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***Quantitative Risk Estimation in the Credit Default Swap Market  
using Extreme Value Theory***

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## **Abstract**

This paper is motivated by empirical evidence illustrating the non-Gaussian nature of financial returns, (Jondeau et al 2007) and analyses extreme value theory, (EVT) as a proposed improvement (Embrechts et al., 2005) for risk estimation techniques.

Credit default swaps, (CDS's) are analysed due to their increasing importance to financial stability (European Union, 2009) and due to the lack of quantitative univariate risk analysis of this market. EVT is generally applied to currency, equity and bond markets, (Assaf, 2009). Whereas the majority of quantitative analysis of the CDS market has focused on multivariate functions, analysing the dependency of CDS market returns and other asset returns, (Chen et al., 2008). Equity and bond samples are used here as a comparison to the CDS market returns.

The findings are divided into three parts. The first part focuses on the general characteristics of the three asset classes, CDS's, equities and bonds, noting the non-normality of the distributions. As GARCH is widely used in industry to remove dependency in the second and higher moments, the second part of the findings assesses the efficacy of this methodology. Evidence that GARCH removes dependency in the second moment is found but the distribution of the residuals continues to appear non-Gaussian for all three asset classes and non-iid for the CDS sample. In light of these findings, the third section uses a semi parametric approach to estimate the tail parameter of the distribution of the three CDS samples. The result of the investigation suggests that the parametric GARCH-EVT approach may be suitable for equity and bond market univariate risk estimation but that this approach and the semi-parametric EVT approach may both have limitations in assessing risk in CDS market returns.

**JEL Classification: G10, G11, G17**

## Section I

### Introduction

Bachelier, (1900) first suggested that financial data returns form a martingale series. From the 1950's onwards, this hypothesis lead Cootner, Fama and others to the use of the Gaussian distribution when developing models for assessing risk and return in financial data. The use of a mean-variance model has since become pervasive, (Brealey, 2008). However, there exists a large body of empirical literature documenting the non-Gaussian nature of the return distributions observed in the financial markets. Some of the *stylized facts* that emerge from this literature show that the return distributions across asset classes exhibit fat tails, volatility asymmetry and time-dependence in both volatility and higher moments (Jondeau et al., 2007). In the literature, among other approaches, extreme value theory has been proposed as an alternative to handle the challenges posed by the *stylized facts* of the financial markets. It has been argued that extreme value theory gives a more accurate estimation of the asymptotic tails of the density function (Embrechts et al., 2005). The advantages of this family of distributions are that they include an additional parameter which allows for the size of the tails to change and also the distributions can be positively or negatively skewed. The revision of techniques, such as Value at Risk, for the inclusion of this alternative methodology to the mean-variance approach, has been suggested will improve estimation of market risk, (Cotter, 2001). This may, for example, improve financial institutions estimates of adequate bank capital, when implementing the revised Basel II Capital Framework, (BIS., 2009)

In this paper, our initial objective is to compare and contrast the univariate characteristics of CDS returns to that of equity and bond market returns. The methodological motivation for this is to test the *stylized facts* observed for the three asset classes, (Jondeau et al., 2007). In light of the existence of these facts, the mean-variance model may not be appropriate and alternative methods are evaluated. As part of this assessment, the second objective is to assess GARCH as a method of removing dependency in the second and higher moments. This, Bollerslev, (1986) suggests will allow for the use of the mean-variance model. The third objective is to assess parametric and semi-parametric EVT as

an improvement in market risk estimation techniques. In light of the support shown below for the stylized facts, there are two research questions discussed in this paper;

1. Should GARCH be used to remove conditionality in financial assets' returns?
2. Can GARCH and EVT be used to measure market risk in financial data, especially credit default swaps?

The reasons for analysing the credit default swap market are twofold. Firstly, due to the increasing importance of the CDS market to the overall stability of the financial system, and secondly due to the lack of literature using a univariate model when analysing the distribution of credit default swap returns.

In September 2009, the European Commission observed that;

*“The crisis has highlighted that these [market] risks are particularly evident in the over-the-counter (OTC) part of the market, especially as regards credit default swaps (CDS).”*

(European Union, 2009).

Also, ECONET, the network of economists from CESR Regulators report on CDS market trends, on a regular basis including analysis of *“appropriate indicators of uncertainty and the potential for contractions (like implied volatility, value-at-risk) ...”*

(CESR and Regulators, 2009)

Thus there is increasing demand from regulators as well as financial institutions to improve univariate risk estimation techniques for credit default swaps.

For a market which has only been in existence since 1995, the CDS market has grown significantly in size in the last few years. One way to illustrate the size of the market is the notional value of the underlying credit outstanding. This was valued at US\$42 trillion as at December 2008, (BIS, 2009). In comparison, global equity markets were valued at approx. US\$32 trillion and the global bond market at approx. US\$35 trillion as at Dec

2008,(Exchanges, 2008). As a comparison, the sum of outstanding international and domestic debt related securities was approx. US\$84 trillion, at the same time (BIS, 2009).

Some authors would criticise the use of notional value as an indication of the size of the market, suggesting that this approach leads to multiple counting of credit risk as there may be more than one contract reflecting the value of underlying outstanding credit, (Wallison, 2008). Recently the US DTCC, (Depository Trust and Clearing Corporation) began measuring the size of the CDS market and they estimate the gross notional amount of CDS's outstanding at \$25.6 trillion, for Dec. 2008, (DTCC, 2008). This figure has been questioned by the ISDA as the DTCC only counts trades which are registered with them, (ISDA, 2010). Therefore there is some disagreement as to which is the correct approach to measuring the size of the market but it is clear that the market is significant on a global scale. It is clear that the CDS market is in many ways different to the traditional equity and bond markets, for a comprehensive description and analysis of the credit default swaps market see Mingle, (2007). Our methods of evaluating risk may not be appropriate for the CDS market. The objective of this study is to test the relevance of two of the existing methodologies that is GARCH and EVT, when assessing risk in CDS returns.

The growing importance of the CDS market has highlighted the potential for systemic risks. For example, the collapse of Lehman Brothers in September 2008, lead to the CDS sellers net payment of approximately US\$6 billion, on outstanding credit of approximately US\$400 billion, (ISDA, 2008). As CDS contracts are tradable, are marked to market and as counterparties can be required to post collateral, the payout was significantly less than the notional value of the outstanding credit. This payout reflects the final payout of the protection sellers as a result of the collapse of Lehman Brothers. CDS contracts, like other derivative contracts, are a zero sum game, therefore should a credit event occur, the seller's loss equates to the buyer's gain. Unlike Wallison, (2008) the Basel II committee wish financial institutions to assess the impact of counterparty risk, cash flow risk and the asymmetric information risks associated with securitising credit risk, (BIS., 2009). For example, these risks were highlighted by AIG's recent de-rating which caused the collateral clause to take effect in many of AIG's CDS contracts.

The resultant cash flow requirement caused financial distress for AIG which, it has been estimated, cost the US Treasury approx. US\$30 billion,(Soros, 2009). The increasing importance of financial innovations and the potential for financial crisis and fiscal costs is such that significant further research is merited.

As mentioned above, the majority of existing quantitative empirical research has focused on cross correlation relationships between CDS contracts themselves and between CDS contracts and other asset classes, for example, Li (2000) and Chen et al. (2008). This literature places credit default swaps in a multivariate dependency model, focusing on co-dependency and joint extremes. For example, Chen et al, (2008) considers the dependence structure between credit default swaps returns and the kurtosis of the corresponding equity market distribution. This paper focuses on univariate tail estimation and although this area is currently being examined by regulators, the univariate model has been relatively less explored for credit default swaps returns.

Secondly, the lack of univariate analysis in the CDS market (in this field of research) justifies the need for an investigation of the market using the methods and tools of EVT. In the literature, the majority of analysis based on EVT focuses on currency, equity and bond markets, see Assaf , (2009), for a review of recent studies. Therefore this paper assesses the relevance of EVT to the assessment of risk in a univariate CDS model.

The outline of the paper is as follows; in the following section, a brief overview of extreme value theory will be provided. The aim of the overview is to outline the development of the theory and the underlying assumptions upon which the theory is based.

