Credit Default Swap Spread (CDSs) to predict a default

Abstract:

This paper investigates the ability of the Credit Default Swap Spread (CDSs) to predict a default. As a result, I started to build a regression and correlation model to examine and check if there is a relation between two important variables, which are Credit Default Swap (CDS) and Expected Default Frequency KMV (EDF) KMV. The study concentrates on the degree of variation on the prices for both variables as I believe that if one variable, which should be a predictor, changes the other variable, it should respond to this predication and change its price too.

The study concentrates on five U.S. financial institutions, which are Citigroup Inc., JP Morgan Chase & Co., Goldman Sachs Group, Lehman Brother, and Morgan Stanley from 16 January 2007 to 23 May 2011. In conclusion, my analysis approves that the CDSs is classified as either risk exposures accumulator or predictor from year 2007 based on the findings, which prove that there is a relationship between credit default swaps and KMV EDFs.

Keywords: credit default swap, expected default frequency KMV, credit risk, counterparty risk, clearing house, credit rating, credit rating agencies, linear regression, correlation.

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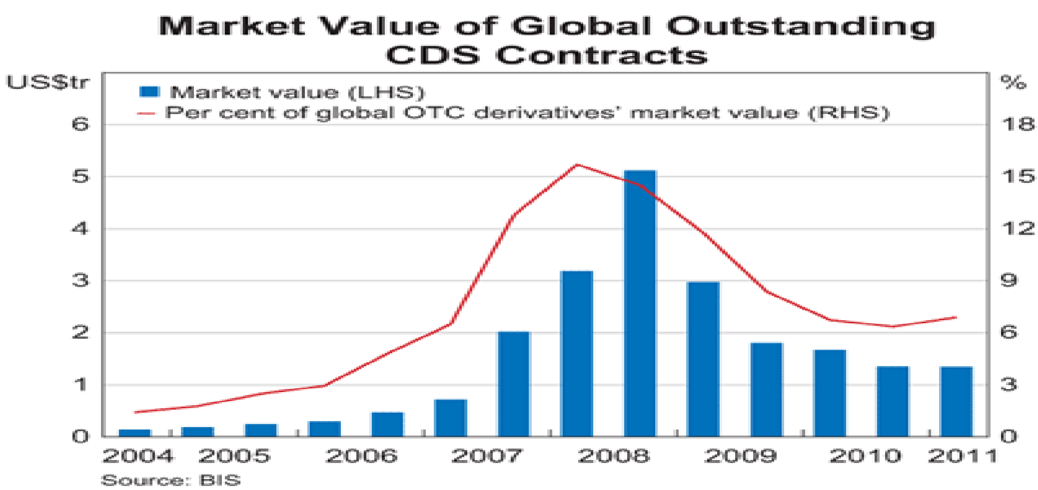
Chapter (1):

I. Introduction

During last decade, the OTC market has grown enormously due to the different range of products that the market provides, which led to tremendous growth in the trading as well. This can be justified with the International Swaps and Derivatives Association (ISDA) reports which indicated that the amount of dealing in the derivatives market in the middle of year 2010 was $434.1 trillion where credit default swap CDS dealings were $26.3 trillion. Besides this, is if we compared 2010 to year 2009 we will find that the ISDA report shows the total amount of contracts were $426.8 trillion with $30.4 trillion for CDS only. This remarkable growth in the trading environment comprises extra risks to the dealers. For instance, the counterparty risk, CDS contract language/protocols and operational risks are greater.

Market Value of Global CDS Contracts: 2004-2011, Figure (1)



Source: BIS, 2012.

“The credit default Swaps (CDS), which was designed by Gregg Berman, is just as an insurance contract against some specified risks, where the protection buyer agrees to pay the protection seller a periodic premium (usually quarterly) and in return the seller adverse credit event of the buyer”.

With all appreciations to the CDS, market participants are capable after CDS invention to separate the credit choice from the funding choice. As a result, the investors, who preserve the higher funding costs here, are able now to move in the derivative market with less or maybe no trouble, this refers to the CDS flexibility in different areas such as legal, arrangement, structure, settlement, liquidity and valuation.

“The use of default swaps will increasingly become a necessary component of any successful portfolio management strategy”, according to a manager at Goldman Sachs.

It is essential here to state that there is no physical or real asset that can assure a payment. In some circumstances, CDS will not protect or defend the contract buyer from all credit events. Only in some agreed default cases such as bankruptcy, failure to pay, or revised restructuring (in European corporate it is referred to as modified-modified restructuring), repudiation, or moratorium and reorganization. As a result, many argued that CDSs tends to be more sensitive to any credit events in the market since information and transparency are very important.

On the other hand, some analysts argue that the amount of information does not badly affect the prices or liquidity of the CDSs such as Blanco et al. (2005), who investigate the credit default swap spreads using Duffie (1999). Recently, some research argued that most of the figures, which are issued by the Bank for International Settlements (BIS) and taken by the analysts to judge the market, are unreliable as these figures ignore foreign exchange ($63 trillion).

Instead, there are many people who claim that the CDS weakened the financial system in 2008. For example, after Lehman Brothers collapsed many CDS contracts, buyers were unrewarded. Washington Mutual decided to subscribe the corporate bonds in year 2005 and believed it was better to hedge their risk by purchasing the CDS from Lehman brothers, however, it was not.

Now, let us discuses about CDS in different areas and I will start by CDS's definition, advantages and disadvantages, pricing methods, clearing, and then the most important part in this area of discussion part is tool of measurements.

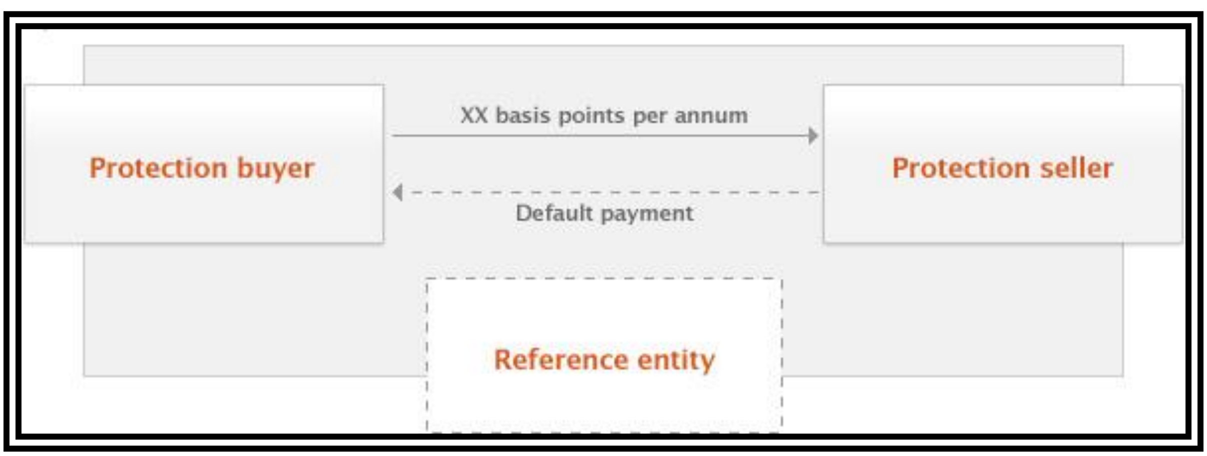
I.1. Credit Default Swap:

Despite the different financial innovations in the markets, the CDS is considered to be the most popular innovation due to different specifications that the investors find. These include the liquidity, quality and large number and selection of members and investors.

In 2007, the International Swaps and Derivatives Association announced that the CDS market was more than $45 trillion, which is approximately double the size of the U.S. stock market or mortgage market.

Credit default swap is nothing more than an insurance contract, where the seller promises the buyer to cover his losses on certain securities in the event of a default. In return, the buyer of the insurance contract pays premium to the seller over the agreed period of time. Moreover, this contract can be used as a tool that can easily be bought and sold from both parties, who are the insured and the insurer.

CDS Insurance Contract. Figure (2)



Source: Rutker, 2011.

The banks CDS considered to be easy money especially included commercial banks, which were the most dynamic partners in the market, such as JP Morgan Chase, Citibank, Bank of America and Wachovia. The top 25 banks held more than $13 trillion in at the third quarter of 2007.

