Dependence Structure of Insurance Credit Default Swaps

Mudiangombe, Benjamin and Muteba Mwamba, John Weirstrass

University of Johannesburg; School of Economics, University of Johannesburg; School of Economics

5 September 2019

Dependence Structure of Insurance Credit Default Swaps

Benjamin Mudiangombe and J.W. Muteba Mwamba

School of Economics

University of Johannesburg

Abstract

We examine the dependence structure of insurance credit default swap (CDS) indices in the pairs of markets of the United Kingdom (UK), Eurozone (EU) and United States (US) insurance industries during the period of January 2004 to October 2018. We applied the Archimedean Clayton copula to model the lower tail and the Gumbel copula to model the upper tail of the empirical distributions. The empirical results show a significant dependence structure for both constant and time-varying copulas, implying the co-movement in the pairs of markets during the study period, influencing the contagion risk and showing strong dependence among Markets. The highest tail dependence and positive adjustment parameters seen in crisis and debt-crisis in the lower regime explains the link between these markets. The crucial findings show confirmation of asymmetric tail dependence proposing the propagation of risks of default among UK, EU and US markets. The conditional tail of the time-varying dependence structure explains the behaviour of dependence better than the constant level. This finding is robust when measuring the evolution of the dependence structure over time. The results are consistent for risk managers and investors to select the portfolio investment in different markets during stress period.

Keywords: 'Dependence structure', 'Insurance credit default swaps', 'Constant and Time-varying Copulas'

I. Introduction

The literature in credit default swaps (CDS) has increased over this last period. This is due to the fact that the latest financial crisis has shown more failings in the structure of the application of credit default swaps. Sometimes the failing is due to: insufficient information in the financial sector; the lack of information for risk managers; or some shortage in the contracts between the two parts. The survey of the British Bankers Association (BBA) shows that the credit derivatives markets rose from $40 billion in notional amount in 1996 to $5 trillion in 2004 and reached $8.2 trillion in 2006. Later, with the 2008 financial crisis, the notional value of CDS contracted rose to $31.22 trillion. The announcement of the International Swaps and Derivatives Association (ISDA) in the half-year 2005 market, and its survey in private talk of derivatives, showed the notional amount rise about 48% in the half-year 2005 to 12.43 trillion, revealing more increase than what was expected by the BBA. The largest extensive trades in credit derivatives are the credit default swaps, having almost 45% of market shares. The reason why the ISDA in 2015 were still taking conferences around the world, that was to discuss in what way and why they use CDS markets to hedge and then manage and take the risk. But, since the recent meeting held in New York in 2015, on the 19th of November; it is clear that, in spite of the benefits and the single-name of CDS; the volume of trade is decreasing continuously. This is due to confusions such as the conviction of the application of CDS that had an influence on the crisis. Some stated that it is due to the uncertainty of regulation; others said it is the result of a benevolent default risk environment, and still others asserted that it is the results from the overall decline in organised finance.

1.2 background

The crisis that began in 2007 is a pivotal point of reference for all risk managers, Chief Executive Officers (CEO) of companies and investors to be awake in how the system economic behaviour and aware of what strategy to implement, and how to avoid similar crises in the future or, should they occur, reduce their effects. The recent global financial crisis arising from the bankruptcy of September 2008 started with the failure of the biggest investment companies in the United States predominantly and affected the world over, especially those operated according to the European financial system.

A large number of studies have concentrated to the analysis of credit defaults and examining the motives of the credit default swap spreads, which have the better substitution for default risk. Arouri, et al. (2014) assess the interactions between the insurance sector and the five-years banking financial credit default swaps indices spread that has dynamically expanded for short and long-term over the latest worldwide financial crisis. Wang & Moore (2012) investigate the 38 developed markets of credit default swap (CDS) and emerging countries integrated with the US market in the stress period of subprime crisis by applying the multivariate GARCH model specifically the dynamic conditional correlation. Fenech, et al. (2014) examine the co-movement in the empirical study of equity stocks during the pre- and post-global financial crisis contexts of CDS spreads. The copula method allows us to differentiate whether misspecification comes from the dependence structure or the marginal distribution.

Some previous studies analysis the credit default swaps using copula models with multivariate time series to determine the dependence structure. For example, Gatfaoui (2010) employs the copula method toward identification of the dependence structures between the credit risk fundamentals and market risk fundamentals. Creal & Tsay (2005) investigate the time-varying dependence through 200 dimensional panels of financial assets composed of credit default swaps and daily equities returns for 100 corporations of United States. Brechmann, et al. (2013) investigate the dependencies in the credit default swaps market using copulas, specifically vine copula. Naifar (2011) applies Archimedean copulas to study the dependence structure between jump risk and CDS index. Wu & McMillan (2014) used different copulas to examine the dynamic dependence structure in credit risk between Treasury Euro Dollar (TED) spreads and the credit default swap index spread during 2004 to 2009. The tail properties of univariate and dependence models have an impact on the probability of risk analysis for insurance and finance when huge losses happen simultaneously. Patton (2007) gives a general idea of the literature on applications of copulas in modelling the financial time series. We understand the challenges of the distribution are non-normal by dealing with the dependence that does not hold with the multivariate Gaussian distribution. This challenge of multivariate perception in dependence is not a simple process to satisfy the cumulative, multivariate, conditional distribution function (see Joe (1997). Then, comes Sklar (1959) theorem, which made this challenge useable in separating the marginal distribution to the joint distribution, thus making copulas more useful. The new alternative to the dependence of copulas appeared with the flexibility of Sklar's theorem