Section III is divided into four parts. Section III.I describes the data to be analysed. Section III.II, reports the findings of the initial analysis of the eight samples of data from three asset classes, credit default swaps, equities and bonds. Descriptive statistics are discussed and the samples are tested for normality, serial correlation in the first two moments and stationarity. The findings support previous work emphasising the non-Gaussian and conditional nature of financial data. In section III.III, we test the efficacy of

generalised auto-regressive conditional heteroskedasticity (GARCH) in removing evidence of second and higher moment conditionality in each of the samples. We develop the descriptive statistics and test the residuals of the GARCH model for normality and iid, (independently and identically distributed) characteristics. This is motivated by the work of Bollerslev, (1986) when he suggested that the conditionality in financial returns can be removed through a GARCH model. McNeil and Frey (2000) developed this further by suggesting that that the conditionality in financial returns can be removed through implementation of the GARCH model and post-GARCH, an EVT type distribution will better reflect the characteristics of the residuals rather than a Gaussian distribution. Thus in Section III.IV we review the McNeil and Frey model for the three asset classes and accept its relevance for equities and bonds whereas we reject its relevance for CDS market returns, due to the non-iid characteristics of the data. In this case we use the model proposed by Cotter when analysing volatility in futures contracts returns, (2001). Cotter uses a semi-parametric approach, the Hill Index to estimate the tail index of a Generalised Extreme Value, (gev) distribution. When estimating the tail parameter of the distribution of a credit default swap sample, we note that if a random variable,  $X$ , is distributed with a tail index  $\xi$ , for all integers  $r < 1/\xi$ , then the  $r^{\text{th}}$  moment exists, (Embrechts et al., 1997). Except for one limited exception, we find  $1/\xi < 2$  for all three of our CDS samples and hence this suggests that only the first moment is finite in our samples. This contrasts with work of others, for example, Jondeau and Rockinger, (2003) who found  $\xi$  to range between 0.16 to 0.3 for equity markets, Cotter (2001) found  $\xi$  to range between 0.19 to 0.37 for futures markets. Bystrom (2008), found  $\xi$  to range between 0.23 to 0.28, for the CDS market. Although Bystrom uses a different methodology to our own, his approach is parametric and ignores the dependency issue, as he focuses on a comparative analysis of an unconditional EVT and an unconditional Gaussian distribution when estimating Value at Risk. He notes the weaknesses in his approach and the lack of accuracy due to the “extreme turbulence” (Byström, 2008) to be found in the CDS market. Thus this paper attempts to take account of this turbulence by testing for conditionality. The implications of the findings of this paper are discussed in section IV, with some concluding remarks highlighting some of the potential limitations of the application of GARCH and EVT to credit default swap market returns.



## Section II

### Extreme Value Theory

This paper analyses extreme value theory as an alternative methodology for the quantitative estimation of financial market risk. As the Central Limit Theorem summarizes, the Gaussian distribution is the limiting distribution for sample means, EVT proposes that one of the three distributional forms of extreme value theory is the limiting distribution for the sample extrema. EVT allows the estimation of the population parameters for the sample extrema, without making any assumptions about the distribution of the original sample.

Let  $X_1, X_2, \dots$  be a sequence of random variables

Let  $M_n = \max(X_1, X_2, \dots, X_n)$

The Fisher and Tippett, (1928) theorem, formerly proved by Gnedenko, (1943), states that the asymptotic distribution of the maxima will belong to one of the three distributional forms, irrespective of the original distribution of the observed data.

Thus the theorem states that the maxima at the limit converge to H after normalising and centring, formally this is expressed as;

$$c_n^{-1} (M_n - d_n) \xrightarrow{d} H$$

s.t.

$c_n$  = a normalising constant

$d_n$  = a centring constant, determined as a particular quantile or related measure

$M_n$  = Maxima of returns n

H = distribution

$\xrightarrow{d}$  represents convergence in distribution

for:  $c_n > 0$

$$-\infty < d_n < \infty$$

(Cotter, 2001)

Following the work of Jenkinson, (1955) and Von Mises, (1936), the distributions have been generalized into the below forms. The below is a cumulative density function and is formally expressed as;

$$\begin{aligned}
H_{\xi}(y) &= \exp(-(1+\xi y)^{-1/\xi}) && \text{if } \xi \neq 0, \text{ and } 1+\xi y > 0 \\
&= \exp(-\exp(-y)) && \text{if } \xi = 0,
\end{aligned}$$

$y$  = standardized maxima/minima; that is  $= (m-\mu)/\psi$ ;

s.t.  $m$  = max return = -min return

$\xi$  = tail index, s.t. the greater  $\xi$ , the fatter the tail.

$\mu$  = location parameter and  $\psi$  = scale parameter

(Longin 1996, p. 387)

The tail of the distribution is either declining exponentially (Gumbel distribution, type 1,  $\xi = 0$ ) or by a power (Frechet distribution, type 2,  $\xi > 0$ ) or is finite (Weibull distribution, type 3,  $\xi < 0$ ) (Jondeau et al., 2007). As  $\xi$  increases, the probability mass in the right tail increases. The location parameter,  $\mu$  indicates where on average extremes are located and the scale parameter,  $\psi$  indicates how dispersed the extrema are.

Should the three parameters be required, it is necessary to assume that either the parent sample variables are iid or should the distance between maxima be large enough, that the maxima are iid, (Jondeau et al., 2007). Also that the parent sample is exactly asymptotically distributed following one of the generalised extreme value distributions,  $H_{\xi}$  (Jondeau et al., 2007). Maximum likelihood estimation can be used to estimate the parameters.

An alternative to the generalized extreme value distribution is the generalized Pareto distribution first proposed by Balkema and De Haan (1974); this relates the limit distribution of the scaled excesses (over a chosen threshold  $u$ ) to the tail index  $\xi$ . It can be used should the threshold  $u$  be large.

Thus for  $0 \leq y \leq x_F - u$  as follows;

$$\begin{aligned}
G_{\xi,\psi}(y) &= 1-(1+(\xi/\psi)(y))^{-1/\xi} && \text{if } \xi \neq 0 \\
&= 1-\exp(-(y/\psi)), && \text{if } \xi = 0
\end{aligned}$$

The advantage of the above approach is that it allows the density of the tails to be estimated from a Pareto distribution, (Jondeau et al., 2007). The procedure assumes that the observations in the parent sample are iid and that the distribution of the parent sample is in the domain of attraction of  $H_\xi$ . The limitation of this approach is that if a high threshold value for  $u$  is chosen, this will reduce the sample size of the maxima, this in turn can make the estimation of the parameters unstable with large sample errors. Although no optimal method of estimating the threshold has been agreed, the mean-excess plot is commonly used, (Jondeau et al., 2007). As with the gev distribution the maximum likelihood estimation approach can then be used to estimate the parameters.

The alternative is the semi-parametric approach which requires neither of the above assumptions, that is, it does not require that the distribution of the parent sample be a gev distribution, neither does it require that the observations be iid. This is as long as the parent data are, at the most, weakly dependent and that the parent sample is in the domain of attraction of the gev distribution. If the parent sample observations are iid, the Hill Index has been shown to be strongly consistent. For weakly dependent data where the sample are generated from a Frechet distribution, (where  $\xi > 0$ ) the Hill Index yields a more efficient tail estimate than the alternative Pickands estimator, (Jondeau et al., 2007). The semi-parametric Hill Index (Hill, 1975), estimates the tail estimates by using the original parent data sample observations, as follows;

$$\xi_h = 1/\alpha = (1/q) \sum [\log r_{(n+1-i)} - r_{(n-q)}] \quad \text{for } i = 1 \dots q$$

q = no. of exceedences included in the Hill estimate

(Hill, 1975)

The tail estimator is asymptotically normal, (Hall, 1982). By drawing a Hill plot, that is a graphical illustration of the Hill estimate for different values of  $q$ , an appropriate value for  $q$  can be found.

## II.1 Choosing the correct distribution for financial data

Generally, a Frechet distribution, (where  $\xi > 0$ ) corresponds to a fat tailed distribution and is thus suggested as the most appropriate for financial data, (Jondeau and Rockinger, 2003). The necessary and sufficient condition for a Frechet distribution is that the tail must have regular variation at infinity, (Cotter, 2001). Gnedenko, (1943) showed that if the tail of  $F(x)$  decays like a power function; it is in the domain of attraction of the Frechet distribution. The Frechet distribution is asymmetric, bounded on the left and as the tail index,  $\xi$ , increases, the probability mass in the right tail increases, (Jondeau and Rockinger, 2003)

One of the important points to note is that the gev distributions are used to analyse the behaviour of the tails of the original distribution, not the distribution as a whole or the middle of the distribution. Therefore to use gev, one must separate out the extreme points to focus on the shape of the tails.