Shortly the ideas of CDS then extended and create another structured finance, such as Collateralized debt obligation (CDOs), Constant maturity credit default swap (CMCDS), Constant Proportion Debt Obligation (CPDO), and Credit-linked note (CLN). "They're betting on whether the investments will succeed or fail", said Pincus. "It's like betting on a sports event. The game is being played and you're not playing in the game, but people all over the country are betting on the outcome."

Here the International Swaps and Derivatives Association (ISDA) information and documents that should be provided in order to have an acceptable CDS contract:

1. The reference obligor—or reference assets, as it is important to identify which asset is insured, and the definition of the credit/default event definition, which the most controversial area, as a result ISDA defined it as below:

- Bankruptcy (Chapter 11 in the US)
- Failure to Pay
- Obligation default or acceleration
- Repudiation/moratorium
- Restructuring

2. The start date--which is usually 3 days after the trading date, however, it can also be for a later date.

3. The maturity or liquid date—the most used and traded CDS maturity is five years but also the dealers can quote from 1 to 10 years.

4. The CDS spread--the price of protection to be paid quartile or annually as agreed upon, and it is considered as the most confusing part since the spread does not depend on a specific thing. Whereas other markets refer to the CDS spread as a rate or price.

5. The frequency of the spread payments--means usually the premium will be either quarterly or semi-annually with an actual 360 day count convention.

6. The payment at the credit event and how it will be settled--physical settlement is more popular than cash settlement and settlement will be within 4 to 6 weeks.

In addition, in this type of contract there is a short of regulations, which helped in increasing the volume of trade to this instrument. For example, a CDS can be traded for more than 12 times. When default happens, the insured or hedged party is not able to know who is responsible to pay him back.

Furthermore, there are some special market terminologies when trading CDS or other OTC derivatives that can be listed:

- Long position: protection for buyer
- Short position: protection for seller
- Bid of xx bp on a CDS: the bidder is willing to enter a CDS as protection for buyer at a spread of xx bp, and it will be below the offer quotes
- Offer of xx bp on a CDS: the trader is willing to enter a CDS as protection for seller at a spread of xx bp

Another market terminology is "to go long defaults", which means how long the credit is available for selling the protection. For example, if you are the CDS seller, you are selling the protection contract with the hope that the credit risk declines so the CDS spreads drop, whereas the buyer of the protection shorting the credit and hoping that the credit risk rises and CDS spreads rise too.

I.2. CDS Advantages and Facts

1. For private companies and banks CDS is just like other forms of contracts which offer an exceptional value to them and also to the economy, since CDS enables all different markets participants to do better by offering them the chance to manage their risks.

2. The participants see the CDS as versatile tool where they can modify it according to their needs and that is what made CDS as a unique and popular tool.

3. During financial crisis everybody blamed CDS as the main player and cause for the crisis, however, participants' credit decisions led to the crisis.
4. Many analysts announced that there are signals for risk and losses that have been showing since 2003. However, no regulators or managers listen to them.

Researchers always state that there are some serious problems with acknowledging risk, such as:

a) Investors' strategy

- In the Swap market there are many different investors who have different desires and objectives from trading in CDS. In a normal lifecycle when investors buy an asset, the investor will do his best to increase the value of the asset he owns. However, a CDS investor will buy the CDS with the hope that the CDS will decrease in value as he wants it to fail.
- This strategy developed a large number of traders who are heavily invested and were successful at failing some of the CDS, as they found that the investors who worked in failing the CDS gained more than the investors who invested and waited for the profit.

b) CDS regulations

There are no records that show who owns which CDS and whether the issuer is able to pay the buyer in case of default or not. However, the most important thing is that there is no rule stopping a CDS holder from selling it, which creates major conflicts of interest between the investors, and in case of default.

I.3. CDSs Pricing Methods

After the contract is defined it is necessary now to value CDS price. There are only a few key methods to valuing CDS:

- Ratings-based Approaches
- Structural (or Firm-Value) model based Approaches
- Reduced Form model based Approaches
- Asset Swap Replication based Approach

Giesecke (2001) argues that the rating based approach, structural approach and reduced approach can produce a great deal and contract, whereas, Schonbucher (2003) presents a full and practical insight into the use of these default models for CDS pricing. However, the two key methodologies are:

- Probability of Default (PD), and
- Expected Loss Given Default (LGD)

In reality, the market participants regularly use the asset swap market as a proxy for the CDS market or the asset swap replication based approach (number four approach) because it is considered to be the simplest version, where the trader will take the fixed rate note and interest rate swap of the same notional to pay a fixed and receives a floating till maturity of the underlying fixed rate note.

When the swap is created it is important to match the face value of the fixed rate and the spread, which became a benchmark for any CDS contract pricing and hedging, to ensure zero initial value for the package.

Finally, it is important to know that the combinations of the two that are the CDS and asset swap markets created the credit markets what they are today, and their importance increase rapidly giving more liquidity and more investors to the markets.

I.4. Tool to Measure CDSs

The first tool is the EDF-KMV, which is directly linked to my research:

I.4.1. Expected Default Frequency KMV (EDF KMV):

In this tool, there are too important mechanisms, which have the ability to predict a default and second the accuracy of the default predictive measure. This is exactly what Banking Supervision Accords or The Basel Accord, which usually recommends banking regulations, emphasizes that “Assessments must be subject to ongoing review and responsive to changes in financial condition. Before being recognized by supervisors, an assessment methodology for each market segment, including rigorous back-testing, must have been established for at least one year.”

As a result, the EDP should be dynamic enough to understand and study any signal especially if there is any possible future decline in the credit quality.

Moreover, since the Expected Default KMV (EDF KMV) concentrates more on the accuracy of the credit assessment measures and in the same time it can provides the traders with the expected probabilities of a default or the distance to default, many banks and financial institutions considered it as a useful tool to their investments when they want to measure any possible risk, assets valuation, and the capital allocation.

Mathematically, the EDF gives the standard deviations of asset growth at a given maturity exceeds a measure of a firm’s book liabilities depending on the historical data and the observations of the firm’s equity-market capitalization of the liability measure.

In summary, EDF KMV provides its trades with estimation of firm-by-firm current probabilities of default over time horizons and in the same time it includes the benchmark horizons for one to five years. In addition to that, EDF gives an estimation of default probability foe a firm depending on the historical default frequency of other firms, which faced and had similar "distance to default", which gives a leverage measure adjusted to the current market asset volatility. Roughly speaking, distance to default is "the number of standard deviations of annual asset growth by which the firm's expected assets at a given maturity exceed a measure of book liabilities", and here we have to put in mind that the estimation of the current assets and the current standard deviation of asset growth or volatility are adjusted and calculated from historical data of the firm's equity-market capitalization and liability.

Then the second tool is the Credit Rating Agencies or (CRG), where many markets investors, economists and analysts argue that the (CRG) played and were behind recent financial crisis.

I.4.2 Credit Ratings Agencies

In 1900s, John Moody realized that investors/stakeholders/traders/shareholders and others were willing to pay in order to collect and gather all of the complex data in different reports for different industries into one single and simple rating. As a result, Moody and other contestants started in 1920s to rate available and new bond issues together with government bonds. In beginning, their works approached as rating agencies and their letter ratings reflected valuable information.

After the 1929 crash, the rating agencies, conspicuously Moody's and Standard & Poor's, moved from selling information to selling regulatory licenses, which shows any private entity's and the ability to define the effect of legal rules. The regulatory license explains why market members might continue to trust and relay on the rating agencies and, in the same time, these participates should and continue to pay the rating agencies a great margins even thou their ratings did not reflect a valuable information.

Next trend for rating agencies started in 1975, when the Securities and Exchange Commission (SEC) introduced the Nationally Recognized Statistical Rating Organization NRSRO (rules relate to the banks and other broker dealers' net capital requirements, and the idea behind it is that there is no need for the banks. For instance, to keep in reserve the same amount of capital to protect the banks against a risk that large number of depositors withdrew their deposits in the same time) and this step encouraged the regulators. First, to depend more on the ratings, and second, to shift their attention from investors to issuers creating more and higher demand for rating agencies' services, which lead to increase the rating agencies wealth and profit.

To summarize, first, the credit rating agency (CRA) is nothing than a corporation that gives "credit rating" for borrowers for both their debt obligations and also their debt instruments.

Second, the credit Rating Agencies role is supposed to rate or assess the financial strengths for companies and governmental entities, both domestic and foreign, mainly to assess their ability to meet the interest and principal payments on their bonds and other debts.

