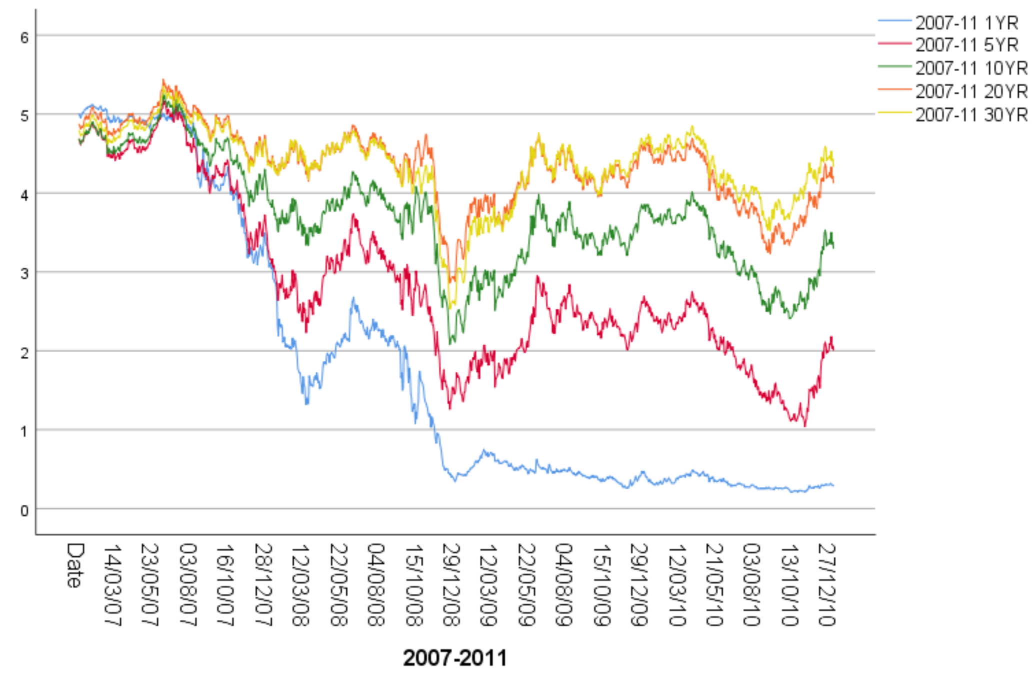

Table 3.1 – 2007-2011, 1yr, 5yr, 10yr, 20yr & 30yr US Treasury Yield Curve.

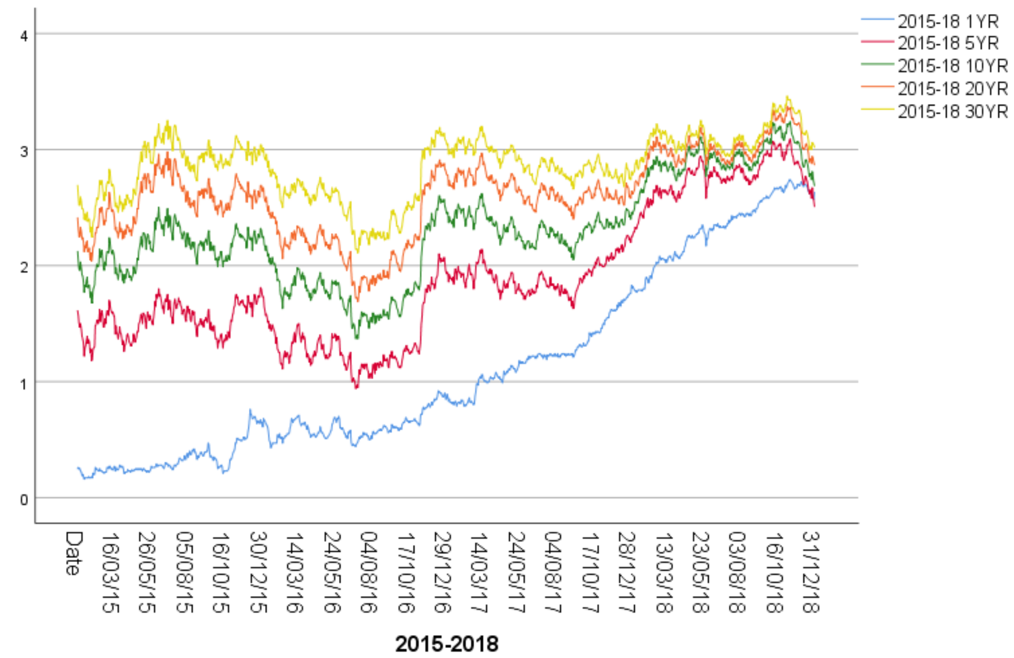

Table 3.2 – 2015-2018, 1yr, 5yr, 10yr, 20yr & 30yr US Treasury Yield Curve.

Through the years 2007-2010, we can see that 30yr treasury bonds were yielding the same rate or lower than the 20yr and 10yr treasury bonds specifically in 2007 where there was assumption that on recession was on its way. This transpired to be true and the inverted yield curve turned out to be extremely accurate. Between 2016 and 2018 however, we can see that the rates yielding for the longer-term bonds are substantially higher than that of the short term and medium-term bonds which is significant sign that the American economy and therefore world economy is in a healthy position. In 2018, we can see the rates tightening quite a lot which can be attributed to the Federal Reserve's monetary tightening exercises. The question though is what has the inverted yield curve got to do with the CDS bond basis. As discussed, the inverted yield curve is a key parameter used by economists, central banks and financiers to predict recessions and how healthy an economy is. The purpose of this paper is to find out if the diversion of CDS from its bond spread can be a valid method of predicting systemic risk. By comparing our theory with a known and already robust method of predicting economic slowdown and therefore recessions, we can make the argument that CDS bond basis has the ability to replicate what the inverted yield curve does and therefore it could potentially be used as a valid measure of predicting economic shocks and/or systemic risk.

3.7 Concluding Remarks:

Previous literature on this topic has suggested quite a strong relationship between CDS spreads and bond spreads and descriptions and studies in the topic area have only grown exponentially since the financial crisis where CDS soaked up quite a lot of blame. It is quite interesting to note that although quite a substantial volume of literature has been published in this area, the original material that set the foundations for all future work appear to still hold quite substantial weight in the debate. The aim of this paper is to add to this existing literature but with an aim of viewing the deviation of CDS spread from the bond spread as a predicator or signal of systemic risk. In the analysis and test results section, the information gathered from the tests through SPSS will look to provide sufficient evidence of this theory and if not reasons to the contrary.

4.1 Data Analysis and Discussion:

This section will outline the empirical results of the paper and the aim will be to analyse and critique these based upon what was outlined in the data and methodology section. The chapter will be broken down into two key areas, the data analysis which will be divided into various different sub headings and the discussion of the results with specific reference to the hypothesis, methodology and overall research question. In concluding this chapter, the author will use the analysis of the results to determine firstly if with a reasonable level of confidence that both positive and negative CDS-Bond basis can be used as a further measurement of predicting systemic risk and secondly does the data provide evidence of this to answer the research question. The discussion aspect of this chapter will outline reasons for why it does or does not answer the research question.

4.2 Data Analysis:

4.2.1 Explanation of Techniques Used:

As was outlined in the data and methodology section, the statistical tests ran to outline the relationship between CDS and bond spreads specifically focused upon mean, standard deviation, correlation and regression. Pearson correlation of coefficients was the statistical tool used for the correlation and covariance. Linear regression was the main tool used in studying the regression relationship. Through linear regression, the author focused upon r_2, F tests through ANOVA and the coefficient values of each CDS/bond relationship. Finally, in comparing the difference in CDS bond basis and attempting to use the large differentiations in this basis as a method of anticipating systemic risk, one must look at other relevant metrics used worldwide to predict potential economic shocks. One such method and as discussed in the methodology is the inverted yield curve and a comparison will be made between CDS spreads and said inverted yield curve.