A density test of the extrema should indicate if the data is in the domain of attraction of the Frechet distribution. If the variables  $X$  are statistically independent, the generalised Pareto Distribution and the parametric approach can then be used. (Jondeau and Rockinger, 2003). If the variables  $X$  are stationary but not independent, a parametric approach is not suitable. If we can show that the series is stationary and belongs to the maximum domain of attraction of the Frechet distribution then the semi-parametric approach is more suitable.

This is known formally as

$X_1, X_2, \dots, X_n$  are stationary from  $F \in \text{MDA}(H_\xi)$

(Daniélsson and de Vries, 1997).

The semi-parametric estimates obtain better bias and mean-squared properties than their parametric counterparts under non-Gaussian conditions.(Cotter, 2001).

McNeil and Frey, (2000) suggest that conditionality in the second moment can be removed through a GARCH model and the parametric approach for the generalized

Pareto distribution can then be applied. As discussed above, the GARCH model was first suggested by Bollerslev, (1986), recognising the autoregressive nature of heteroskedasticity in financial data, and updating Engle's work, (1982), suggesting that;

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

(Bollerslev, 1986)

One of the key assumptions of the effectiveness of the GARCH model is that  $\varepsilon_t \sim N[0, \alpha_0 + \alpha_1 \varepsilon_{t-1}^2]$  (Bollerslev, 1986). McNeil and Frey (2000) argue that the data will be iid once GARCH has been applied and that the generalized Pareto distribution will better reflect the characteristics of the distribution as the data still exhibits skewness and kurtosis.

There are two methods of separating out the extrema, depending on the underlying assumptions and the family of distributions to be used, (as outlined above). The Peaks over Threshold (POT) method extracts only the maxima and minima that are in excess of a threshold, ( $u$ ). This technique fits the data to the generalized Pareto distribution, see Embrechts et al., (2005) for further details of the generalised Pareto distribution. Two of the drawbacks of this method are firstly the estimation of  $u$ . And secondly, if the series is a dependent process, (for example a GARCH process), the tail-index estimates are likely to be bias. By applying McNeil and Frey, (2000) methodology outlined above we may remove the bias from the estimates.

The Block Maxima method suggests that the data is divided into sub samples or blocks and the absolute largest observation is extracted for further examination. This technique fits the data to the gev distributions. The advantage of this method is that if we find dependency in the parent sample, we may remove this dependency by having large block sizes and thus the maxima will be iid, (Jondeau et al., 2007).

Parameters can be estimated using the Maximum Likelihood method, and the standard likelihood ratio test, (LRT) can also be applied. Monte-Carlo simulations can be used to see if the parameters are unbiased. Alternatively as mentioned, semi-parametric estimates

can be used, for example, the Pickands, Hill and DEdH estimates, (Jondeau et al 2007) in order to estimate  $\xi$ . As argued above, semi-parametric measures can offer superior estimates of  $\xi$ , (Cotter, 2001).

Once the parameters have been estimated, they can be used in risk estimation techniques such as Value at Risk, to estimate the maximum potential loss from holding a certain asset at a given probability level, over a certain time period, (Danielsson and De Vries, 2000). Thus the correct application of EVT will affect the extent to which improved accuracy is attained by replacing the Gaussian Value at Risk methodology with a conditional/unconditional EVT Value at Risk approach. This application could be an important improvement in the estimation of market risk in individual financial assets. It is noted that this paper does not attempt to measure cross-correlations between asset returns but is focusing on individual asset's market risk estimation.

## **II.II Quantile Plot**

The quantile plot method designed by Jenkinson, (1955), can be used to analyse the data to indicate which of the 3 gev distributions it is closest to. This is done by placing the extremal points in their absolute form and in increasing order. These ordered maxima are then plotted against the theoretical quantile  $-\log\log(i/n+1)$ , thus testing for a Gumbel distribution. If the data is truly generated by a cumulative density function that belongs to the domain of attraction of  $H_{\xi}(y)$ , then the empirical quantiles of the maxima and the theoretical quantiles of  $H^{-1}_{\xi}(y)$  should match approximately. The method assumes monotonicity, (i.e. one to one mapping) between the variables. If the estimated curve is convex, then the sample follows a type III Weibull distribution. If the estimated curve is a straight line, then the sample follows a Gumbel distribution and if estimated curve is concave then the sample follows a type II Frechet distribution.

## **Section III.I The Data**

The spread premium in the Credit Default Swap market is quoted as a percentage of the underlying notional value of the credit and reflects the annual premium required to receive compensation in the event of the reference entities default, known as a credit event, (Mengle, 2007). Therefore, when quoting the US\$42 trillion above, this is in reference to the underlying value of the notional credit being covered in the CDS contracts. The spread premium is usually around 4% of the notional, (for example, the sample mean spread in CDS data sample 1 is 4.33 %). It is the volatility in this spread premium that is being analysed in this paper. The analysis of volatility in the spread premium should reflect the market risk of trading in the credit default swap market.

The first three samples are taken from the family of iTraxx European indices. These indices were chosen due to their diversified nature and liquidity which should improve the robustness of the findings of this paper for the CDS market in general. The indices were created to allow financial institutions access to a diversified portfolio of credit risk and to encourage the development of the market and to increase liquidity. The index is made up of the credit default swaps of 125 investment grade rated corporate European entities. The entities are chosen for their liquidity and from a number of underlying industries, as follows;

- 30 Autos & Industrials
- 30 Consumers
- 20 Energy
- 20 TMT
- 25 Financials

Each entity is equally weighted within the index. The index has been subdivided into a number of tranches to reflect total recovery rate, as well as maturity. In the case of a credit event, the protection seller pays 1-recovery value of the defaulted issue to the protection buyer. Therefore the higher the recovery rate, the less compensation the buyer will receive. The recovery rate indicates the percentage of the credit risk which the CDS buyer is not being compensated for. For example, if the recovery rate is 0%, the buyer will receive par value from the protection seller after a credit event has occurred, (Felsenheimer et al., 2004)

The three samples we have chosen are as follows; CDS sample 1 is a sample of 391 observations from 3<sup>rd</sup> August 2007 to 18<sup>th</sup> February 2009, taken from the iTraxx 12-22% recovery rate 5 year index. CDS sample 2 is a sample of 335 observations from 20<sup>th</sup> March 2006 to 29<sup>th</sup> June 2007 taken from the iTraxx 12-22% recovery rate 5 year index. CDS sample 3 is a sample of 330 observations from 20<sup>th</sup> March 2006 to 22<sup>nd</sup> June 2007 taken from the iTraxx 22-100% recovery rate 5 year index. All data samples are taken from DataStream.

The iTraxx index is priced so that the data is available for approximately 18 month intervals. The recovery rate range in CDS data sample 1 and 2 are equal and lower than the recovery rate in CDS sample 3. This would imply higher compensation levels for the CDS buyer in CDS sample 1 and 2. For a given notional value, these contracts will be considered as higher risk from the protection sellers' viewpoint. Thus by comparing the results of sample 1 and 2 to 3 we can consider the impact of recovery rates on the characteristics of the index. Secondly, CDS sample 1 reflects a later time period than CDS sample 2 and 3 and thus we can compare the influence of the development of the financial crisis on risk in CDS returns.

The four equity indices chosen represent four of the main equity markets and are chosen to cross check results with existing literature. These include the S&P 500 Index sample of 14,821 observations from 3<sup>rd</sup> January, 1950 to 26<sup>th</sup> November, 2008, the FTSE 100 Index sample of 6,228 observations from 2<sup>nd</sup> April 1984 to 25<sup>th</sup> November 2008, the Dax Index sample of 4,544 observations from 26<sup>th</sup> November 1990 to 27<sup>th</sup> November 2008 and finally the Nikkei 225 Index sample of 6,127 observations from 4<sup>th</sup> January 1984 to 27<sup>th</sup> November 2008. By choosing four long samples of data for the equity indices, it is hoped that the samples will robustly reflect the characteristics of these asset classes.