The importance of these CRA is that the issuers of securities, such as companies, banks and governments, issue debt securities like CDS or bonds, which can be later traded in the secondary market. The role of the CRA is to give a credit rating for those issuers so the buyers of these securities can take into consideration the issuer's credit risk, for example default risk or the issuers' ability to pay back their loans.

After the rating, the debt issues with the highest credit ratings will sustain the lowest interest rates. The stronger the borrowers are, the lower the payment will be, and the weaker the borrowers are, the higher the payment will be.

On the other hand, the rating of these agencies was widely questioned and criticized especially after recent financial crisis that happened from 2007 to 2009, particularly if we know that In 2003, the U.S. Securities and Exchange Commission gave a report to US Congress asking for an investigation for the anti-competitive practices of credit rating agencies and the conflicts of interest. Furthermore, after CRA downgraded many governments during the recent European sovereign debts crisis the criticism from the EU and other individual countries increased.

Likewise, many criticisms are concerning the quality of these agencies researches. Many observers claim that the agencies failed due to different reasons that are first, do not have high quality in the financial forecasting, second, these agencies were/ are too slow to grip the negative trends for the issuers that they track. Finally, CRA were/are, besides, revise their ratings too late.

Lastly, there are only three firms dominant this sector, which are Standard and Poor (S&P), Moody and Fitch.

I.5. Importance of my study:

What happened to many CDS buyers before and after the global financial crisis was due to the fact that the main target behind issuing or buying CDS is to get rid of creditor conflicts between the two CDS partners (seller and buyer).

The problem here is that all the of the market traders want to hedge the risk by using CDS contracts, so each trader will offset his risk to another trader, who will also transfer it to another, which create a linked chain where each participants know his direct counterparty and doesn't know other participants in the chain. Lehman Brothers is a very good example of this case.

To add more, different researches examine the credit default spread counterparty risk, for example, Artzner & Delbaen (1995), Jarrow & Turnbull (1995) and Duffie & Singleton approve that the default happens without any warnings.

In contrast, Hull (2000) disagrees with them and claims that any counterparty risk can easily be predicted and then the participants can manage their risk by using the “default barrier correlated model”.

Because of this confusion, I decided to start a study to analyze the ability of the Credit Default Swap spread to forecast and predict the credit risk default, as a result, my research can help many market participants such as risk managers, investors, debt holders, and share and stock holders.

Furthermore, to my knowledge is the first paper in the Middle East which discusses the ability of CDS to forecast a risk, as a result, I think this thesis can contribute effectively to existing literatures that discus CDSs.

In the beginning, I started my model to know how strong the relationship is between two variables (CDS and EDF). I faced one important question, which was whether CDS is informative enough to cause a change in the other variable or EDF, especially if there is important announcement or change.

On the other hand, one difficulty I challenged was due to the large quantity of data, especially Moody KMV EDF, since I was forced to buy this data. Otherwise, the missed data would have weakened my study.

Furthermore, the empirical literatures on the CDS testing its ability to predict default using Moody's KMV EDF measures of default probability is still limited due to the huge amount of data.

My analysis is based on senior CDSs database from Bloomberg and EDF, and from Moody's KMV for five US financial institutions, which are Citigroup Inc., JP Morgan Chase & Co., Goldman Sachs Group, Lehman Brother, and Morgan Stanley from 16 January 2007 to 23 May 2011.

I.6. Research Objectives and question

The purpose of this research is to explore and study the ability of the Credit Default Swap spread (CDS) to predict credit risk default and, as a result. I used the regression and correlation methodologies to inspect if there is a significant relationship between two-default probabilities which are credit default swap (CDS) and expected default frequency (EDF).

The primary research questions of the present study are as follows:

i. Does the CDS spread predict a credit risk?

ii. In case of default, does the credit default swap spread (CDSs) highlights any expectation for any default happened in the large CDSs' firms?

I.7. Research Methodology

The daily CDS data here is collected from Bloomberg L.P Between 16 January 2007 to 23 May 2011 for US financial entities, which are Citigroup Inc., JP Morgan Chase & Co, Goldman Sachs Group, Lehman Brother and Morgan Stanley. The maturities of the CDS contracts that I chose are five years senior debt, since these contracts are known as the most liquid and the most traded CDS.

Moreover, in my research I intend to show the CDS spreads before and after failure of Bear Stearns and Lehman companies, when the global systemic and financial markets crisis began.

Besides, since I choose to do regression and correlation model, where one variable depend on the other variable, and as in theory, credit ratings are theoretically valuable source of information. Moody's KMV is another source of data to include Expected Default Frequency (EDF) in my analysis as the second variable with CDS.

I.8. The hypotheses

According to the scientists, it is impossible for the null hypothesis to be approved, but there is tow possible ways, which is either to reject or fail to reject the null hypothesis. In specifically, in cases of statistical comparison of significant relationship between two groups, the null hypothesis never is really approved but the result will confirms that there are no sufficient observations to reject the null hypothesis

According to my research's questions and the selected variables, there are two possible hypotheses that can be resulted from the driven data. For more clarification, both hypotheses focus on the changes and the influence that will and happened in the market should have an impact on the predictor variable, which is CDSs, and in return, the other variable that is expected default frequency (EDF), must also change accordingly. Consequently, if the result approve that then we can say that both variables have a significant relationship and we can reject the hypothesis.

In this case, there are two possibilities either to accept the null-hypothesis and we conclude that there is no relation between the variables, or rejected the null hypotheses, where we can conclude there is a relation between the two variables. The technique is first test H0, where H0 = 0, against H1, where H1≠ 0, so the two possible hypotheses are:

1. Hypothesis 1:

The CDSs do not have a significant influence on the EDF, and the researcher in this case fails to reject the null hypothesis as there is no significant relationship between the two variables, so the CDSs doesn't have the ability to predict a credit risk default.

2. <u>Hypothesis 2:</u>

The CDSs do have a significant influence on the EDF, so the researcher can reject the null hypothesis and conclude that there is a significant relationship between the two variables, which are the CDSs and EDF. As a result, CDSs can predict a credit risk default.

Furthermore, in case of falls hypothesis, beta is presented here as the probability of holding a false null hypothesis

<u>So:</u>

H_0: ß = 0

H_1: ß ≠ 0

Where P value ≥ .05

This study is organized and planned as follows; in the first chapter there is the introduction for the study and the problem with the objective behind this research. Then in chapter two the researcher deliberates the Literature review to demonstrate different researchers' point of view and findings. Moreover, when the third chapter discuss the sample data, the forth and the fifth chapters display and present the data analysis and the findings. Finally the last chapter states the empirical results and conclusion.

Chapter (2)

II. Literature Review

The credit default swap (CDS) as a product is considered to be a unique product and tool compared with other over-the-counter (OTC) derivative products, due to the large level of hedging it provides to the traders in accordance to the other OTC derivatives. Hence, any losses or gains resulting from using large CDS contracts can easily affect the underlying instrument and market.

As a result, almost all of the financial analysts claim that the 2007- 2009 financial crisis was linked directly to the CDS market, and also they argue that there was many signals from the CDS market, which they considered it as a risk indicator, and if the economists and traders took these signals seriously, the crisis could be voided and maintained.

This paper will look to the CDs spread, Moody rating and Expected Default Frequency KMV (EDF-KMV) changes during and after the crisis and examine the ability of the CDSs to predict the risk or not.

Below there are some studies, which discussed and examine the CDSs as a risk indicator or not in different ways:

A. Time Series

First, Katrin G. and Paddy W. (2010) examines the ability of the CDS spreads to predict a default before it happened by answering one main question "how long before the default the CDSs change? "

The study includes a sample of 466 firms, where there were 233 default events for some systemic financial institutions, such as Lehman Brothers, GMAC, and Washington Mutual. Also, these defaults data were gathered from Moody corporate from 2004 to 2008.

In addition, the CDSs data (5-year Senior) is collected from both Bloomberg and DataStream for 9 months before the event and 1 month after the event and also from Moody a 233 default events from January 1, 2004 to December 31, 2008. However, there were only 39 companies had sufficient CDS data for this analysis.

In order to study the timeliness that is needed for CDS spread to changes before default, the researchers estimate two hypotheses that are:

"Ho (1): The adjusted spread change in the 1, 3, and 6 months before default is not significantly different from zero".

"Ho (2): The adjusted spread change in the 1, 3, and 6 months before default is not significantly different to the adjusted spread change during the estimation period (the 3-month period prior to the event window being tested)".