The principal objective of this study is to capture the dependence structure evolved over time (in the extremes events) of insurance CDS during the financial crisis and debt crisis period for the pairs of markets selected. The second objective is to fill the gap and expand the study of Tamakoshia & Hamori (2014), who used constant copula theory modelling, with the objective to detect the dependence structure. The inconsistent result of the dependence structure evolving over time in the study of Tamakoshia & Hamori (2014) is clearly evident. We also noticed the inconsistency in using elliptical copula models for asymmetry distributions. We noticed that asymmetries couldn't be used with the elliptical copulas' models. We understand that a basic reality of dependence structure over time is worthy with the use of the time-varying copula. It is a useful way to conclude without underestimating or overestimating the level of dependence of the pairs of markets evolving over time.

Most of the studies in this field of CDS used different sectors of financial derivatives and came out with mixed findings, but the research done in insurance CDS indices is rare, except for Tamakoshia & Hamori (2014). As seen above, none of them used the two regimes of residuals separately in their analysis of data nor financial derivatives.

In this case, our data will be extracted from the Markov switching model, which considers the two regimes of residuals, namely, the lower regime and the higher regime. Assuming that this distribution is an asymmetric and the assumption of normality is not met, then a crucial class of copulas, named 'Archimedean copulas', is worth studying for some motives.

We are interested in this family of parametric copulas, specifically Clayton and Gumbel copulas, as this classification of copulas allows a big diversity of dissimilar dependence structures. Regarding the literature above, we may be the first to use the two regimes of residuals in insurance credit default swaps to analyse this series separately. We used the constant then the time-varying Clayton copula for the lower regime and in the same way the constant then the time-varying Gumbel copula for the higher regime. They are used as they are the specific models used to detect extreme events. These are well suited to this study as we deal with the risk of co-movement of the markets of insurance CDS, that is, the dependence structure between the pair of markets. Knowing that the risk of losses has detected to the tail of the distribution, reason why the choice of Archimedean copulas is crucial. The three pairs of markets are selected firstly because of the availability of data and secondly, they are the references markets in the world as benchmark.

This study is organised in the following structure: Section one will be an introduction; Section tow, a literature review of the study; Section three, the methodology of the study; Section four, the empirical evidence found and interpretation of these results; and Section five, conclusions of the study.

II. Literature Review

This section, review the literature on insurance credit default swaps that focused on financial derivatives to determine the dependence structure of default risk of different markets. The Archimedean copula will be used as a tool to relay a dependence structure for extreme events during a crisis period. There is not a long history of insurance CDS indices, and the unavailability of data makes the credit derivatives insufficient; therefore more contribution in this area of study is still needed.

2.1 Role of insurance sector during crisis period

The insurance sector played an important role in the global financial crisis: the failure and bailout of American International Group (AIG) was the main subject of discussion regarding this matter and generated a remarkable effect that insurance was, in some way, a dominant part of the crisis. Nevertheless, the visibility of insurance sector, in the periphery as a whole, was mainly seen during crisis. With regard to American International Group, most of its complications emanated from non-insurance activity: several life health insurers and assets fatality insurers avoided strict antagonistic causes from the subprime collapse and associated financial crisis. Some insurance corporations have required and got authorisation in certain states to adjust financial report to ameliorate their capital reported.

2.2 Related works

2.2.1 Market Risk of financial derivative

Among the studies in CDS, these authors examined the use of the CDS to detect the level of market risk. Fung et al. (2012) study the effects of credit default swap used on the risk and performance life, firm value of United States insurance companies during 2001 – 2009 period . They find reliable indication that the utilisation of CDS for income generation purposes is connected with a large risk market, the decline of financial performance, and lower firm value, for both life and property insurers. Reboredo &Ugolini (2015) study systemic risk in European sovereign debt markets using the copulas model. Their results indicate the strong co-movement in risk trends of European debt markets in pre-period and the starting of the debt crisis showing the systemic risk the same across markets.

Some studies investigate the relationships between the CDS and stock index market or between CDS and financial markets, as in the cases of the following authors Forte & Lovreta (2015) investigate the rudimentary questions further, paying precise attention to the stock and credit default swaps markets and their relative informational supremacy in crisis compared to non-crisis periods. They used the data on CDS spreads, during the period 2002 – 2008, and the stock market implied credit spreads for 92 non-financial European companies. The results show some conclusions, such as the fact that credit risk discovery in the stock and credit default swaps markets is a procedure that is dynamic. During the financial crisis, the stock market led the market; while, in post-crisis period, the credit default swaps market improvements were significant. There is a positive effect of credit condition of the reference entity on the information share of its stocks, which drives overhead the effect of the general economic state. Kim & Jung (2014) investigate the constituents of the sovereign CDS spread of China in a regime switching framework. The results show that the cross-asset-class contagion is strongly significant, but the contagion from sovereign credit default swap markets of China's highest trade associates is not significant.