4.3 Test Analysis:

4.3.1 Mean & Standard Deviation:

	CDS		BOND			CDS		BOND	
2008-2010	**MEAN**	**STD DEV**	**MEAN**	**STD DEV**	**2016-2018**	**MEAN**	**STD DEV**	**MEAN**	**STD DEV**
AIG	565.49	317.29	36.73	8.31	**AIG**	79.71	15.04	67.45	19.77
BONY	322.66	172.69	46.77	7.66	**BONY**	117.76	29.16	59.91	16.69
BOA	125.74	49.75	42.82	5.12	**BOA**	71.8	23.01	64.87	19.01
BANK OF CAN	60.83	34.36	36.48	10.21	**BANK OF CAN**	79.62	16.19	60.96	14.01
CAPITAL ONE	368.94	178.96	44.44	8.51	**CAPITAL ONE**	132.77	33.21	59.43	16.33
CITI BANK	213.05	115.82	42.53	5.89	**CITI BANK**	77.96	20.31	59.74	16.47
HSBC	99.18	32.5	46.74	8.35	**HSBC**	77.84	15.44	59.21	16.68
JP MORGAN	110.09	32.51	46.05	6.08	**JP MORGAN**	64.05	17.11	59.55	16.44
MIZUHO BANK	268.78	85.54	50.12	2.54	**MIZUHO BANK**	54.30	11.96	59.9	16.64
MORGAN STAN	252.34	140.03	44.91	8	**MORGAN STAN**	154.85	27.84	64.2	18.73
MUFJ	219.45	63.77	50.82	3.6	**MUFJ**	N/A	N/A	N/A	N/A
RBS	152.51	63.07	14.15	6.14	**RBS**	116.6	34.64	59.95	15.09
STATE STREET	385.16	251.88	46.54	6.1	**STATE STREET**	108.58	24.69	63.15	16.19
WELLS FARGO	119.09	40.31	46.35	7.42	**WELLS FARGO**	56.51	12.29	60.69	17.11

Table 4.1 – MEAN & STANDARD DEVIATION

Looking firstly at the mean and standard deviation of both the bond spreads and CDS from both periods included in the study. It is firstly quite clear the large differences between the mean and standard deviations of each firms' bond and their CDS in the period 2008-2010. Throughout all the firms, all the means on CDS are much greater than that of the underlying bond. We can see no relationship where the mean on the bond corresponds with the mean on the CDS spread. This too is also the case with the standard deviation which as discussed applies a more fundamental test that reverses the skewness of mean testing. This level of difference in means and standard deviations in the period of 2008-2010 calls in to question the no arbitrage relationship that is theoretically supposed to exist between CDS and bond spreads. It would appear in these circumstances that an arbitrage relationship does exist. What the above mean and standard deviation data suggests is at the most basic level, the highly volatile market that existed between 2008-2010 can potentially be the cause for the deviation of the spreads which translates into vastly different means and standard deviations between the variables.

On the contrary however, between 2016-2018 the means and standard deviations appear to resemble a more theoretical no arbitrage relationship. What is noticeable about the results is that there is quite a lot of consistency between the CDS and bond spreads, although we do see some outliers such as RBS which appears to have a much higher standard deviation on its CDS than on its bond, although other than that the relationships between means and standard deviations are quite consistent. Outside of that, we can see large variations in the means on the CDS and this is due mainly to the larger overall changes in the CDS spreads which skews the overall mean. The standard deviation on both CDS and bond spread provides a clearer analysis suggesting that in more stable market conditions, there is little difference between the CDS and bond spread. However, the issue with mean and standard deviations is that they are based upon averages and the sum of variables and do not provide enough statistical significance on their own to make assumptions about the relationship between these variables and whether we could use CDS-Bond basis as a metric for predicting systemic risk.

4.3.2 Correlation:

Correlation is the statistical analysis focusing upon the relationship between variables and whether one variable affects another. It is normally carried out between two bivariate variables to extract the relationship between them. Pearson correlation coefficient as outlined in the methodology was the method used in this study.

	CDS/BOND			CDS/BOND	
2008-2010	**PEARSON**	**Sig. 2 tailed**	**2016-2019**	**PEARSON**	**Sig. 2 tailed**
AIG	-0.436	0.000	**AIG**	0.683	0.000
BONY	-0.21	0.805	**BONY**	0.573	0.000
BOA	0.202	0.035	**BOA**	0.700	0.000
BOC	0.667	0.000	**BOC**	0.188	0.020
CAPITAL ONE	-0.121	0.163	**CAPITAL ONE**	0.66	0.000
CITI BANK	0.231	0.015	**CITI BANK**	0.611	0.000
HSBC	0.403	0.000	**HSBC**	0.647	0.000
JP MORGAN	0.062	0.489	**JP MORGAN**	0.69	0.000
MIZUHO BANK	-0.588	0.000	**MIZUHO BANK**	0.301	0.000
MORGAN STAN	-0.28	0.001	**MORGAN STAN**	0.691	0.000
MUFJ	-0.455	0.000	**MUFJ**	N/A	N/A
RBS	0.366	0.000	**RBS**	0.708	0.000
STATE STREET	-0.53	0.538	**STATE STREET**	0.813	0.000
WELLS FARGO	0.171	0.049	**WELLS FARGO**	0.654	0.000

TABLE 4.2 – PEARSON CORRELATION OF COEFFICIENT

In in order to get an understanding of the relative impact of the results above, the significant factor of the Pearson correlation is what we must first focus on. The study was conducted at a 95% level of significance i.e. if the value of the significant factor is below 0.05 then the results are significant. What is also worth mentioning, particularly between 2016-

2018 is that the significance of the results increased to a 0.01. This states that the results are significant to 99% confidence level which makes them quite compelling in the overall context of the analysis. However, there is a quite a few instances where the significance is above 0.05 especially between 2008-2010 suggesting the relationship between the variables are either poorly correlated or the results are insignificant.

The totality of the Pearson correlation statistical study is based upon one result. As discussed thoroughly in the methodology, the study of correlation is based upon results within the parameters of -1 and 1, the closer the value is to either -1 or 1, the stronger the correlative relationship is. Focusing firstly upon 2008-2010, nine of the entities suggest there is very littles correlation between the CDS and the bond spreads. Three out of the five entities have moderate significant correlation and only one entity where there is a significant relationship between the variables, that being the Bank of Canada. In comparison, eleven entities between 2016-2018 show a strong correlative relationship, interestingly the one entity with a low level of correlation is also Bank of Canada which had a strong level significance between 2008-2010. So, what do results suggest? Essentially, between 2016-2019, 78% of the firms studied test for a significant level of correlation between the CDS and bond spread. It can be therefore assumed that there is a strong evidence to suggest that in periods of low volatility and positive economic activity, bond spreads and CDS do correlate leaving little arbitrage to be achieved. On the other hand, 64% of the entities in the study showed next to no correlation between 2008-2010 further implying that in periods of market distress the lack of correlation between CDS and bond spreads assumes CDS spreads do react quite quickly to market forces and could potentially be used in the study of economic shocks.

4.3.3 Regression:

	CDS/BOND				CDS/BOND		
2008-2010	**r2**	**f-statistic**	**Coefficient**	**2016-2018**	**r2**	**f-statistic**	**Coefficient**
AIG	0.19	25.327	1177.12	**AIG**	0.466	94.236	-3.341
BONY	0.000	0.061	345.285	**BONY**	0.329	65.154	48.087
BOA	0.041	4.575	39.679	**BOA**	0.490	127.766	7.803
BOC	0.445	120.121	-21.049	**BOC**	0.035	5.513	34.576
CAPITAL ONE	0.015	1.967	481.770	**CAPITAL ONE**	0.436	102.850	40.435
CITI BANK	0.053	6.157	19.737	**CITI BANK**	0.374	79.353	25.778
HSBC	0.162	25.785	26.298	**HSBC**	0.418	79.157	39.387
JP MORGAN	0.004	0.481	94.909	**JP MORGAN**	0.475	120.570	15.032
MIZUHO BANK	0.345	35.317	1262.420	**MIZUHO BANK**	0.090	13.230	39.271
MORGAN STAN	0.078	11.280	472.059	**MORGAN STAN**	0.478	121.835	77.790
MUFJ	0.207	21.785	627.987	**MUFJ**	N/A	N/A	N/A
RBS	0.134	20.598	-17.173	**RBS**	0.501	133.579	8.513
STATE STREET	0.003	0.382	486.954	**STATE STREET**	0.661	259.128	21.923
WELLS FARGO	0.029	3.965	76.131	**WELLS FARGO**	0.428	99.439	23.473