Later, the researchers compared these hypotheses results during stable economic condition from January 2004 to June 2007 with the results found during the financial crisis from July 2007 to December 2008.

In conclusion, their results recommend that:

- 55 days in advance the default can be projected for the six months spread.
- For quarterly spread or the three months spread, the default can be forecasted 45 days before.
- When they used the “Constant-Mean model” in the course of the financial crisis for the firms they choose and defaulted in the crisis, they found that there were major modifications in the CDSs.

As a result, the researcher agrees with these researchers when they argue that all of the investors and the risk managers can use CDSs as a risk screen device for predicating the default.

Second, Stefano Giglio (2011), who was motivated by a literature on contagion in financial networks 17, focuses on his paper on the systemic events, which were directly linked to the global financial crisis; as a result, he concentrates on the largest and most connected financial institutions and dealers, who had the highest gross exposures to the CDS market. In particular, the analyst chooses a group of 15 institutions in America and Europe within a certain time horizon, which is January 2004 to March 2009. In addition, the group includes 8 American and 7 European investment banks, commercial banks and broker/dealers, which are Bank of America, Citigroup, Goldman Sachs, Lehman Brothers, JP Morgan, Merrill Lynch, Morgan Stanley, Wachovia, ABN-Amro, Bnp-Paribas, Barclays, Credit Suisse, Deutsche Bank, HSBC, and UBS.

Also, the analyst uses Bloomberg and DataStream to include some senior unsecured zero, fixed coupon and dollar bonds for both US European firms with maturity less than 10 years.

Furthermore and in point view of the analyst and despite the several limitations; this paper can be effective in several ways, which are:

First, it is capturing market views about probabilities rather than the true probabilities, which means that the bounds can be imperfections and mispricing due to the slow incorporation of information and underestimation of risks. In addition, when I did some private and personal questioners about the mispricing most of the financial traders claimed and refer it back to the slow transfer of information.

Secondly, although the analyst tries in his methodology to minimize any assumption about the correlation structure of the network, there are some assumptions still necessary to obtain the bounds. For example, remove the risk neutral and default probabilities from prices to imposing a pricing liquidity model.

Finally, because it is difficult to differentiate the effect of counterparty risk on the bond or CDS spread from other factors such as liquidity, it is difficult to find out another alternative to explain this difference. However, the researcher thinks that the counterparty risk is more important than other risk.

To conclude, this paper shows that in 2007 when the bond yield and CDS spread began to fluctuate, it happened because of some financial instates defaulted but was not due to the systemic risk and this exactly what happened for both financial institutes which are Lehman and Merrill Lynch. Besides that, the researcher argues that what happed was not a surprise for the markets participants especially there paper approves that the markets were prepared for their collapse weeks before it happened.

Moreover, John Hull, Mirela Predescu, and Alan White (2004) carried out a study in CDS market to examine the theoretical relationship between credit default swap spreads and bond yield spreads, and then they perform a series of tests to find out how the participants in the credit default swap market react toward the credit rating agency (Moody) announcements.

The sample was provided by GFI, a broker specializing in the trading of credit derivatives, for 233,620 individual CDS quotes (1,502 corporations, 60 sovereigns and 37 quasi-sovereigns. Of the reference entities 798 are North American, 451 are European, and 330 are Asian and Australian. The remaining reference entities are African or South American) from January 5, 1998 to May 24, 2002 with maturities of % years.

Six types of Moody's rating announcements were considered in this study, which are:

- Downgrades
- Upgrades
- Review for downgrade
- Review for upgrade
- Positive outlook
- Negative outlook.

This helps them to do two types of analyses, the first analysis where they take the announcements of downgrades, reviews for downgrade and negative outlooks as (negative events), and the second analysis where they take the announcements of upgrades, reviews for upgrade, and positive outlooks as (positive event).

For the first analysis or the negative rating event they found that there is a significant increase in the CDS spread by 1% in advance in case of a downgrade event, reviews for downgrade and negative outlooks during the 30 days before the event.

In particular, CDS spreads increase 90 days before by:

1) 38 bps for downgrade.

2) 24 bps for review for downgrade.

3) 29 bps for negative outlook.

The second analysis is for positive events, where they found that there is no significant change and suggests that this refer to two possible reasons, which are, first, is that positive rating events are predicted and considered much less than negative rating events. Or maybe that, the researchers sample for the positive rating events did not include enough events to get a clear result, especially if we know that the total number of positive rating events in their sample was only 59, while the number of negative rating events was 266.

In conclusion, their research claims that, first, if the investors want to find out the best and the correct yield spreads, the investors have to use CDs, and secondly, there will be a significant effects on all market participants, such as the investors, the risk managers, and the regulators, if the relationship between two variable which are the CDSs and the PD well established.

Finally, their finding agree with other analysts' finding such as Katrin G. and Paddy (2010) about how and when CDS can predict risk before it happened, thus I think if their findings can be seriously established and employed by regulators, risk managers and investors as soon as possible, it may have the chance and the ability to predict and avoid any future credit crisis.

In addition, Antje Berndt, Rohan Douglas, Darrell Duffie, Mark Ferguson and David Schranz (2008) test the degree of change of the price for U.S. companies' default risk over time during year 2000 to year 2004 depending on the correlation between default probabilities and default swap (CDS).

The CDS data for 93 entities (for three different sectors: broadcasting and entertainment, healthcare, and oil and gas.) is collected from two main sources which are CIBC and also from some specialty dealers in order to give the researchers the chance to found the relation between actual and risk-neutral default probabilities. Also, Moody's KMV is another source from them to collect expected default frequency (EDF) data to do panel-regression models and after that they did arbitrage-free term-structure time-series models to estimate how default risk premium differ over time

Their study has some weakness due to the influence of four arguments, which can be summarized in:

"•Miss measurement of actual conditional default probabilities".

"•Time variation in risk-neutral conditional expectation of loss given default."

"• Changes in the supply of and demand for risk bearing, whose effects are exaggerated by some limits on the mobility of capital across segments of the capital markets."

"• The impact of principal-agency inefficiencies in the asset management industry."

Furthermore, their study also misses and ignores the correlation between an issuer's default and time to default.

In construction, they argue that EDF is a fair measurement to assess the default rates on over the time and claim that Moody's KMV EDF is "too smooth" over the time as the EDF decreases when true conditional default probability is high, and rise when true conditional default probability is low.

Also Roberto B., Simon B. and Ian W. (2009) investigate the behavior of both the credit default swaps (CDS) and credit risk spread for the European and US firms in time series. Furthermore, in their analysis they present three questions to be answered, which are, first are both variables (they studied) are equal, second, is the discovery of the credit risk is involved the cash bond or credit derivative market. Finally, which elements can affect the CDSs and credit spreads more and strongly in the short-run.

Their study collects all the required data for CDSs data from J.P. Morgan and Bloomberg for all European and US entities between years 2001 to June 2002 and with a maturity vary from three to five years.

They argue that in the short run the CDSs can be taken as the best technique to project and discover any credit risk price; although it can also be used and reveal the long run

Likewise, Navneet Arora, Priyank Gandhib and Francis Longstaff (2010) inspect the dealers of credit risk ability to reflect the risk level when selling the credit protections and they find strong evidence that the higher the credit risk of a dealer, the lower is the price at which the dealer can sell credit protection in the market due to three different conclusions, which are:

- The CDSs is very small for the securities where the CDS liabilities are unsecured.
- After the Lehman default, the counterparty credit risk was higher and remarkably priced after the analysts believed that that CDS were exposed potential weaknesses with existing collateral protocols and/or legal protections.
- There were many financial institutions respond to major shocks.

B. Credit Default Swap Spread Changes

Klaus D. and Agnieszka S. (2005), also, examine the changes of the CDS spread for large German banks and the different risks behind the changes. The sample consists of three large Dutch banks, which are Commerzbank, Deutsche Bank and HypoVereinsbank.

The study built on analyzing the influence of three risk sources, which are idiosyncratic credit risk, systematic credit risk, which has two mechanisms 1) one related to the overall state of the economy and 2) the other to a banking–sector specific component, and finally the liquidity risk.

First they compare the default probabilities with the expected default frequencies (EDF) from Moody's KMV model. In the same time, they try to estimate a linear regression for the chosen sample based on the weekly observations from 13 March 2002 to 16 February 2005, with 152 observations, however, their study was limited due to the data availability, as a result, the researchers decided to exclude the unavailable data.