The bond fund chosen is the Barclays Capital Pan-European Aggregate Bond Index; the sample size is 2,512 observations running from 30<sup>th</sup> March 2000 to 16<sup>th</sup> November 2009. This bond index was chosen as it represents a broad spread of both corporate and



government bonds and should give a general reflection of the characteristics of bond return variability.

### **III.II Descriptive Statistics and tests for normality in the three asset classes**

The focus of the initial analysis is to highlight and contrast the characteristics of financial assets' returns, as well as to facilitate the correct choice of asymptotic probability distribution function. The first objective was to test the samples for the first 3 of the 6 recognized *stylized facts* of financial data (Jondeau et al., 2007), which are;

1. **Fat tails:** The unconditional distribution of returns has fatter tails than that expected from a normal distribution.
2. **Asymmetry:** The unconditional distribution is negatively skewed. The asymmetry and the fat tails persist even after adjustment for conditional heteroskedasticity, thus the conditional distribution is also non-normal.
3. **Aggregated normality:** As the frequency of returns lengthens the return distribution gets closer to the normal distribution.

**Table 1: Descriptive Statistics for CDS, Equity and Bond Index Logged Returns**

<b>Sample</b>	<b>Dates Covered</b>	<b>Observations</b>	<b>Mean</b>	<b>St Dev.</b>
<b>CDS Spread 1</b>	03/08/07-18/02/09	391	0.0001	0.0136
<b>CDS Spread 2</b>	20/03/06-29/06/07	334	-0.0026	0.2277
<b>CDS Spread 3</b>	20/03/06-22/06/07	329	0.0000	0.2327
<b>S&amp;P 500</b>	3/01/1950-26/11/2008	14821	0.0003	0.0094
<b>FTSE 100</b>	02/04/1984-25/11/2008	6228	0.0002	0.0110
<b>DAX</b>	26/11/1990-27/11/2008	4544	0.0003	0.0145
<b>NIKKEI 225</b>	04/01/1984-27/11/2008	6127	-2.780E-05	0.0145
<b>Bond Index</b>	16/11/2009-30/03/2000	2512	6.870E-06	0.0021

<b>Sample</b>	<b>Minimum</b>	<b>Maximum</b>	<b>Skewness</b>	<b>Kurtosis</b>
<b>CDS Spread 1</b>	-0.0935	0.1390	4.0685	55.5861
<b>CDS Spread 2</b>	-1.8351	1.9523	0.6461	36.5864
<b>CDS Spread 3</b>	-1.0975	1.1340	-0.1831	9.0769
<b>S&amp;P 500</b>	-0.2290	0.1096	-1.1413	35.4345
<b>FTSE 100</b>	-0.1303	0.0938	-0.4351	12.7775
<b>DAX</b>	-0.0987	0.1080	-0.1021	8.3384
<b>NIKKEI 225</b>	-0.1614	0.1323	-0.2268	12.1477
<b>Bond Index</b>	-0.0096	0.0090	-0.2938	4.2721

<b>Sample</b>	<b>JB test for Normality</b>
<b>CDS Spread 1</b>	46129.94
<b>CDS Spread 2</b>	15721.89
<b>CDS Spread 3</b>	508.07
<b>S&amp;P 500</b>	652884.70
<b>FTSE 100</b>	25004.45
<b>DAX</b>	5403.52
<b>NIKKEI 225</b>	21415.29
<b>Bond Index</b>	205.52

(1% significance)

As we can see in Table I, all the samples are varying around a mean close to zero. The standard deviations vary significantly and specifically we can see that the standard deviations for the CDS samples can be of a scale of over twenty times higher than the

other two asset classes. As noted in previous literature, financial data generally has a negative skew although for the CDS data, the two data samples with lower recovery rates have a positive skew; this could be reflecting the higher risk of the contracts from the sellers' viewpoint. Should the risk of default increase, the premium on the CDS contract is likely to increase reflecting the higher risk to the seller. These positive jumps seem to be more extreme when the recovery rates are lower. With the kurtosis, we note that CDS sample 1 and 2 have very high levels of kurtosis, even though they have relatively lower standard deviations than CDS sample 3. Thus the non-Gaussian nature of the data illustrates the danger of using a mean-variance model.

When analysing all the data samples together, it is observed that all the samples appear to be skewed in some way and have excess kurtosis. The Jarque-Bera test for normality indicates that in all cases normality should be rejected. The sample which comes closest to the Gaussian distribution is the bond sample. We also note the increasing JB statistic as we move from CDS sample 3 to 1, indicating the increasing non Gaussian nature of the higher moments. As CDS sample 1 has a lower recovery rate than CDS sample 3 and reflects the CDS market during the financial crisis, it may be suggested that this is evidence of increased credit risk or uncertainty causing fatter tails and a positive skew in the distribution. This may suggest time dependency and recovery rate dependency in the data.

As the Jarque-Bera test is a large sample test for normality, two further moment based tests were completed to ensure that the correct conclusions are being made. These are the Anderson-Darling test and the Cramer Von Mises test

**Table 2: Further tests of normality and QQ plot of residuals**

Sample	Anderson-Darling Test for Normality	Cramer Von Mises test for Normality	QQ plot of residuals
<b>CDS Spread 1</b>	66.91000, (p= 0.000)	12.4239, (p= 0.000)	wavy
<b>CDS Spread 2</b>	47.11306, (p=0.000)	9.003445, (p=0.000)	wavy
<b>CDS Spread 3</b>	25.93207, (p=0.000)	5.441746, (p=0.000)	wavy
<b>S&amp;P 500</b>	203.9662 (p=0.000)	35.32804, (p=0.000)	not straight line
<b>FTSE 100</b>	60.63132, (p=0.000)	9.39917, (p=0.000)	not straight line
<b>DAX</b>	52.80334, (p=0.000)	9.120281, (p=0.000)	not straight line
<b>NIKKEI 225</b>	73.69169, (p=0.000)	13.08707, (p=0.000)	not straight line
<b>Bond Index</b>	7.672091, (p=0.000)	1.314972, (p=0.000)	quite straight

(1% significance) (1% significance)

Both tests reject the null hypothesis of normality in all cases. A Quantile, (QQ) plot of the residuals was then taken, to reflect the density of the samples. A straight line would imply a normal/Gumbel distribution and only in the case of the bond fund did the line appear to be close to straight as shown below in Figure 1.

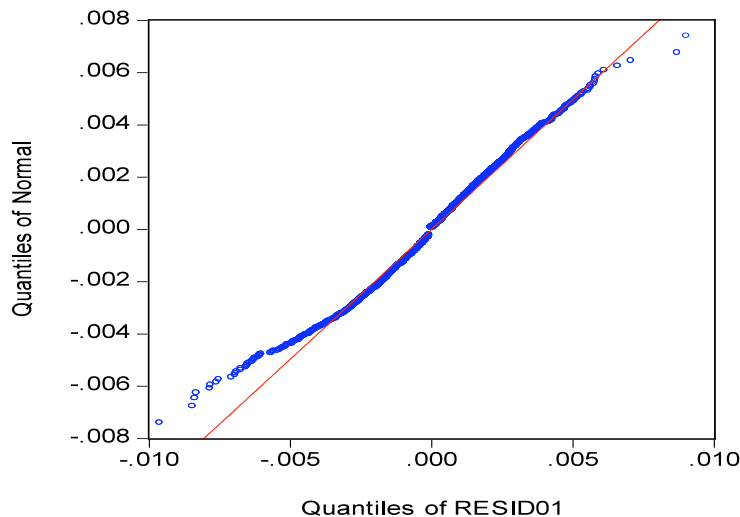


Figure 1: Quantile plot of pan-European bond fund

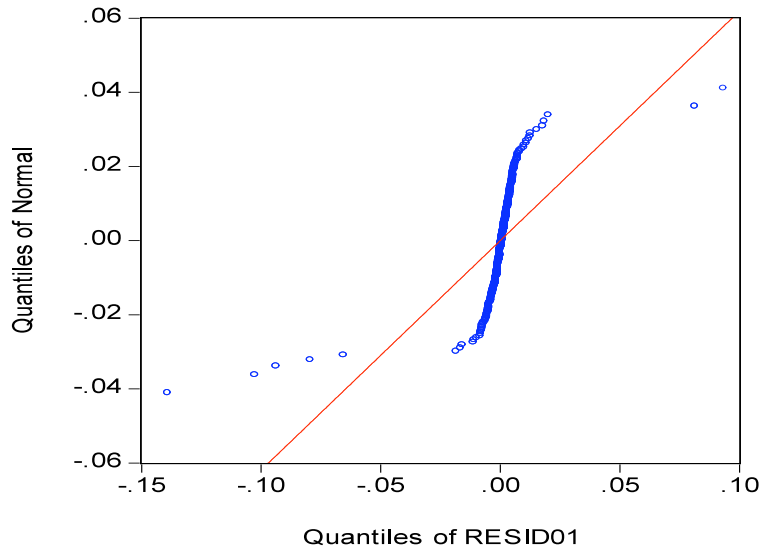


Figure 2: Quantile plot of CDS iTraxx sample 1

As we can see in figure 2, the quantile plot for the CDS data waves around the straight line, and reflects the non-Gaussian nature of the distribution.