Table 4.3 – Linear Regression Analysis

Unlike the Pearson correlation, mean and standard deviation derivations, regression analysis is spread across a number of statistical results that when used together provide analysis on the overall relationship between the dependent and independent variables. The r^2 statistic is actually very closely related to that of correlation calculation, it computes the percentage variability of the dependent variable based upon the independent variable. Assuming that bond spread does in fact effect the value of the CDS which under the theory of no arbitrage it should then the r^2 value should theoretically be pertinent. However, in reviewing the results this isn't necessarily always the case. Through 2008-2010 respectively, apart from the Bank of Canada there was no other significant correlation between any of the rest of the variables. Out of the fourteen firms studied, only three entities show that the variability in CDS is slightly dependent of the change in bond spread with the highest value being 44.5%. With respect to the period between 2016-2018, nine out of the fourteen entities studies show significantly higher values i.e. 40% of the variability in these entities CDS can be assumed by the bond spread. Again, Bank of Canada as was with the mean, standard deviation and correlation is the biggest outlier in the results.

The coefficient value is used to describe what level of change the independent variable would effectively have on the dependent value but rather than studying a positive or negative change in the independent variable value, we look at what the value of dependent variable i.e. CDS would be if the bond spread dropped to a value of zero. In comparing the timeframes, there is significant differences. Between 2016-2018 and outside of the Morgan Stanley coefficient value, all other values suggest that if the bond spread were lowered to a value of zero, the CDS spread would follow to a similarly low value, the results confirm this as we see by evidence of the coefficient of each firm value. On the other hand, 2008-2010 paints a different picture, when the bond spread is at zero between these timeframes, we see it has very little impact upon the CDS spread which therefore suggests that decoupling between these variables has taken effect providing enormous opportunity to capture arbitrage.

The f statistic/f value is computed within a one-way ANOVA test and the test is used to find out if the relationship between variables is statistically significant. It is usually used after a correlation has been performed so as to add further evidence to the significance between a specific set of variables. Essentially the higher the f value computed where the results are at or below the level of significance the stronger the significance is assumed to be. In assessing the results on this basis, within the period of 2016-2018, twelve out of fourteen financial institutions suggest that a significant relationship between the variables exists which computes into 85% of the total results of the study. On the contrary, 57% of the entities in 2008-2010 have computed f values quite close to zero meaning there is a very frugal, if not non-existent relationship between the variables furthering the argument that in uncertain market conditions the ability of bond spreads to assume the value of CDS spreads is quite minimal.

4.3.4 Inverted Yield Curve Assumption:

As discussed in the methodology section, the inverted yield curve is an industry wide used parameter for predicting a future recession. To put this information into perspective, an inverted or humped yield curve has occurred no more than five quarters before every recession since the mid-1950s. Except it occurred in quarter three before the 1990-1991 recession, proving the yield curve has inverted before every recession since the mid-1960s (Cwik, P.F. 2016).

The statistics speak for themselves that in every decade in the last half century before a recession occurred in the US economy, there was inverted yield curve. In the analysis above, it suggests that there is a strong correlation between CDS and bond spreads between 2016-

2018 while the correlation is very limited if not non-existent between 2008-2010. The level of significance in the period between 2016-2018 was always below 0.01 suggesting how significant the correlation was between 2016-2018 and was not between 2008-2010. It was noted when testing the data for the paper, CDS spreads in many of the entity's studied began to really deviate from their respective bond spread in the wake of the collapse of Lehman Brothers in September 2008. However, the yield curve had already inverted at this stage as was previously noted in a graphical explanation.

So, what can be assumed from this? Firstly, CDS spreads act independently from bond spreads in periods similar to when the yield curve becomes inverted or not long after. Some critics argue that due to the labour market remaining consistent and economic indicators acting similarly, confirming that the inverted yield curve isn't all that reliable in its predictive prowess. So in theory, there is potential opportunity to use the highly volatile nature of CDS spreads in times after the yield curve has inverted to solidify the idea that a potential economic slowdown or recession is about to occur, condemning critics that it isn't a reliable metric and also using CDS for more reasons other than to hedge risk. This could possibly speak volumes in arguing for the further use of CDS spreads for a more proactive role in the global financial market rather than their current role. This will be further elaborated on in the discussion aspect of the paper.

4.4 Discussion:

Having looked at CDS bond basis from both a literature and quantitative perspective, the aim of the discussion aspect of this paper is to address the research question through the quantitative results and determine if it meets the criteria to satisfy the hypothesis and from there whether it ultimately answers said research question. The research question proposes the following, can the divergence of an entities CDS spread from its reference bond spread be used as a method for predicting systemic risk. The last aspect of this discussion will look at the limitations of the paper and how these could be overcome as well as what further research could look like in the area.

4.4.1 Hypothesis:

Throughout the paper it was discussed that although a CDS contract exists because of its relationship to a particular bond, this does not necessarily mean they have the same characteristics. The previous literature suggests that due to the highly liquid nature of CDS, they move much quicker with market forces than that of the bond spread which in contrast has its fundamental changes rooted in macro environment fundamentals like interest rates, equity market returns and term structure. It was also noted that the 80% of price discovery can be found in the CDS market over the bond market. Finally, CDS spreads are more sensitive to changes that may cause systemic risk than that of bond spreads. Specifically, the main objective of this paper was to study the sensitivity of CDS spreads when it is faced with systemic risk and to investigate whether the separation of CDS from their bond spreads could potentially be used as a valid metric for predicting systemic risk. The (null) hypothesis is based upon this and aims to prove with a reasonable level of confidence that the positive and negative movements in CDS spreads can be a further measure of predicting systemic risk with the alternative hypothesis suggesting that there is no basis to suggest this deviation can determine systemic risk and these fluctuations are purely based upon chance.

Comparing the time frames with respect to the hypothesis, the correlation relationship and regression analysis confirm similar details in each timeframe. Between 2008-2010, there is very little correlation between the variables except for one outlier in the testing which makes it statistically insignificant in the overall context of the results. Regression analysis paints a similar picture through its r^2, coefficient and f-statistic results where we see that the variables are both technically independent of one another. On the contrary however, the period between 2016-2018 confirms a vastly different set of results. Outside of one or two outliers in the correlation relationship, there is quite significant relationships between the CDS and bond spreads. This is also the case in the regression analysis and through the results of the means and standard deviations. By putting these results into context, 2008-2010 was a timeframe of vastly volatile markets where investors looked to minimize losses at all costs whereas 2016-2018 is seen as time period of market confidence, economic growth and lower risk. We can see that in the initial time frame CDS actually translates into an independent variable as it no longer correlates and moves independently from that of the bond spread. Where both variables are independent there will be no relationship and this appears to be the scenario between CDS and bond spreads. Circling back, yes with a reasonable level of confidence we can assume that the movement of CDS spreads both positively or negatively can be used as method of predicting systemic risk based upon the timeframes conducted in the study. Thus, we reject the alternative hypothesis in favour of the null hypothesis.

4.4.2 Research Question:

The research question was developed with an aim to fill in a gap in the current literature where a comparative study of CDS and bond spreads had not been conducted. To the best of the authors knowledge and at the time of writing, no other paper has focused upon this specific topic area. The aim of policy makers is to implement legislation and measures to stop recessions or at least curb their effect. However, this can only be done if the metrics used in predicting such scenarios are accurate. Currently there are many metrics and without these the accurate policies would not be implemented. The questions outstanding currently are, can the movement of CDS spreads actually be trusted as a metric for predicting systemic risk with its previous involvement in the financial crisis and does the data presented sufficiently answer the research question.