Moreover, the researchers choose senior 5 year CDS prices for the bid and ask price, where the average of the quoted bid and ask prices of the day are extracted from Bloomberg from 5 September 2001 to 16 February 2005 on a daily basis. The model was successful in explaining 27%–40% of the total variation of the CDS spread and approves that the highest power has the market systematic risk factor compared with other risks power.

Their findings agree with others' papers previously presented and support their results as they find that there is a positive relation between the changes in both the interest rates and the CDS spread, especially in the liquidity risk, which is able enough to bind the value of CDSs. Furthermore, they suggest that both of the equity price and CDSs should be taken into account together if we want to have a full market picture as this can easily lighten any individual weaknesses.

C. Market Influence

In order for Dr. Hayette G. (2006) to analyze the relations and influence of the related systematic and unsystematic default risk components on credit risk level, he tried to separate the development that happened in the US credit spreads into two parts, first, the changes that happened due to the market risk influence, and second, the changes resulted from default risk influence,

To do so, he extracts the credit spread data in the light of three risks' influences, which are credit rating, maturity and industry. Second, the researcher examines the relation between the common latent factor and S&P 500 stock index together with the three previous mentioned risks' influences.

Thus, Dr. Hayette uses Bloomberg database spreads and S&P 500 stock market index to collect a sample of a monthly data started from May 1991 to November 2000 for a total of 115 companies in different financial sectors (banking, finance, power, and telecommunications).

Furthermore, the researcher's study focus on the risky bonds' whose ratings range from AAA to BAA with maturities range from one year to twenty years, consequently, the researcher uses Moody's rating agency and collects data for a total number of 116 credit spread time series for all sectors with their maturities and their credit ratings. Moreover, Standard & Poor's is used as a proxy to evaluate the systematic risk influence and uses the continuous monthly returns of S&P 500 index.

Lastly, the researcher's paper has fascinating and different judgments as his findings suggests that S&P 500 index was not successful to capture the systematic risk determined by the credit spreads despite their sectors or ratings or even the maturities, as a result, there is always an essential need to filter almost all the information comes from S&P 500 index if the investors want to predict the market risk.

D. CDS Determinants

Antonio Di Cesare and Giovanni Guazzarotti (2010) study the determinants of credit default swap spread changes for a large sample of US non-financial companies between January 2002 and March 2009. In their analysis they use Merton model theory's variables, which they assume it may have an impact on CDS spreads.

The analysts used Bloomberg to select US CDS contracts with maturity of 5 years from January 2002 and March 2009, and restricted their sample to listed firms only ending up with a sample of 167 companies.

In addition, DataStream was used to select US government zero coupon bonds with risk free interest rate, and also, they used S&P Composite index to collect the daily data of credit spreads for AA and BBB US industrial, and finally they used VIX index as a broad index of US market implied volatility.

After that the researchers divided their analysis and finding into four groups, which are:

a) During the crisis period:

According to their findings, the CDS spread changes and regression residuals have been moving increasingly during the crisis, and also, they propose that spread changes were motivated by common or systematic factors (such as economic activity, uncertainty, and risk aversion) rather than the firm-specific factors. However, there is large number of CDS spread differences during the crisis is still not clear.

b) Leverage Analysis:

The study shows that increase of the CDSs for the low and high leverage companies have different reasons depend on their leverage size. As the CDSs increase for the low leverage firms is not related to the leverage or volatility factors, but it's related to the market factors such as the interest rate and the market price. On the other hand, for the higher levels of leverage firms have a different reason which is the investors, who became more worried about the firms' balance sheets weaknesses.

c) Economic sector:

According to their model, the researchers argue that during the crisis the performance of the CDSs sharply increases for firms in the Basic materials/Energy and Consumer non-cyclical.

d) Liquidity change

First, the researchers grouped the companies into four groups depend on the change in the average of the bid-ask spread before and after the crisis and argued that the model remains approximately the same during the crisis period for both the contracts in the lowest and highest bid-ask spread changes, especially the firms with high quartile didn't show any important change during the crisis.

Moreover, they claim that due to the lack of liquidity during the crisis and because the study takes the large bid-ask spreads as a proxy for their model, no relationships founded between the CDS spread changes and their explanatory factors.

In conclusion, their study is able to clarify more than 50% of CDS spread deviations before and after July 2007, in the same time; they approve that during the crisis the CDS spreads have become more sensitive to level of leverage more than other volatility.
Furthermore, their findings approve that since the beginning of the crisis CDS spread change due to other common factor, which cannot be explained by known and theoretical indicators such as economic activity, uncertainty, and risk aversion.

Additionally Benjamin Yibin Zhan, Hao Zhou and Haibin Zhu (2008) try to investigate the determination of credit default swap spreads at firm level, by using a new approach (as they claim) to recognize the volatility and the jump risks of some firms from high frequency equity prices.

First, they standardize Merton model with stochastic volatility and jumps in a way which it can help them to match the credit with the spreads after monitoring the historical default rates. By the help provided by Markit, a sample information was collected, which starts from January 2001 to December 2003 include five years CDS contracts for 307 US entities (excluding sovereign entities and only the entities with rating of A 30%, BBB 43% and BB 13%) and amend these contracts by restructuring (MR) clauses as they are the most traded in the U.S. market and after that they link the CDS data with the equity prices and balance sheet information. Furthermore, in order to calculate the average jump intensity, jump mean, and jump standard deviation for one year horizon, they started to calculate from the five-minute transaction data on equity prices.

So, their research includes the leverage ratio (LEV), return on equity (ROE), and dividend payout ratio (DIV), which all acquired from Compustat, and from Bloomberg they got the four macro-financial variables as proxies for the overall the economy of the state, which were provided by the S&P 500 (average daily return for the past six months, the implied volatility—VIX—from the option market, the average three-month Treasury rate, and the slope of the yield curve).

They argue that their model was successful in explaining 48% of the variation in CDS spread levels. Nevertheless, when they were able to control the credit ratings, macroeconomic conditions, and firms’ balance sheet information, their model was successful to explain 73% the total variation and predicate 19% of the risk jump.

According to their findings they argue that they are able to explain 14 to 18% of the total variation in levels of credit spreads after they controlled the rating information and other structural factors and insist on that these variables affect any economy.

Overall, when controlling for the historical default rates, the improvement is likely for A investments, nevertheless there is less satisfactory results for the lower investments such as BBB which agree with the incorporating a countercyclical default boundary as in Collin-Dufresne and Goldstein (2001); Chen, Collin-Dufresne, and Goldstein (2008).

In addition, Laura Chiaramonte and Barbara Casu (2010) inspect the determinants of CDS spreads and if CDS spreads can be considered as a risk proxy for the banks or not, for that reason, the analysts focus on the banks' balance sheet and conduct a research that cover three periods, which are pre-crisis from 1 January 2005 to 30 June 2007, crisis period from 1 July 2007 to 31 March 2009 and the crisis period from 1 July 2007 - 31 March 2010.

Since their decision is to focus on CDS spreads for the banking sector, their problem was that the sample size due to the limited number of banks, which trade in CDS and other credit derivatives. As a result, the final sample is composed of 57 international banks, where there are 43 European banks (2 from Austria, 3 from Belgium, 1 from Denmark, 1 from Norway, 5 from France, 2 from Germany, 3 from Ireland, 5 from Italy, 1 from The Netherlands, 1 from Portugal, 6 from Spain, 4 from Sweden, 1 from Switzerland, and 8 from United Kingdom), 7 American banks, 4 Australian and 3 Japanese banks.

Similarly, DataStream was the source of data for the selected with a maturity of five-year and used quarterly as this choice strictly linked to the type of descriptive variables considered (balance sheet variables).

Moreover, in this research Bloomberg is used to collect eight balance sheet ratios in order to examine the profile, however, this data is limited to the available data, as that there are only few banks with CDS contracts report their financial data on a quarterly basis.

In summary, the eight ratios are:

- Asset quality:

1. Loan Loss Reserve/Gross Loans.
2. Unreserved Impaired Loans/Equity (%) or capital impairment ratio and here the increase in the ratio should signal a greater probability of default.

    - Capital:

3. TIER 1 ratio, which measures the capital adequacy.

    - Leverage:

4. Equity/Total Assets, which investigates the determinants of short-and long-term CDSs.

    - Operations:

5. ROA (Return On average Assets), which indicates the return of banks' investments.
6. ROE (Return On average Equity). This ratio is a key for the return on equity and the higher the ratio, the lower the expected the default risk.