The second objective of this section is to test the samples for the next two out of the six recognized stylized facts of financial data to be tested in this paper, which are;

- 4 Absence of serial correlation: Returns generally do not display significant serial correlation except at high frequencies.
- 5 Volatility clustering: Volatility of returns are serially correlated.

It should be noted that this paper does not test for the final of the six recognized stylized facts that is;

- 6 Time-varying cross correlation: Correlation between asset returns appears to increase across periods of high volatility.  
(Jondeau et al., 2007)

As previously discussed the cross correlation of CDS returns with other asset classes is not assessed in this paper as this analysis is more prevalent in existing literature.

**Table 3.1: Tests of conditionality in the first moment**

	<b>Ljung Box Q stat</b>	<b>Breusch–Godfrey LM test</b>
<b>CDS Spread 1</b>	Reject Ho AR(8)	Reject Ho
<b>CDS Spread 2</b>	Reject Ho AR(2)	Reject Ho
<b>CDS Spread 3</b>	Reject Ho AR(2)	Reject Ho
<b>S&amp;P 500</b>	Reject Ho, AR(2)	Reject Ho
<b>FTSE 100</b>	Accept Ho	Accept Ho
<b>DAX</b>	Accept Ho	Accept Ho
<b>NIKKEI 225</b>	Accept Ho	Accept Ho
<b>Bond Index</b>	Accept Ho	Accept Ho
	Ho: no SC; To accept Ho, $Q_{LB} \sim \chi^2(p)$ (1% significance)	Ho: no SC; To accept Ho, $nR^2 \sim \chi^2(p)$ (1% significance)

Note: the Null hypothesis in both tests above is that there is no serial correlation in the returns

In order to test for serial correlation in the residuals, the Ljung Box Q statistic is used initially to give an estimate for the lag, note that we find the lag through trial and error and the use of autocorrelations and partial autocorrelations. Then the Breusch–Godfrey LM test statistic tests this lag level. As a result of these two tests, we find evidence of serial correlation in the CDS samples and the S&P sample, whereas in the other equity samples and the bond sample we can accept the hypothesis of no serial correlation.. The evidence for the first CDS sample is that autocorrelation exists up to 8 lags, whereas for the other two CDS samples and the S&P sample the conditionality is summarised in two lags. The drawback of using the Ljung Box Q statistic is that if too small a lag is chosen, the test may not detect serial correlation at high-order lags. Whereas if too large a lag is chosen, the test may have lower power since the significant correlation at one lag may be diluted by insignificant correlations at other lags, (Ljung and Box, 1979). Hence the LM test is used to test the results of the LB Q analysis.

**Table 3.2: Tests of conditionality in the second moment and stationarity**

	<b>ARCH LM Test</b>	<b>Stationarity (ADF)</b>
<b>CDS Spread 1</b>	ARCH(1)	Reject unit root
<b>CDS Spread 2</b>	No ARCH (1), ARCH(2)	Reject unit root
<b>CDS Spread 3</b>	ARCH(1)	Reject unit root
<b>S&amp;P 500</b>	ARCH(4)	Reject unit root
<b>FTSE 100</b>	ARCH(5)	Reject unit root
<b>DAX</b>	ARCH(6)	Reject unit root
<b>NIKKEI 225</b>	ARCH(7)	Reject unit root
<b>Pan Europe Bond Index</b>	ARCH(5)	Reject unit root,
	Ho; no Heterosked/ARCH	
	(1% significance)	(1% significance)

The LM test for ARCH appears to indicate evidence of ARCH in all cases, although as mentioned previously, there are issues in determining the correct number of lags. For CDS 2, we see no evidence of ARCH at lag 1 but evidence exists at lag 2, there may be seasonality in the ARCH. Finally, in table 3, we test for stationarity using the Augmented Dicky Fuller (ADF) test and in all cases stationarity can be accepted.

### **III.III GARCH**

This section of the paper aims to model for conditionality in the second moment in the form of GARCH. The section will then test the GARCH residuals to see if conditionality in the second moment has been removed and to see if the residuals follow a Gaussian distribution, and finally to see if the GARCH residuals are iid.

**Table 4: Analysis of the GARCH model**

<b>Sample</b>	<b>GARCH Model</b>	<b>Descriptive stat's</b>
<b>CDS Spread 1</b>	GARCH(0,1); one coefficients =0.26	Skew =-5.34; Kurtosis = 55 JB = 86,099
<b>CDS Spread 2</b>	GARCH(2,2); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1,2 and q= 1,2	Skew =-4.16; Kurtosis = 40 JB = 20,371
<b>CDS Spread 3</b>	GARCH(1,2); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1 and q= 1,2	Skew =-0.83; Kurtosis = 13 JB = 1,311
<b>S&amp;P 500</b>	GARCH (1,1); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1 and q= 1	Skew = 0.06; Kurtosis = 4.6 JB = 1,534
<b>FTSE 100</b>	GARCH(1,1); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1 and q= 1	Skew = 0.05; Kurtosis = 3.79 JB = 165
<b>DAX</b>	GARCH(1,2); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1 and q= 1,2	Skew = 0.06; Kurtosis = 4.22 JB = 284
<b>NIKKEI 225</b>	GARCH(2,1); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1,2 and q= 1	Skew = 0.17; Kurtosis = 4.56 JB = 650
<b>Bond Index</b>	GARCH(1,1); $\sum \alpha_p \beta_q \approx 1$ ; for p = 1,2 and q= 1	Skew = -0.22; Kurtosis = 3.65 JB = 65

Note if  $\sum \alpha_p \beta_q \approx 1$ ; for all p and q, this implies persistence in volatility shocks



<b>Sample</b>	<b>ARCH LM Test</b>	<b>BDS test</b>
<b>CDS Spread 1</b>	Accept Ho	Reject Ho
<b>CDS Spread 2</b>	Accept Ho	Reject Ho
<b>CDS Spread 3</b>	Accept Ho	Reject Ho
<b>S&amp;P 500</b>	Accept Ho	Accept Ho
<b>FTSE 100</b>	Accept Ho	Accept Ho
<b>DAX</b>	Accept Ho	Accept Ho
<b>NIKKEI 225</b>	Accept Ho	Accept Ho
<b>Bond Index</b>	Accept Ho	Accept Ho
	(1% significance)	(1% significance)

Note that the Null hypothesis of the BDS test is that the GARCH residuals are iid.

Generally we find evidence of GARCH in the data samples, ranging from a GARCH (2, 2) process for the CDS sample 2 to a GARCH (0,1) or an ARCH(1) process for CDS sample 1. Except for CDS sample 1, the coefficients of the independent variables in the GARCH process add up to one, indicating persistence in the volatility shocks. Once the GARCH model has been applied, in all cases, the Jarque-Bera test for normality in the standardized residuals was rejected. The four equity markets exhibited a positive skew whereas the bond fund and the CDS indices indicated a negative skew. The kurtosis was between 3.6 and 4.6 for the bond and equity indices and was much higher for the CDS indices ranging from 13 to 55.

The LM tests for ARCH in the residuals lead us to accept Ho in all cases and thus accept the hypothesis that by applying a GARCH model we will remove conditionality in the second moment. But it is noted that the GARCH model residuals remain non-Gaussian. This would imply that although the GARCH model removes conditionality in the second moment, it does not cause the residuals to be Gaussian.