Since 2008, CDS have been riddled with controversy and no matter how much time has passed, this reputation still exists. A good example to compare CDS with is the negativity associated with the inverted yield curve. Instead of it being used to describe the bearish attitude of investors, it is associated with recessions. This reputation has built up over the last sixty years and causes the financial market to reduce to turmoil when it occurs. In viewing CDS and CDS spread movements as a potential risk measurement, it is hard to see the uptake and this is not due to reliability but rather its reputation. So, are CDS spreads a reliable metric of predicting systemic risk? The previous literature confirms that due to their highly liquid nature, they are susceptible to vast fluctuations in investor sentiment which therefore means they move quite substantially with negative market changes. The data results of this paper suggest that in times of volatility, CDS will deviate from their respective bond spreads and act independently. What this tells us that yes, the CDS spreads have the potential to act as a metric in predicting systemic risk, however due to the nature of their creation and their involvement in the financial crisis, the potential of them being used in such a manner is minimal.

The data derived argues that yes in times of market uncertainty, CDS spreads will act differently to that of their respective bond spread and will only begin to correlate once again when this uncertainty subsides. This is in comparison to periods of economic growth where we see significant correlation between the movements of CDS and bond spreads. Therefore, in answering the research question. Yes, the paper has found statistical evidence to suggest that the divergence of CDS from their respective bond spreads could potentially be used as a method of predicting systemic risk. However, as this is the first comparative study of its kind between CDS and bond spreads these results no doubt come with limitations.

4.5 Limitations of this study:

4.5.1 Limited Sample Size

The study used fourteen entities in the study that incorporated fixed rate coupon bonds with a fixed maturity that were currently in their final cycle before maturity. The issue with such a study is that entities must have fixed rate coupon bonds in both time frames with underlying CDS contracts. It was quite difficult to source entities with bonds and CDS in both timeframes which therefore limited the capacity of the study and potentially the results.

4.5.2 Industry Imbalance

The data used in the study focused specifically on large publicly listed firms in the financial sector. Entities from the tech, airline, oil and car manufacturing industries were excluded but from previous studies it was noted that firms from these industries were incorporated. The difficulty was that many of these firms didn’t meet the criteria for what was required i.e. as explained in the limited sample size above. The issue with only using one industry is the study could be scrutinized for bias. However, it should be noted, the analysis for this paper did produce statistically significant results for the financial industry.

4.6 Recommendations for Further Research:

The main issue when investigating the objectives of this study was the limited number of valid firms that could potentially be studied on the basis of missing data in key times frames and no valid firms in specific industries. Using the research conducted in this paper, the following areas and objectives are recommended for further study.

- Can a similar set of results be gathered if the sample size increases to include all firms listed on the iTraxx index and if not, what are the fundamental differences?
- What kind of results would be achieved if the study was conducted in the same time frame on euro denominated debt where there is a larger regulation on CDS contracts?
- Could more information be gathered from using speculative graded bonds instead of investment grade bonds and how would the results differ from the current study?

5.1 Conclusion:

In the decade since the recession, the focus of many of the major central banks was to implement measures and legislation so as to guarantee the mistakes of the past will not be repeated. This included legislation such as the Dodd-Frank, Basel III and an array of other measures where the ECB leads the Federal Reserve in implementing such measures to curb a future recession. The interesting aspect about the current timeframe is that now more than ever, after a prosperous number of years where economic growth has sky rocketed and returns on equities has also hit the same trajectory, the aim of economists and financiers should be to focus on measures to predict economic downturns and recession as the business cycle comes to an end. The focus of this paper was to analyse the differentiating relationship between CDS and bond spreads in both a period of volatility and economic growth and argue whether it could potentially be used as a metric for predicting systemic risk alongside other measures currently used.

The empirical data suggests that CDS spreads move with market sentiment and do deviate from the respective bond spreads in times of economic unrest and therefore could potentially be analysed for arguing that a future recession is imminent. The hypothesis set out to potentially prove such a theory and with a sufficient level of confidence it can be argued that positive and negative movements of CDS from their respective bond spread has the possible potential to predict systemic risk. However, the largest issue facing CDS going forward is the reputational damage sustained throughout the financial crisis where it took a large amount of blame for the recession. This will make it quite difficult for members of central banks and economists alike to ever really trust the predictability of CDS as a metric without being scrutinized for using a product that had a large role in the financial crisis. Nonetheless, this does not diminish the ability of CDS to do so. In addition, the research conducted in this paper could be used as benchmark for further study with regards to the association between CDS bond basis and systemic risk where a more complex and robust model could be developed to prove or disprove the theory.

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7.1 Appendices:

2008-2010

CITI BANK:

Security	ED818977 Corp
Start Date	05/01/2007 00:00
End Date	12/02/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		CITI CDS 08-10	CITI BOND 08-10	CITI CDS 16-18	CITI BOND 16-18
N	Valid	111	111	135	135
	Missing	24	24	0	0
Mean		213.0541	42.5340	77.9630	59.7419
Std. Deviation		115.82077	5.89245	20.31006	16.46486

Statistics

		CITI CDS 08-10	CITI BOND 08-10	CITI CDS 16-18	CITI BOND 16-18
N	Valid	111	111	135	135
	Missing	24	24	0	0
Mean		213.0541	42.5340	77.9630	59.7419
Std. Deviation		115.82077	5.89245	20.31006	16.46486

Correlations

		CITI CDS 08-10	CITI BOND 08-10
CITI CDS 08-10	Pearson Correlation	1	.231*
	Sig. (2-tailed)		.015
	N	111	111
CITI BOND 08-10	Pearson Correlation	.231*	1
	Sig. (2-tailed)	.015	
	N	111	111

*. Correlation is significant at the 0.05 level (2-tailed).

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.231[a]	.053	.045	113.19765

a. Predictors: (Constant), CITI BOND 08-10

b. Dependent Variable: CITI CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	78895.475	1	78895.475	6.157	.015[b]
	Residual	1396694.201	109	12813.708		
	Total	1475589.676	110			

a. Dependent Variable: CITI CDS 08-10

b. Predictors: (Constant), CITI BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	19.737	78.645		.251	.802	-136.135	175.609
	CITI BOND 08-10	4.545	1.832	.231	2.481	.015	.915	8.175

a. Dependent Variable: CITI CDS 08-10

Bank of New York (BNY)

Security	EF813976 Corp
Start Date	02/02/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		BNY CDS 08-10	BNY BOND 08-10	BNY CDS 16-18	BNY BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		322.6519	46.7775	117.7630	59.9085
Std. Deviation		172.69706	7.66024	29.16300	16.69156

Correlations

		BNY CDS 08-10	BNY BOND 08-10
BNY CDS 08-10	Pearson Correlation	1	-.021
	Sig. (2-tailed)		.805
	N	135	135
BNY BOND 16-18	Pearson Correlation	-.021	1
	Sig. (2-tailed)	.805	
	N	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.021[a]	.000	-.007	173.30515

a. Predictors: (Constant), BNY BOND 08-10

b. Dependent Variable: BNY CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1840.870	1	1840.870	.061	.805[b]
	Residual	3994611.767	133	30034.675		
	Total	3996452.637	134			

a. Dependent Variable: BNY CDS 08-10

b. Predictors: (Constant), BNY BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	345.285	92.631		3.728	.000	162.064	528.507
	BNY BOND 08-10	-.484	1.954	-.021	-.248	.805	-4.350	3.382

a. Dependent Variable: BNY CDS 08-10

AIG:

Security	EF771861 Corp
Start Date	05/01/2007 00:00
End Date	05/02/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		AIG CDS 08-10	AIG BOND 08-10	AIG CDS 16-18	AIG BOND 16-18
N	Valid	110	110	135	135
	Missing	25	25	0	0
Mean		565.4909	36.7256	79.7111	67.4543
Std. Deviation		317.49879	8.30908	15.04663	19.77281

Correlations

		AIG CDS 08-10	AIG BOND 08-10
AIG CDS 08-10	Pearson Correlation	1	-.436**
	Sig. (2-tailed)		.000
	N	110	110
AIG BOND 08-10	Pearson Correlation	-.436**	1
	Sig. (2-tailed)	.000	
	N	110	110