- Liquidity:

7. Net Loans/Deposits & Short Term Funding8 (%), which measure the liquidity.

8. Liquid Assets/Deposits & Short Term Funding (%) and it is considered to be a further liquidity measure, where it measures the ratio of Liquid Assets to Deposits & Short Term Funding.

The analyst findings claim that the ratio of the Loan Loss Reserve to Gross Loans is the only important ratio in all chosen periods, besides; they find that the probability of default seems to increase mainly for those banks with low quality loan portfolios.

On the other hand, their findings for both Leverage and the TIER 1 Ratios did not agree with their expectation as both ratios were not among the determinants of bank CDSs, but in the same time, their findings confirm the high effect of leverage ratio during both in the pre-crisis period, where the bank CDS spreads in this period was satisfactory, and also during the crisis period, where banks' CDSs reached the peak.

Furthermore, the sample findings show that the TIER 1 Ratio for the banks, which faced difficulty, were above the minimum requirements, and suggest that the efficiency of the capital index TIER 1 Ratio for assessing the future default.

Obviously and as it was expected, the liquidity ratio was not taken as a serious indicator during the pre-crisis period, which helped a lot in increasing the risk in the recent financial crisis.

From their research they conclude that the bank CDS spreads in all periods especially the crisis period reveal the risk, which was captured by the banks' balance sheet ratios, besides that, they argue that the determinants of bank CDS spreads, such as economic and financial conditions, differ and change strongly from time to time, however liquidity indicator is considered to be the most significant indicator during and post crisis.

Finally, this paper agree with other studies, which investigate for both bond and CDSs spreads and argue that any model should be change and re-estimated as macro-economic conditions change if we want to get the correct information to help the regulators and policy makers.

Similarly, Pedro Pires, Jiao Pedro and Luis Filipe Martins (2010) use the quantile a regression to study the determinants of Credit Default Swap (CDS) spreads. The quintile regressions that the researchers use help them to discover the significant the response of the firms' in the low risk condition contrasted with the high risk condition, using both the coefficients and the "goodness-of-fit of the model" to increase the quantile regression of CDS spread.

The 5-year senior CDS data, which include monthly observations of US and European corporate CDS names, was gathered from Bloomberg Financial Services from August 2002 to February 2007 for 260 firms and 13,470 CDS spread quotes.

Moreover, the researchers' paper looks to the credit rating history for the chosen entity that is collected from the S&P Credit Rating; however, when the rating history is not available they use the Moody's Senior Unsecured Debt Rating

Furthermore, they argue that the CDS spreads are strongly determined by three different key which are the traditional theoretical variables, such as the implied volatility and put skew and the illiquidity costs. Though the CDS transaction costs should be measured by absolute, rather than relative, bid-ask spreads.

Additionally, they approve that the absolute bid-ask spread can be used as a measurement of the cost of trading a CDS but not the relative bid-ask spread. In addition, the model that they created allows them to estimate the Credit VaR directly from the key determinants of CDS spreads, instead of relying only on historical quotes or external credit ratings. However, they argue that the previous studies which based on the conditional mean approach must also complement with their results and findings for the entire distribution.

Likewise, Caitlin Ann (2008) investigates the ability of the variables to describe the variation in CDS spread changes in the market, as a results, the researcher uses the monthly changes in CDS spreads for 333 companies from January 2001 to March 2006. From the data collected, he finds that the variables are able to explain 30% of the variation in CDS spread changes.

Also, there different variable that can be used to predicts CDSs which are the credit risk, overall market conditions, leverage and volatility , which agrees with Blanco et al. (2005), who argues that the equity returns and leverage are comparable proxies for a firm's health when using high frequency data over a relatively short time horizon.

Likewise, he claims that the interest rate variables do not work perfectly such as the equity market variables since the interest rates variable seems to be less predictive in the regression model.

Douglas Dwyer, Zan Li, Shisheng Qu, Heather Russell and Jing Zhang (2010) investigate the link between two variables, which are credit default swap (CDS) and expected default frequency (EDF) and constructing on the link between PD and CDSs, so thy used the risk metric and the risk-neutral PD.

Despite the number of entities that use and deal with EDF, there are many companies are not covered by the CDS contracts, as a results, it is noticeable that the EDF's deals is considerably more than the number of entities that use and deal with CDS spreads (about 1,464 public organizations), however, the researchers use both a CDS-implied EDF for their analysis, so the Fair-value Spreads was used without a need for direct observed of CDS spreads. Therefore, their paper covers 100 entities only from North American HY CDX index (CDX.NA.HY.13-v2), where there are 13 private firms, 8 private companies and 11 public companies; however, there are 32 entities do not have EDF credit due to a lack of information.

In conclusion, the researchers' model framework approved that the CDS-implied EDF and of EDF are linked together, and also they recommend that their model is considered to be a valuable and useful reference for both risk management and credit investment, so they suggest that the two tools, which are the CDS and EDF are powerful enough that the risk managers can use them to hedge their investments risk. Beside risk manager, investors can use them too to assess their assets values and credits

E. Liquidity Risk

Dragon Yongjun Tangy and Hong Yan (2007) construct to study the effect of pricing on the liquidity and its risk in the CDS market in different aspects of CDS liquidity such as adverse selection, search frictions, and inventory costs.

First of all, the CDSs data was gathered from Credit Trade with a period of June 1997 to March 2006 for 12,984 U.S. bond firms (non-Sovereign) for only senior contract and maturities between 4.5 and 5.5 years.

Furthermore, from the information gathered, the analysts realized that there was considerable time series variation in average CDS spreads in the second half of 2002 and referred that to the credit market turbulence at that time. On the other hand, CDS spreads later started to declined due to three different possible reasons, which are the improve in the macroeconomic conditions, bigger control of high quality issuers in the market, and finally the increase of the competition in the CDS market.

To simplify their study, therefore, three hypotheses were formed by the researchers to enable them to test the sample's data:

1) "Hypothesis 1: CDS spreads are higher for less liquid contracts, ceteris paribus. These include contracts with higher search costs, higher price sensitivity to trading, higher level of adverse selection, and higher level of inventory constraints".

2) "Hypothesis 2: All else being equal, CDS spreads are positively related to the sensitivity of individual liquidity shocks to market-wide liquidity shocks (β2), negatively related to both the sensitivity of shocks in individual CDS spreads to market-wide liquidity shocks (β3) and the sensitivity of individual liquidity shocks to shocks in aggregate CDS spreads (β4)".

3) "Hypothesis 3: All else being equal, CDS spreads are positively related to the volume of trade in the underlying contracts".

As a final point, they claim that all of the liquidity level and liquidity risk are important determinants in the CDS spreads, which highlight the need for a CDS pricing model to be clear for everybody. Furthermore, they argue that the liquidity and the liquidity risk together could account for about 20% of CDS spreads.

On the other hand, they found that the CDS spreads may respond to news more quickly than credit ratings, which agree with Hull, Predescu, and White (2004) and Norden and Weber (2004) searchers, where they argue that the CDS market can easily estimate rating announcements especially the negative rating events. For example, the AAA bonds have one possible change in its rating which is downgrading only. Therefore, in this case the CDS market can incorporate with this information immediately before credit rating agencies change their ratings for the corresponding entities.

Besides, Armen Arakelyan and Pedro Serrano (2012) investigate the relationship between liquidity and CDSs and how the liquidity supply influences the Credit Default Swap CDSs. Hence, two different analyses were carried out, that are panel data analysis and then they started to observe the panel result to know if the liquidity is priced by CDS investors or not, where the distress risk and default compensation plays a role in this relation.

In addition, the daily quotes CDSs data for North American was provided by Markit Group Ltd of CDS spreads from January 2004 to April 2011 with different maturities of one , three, five, seven and ten years. As well, the final sample is composed of 100,500 observations for 283 firms with different credit rating vary from AA to CCC and for different industrial sectors (basic materials, consumer goods, consumer services, financial, health care, industrial, oil and gas, technology, telecommunications and utilities).

Furthermore, the analysts specified five different methods to help them in their research which are:

- CDS bid-ask spread,

- Using Markit, the analysts acquired total number of contributors.
- Gamma measurement for CDS illiqudity.
- Return to-volume measurement.
- Fitch liquidity score.