Finally the residuals were tested for iid, (independent and identically distributed) characteristics. Following from Caporale et al. (2005) , the BDS test for assessing the hypothesis that the residuals are iid was then applied. The residuals were first transformed to log squared standardized residuals, as according to Caporale et al.'s findings (2005), this removes the risk that the innovations exhibit some form of

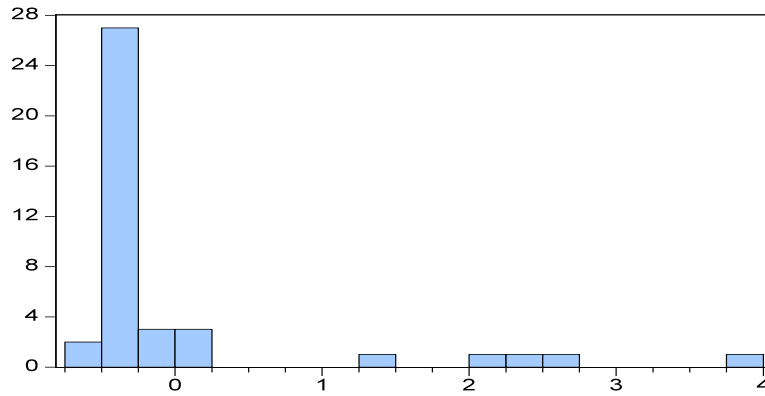
dependence even though the true innovations are iid. In all the equity and bond samples, the residuals were found to be iid but the CDS sample residuals were not. Caporale et al's (2005) notes that if the residuals do not follow a Gaussian distribution, the estimates improve as the sample size moves towards 500. As the CDS sample sizes are greater than 250, the lower boundary, but not equal to 500, there may be some sampling error in this analysis. Caporale et al's (2005) conclude that when the sample size is within the 250-500 range, the estimates are still efficient. This result would suggest that in the case of the equity and bond markets, it may be appropriate to apply a GARCH-EVT model. Whereas with the CDS data this methodology may have limited application as the data does not appear to be iid, post application of GARCH. We note that Jondeau et al. (2007) suggest that in large dependent samples, the extrema may be independent if the block size chosen is large enough. Given the inherent small sample size of the CDS iTraxx Index data, this hypothesis could not be tested on the CDS data samples.

#### **Section III.IV Semi-parametric estimation of $\xi$ for CDS samples**

In the third stage of the analysis, extreme value theory was applied to the three samples of the CDS iTraxx data. By analyzing the distribution of the premia extrema we can estimate the daily changes in the market's estimate of the probability of credit default.

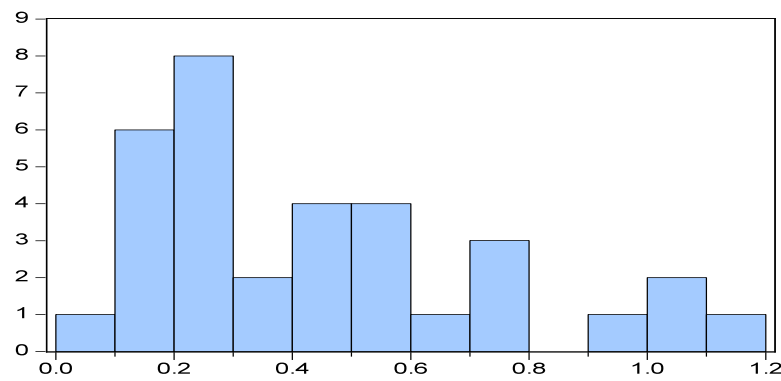
Following the findings above, it is suggested that McNeil and Frey's, (2000) GARCH-EVT model is not applicable for the three samples of CDS data being assessed in this paper as the CDS data appears to be stationary but not iid. Therefore the semi-parametric approach must be applied. As mentioned above, to use the semi-parametric approach, the parent sample must be in the domain of attraction of the gev distribution. Therefore before the Hill Index can be used to estimate the tail index, the data should be assessed to ensure that the sample follows a Frechet distribution.

Thus the data samples were transformed using the Block Maxima method as suggested by Jondeau (2007). Block sizes of 10 were taken and the absolute maxima were extracted from each block. This generates a small sample of 40 or 33 absolute maxima in each case. The histogram and descriptive statistics were calculated on the three samples as below;



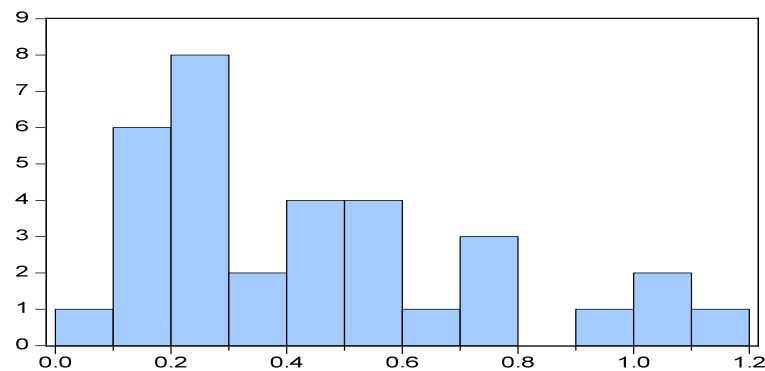
Series: STANDARDIZED_MAX	
Sample 1 40	
Observations 40	
Mean	8.88e-17
Median	-0.384607
Maximum	3.829314
Minimum	-0.504977
Std. Dev.	1.000000
Skewness	2.554103
Kurtosis	8.455725
Jarque-Bera	93.09785
Probability	0.000000

Figure 3: Descriptive Statistics for standardized maxima of CDS 1



Series: SORTED_MAX_CDS2	
Sample 1 33	
Observations 33	
Mean	0.442925
Median	0.371564
Maximum	1.133979
Minimum	0.000000
Std. Dev.	0.308036
Skewness	0.790039
Kurtosis	2.716647
Jarque-Bera	3.543288
Probability	0.170053

Figure 4: Descriptive Statistics for standardized maxima of CDS 2



Series: SORTED_MAX_CDS_3	
Sample 1 33	
Observations 33	
Mean	0.442925
Median	0.371564
Maximum	1.133979
Minimum	0.000000
Std. Dev.	0.308036
Skewness	0.790039
Kurtosis	2.716647
Jarque-Bera	3.543288
Probability	0.170053

Figure 5: Descriptive Statistics for standardized maxima of CDS 3

Interestingly, using the Jarque-Bera test statistic, only in the first sample would the hypothesis that the sample is drawn from a Gaussian distribution be rejected. In this case, the distribution of that data appears to have a positive skew with high kurtosis. We can see from the histogram for CDS sample 1 that many of the extrema cluster around the

mean with a small number of large positive extrema. This could be interpreted as occurring when the risk of default was considered to increase significantly in the market and thus the premia returns increased significantly. Whereas with the other two data samples, the distributions look more Gaussian in nature with low kurtosis and low skew. In these two cases the Jarque-Bera test implies that the Gaussian hypothesis cannot be rejected.

As the Gaussian distribution is part of the family of Gumbel distributions, such that  $\xi=0$ , the latter two samples may be closer to a Gumbel distribution than a Frechet distribution. These results are unexpected and may occur due to small sample size inhibiting our estimates.

The quantile plot density test will further test this finding; a regression line of best fit is also applied to see if the quantile plot is close to a straight line.