**. Correlation is significant at the 0.01 level (2-tailed).

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.436[a]	.190	.182	287.07592

a. Predictors: (Constant), AIG BOND 08-10

b. Dependent Variable: AIG CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2087238.239	1	2087238.239	25.327	.000[b]
	Residual	8900559.252	108	82412.586		
	Total	10987797.491	109			

a. Dependent Variable: AIG CDS 08-10

b. Predictors: (Constant), AIG BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1177.122	124.579		9.449	.000	930.185	1424.058
	AIG BOND 08-10	-16.654	3.309	-.436	-5.033	.000	-23.214	-10.095

a. Dependent Variable: AIG CDS 08-10

Bank of America:

Security	EC226702 Corp
Start Date	05/01/2007 00:00
End Date	29/01/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		BOA CDS 08-10	BOA BOND 08-10	BOA CDS 16-18	BOA BOND 16-18
N	Valid	109	109	135	135
	Missing	26	26	0	0
Mean		125.7339	43.8172	71.8000	64.8741
Std. Deviation		49.74298	5.12865	23.00642	19.00066

Correlations

		BOA CDS 08-10	BOA BOND 08-10
Pearson Correlation	BOA CDS 08-10	1.000	.202
	BOA BOND 08-10	.202	1.000
Sig. (1-tailed)	BOA CDS 08-10	.	.017
	BOA BOND 08-10	.017	.
N	BOA CDS 08-10	109	109
	BOA BOND 08-10	109	109

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.202[a]	.041	.032	48.93963

a. Predictors: (Constant), BOA BOND 08-10

b. Dependent Variable: BOA CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10956.982	1	10956.982	4.575	.035[b]
	Residual	256274.303	107	2395.087		
	Total	267231.284	108			

a. Dependent Variable: BOA CDS 08-10

b. Predictors: (Constant), BOA BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	39.679	40.506		.980	.329	-40.619	119.977
	BOA BOND 08-10	1.964	.918	.202	2.139	.035	.144	3.784

a. Dependent Variable: BOA CDS 08-10

Bank of Canada:

Security	ED785426 Corp
Start Date	02/02/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		BOC CDS 07-09	BOC BOND 07-09	BOC CDS 15-17	BOC BOND 15-17
N	Valid	152	152	152	187
	Missing	35	35	35	0
Mean		60.8289	36.4876	79.6118	60.9590
Std. Deviation		34.36650	10.21273	16.19216	14.01458

Correlations

		BOC CDS 07-09	BOC BOND 07-09
Pearson Correlation	BOC CDS 07-09	1.000	.667
	BOC BOND 07-09	.667	1.000
Sig. (1-tailed)	BOC CDS 07-09	.	.000
	BOC BOND 07-09	.000	.
N	BOC CDS 07-09	152	152
	BOC BOND 07-09	152	152

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.667[a]	.445	.441	25.69478

a. Predictors: (Constant), BOC BOND 07-09

b. Dependent Variable: BOC CDS 07-09

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	79306.332	1	79306.332	120.121	.000[b]
	Residual	99033.220	150	660.221		
	Total	178339.553	151			

a. Dependent Variable: BOC CDS 07-09

b. Predictors: (Constant), BOC BOND 07-09

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-21.049	7.756		-2.714	.007	-36.374	-5.724
	BOC BOND 07-09	2.244	.205	.667	10.960	.000	1.839	2.649

a. Dependent Variable: BOC CDS 07-09

CAPITAL ONE BANK:

Security	EF682952 Corp
Start Date	02/02/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		CAP1 CDS 08-10	CAP1 BOND 08-10	CAP1 CDS 16-18	CAP1 BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		368.9407	44.4362	132.7778	59.4344
Std. Deviation		178.95838	8.51159	33.20890	16.32793

Correlations

		CAP1 CDS 08-10	CAP1 BOND 08-10
Pearson Correlation	CAP1 CDS 08-10	1.000	-.121
	CAP1 BOND 08-10	-.121	1.000
Sig. (1-tailed)	CAP1 CDS 08-10	.	.082
	CAP1 BOND 08-10	.082	.
N	CAP1 CDS 08-10	135	135
	CAP1 BOND 08-10	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.121[a]	.015	.007	178.31597

a. Predictors: (Constant), CAP1 BOND 08-10

b. Dependent Variable: CAP1 CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	62551.599	1	62551.599	1.967	.163[b]
	Residual	4228945.926	133	31796.586		
	Total	4291497.526	134			

a. Dependent Variable: CAP1 CDS 08-10

b. Predictors: (Constant), CAP1 BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	481.737	81.871		5.884	.000	319.798	643.675
	CAP1 BOND 08-10	-2.538	1.810	-.121	-1.403	.163	-6.118	1.041

a. Dependent Variable: CAP1 CDS 08-10

HSBC:

Security	EC782450 Corp
Start Date	02/01/2007 00:00
End Date	02/03/2011 00:00
Period	D
Pricing Source	BGN

Statistics

		HSBC CDS 08-10	HSBC BOND 08-10	HSBC CDS 16-18	HSBC BOND 16-18
N	Valid	135	135	112	112
	Missing	0	0	23	23
Mean		99.1852	46.4724	77.8393	59.2059
Std. Deviation		32.49849	8.34991	15.44450	16.68516

Correlations

		HSBC CDS 08-10	HSBC BOND 08-10
Pearson Correlation	HSBC CDS 08-10	1.000	.403
	HSBC BOND 08-10	.403	1.000
Sig. (1-tailed)	HSBC CDS 08-10	.	.000
	HSBC BOND 08-10	.000	.
N	HSBC CDS 08-10	135	135
	HSBC BOND 08-10	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.403[a]	.162	.156	29.85460

a. Predictors: (Constant), HSBC BOND 08-10

b. Dependent Variable: HSBC CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22981.828	1	22981.828	25.785	.000[b]
	Residual	118542.542	133	891.297		
	Total	141524.370	134			

a. Dependent Variable: HSBC CDS 08-10

b. Predictors: (Constant), HSBC BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	26.298	14.582		1.803	.074	-2.545	55.141
	HSBC BOND 08-10	1.568	.309	.403	5.078	.000	.957	2.179

a. Dependent Variable: HSBC CDS 08-10

JP MORGAN:

Security	EC263108 Corp
Start Date	05/01/2007 00:00
End Date	31/12/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		JPM CDS 08-10	JPM BOND 08-10	JPM CDS 16-18	JPM BOND 16-18
N	Valid	128	128	135	135
	Missing	7	7	0	0
Mean		110.0938	46.0567	64.5407	59.5445
Std. Deviation		32.51540	6.08435	17.11452	16.44022

Correlations

		JPM CDS 08-10	JPM BOND 08-10
Pearson Correlation	JPM CDS 08-10	1.000	.062
	JPM BOND 08-10	.062	1.000
Sig. (1-tailed)	JPM CDS 08-10	.	.245
	JPM BOND 08-10	.245	.
N	JPM CDS 08-10	128	128
	JPM BOND 08-10	128	128

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.062[a]	.004	-.004	32.58199

a. Predictors: (Constant), JPM BOND 08-10

b. Dependent Variable: JPM CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	511.031	1	511.031	.481	.489[b]
	Residual	133759.844	126	1061.586		
	Total	134270.875	127			

a. Dependent Variable: JPM CDS 08-10

b. Predictors: (Constant), JPM BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	94.909	22.074		4.300	.000	51.225	138.593
	JPM BOND 08-10	.330	.475	.062	.694	.489	-.611	1.270

a. Dependent Variable: JPM CDS 08-10

MIZUHO BANK:

Security	EC237665 Corp
Start Date	02/02/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		MIZUHO CDS 09-10	MIZUHO BOND 09-10	MIZUHO CDS 16-18	MIZUHO BOND 16-18
N	Valid	69	69	135	135
	Missing	66	66	0	0
Mean		268.7826	50.1203	54.3037	59.9065
Std. Deviation		85.53875	2.53493	11.96654	16.64297

Correlations

		MIZUHO CDS 09-10	MIZUHO BOND 09-10
Pearson Correlation	MIZUHO CDS 09-10	1.000	-.588
	MIZUHO BOND 09-10	-.588	1.000
Sig. (1-tailed)	MIZUHO CDS 09-10	.	.000
	MIZUHO BOND 09-10	.000	.
N	MIZUHO CDS 09-10	69	69
	MIZUHO BOND 09-10	69	69