Finally, the analysts argue that they were able to find strong evidence that there is strong statistical relationship between the two changes in both variables, which are liquidity proxies and changes in CDS constituents.

Furthermore, all the three methods that are used in researches are considered to be important dynamics to explain the influence of liquidity on both the CDSs and CDS implied risk premia, however, the other two methods, which are the number of contributors and Fitch liquidity score are considered to be a weak measurement.

In overall, in CDS predicting a default, I recommend using regression and correlation methodologies as a coherent concept to understand and find out if the CDSs can predict a default or not. Moreover, most of the researchers use these models as a coherent way to find out if there is a significant relationship between the two variables.

Chapter (3)

III. Sample and data description:

- **The CDS quotes:**

The 5-year CDS data in this study is obtained from Bloomberg Financial Services on monthly observations for US five financial corporates' CDS names, which are Citigroup Inc., JP Morgan Chase & Co., Goldman Sachs Group, Lehman Brother, and Morgan Stanley. All monthly bid and offer quotes are captured on the last business day of each month with 1131 observations.

- **The EDF Data:**

Usually Moody's KMV offers its clients with the current firm-by-firm estimates conditional probabilities of default for time horizons of 1 and 5 years and this is called as the "KMV-EDF" or the Expected Default Frequency. Moreover, since Moody's KMV covers over 26,000 publicly traded firms, it is considered as the most commonly used or the source for the default probability.

Therefore, my EDF data is composed by daily 5-year EDFs for a sample of 5 US firms which are Citigroup Inc., JP Morgan Chase & Co., Goldman Sachs Group, Lehman Brother, and Morgan Stanley and it covers from 16-Jan-2007 to 23-May-2011 with 1131 observations. This data was provided by Moody's Analytics (DIFC) LTD.

Chapter (4)

IV.1. Data Analysis and Model:

- **The Regression and Correlation:**

In the previous literature review on the CDS, many researchers frequently use theoretical framework model presented by Merton (1974) and argue that using regression methodology is the key drivers to discover credit default.

Regression analysis simply is a statistical method that allows the user to find if there is a relationship between two or more variables using a straight line, and in my analysis I want to identify and know if there is a relationship between CDS and EDF.

To find the statistical relation between x (CDS) and y (EDF) we can convey the equation to one form which is: $y = a + bx$

First you have to find slope (b) then the equation is = $(N\Sigma XY - (\Sigma X)(\Sigma Y)) / (N\Sigma X^2 - (\Sigma X)^2)$

Then find (a) = $(\Sigma Y - b(\Sigma X)) / N$

Where:

b = the slope of the regression line

a = the intercept point of the regression line and the y axis.

N = number of values or components

ΣXY = Sum of the CDSs and EDF

ΣX = Sum of First variable (CDSs)

ΣY = Sum of Second variable (EDF)

ΣX^2 = Sum of square of CDSs.

Hence, my main objective behind using this type of analysis is simply to measure the sensitivity of credit default swap spreads (CDSs) to default probabilities (EDF); therefore, I undertook a linear regression analysis between EDF and CDS observations from January 2005 to May 2011 using SPSs.

On the other hand, correlation model tells you how accurate are your regression equation especially the coefficients statistics, which tells you how strong are the relationship between two variables. Despite the several types of correlation coefficient, I use Pearson's correlation in my study to analyze my data.

IV.2. Findings and Results

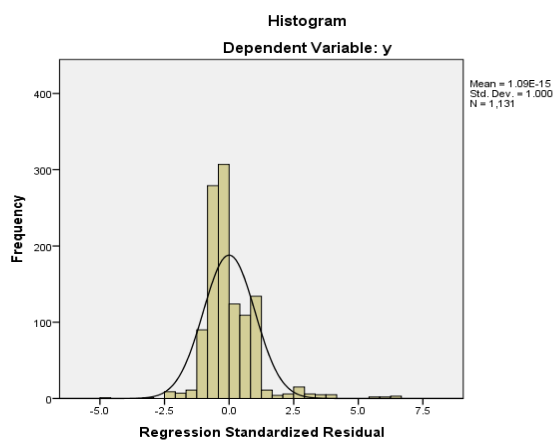
My empirical work concentrates on analyzing the ability of CDS spread as a credit risk indicator or not. Therefore, I start by applying the linear regression in order to discover if there is any significant relationship between the two variable *CDS and EDF or not* by testing the null hypothesis.

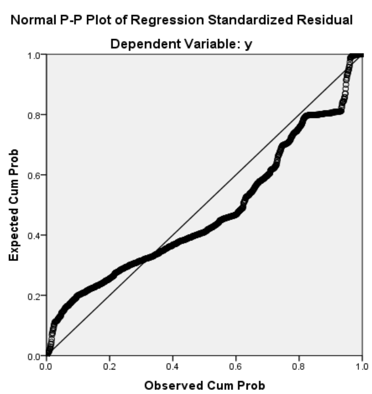
Besides, since the p-value should be less than 0.05, I reject the null hypothesis that H_1: ß ≠ 0 which means that there is a significant relationship between the variables in the linear regression.

Below I listed my results and analysis:

❖ Graphically scatter diagram: (see table 1).

The First step to do when you inspecting a relationship between two variables in a regression correlation is to examine the graphically scatter diagram.





From the above scatter diagram, there is a link or correlation between variables, as the scatter plot is consider being a useful summary for the variables data. The above normal probability plot of the residuals suggest that the points are close to a diagonal line. Consequently, the residuals seem to be normally distributed, which suggest that the molds for regression analysis seem to be met.

Moreover, the above scatter diagram we can assure that there is a positive linear relationship between CDS and EDF.

- **Correlation:** (See table2).

Correlation or correlation coefficient is used to measure the strength of the relationship between two or more variables, so statistically we can follow the following equation:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Where $\bar{x}$ and $\bar{y}$ are the mean of x and y values.

From the equation, we can find the r value, which is always should be between -1 and +1.

However, there are three possibilities, which are:

a. The value is equal to +1 or closer, which indicates a strong positive linear relationship
b. The value is close to -1, which indicates strong negative linear relationship.
c. A value close to 0 and it indicates that there no linear relationship.

Below is CitiGroup's correlation:

Correlations			
		x	y
X	Pearson Correlation	1	.776**
	Sig. (2-tailed)		.000
	N	1131	1131
Y	Pearson Correlation	.776**	1
	Sig. (2-tailed)	.000	
	N	1131	1131

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

According to my analysis, I found the below listed results for the correlation coefficient:

a. Citigroup Inc. is".776" and it is considered as high and strong positive relationship.

b. In the same time, JP Morgan Chase & Co.'s correlation is ".565" and that considered as moderate positive.

c. On the other hand, Goldman Sachs Group with a correlation of ".477", Morgan Stanley with correlation of ".399" and Lehman Brother with correlation of ".407" are considered as a weak correlation.

- P-value: (See table 2).

The main objective behind interpreting the p-value in the regression coefficients is to test the significant level at 5% or .05 and in this case we usually reject the null hypothesis and consider as evidence that there is relationship between two variables.

Though, SPSS (the model that I used) reports p value as “Sig.", and frequently SPSS’s report misleads us and gives us the output as”.000" whenever the p-value is “< 0.0005".

On the other hand, we can reject the null hypothesis (H_0: ß = 0) and this is another evidence that there is relationship between CDS and EDF.

- R and R^2 :(See table 3)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.78	0.60	0.60	2.20

a. Predictors: (Constant), x

b. Dependent Variable: y

As a general rule, R and R squared shows the amount of variation in the dependent variable explained by the regression model, so it indicates the strength of linear trends. When R tells us how much is the variance of "Y" or “EDF” explained in the regression model, the adjusted R squared (R^2) measures the percentage of the variation of the dependent variable in the regression model. In other word, R-square is nothing than the square of the correlation between two responses, which is the response of EDF and the predicted response of the CDSs.

Furthermore, R-square's value can vary, again, between 0 and 1, and the closer the R squared value to one, the greater the ability of the CDSs to predict a default.

Below you can find my analysis result:

a) The R and R^2 for both Citigroup Inc. and JP Morgan Chase & Co. have a strong relationship between the two variables, as the results are above 70%.

b) Whereas Goldman Sachs Group, Lehman Brother and Morgan Stanley's results show a moderate relationship.