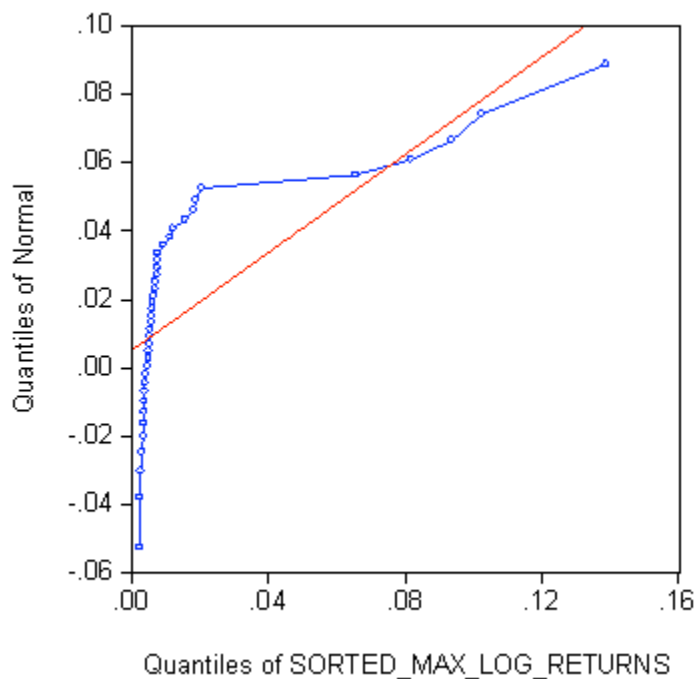


Figure 6: Quantile plot of maxima of CDS 1

As the plot for sample 1 follows a concave shape this would imply a Frechet distribution.

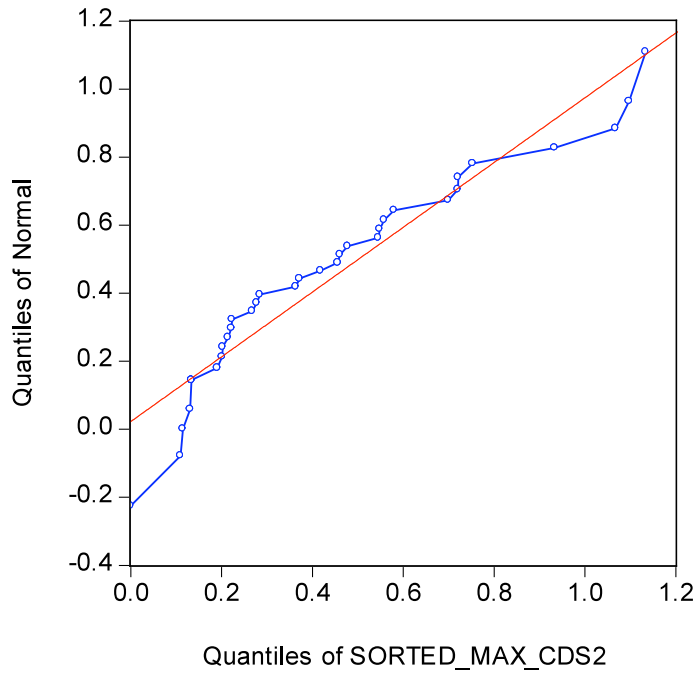


Figure 7: Quantile plot of maxima of CDS 2

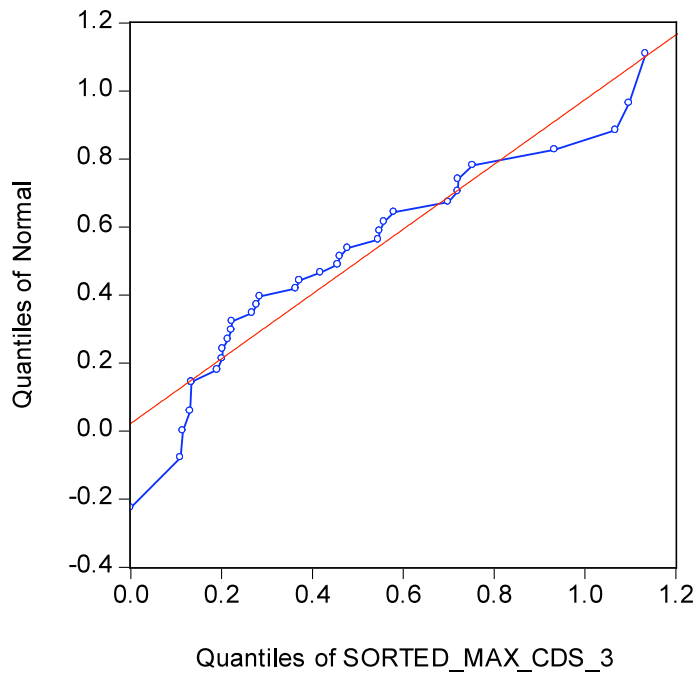


Figure 8: Quantile plot of maxima of CDS 3

With the quantile plots for CDS samples 2 and 3, a concave shape does appear although the concave nature of the plot is less pronounced and we can be less confident of the hypothesis that the data follows a Frechet distribution. In light of these findings goodness of fit tests were performed on the three samples.

<b>Sample</b>	<b>Lilliefors test</b>	<b>Cramer-Von-Mises</b>
<b>CDS Spread 1</b>	Reject Ho	Reject Ho
<b>CDS Spread 2</b>	Accept Ho	Accept Ho
<b>CDS Spread 3</b>	Accept Ho	Accept Ho
	(at 1% significance)	(at 1% significance)

Table 5: Goodness of fit tests for absolute sorted max CDS samples, the null hypothesis is that the samples follow a Gaussian distribution.

The Lilliefors test statistic was used instead of the Kolmogorov statistic since the parameters of the Gaussian distribution have been estimated. CDS sample 1 appears to be non-Gaussian whereas the Gaussian hypothesis cannot be rejected for CDS sample 2 and 3. This would imply that in these two samples, the tail index would be equal to zero. A goodness of fit test was then applied to CDS sample 1 using the Pareto distribution instead of the Gaussian distribution. The hypothesis was accepted. As previously mentioned, Gnedenko, (1943) proves that if the distribution is declining by a power, it is in the domain of attraction of the Frechet distribution.

Thirdly, following the work of Cotter (2001), the Hill estimate is used to estimate  $\xi$ .

$$\xi_h = 1/\alpha = (1/q)\sum[\log r_{(n+1-i)} - r_{(n-q)}] \quad \text{for } i = 1 \dots q$$

q = no. of exceedences included in the Hill estimate

(Hill, 1975)

One of the difficulties in estimating  $\xi$  by using the Hill Index is the choice of the number of exceedences, q. As suggested by Jondeau et al.s, (2007), a Hill Plot will illustrate the value of  $\xi$  for different values of q, (the number of exceedences). This will illustrate a graphical representation of the range of  $\xi$ .

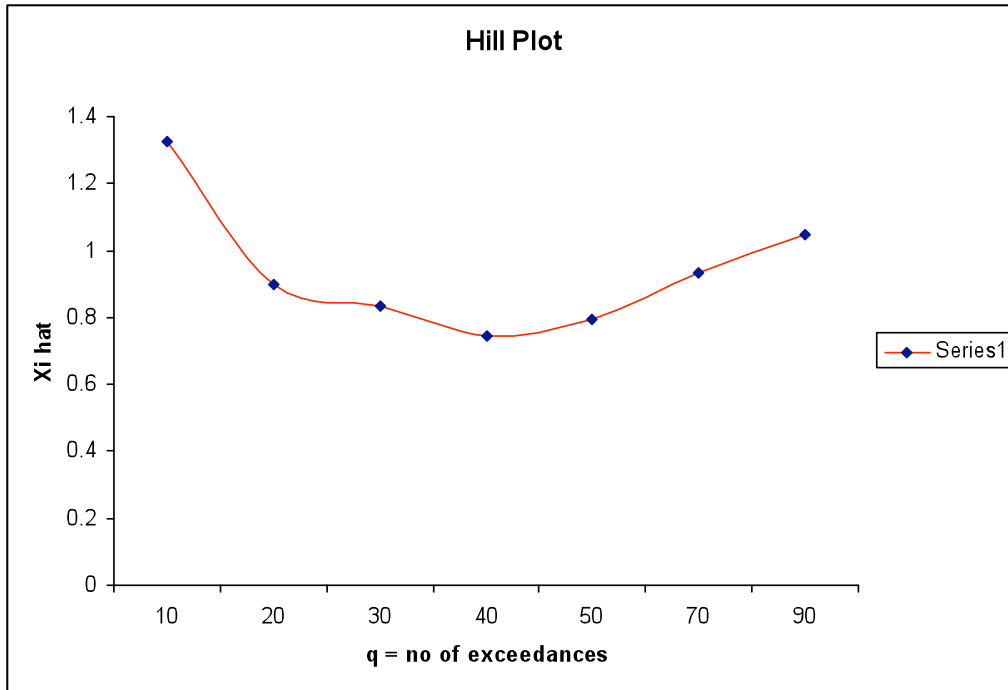


Figure 9: Hill Plot estimating  $\xi$  for maxima of CDS 1

For CDS sample 1, when  $q$  equals 40 the estimate of  $\xi$ , comes in at its lowest point of 0.74582. Bootstrapping exercises can be done to find the optimal  $q$ , but it is clear from the plot above that no value of  $q$  will give us an estimate of  $\xi$ , significantly below 0.74582. As mentioned above, the literature suggests that if the estimates of the tail index,  $\xi < 0.5$ , this would imply at least 2 moments exist. As our estimate of  $\xi > 0.5$ , this would imply that the second moment is non-finite, this is a similar conclusion to Mandelbrot (1963).