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.588[a]	.345	.335	69.73397

a. Predictors: (Constant), MIZUHO BOND 09-10

b. Dependent Variable: MIZUHO CDS 09-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	171738.356	1	171738.356	35.317	.000[b]
	Residual	325809.383	67	4862.827		
	Total	497547.739	68			

a. Dependent Variable: MIZUHO CDS 09-10

b. Predictors: (Constant), MIZUHO BOND 09-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1262.420	167.412		7.541	.000	928.265	1596.575
	MIZUHO BOND 09-10	-19.825	3.336	-.588	-5.943	.000	-26.484	-13.166

a. Dependent Variable: MIZUHO CDS 09-10

MORGAN STANLEY:

Security	EF139717 Corp
Start Date	02/01/2007 00:00
End Date	02/02/2010 00:00
Period	D
Pricing Source	BGN

Correlations

		MS CDS 08-10	MS BOND 08-10
Pearson Correlation	MS CDS 08-10	1.000	-.280
	MS BOND 08-10	-.280	1.000
Sig. (1-tailed)	MS CDS 08-10	.	.001
	MS BOND 08-10	.001	.
N	MS CDS 08-10	135	135
	MS BOND 08-10	135	135

Correlations

		MS CDS 08-10	MS BOND 08-10
Pearson Correlation	MS CDS 08-10	1.000	-.280
	MS BOND 08-10	-.280	1.000
Sig. (1-tailed)	MS CDS 08-10	.	.001
	MS BOND 08-10	.001	.
N	MS CDS 08-10	135	135
	MS BOND 08-10	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.280[a]	.078	.071	134.95645

a. Predictors: (Constant), MS BOND 08-10

b. Dependent Variable: MS CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	205448.863	1	205448.863	11.280	.001[b]
	Residual	2422361.463	133	18213.244		
	Total	2627810.326	134			

a. Dependent Variable: MS CDS 08-10

b. Predictors: (Constant), MS BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	472.059	66.443		7.105	.000	340.638	603.480
	MS BOND 08-10	-4.893	1.457	-.280	-3.359	.001	-7.774	-2.011

a. Dependent Variable: MS CDS 08-10

MUFJ:

Security	EC230470 Corp
Start Date	02/02/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		MUFJ CDS 08-10	MUFJ BOND 08-10
N	Valid	86	86
	Missing	63	63
Mean		219.4535	50.8264
Std. Deviation		63.77196	3.60638

Correlations

		MUFJ CDS 08-10	MUFJ BOND 08-10
Pearson Correlation	MUFJ CDS 08-10	1.000	-.455
	MUFJ BOND 08-10	-.455	1.000
Sig. (1-tailed)	MUFJ CDS 08-10	.	.000
	MUFJ BOND 08-10	.000	.
N	MUFJ CDS 08-10	86	86
	MUFJ BOND 08-10	86	86

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.455[a]	.207	.197	57.14018

a. Predictors: (Constant), MUFJ BOND 08-10

b. Dependent Variable: MUFJ CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71423.282	1	71423.282	21.875	.000[b]
	Residual	274260.032	84	3265.000		
	Total	345683.314	85			

a. Dependent Variable: MUFJ CDS 08-10

b. Predictors: (Constant), MUFJ BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	627.987	87.564		7.172	.000	453.856	802.118
	MUFJ BOND 08-10	-8.038	1.719	-.455	-4.677	.000	-11.455	-4.620

a. Dependent Variable: MUFJ CDS 08-10

RBS:

Security	DD104446 Corp
Start Date	02/03/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		RBS CDS 08-10	RBS BOND 08-10	RBS CDS 16-18	RBS BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		152.5111	45.1492	116.6000	59.9562
Std. Deviation		63.07788	6.14613	34.64408	15.09644

Correlations

		RBS CDS 08-10	RBS BOND 08-10
Pearson Correlation	RBS CDS 08-10	1.000	.366
	RBS BOND 08-10	.366	1.000
Sig. (1-tailed)	RBS CDS 08-10	.	.000
	RBS BOND 08-10	.000	.
N	RBS CDS 08-10	135	135
	RBS BOND 08-10	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.366[a]	.134	.128	58.91657

a. Predictors: (Constant), RBS BOND 08-10

b. Dependent Variable: RBS CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71497.092	1	71497.092	20.597	.000[b]
	Residual	461664.641	133	3471.163		
	Total	533161.733	134			

a. Dependent Variable: RBS CDS 08-10

b. Predictors: (Constant), RBS BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-17.173	37.730		-.455	.650	-91.802	57.457
	RBS BOND 08-10	3.758	.828	.366	4.538	.000	2.120	5.396

a. Dependent Variable: RBS CDS 08-10

STATE STREET:

Security	EC266598 Corp
Start Date	02/02/2007 00:00
End Date	30/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		SS CDS 08-10	SS BOND 08-10	SS CDS 16-18	SS BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		385.1630	46.5401	108.5852	63.1551
Std. Deviation		251.88016	6.15969	24.69981	16.18621

Correlations

		SS CDS 08-10	SS BOND 08-10
Pearson Correlation	SS CDS 08-10	1.000	-.053
	SS BOND 08-10	-.053	1.000
Sig. (1-tailed)	SS CDS 08-10	.	.269
	SS BOND 08-10	.269	.
N	SS CDS 08-10	135	135
	SS BOND 08-10	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.053[a]	.003	-.005	252.46340

a. Predictors: (Constant), SS BOND 08-10

b. Dependent Variable: SS CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24321.031	1	24321.031	.382	.538[b]
	Residual	8477123.384	133	63737.770		
	Total	8501444.415	134			

a. Dependent Variable: SS CDS 08-10

b. Predictors: (Constant), SS BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	486.954	166.210		2.930	.004	158.196	815.711
	SS BOND 08-10	-2.187	3.541	-.053	-.618	.538	-9.190	4.816

a. Dependent Variable: SS CDS 08-10

WELLS FARGO:

Security	EF656387 Corp
Start Date	02/02/2007 00:00
End Date	23/07/2010 00:00
Period	W
Pricing Source	BGN

Statistics

		WF CDS 08-10	WF BOND 08-10	WF CDS 16-18	WF BOND 16-18
N	Valid	134	134	135	135
	Missing	1	1	0	0
Mean		119.0970	46.3493	56.5185	60.6932
Std. Deviation		40.30949	7.42570	12.29176	17.11117

Correlations

		WF CDS 08-10	WF BOND 08-10
Pearson Correlation	WF CDS 08-10	1.000	.171
	WF BOND 08-10	.171	1.000
Sig. (1-tailed)	WF CDS 08-10	.	.024
	WF BOND 08-10	.024	.
N	WF CDS 08-10	134	134
	WF BOND 08-10	134	134

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.171[a]	.029	.022	39.86755

a. Predictors: (Constant), WF BOND 08-10

b. Dependent Variable: WF CDS 08-10

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6302.099	1	6302.099	3.965	.049[b]
	Residual	209803.640	132	1589.422		
	Total	216105.739	133			

a. Dependent Variable: WF CDS 08-10

b. Predictors: (Constant), WF BOND 08-10

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	76.131	21.851		3.484	.001	32.909	119.354
	WF BOND 08-10	.927	.466	.171	1.991	.049	.006	1.848

a. Dependent Variable: WF CDS 08-10

2016-2018:

CITI BANK

Security	EK402154 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		CITI CDS 08-10	CITI BOND 08-10	CITI CDS 16-18	CITI BOND 16-18
N	Valid	111	111	135	135
	Missing	24	24	0	0
Mean		213.0541	42.5340	77.9630	59.7419
Std. Deviation		115.82077	5.89245	20.31006	16.46486