❖ The ANOVA: (see table 4)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8285.54	1.00	8285.54	1711.27	.000[b]
	Residual	5466.34	1129.00	4.84		
	Total	13751.87	1130.00			

a. Dependent Variable: y

b. Predictors: (Constant), x

Again in SPSS output for ANOVA is just concise and this case I can really once again in one value to answers my question, which is the *P*-value. As a result, we can ignore ANOVA table as the null hypothesis already rejected.

- Coefficients: (see table 5)

Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
1 (Constant)	-2.06	0.11		-18.94	0.00	-2.28	-1.85
x	0.02	0.00	0.78	41.37	0.00	0.02	0.02

a. Dependent Variable: y

First of all, Beta (**β**) suggests that for every one x or CDS increase, the model predicts an increase of 0.02 standard marks, so we can interpret that the constant or the coefficient regression equation from the table: thus, we can say that when X = 0.02 y or EDF= 2.06+ 0.02 (CDS).

Second, as I stated previously that my hypothesis is already rejected due to the P value, however, we can again check "sig" or "p-value" is lower than ".05", so again I'm going to reject the null hypothesis.

Moreover, the last column tells us that 95% we can assure that the regression slope is between ".02". This means that in case x increase by one unit, as an average, y is predicted to reflect this increase by .02.

Chapter (5)

IV. Empirical Results and Conclusion:

This research has focused on the ability of the credit default swaps (CDS) to predict a default and react to this risk, and I address this behavior by testing the relationship between EDF and CDS using regression and correlation methodology using SPSs model. As a result, I collected sample of five US financial institutions, which are Citigroup Inc., JP Morgan Chase & Co., Goldman Sachs Group, Lehman Brother, and Morgan Stanley from 16 January 2007 to 23 May 2011.

Despite lack of data, I employ the collected data that include both default swaps and KMV Moody's default probabilities to study the degree of variation on prices for both CDS and EDF, since I believe that its logic if CDS is a risk indicator then this will reflect other variable too.

From above, the findings suggest that both variables, which are CDS and EDF, are significantly correlated and have strong relationship. As a result, my findings agree with other researchers, who previously I illustrate their researches in the literature review, argued and suggested that CDS is considered to be good risk indicator and it appears to me from the findings that it is possible to construct an accurate default forecasting model using credit default swap (CDS).

Moreover, previously the researcher mentioned that there is a lake of data and this refers to that there is no EDF data for Lehman Brothers after 2008 as the company went bankruptcy. In addition, one of the research questions is that does the CDSs highlights any exaptation for any default in case of default, and according to the results **YES** it is. Going back to the analysis, we can find that the Lehman Brothers correlation and R and R square are vary from weak to moderate relationship and even the CDSs and EDF data started to increase before the default, as a result, all these findings conclude that CDSs don't only predict a default but also CDSs highlights all defaults including large firms' CDSs.

Here I can conclude that all of the investors, risk managers and other market participants can use CDSs as a risk indicator.

References

1. *Levy Amnon (2008). An overview of modeling credit portfolios. Moody's Analytics, Inc.: Moody's KMV Company. pp. 5-18.*

2. *Fontana Alessandro and Scheicher Martin (2010). An analysis of Euro area sovereign CDS and their relation with government bonds. Venice: European Central Bank, Working Paper Series no 1 2 7 1. Pp.15-28.*

3. *Berndt Antje, Obreja Iulian (2007). The pricing of risk in European Credit and corprate bond markets. 2nd ed. Frankfurt, Germany: European Central Bank. Financial Analysts Journal 805, pp. 18-32*

4. *Berndt,Rohan Antje Douglas, Duffie Darrell, Ferguson Mark and Schranz David (2008). Measuring Default Risk Premia from Default Swap Rates and EDFs. New York, Toronto: CIBC. Pp.20-47.*

5. *Di Cesare Antonio and Guazzarotti Giovanni (2010). An analysis of the determinants of credit default swap spread changes before and during the subprime financial turmoil. Italy: Financial Analysts Journal no. 749. Pp. 7-23.*

6. *Zhang Benjamin Yibin, Zhou Hao and Zhu Haibin (2008). Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms. 2nd ed. Chicago: Journal of Finance, vol.2. Pp. 9-21.*

7. *Baum Christopher F and Wan Chi (2010). Macroeconomic uncertainty and credit default swap spreads. Boston: Economics journal. Pp. 5-17.*

8. *CREDITEDGE & CREDITEDGE PLUS (2004). The Components of EDF Implied Spread. MIS Quality Management Corp.: Moody's KMV Company. P: 1-2.*

9. *Díaz, Groba J. and Serrano P. (2011). What drives corporate default risk premia? Evidence from the CDS market. Madrid, Spain: University Carlos III. Pp.8-22.*

10. *Don H Kim, Loretan Mico and Remolona Eli M (2009). Contagion and risk premia in the amplification of crisis: evidence from Asian names in the global CDS market. USA: Bank for International Settlements. Pp. 323-352.*

11. *Dragon Yongjun Tang and Hong Yan (2007). Liquidity and Credit Default Swap Spreads. Columbia: Financial Economics Journal. P: 19-29.*

12. *Ericsson Jan, Reneby Joel and Wang Hao (2007). Can Structural Models Price Default Risk? Evidence from Bond and Credit Derivative Markets. Canada: Economist Journal. Pp. 10-16.*

13. *Hull John, Nelken Izzy, and White Alan (2004). Merton's Model, Credit Risk, and Volatility Skews. 2nd ed. Toronto: Financial Journal. Pp.10-25.*

14. *NEZIRI Hekuran (2008). Can Credit Default Swaps Predict Financial Crises? Empirical study on emerging markets empirical study on emerging markets. Bulgaria: Journal of Applied Economic Sciences Volume IV. Pp.125-136.*

15. *Chou Heng-Chih (2005). Expected Default Probability, Credit Spreads and Distance-from-default. Cambridge: he Journal of American Academy of Business Vol. 7. Pp.144-152.*

16. *Buus Ida and Nielsen Charlotte Renneberg J. (2009). The relationship between equity prices and credit default swap spreads. Denmark: The Danish National Bank, Economics and Finance journal. Pp.12-109.*

17. *Korablev Irina and Dwyer Douglas (2007). Power and level validation of MOODY'S KMV EDFTM credit measures in North America, Europe, and Asia. MIS Quality Management Corp.: Moody's KMV Company. Pp.25-55.*

18. *Gottschalka Katrin and Walker Paddy (2009). The timeliness of CDS spread changes in predicting corporate default, 2004-2008. New Zealand: Auckland University of Technology. Pp. 4-27.*

19. *D¨ullmann Klaus, Sosinska Agnieszka (2005). Credit Default Swap Prices as Risk Indicators of Large German Banks. Frankfurt: Deutsche Bundesbank. Pp. 16-18.*

20. *Chiaramonte Laura and Casu Barbara (2009). Are CDS spreads a good proxy of bank risk? Evidence from the financial crisis. Cass Business School: City University London. Financial Analysts Journal 05/10, Pp.21-32.*

21. *Kessler Margaret and Levenstein Laura (2001). Credit Default Swaps versus Financial Guaranties - Are the Risks the Same? New York: WIlliam L. Thompson. Pp.1-6.*

22. *Manning Mark J (2004). Exploring the relationship between credit spreads and default probabilities. London: Bank of England. Pp.5-35.*

23. *Bilal Mohsan and Singh Manmohan (2012). CDS Spreads in European Periphery. IMF: IMF Working Paper, WP/12/77. Pp.7-16.*

24. *Bharath Sreedhar T and Shumway Tyler (2004). Forecasting Default with the KMV-Merton Model. USA: University of Michigan. Pp.16-32.*

25. *Giglio Stefano (2010). CDS Spreads and Systemic Financial Risk 2nd ed. USA: Harvard University. Pp.24-40.*

26. *Siu Tak Kuen, Erlwein Christina, and Mamon Rogemar S. (2008). The Prancing of Credit Default Markov-modulated Merton's Structural Model Swaps under A. London: North American Actuarial Journal Vol.12 No.1. Pp.22-44.*

27. *Leisti Tuomas (2007). The Relation between Credit Default Swap Spread and Corporate Bond Spread: Arbitrage Opportunities in the Finnish Market. Finland: LAPPEENRANTA UNIVERSITY of TECHNOLOGY. Pp.10-41.*

28. *Chen Yaru (2007). What Explains Credit Default Swaps Bid-Ask spread? SINGAPORE: SINGAPORE MANAGEMENT UNIVERSITY. Pp.37- 41.*