Although the density and other tests above did not indicate that CDS sample 2 and 3 follow a Frechet distribution, the Hill plot was still completed to test again the findings and to use a non-parametric estimate of the density of the tail index.

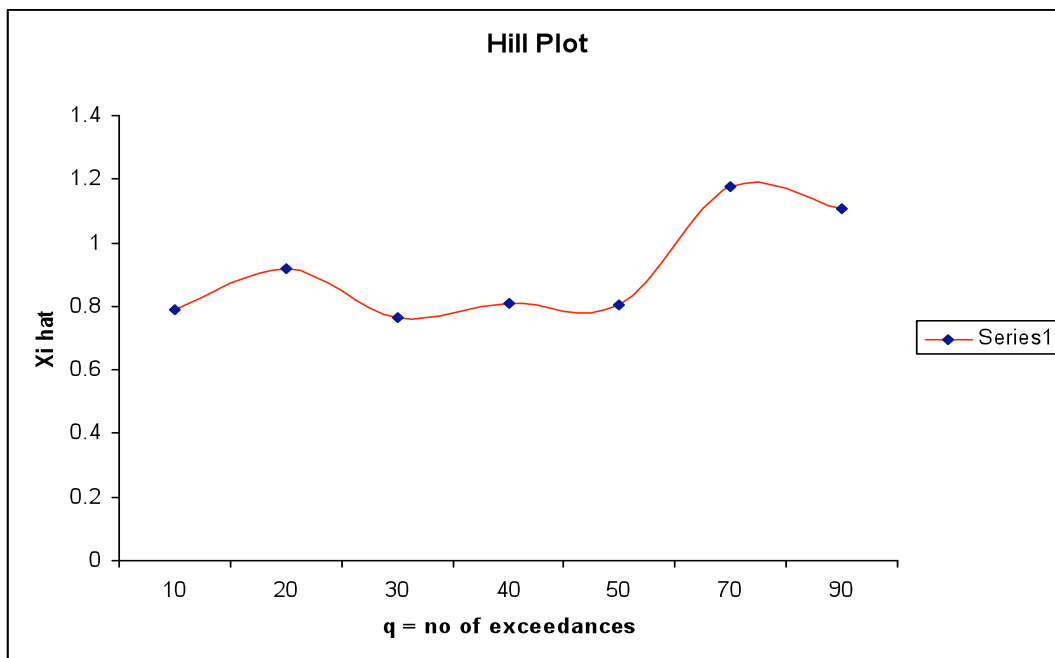


Figure 10: Hill Plot estimating  $\xi$  for maxima of CDS 2

As with the above sample, the estimate of  $\xi$  is greater than 0.5 in all cases.

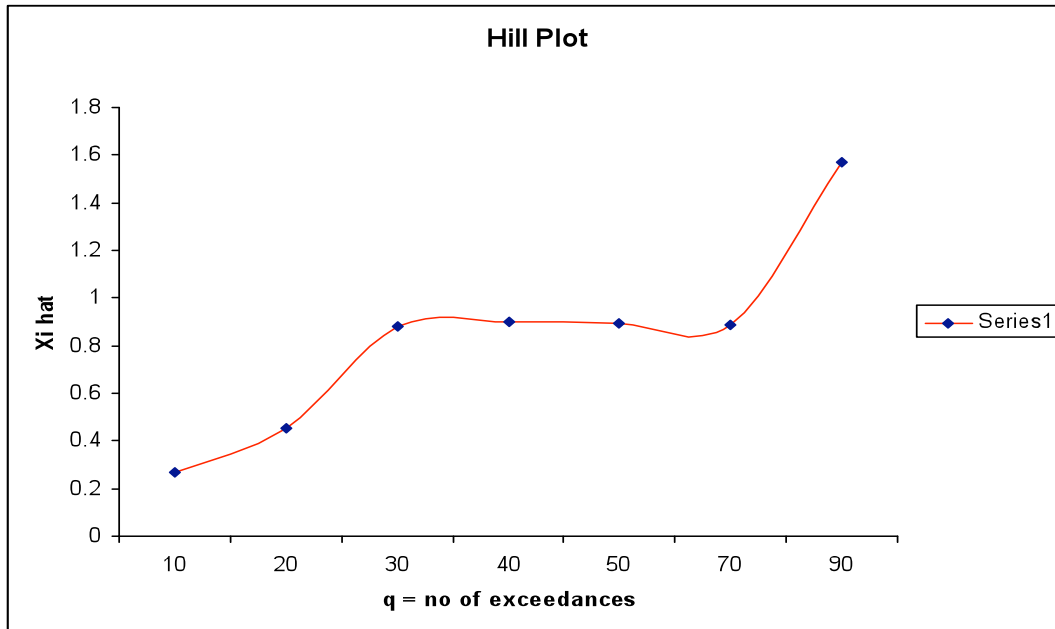


Figure 11: Hill Plot estimating  $\xi$  for maxima of CDS 3



Interestingly, for low values of  $q$ , less than 25 approximately, the estimate of  $\xi$  is below 0.5, this indicates that in the third sample of the CDS data there may be a finite second moment for small values of  $q$ . It is noted that CDS sample 3 has a higher recovery rate than the other two samples and thus the estimate of the second moment may be conditional on characteristics of the CDS contract, such as time and recovery rate. But in the latter two cases, we cannot be confident that the samples are in the domain of attraction of a Frechet distribution and thus for the case of the CDS samples, the methodology of EVT does not appear to be leading us to useful results.

## **Section V**

### **Summary and conclusions**

By analysing the three asset classes we found evidence of non-Gaussian returns distributions in all the data and evidence of conditionality. Thus this paper supports previous work which suggests that the unconditional mean-variance approach is likely to lead to underestimation of risk.

By comparing the results for the CDS data to the other two asset classes, a number of characteristics are noted. Firstly, the CDS data indicates higher variance in general than the other asset classes. Two of the three CDS samples indicated a positive skew whereas the other CDS sample and all the other asset class samples indicated a negative skew. Also the CDS and S&P data indicates very high levels of kurtosis. All the financial data indicated a non-Gaussian distribution to be present with evidence of conditionality, particularly in the second moment. By implementing the GARCH model the conditionality in the second moment was successfully removed and the non-CDS data samples appeared to be iid but non-Gaussian. In answer to our research questions, we conclude that a parametric GARCH-EVT methodology could then be applied to the non-CDS data samples. With the CDS samples, as the data did not appear to be iid, a semi-parametric approach was applied. Only one of the three CDS samples appeared to be in the domain of attraction of the Frechet distribution although this may be as a result of the small sample sizes. In all cases, the Hill Index was used to estimate the tail index. In general it was found that the tail index was greater than 0.5 indicating that the second moment was non-finite.

Thus there is some evidence that parametric and semi-parametric EVT may have limited application for CDS samples. Also, as our results differ from sample to sample, that the estimation of the moments of CDS samples may be conditional on the characteristics of the CDS contracts themselves. The two characteristics highlighted here are time and recovery rate. This may be similar to the influence of financial ratios on equity market returns.

In general, extreme value theory is an improvement in so far as it allows univariate models to take into account the kurtosis and skewness present in the data. This is particularly the case for equity and bond market data. However, this paper indicates that EVT may not be sufficient to capture the extreme volatility in the market for credit default swaps, particularly during times of high volatility and when recovery rates are low. The conclusion of this paper is that although there is a need to estimate risk in CDS returns, the existing methodologies of GARCH and EVT may not be appropriate. We do not intend to generalize the above statement to make a judgement call on the EVT methodology without further analysis using different samples drawn from different periods, which is our future extension of this paper.

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