Correlations

		CITI CDS 16-18	CITI BOND 16-18
Pearson Correlation	CITI CDS 16-18	1.000	.611
	CITI BOND 16-18	.611	1.000
Sig. (1-tailed)	CITI CDS 16-18	.	.000
	CITI BOND 16-18	.000	.
N	CITI CDS 16-18	135	135
	CITI BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.611[a]	.374	.369	16.13372

a. Predictors: (Constant), CITI BOND 16-18

b. Dependent Variable: CITI CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20655.341	1	20655.341	79.353	.000[b]
	Residual	34619.474	133	260.297		
	Total	55274.815	134			

a. Dependent Variable: CITI CDS 16-18

b. Predictors: (Constant), CITI BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	25.778	6.020		4.282	.000	13.870	37.687
	CITI BOND 16-18	.788	.088	.611	8.908	.000	.613	.963

a. Dependent Variable: CITI CDS 16-18

AIG:

Security	EI486306 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		AIG CDS 08-10	AIG BOND 08-10	AIG CDS 16-18	AIG BOND 16-18
N	Valid	110	110	135	135
	Missing	25	25	0	0
Mean		565.4909	36.7256	79.7111	67.4543
Std. Deviation		317.49879	8.30908	15.04663	19.77281

Correlations

		AIG CDS 16-18	AIG BOND 16-18
Pearson Correlation	AIG CDS 16-18	1.000	.683
	AIG BOND 16-18	.683	1.000
Sig. (1-tailed)	AIG CDS 16-18	.	.000
	AIG BOND 16-18	.000	.
N	AIG CDS 16-18	110	110
	AIG BOND 16-18	110	110

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.683[a]	.466	.461	11.85445

a. Predictors: (Constant), AIG BOND 16-18

b. Dependent Variable: AIG CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13242.807	1	13242.807	94.236	.000[b]
	Residual	15177.011	108	140.528		
	Total	28419.818	109			

a. Dependent Variable: AIG CDS 16-18

b. Predictors: (Constant), AIG BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-3.341	8.734		-.383	.703	-20.653	13.970
	AIG BOND 16-18	1.021	.105	.683	9.708	.000	.812	1.229

a. Dependent Variable: AIG CDS 16-18

BANK OF NEW YORK:

Security	EK476474 Corp
Start Date	31/01/2014 00:00
End Date	12/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		BNY CDS 08-10	BNY BOND 08-10	BNY CDS 16-18	BNY BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		322.6519	46.7775	117.7630	59.9085
Std. Deviation		172.69706	7.66024	29.16300	16.69156

Correlations

		BNY CDS 16-18	BNY BOND 16-18
Pearson Correlation	BNY CDS 16-18	1.000	.573
	BNY BOND 16-18	.573	1.000
Sig. (1-tailed)	BNY CDS 16-18	.	.000
	BNY BOND 16-18	.000	.
N	BNY CDS 16-18	135	135
	BNY BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.573[a]	.329	.324	23.98187

a. Predictors: (Constant), BNY BOND 16-18

b. Dependent Variable: BNY CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37472.115	1	37472.115	65.154	.000[b]
	Residual	76492.300	133	575.130		
	Total	113964.415	134			

a. Dependent Variable: BNY CDS 16-18

b. Predictors: (Constant), BNY BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	48.087	8.875		5.418	.000	30.532	65.642
	BNY BOND 16-18	1.050	.130	.573	8.072	.000	.793	1.307

a. Dependent Variable: BNY CDS 16-18

BANK OF AMERICA-MERRIL LYNCH:

Security	EH929384 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		BOA CDS 08-10	BOA BOND 08-10	BOA CDS 16-18	BOA BOND 16-18
N	Valid	109	109	135	135
	Missing	26	26	0	0
Mean		125.7339	43.8172	71.8000	64.8741
Std. Deviation		49.74298	5.12865	23.00642	19.00066

Correlations

		BOA CDS 16-18	BOA BOND 16-18
Pearson Correlation	BOA CDS 16-18	1.000	.700
	BOA BOND 16-18	.700	1.000
Sig. (1-tailed)	BOA CDS 16-18	.	.000
	BOA BOND 16-18	.000	.
N	BOA CDS 16-18	135	135
	BOA BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.700[a]	.490	.486	16.49209

a. Predictors: (Constant), BOA BOND 16-18

b. Dependent Variable: BOA CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34751.042	1	34751.042	127.766	.000[b]
	Residual	36174.558	133	271.989		
	Total	70925.600	134			

a. Dependent Variable: BOA CDS 16-18

b. Predictors: (Constant), BOA BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	7.803	5.837		1.337	.184	-3.743	19.348
	BOA BOND 16-18	.891	.079	.700	11.303	.000	.735	1.047

a. Dependent Variable: BOA CDS 16-18

BANK OF CANADA:

Security	EK122204 Corp
Start Date	02/05/2014 00:00
End Date	12/07/2019 00:00
Period	W
Pricing Source	BVAL

Statistics

		BOC CDS 07-09	BOC BOND 07-09	BOC CDS 15-17	BOC BOND 15-17
N	Valid	152	152	152	187
	Missing	35	35	35	0
Mean		60.8289	36.4876	79.6118	60.9590
Std. Deviation		34.36650	10.21273	16.19216	14.01458

Correlations

		BOC CDS 15-17	BOC BOND 15-17
Pearson Correlation	BOC CDS 15-17	1.000	.188
	BOC BOND 15-17	.188	1.000
Sig. (1-tailed)	BOC CDS 15-17	.	.010
	BOC BOND 15-17	.010	.
N	BOC CDS 15-17	152	152
	BOC BOND 15-17	152	152

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.188[a]	.035	.029	15.95549

a. Predictors: (Constant), BOC BOND 15-17

b. Dependent Variable: BOC CDS 15-17

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1403.462	1	1403.462	5.513	.020[b]
	Residual	38186.636	150	254.578		
	Total	39590.099	151			

a. Dependent Variable: BOC CDS 15-17

b. Predictors: (Constant), BOC BOND 15-17

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	34.567	19.228		1.798	.074	-3.427	72.560
	BOC BOND 15-17	.634	.270	.188	2.348	.020	.100	1.168

a. Dependent Variable: BOC CDS 15-17

CAPITAL ONE BANK:

Security	EK470235 Corp
Start Date	04/07/2014 00:00
End Date	12/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		CAP1 CDS 08-10	CAP1 BOND 08-10	CAP1 CDS 16-18	CAP1 BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		368.9407	44.4362	132.7778	59.4344
Std. Deviation		178.95838	8.51159	33.20890	16.32793

Correlations

		CAP1 CDS 16-18	CAP1 BOND 16-18
Pearson Correlation	CAP1 CDS 16-18	1.000	.660
	CAP1 BOND 16-18	.660	1.000
Sig. (1-tailed)	CAP1 CDS 16-18	.	.000
	CAP1 BOND 16-18	.000	.
N	CAP1 CDS 16-18	135	135
	CAP1 BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.660[a]	.436	.432	25.03164

a. Predictors: (Constant), CAP1 BOND 16-18

b. Dependent Variable: CAP1 CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	64443.805	1	64443.805	102.850	.000[b]
	Residual	83335.528	133	626.583		
	Total	147779.333	134			

a. Dependent Variable: CAP1 CDS 16-18

b. Predictors: (Constant), CAP1 BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	40.435	9.357		4.321	.000	21.927	58.942
	CAP1 BOND 16-18	1.402	.138	.660	10.141	.000	1.129	1.675

a. Dependent Variable: CAP1 CDS 16-18

HSBC:

Security	EI379423 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		HSBC CDS 08-10	HSBC BOND 08-10	HSBC CDS 16-18	HSBC BOND 16-18
N	Valid	135	135	112	112
	Missing	0	0	23	23
Mean		99.1852	46.4724	77.8393	59.2059
Std. Deviation		32.49849	8.34991	15.44450	16.68516

Correlations

		HSBC CDS 16-18	HSBC BOND 16-18
Pearson Correlation	HSBC CDS 16-18	1.000	.647
	HSBC BOND 16-18	.647	1.000
Sig. (1-tailed)	HSBC CDS 16-18	.	.000
	HSBC BOND 16-18	.000	.
N	HSBC CDS 16-18	112	112
	HSBC BOND 16-18	112	112

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.647[a]	.418	.413	11.83106

a. Predictors: (Constant), HSBC BOND 16-18

b. Dependent Variable: HSBC CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11079.967	1	11079.967	79.157	.000[b]
	Residual	15397.141	110	139.974		
	Total	26477.107	111			

a. Dependent Variable: HSBC CDS 16-18

b. Predictors: (Constant), HSBC BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	39.387	4.464		8.823	.000	30.540	48.234
	HSBC BOND 16-18	.570	.064	.647	8.897	.000	.443	.697

a. Dependent Variable: HSBC CDS 16-18

JP MORGAN:

Security	EK549602 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		JPM CDS 08-10	JPM BOND 08-10	JPM CDS 16-18	JPM BOND 16-18
N	Valid	128	128	135	135
	Missing	7	7	0	0
Mean		110.0938	46.0567	64.5407	59.5445
Std. Deviation		32.51540	6.08435	17.11452	16.44022

Correlations

		JPM CDS 16-18	JPM BOND 16-18
Pearson Correlation	JPM CDS 16-18	1.000	.690
	JPM BOND 16-18	.690	1.000
Sig. (1-tailed)	JPM CDS 16-18	.	.000
	JPM BOND 16-18	.000	.
N	JPM CDS 16-18	135	135
	JPM BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.690[a]	.475	.472	12.44138

a. Predictors: (Constant), JPM BOND 16-18

b. Dependent Variable: JPM CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18662.718	1	18662.718	120.570	.000[b]
	Residual	20586.808	133	154.788		
	Total	39249.526	134			

a. Dependent Variable: JPM CDS 16-18

b. Predictors: (Constant), JPM BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	15.032	4.634		3.244	.001	5.865	24.198
	JPM BOND 16-18	.750	.068	.690	10.980	.000	.615	.886

a. Dependent Variable: JPM CDS 16-18

MIZUHO BANK:

Security	EK502184 Corp
Start Date	07/02/2014 00:00
End Date	12/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		MIZUHO CDS 09-10	MIZUHO BOND 09-10	MIZUHO CDS 16-18	MIZUHO BOND 16-18
N	Valid	69	69	135	135
	Missing	66	66	0	0
Mean		268.7826	50.1203	54.3037	59.9065
Std. Deviation		85.53875	2.53493	11.96654	16.64297

Correlations

		MIZUHO CDS 16-18	MIZUHO BOND 16-18
Pearson Correlation	MIZUHO CDS 16-18	1.000	.301
	MIZUHO BOND 16-18	.301	1.000
Sig. (1-tailed)	MIZUHO CDS 16-18	.	.000
	MIZUHO BOND 16-18	.000	.
N	MIZUHO CDS 16-18	135	135
	MIZUHO BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.301[a]	.090	.084	11.45522

a. Predictors: (Constant), MIZUHO BOND 16-18

b. Dependent Variable: MIZUHO CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1736.019	1	1736.019	13.230	.000[b]
	Residual	17452.529	133	131.222		
	Total	19188.548	134			

a. Dependent Variable: MIZUHO CDS 16-18

b. Predictors: (Constant), MIZUHO BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	39.271	4.249		9.242	.000	30.866	47.675
	MIZUHO BOND 16-18	.227	.062	.301	3.637	.000	.103	.350

a. Dependent Variable: MIZUHO CDS 16-18

MORGAN STANLEY:

Security	EH978685 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		MS CDS 08-10	MS BOND 08-10	MS CDS 16-18	MS BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		252.3407	44.9090	154.8593	64.1988
Std. Deviation		140.03758	8.00327	27.83565	18.73038

Correlations

		MS CDS 16-18	MS BOND 16-18
Pearson Correlation	MS CDS 16-18	1.000	.691
	MS BOND 16-18	.691	1.000
Sig. (1-tailed)	MS CDS 16-18	.	.000
	MS BOND 16-18	.000	.
N	MS CDS 16-18	135	135
	MS BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.691[a]	.478	.474	20.18479

a. Predictors: (Constant), MS BOND 16-18

b. Dependent Variable: MS CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	49638.685	1	49638.685	121.835	.000[b]
	Residual	54187.641	133	407.426		
	Total	103826.326	134			

a. Dependent Variable: MS CDS 16-18

b. Predictors: (Constant), MS BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	77.970	7.179		10.860	.000	63.769	92.170
	MS BOND 16-18	1.082	.098	.691	11.038	.000	.888	1.276

a. Dependent Variable: MS CDS 16-18

RBS:

Security	EK290912 Corp
Start Date	07/02/2014 00:00
End Date	12/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		RBS CDS 08-10	RBS BOND 08-10	RBS CDS 16-18	RBS BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		152.5111	45.1492	116.6000	59.9562
Std. Deviation		63.07788	6.14613	34.64408	15.09644

Correlations

		RBS CDS 16-18	RBS BOND 16-18
Pearson Correlation	RBS CDS 16-18	1.000	.708
	RBS BOND 16-18	.708	1.000
Sig. (1-tailed)	RBS CDS 16-18	.	.000
	RBS BOND 16-18	.000	.
N	RBS CDS 16-18	135	135
	RBS BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.708[a]	.501	.497	24.56226

a. Predictors: (Constant), RBS BOND 16-18

b. Dependent Variable: RBS CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	80588.911	1	80588.911	133.579	.000[b]
	Residual	80239.489	133	603.304		
	Total	160828.400	134			

a. Dependent Variable: RBS CDS 16-18

b. Predictors: (Constant), RBS BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	8.513	9.588		.888	.376	-10.452	27.478
	RBS BOND 16-18	1.622	.140	.708	11.558	.000	1.345	1.900

a. Dependent Variable: RBS CDS 16-18

STATE STREET:

Security	STT GB USD SR 5Y Corp
Start Date	07/02/2014 00:00
End Date	28/06/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		SS CDS 08-10	SS BOND 08-10	SS CDS 16-18	SS BOND 16-18
N	Valid	135	135	135	135
	Missing	0	0	0	0
Mean		385.1630	46.5401	108.5852	63.1551
Std. Deviation		251.88016	6.15969	24.69981	16.18621

Correlations

		SS CDS 16-18	SS BOND 16-18
Pearson Correlation	SS CDS 16-18	1.000	.813
	SS BOND 16-18	.813	1.000
Sig. (1-tailed)	SS CDS 16-18	.	.000
	SS BOND 16-18	.000	.
N	SS CDS 16-18	135	135
	SS BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.813[a]	.661	.658	14.43882

a. Predictors: (Constant), SS BOND 16-18

b. Dependent Variable: SS CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	54022.984	1	54022.984	259.128	.000[b]
	Residual	27727.786	133	208.480		
	Total	81750.770	134			

a. Dependent Variable: SS CDS 16-18

b. Predictors: (Constant), SS BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	21.923	5.525		3.968	.000	10.995	32.852
	SS BOND 16-18	1.306	.081	.813	16.097	.000	1.146	1.466

a. Dependent Variable: SS CDS 16-18

WELLS FARGO:

Security	EK032397 Corp
Start Date	03/01/2014 00:00
End Date	19/07/2019 00:00
Period	W
Pricing Source	BMRK

Statistics

		WF CDS 08-10	WF BOND 08-10	WF CDS 16-18	WF BOND 16-18
N	Valid	134	134	135	135
	Missing	1	1	0	0
Mean		119.0970	46.3493	56.5185	60.6932
Std. Deviation		40.30949	7.42570	12.29176	17.11117

Correlations

		WF CDS 16-18	WF BOND 16-18
Pearson Correlation	WF CDS 16-18	1.000	.654
	WF BOND 16-18	.654	1.000
Sig. (1-tailed)	WF CDS 16-18	.	.000
	WF BOND 16-18	.000	.
N	WF CDS 16-18	135	135
	WF BOND 16-18	135	135

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.654[a]	.428	.424	9.33279

a. Predictors: (Constant), WF BOND 16-18

b. Dependent Variable: WF CDS 16-18

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8661.271	1	8661.271	99.439	.000[b]
	Residual	11584.433	133	87.101		
	Total	20245.704	134			

a. Dependent Variable: WF CDS 16-18

b. Predictors: (Constant), WF BOND 16-18

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	23.473	3.410		6.884	.000	16.729	30.218
	WF BOND 16-18	.491	.049	.654	9.972	.000	.394	.589

a. Dependent Variable: WF CDS 16-18