2.2.2 Dependence structure between CDS and financial assets

Most of the studies investigate the dependence structure between credit default swaps and other financial assets and credit derivatives to determine the co-movement in the CDS market and their impact. Chen, et al. (2008) assess the dependence structure between the CDS return and the kurtosis of the equivalent equity return distribution, applying copula, which allowed specifying the non-linear and abnormal relationships. The empirical results show the Gumbel copula fitting well the model in lower rating classes, then the Student's *t,* they observe that the dependence structure is asymmetric and positive. They also find that the non-linear correlation between the CDS returns and kurtosis of stock return, rather than the class rating, is the basis of the change of dependence structure. Wang, et al. (2011) examine the dependence structures between the Chinese market and some other big world markets using dynamic copula models to the time-varying dependence structures. The finding shows the conditional copulas overtake both conventional

GARCH models and unconditional copulas. He reliably found the highest levels of dependence in the Chinese market, compared with the Japanese markets and the Pacific. Gatfaoui (2010) investigates the relation existing between CDS spreads and financial markets using copula methodology and focused on the joint dependence structure of CDS spreads and financial markets. The results show asymmetric dependence structures, presenting some models of tail dependence reliant on the CDX spread in concern. Naifar (2011) applies Archimedean copulas to study the dependence structure between jump risk and the CDS index. The results show an excessive co-movement of stock market conditions and CDS, adding the potential substantial default risk and a huge concurrent loss in stock markets that come from the excessive co-movements of tail dependence. Wu & Mc Millan (2014) used constant and time-varying copulas that allowed investigating the dynamic dependence structure in credit risk between Treasury Euro Dollars (TED) spreads and credit default swap index spreads during the period 2004 to 2009. The result shows the correlations fluctuated between two markets with an upward trend, displaying higher correlations, after 2007 involving the confirmation of credit contagion during the crisis period. Creal & Tsay (2015) investigate the time-varying dependence through 200-dimensional panels of financial assets composed of credit default swaps and daily equities returns for 100 corporations in the United States. Using diverse copula models, they found that the group of Student t copula is favoured to the other seven challenging models. Brechmann, et al. (2013) demonstrate that the dependencies in the credit default swaps market are powerfully driven by geographical regions, which limited a global classification of crucial systemic institutions. In the dependence analysis, he found evidence of non-elliptical structures of asymmetric tail behaviour, which is important to take into account in stress situations. He also found that the US banks are systemic more important than insurers and influence the international financial market strongly. Da Silva & Rebelo, (2014) used the copula model for investigating the association linked to the performance of stock index constitutes by a basket of CDS contracts and European financial institutions, focusing on measuring the dependence structure of the markets when extreme events happen, and checking the rationality of Merton's conclusion. They find fat tail-dependence between the two portfolios. Nevertheless, the dependence structure appears to be the same on negative and positive improvements in the indexes. Abid & Naifar (2005) assess the effect of stock returns volatility of reference entities on CDS rates with a set of data from the Japanese market. They applied the Archimedean copula approach and the result shows the pairs with a higher rating give a weak dependence coefficient, and then the effect of stock return volatility on CDS rates is higher for the lower rating class. The limited constraint to the number of diverse static dependence structures leads to the regime switching copulas remaining more contracting. Conversely, when the approach becomes flexible, it contains the complete dynamic in expanding the dependence structure. The dynamic correlation coefficients were introduced by Engle (2002) as the foundation of modelling the dynamic dependence. But Patton (2006a) in his seminar work, was among the first to discover a new field to model the bivariate time-varying copulas for the dependence structure.

This author investigated the asymmetric behaviour of the financial derivatives see, Arouri, et al. (2014) assess the interactions between the insurance sector and the five years banking financial credit default swap indices spread that has been dynamically examined in the short and long-term over the recent worldwide financial crisis. Applying a Smooth Transition Error-correction model, the result confirms that both have substantial long-term stability connections beyond the three credit default swaps indices that are classically non-linear and asymmetric.

Most of the literature further proposed a change over time in the dependence structure of financial variables, and, on the other hand, the changes in form and intensity; for example, those suggested by (Embrechts, et al., 2009 and Patton, 2006a). The prominent aspects are of major concern for risk management; from the time when unsuitable models for the relationships between financial variables have been recognized as an essential component of the last global financial crisis (see the series of published Financial Services Authority, 2009). So far, the greatest technique to model asymmetries and time-varying of the dependence structure still needs more research to this open question (Dias & Embrechts, 2010; Embrechts & Hofert, 2013).

These authors examine the degree of co-movement in different CDS indices of countries. Giovanni & Christos (2012) run a wide empirical analysis of the influence of magnitude of co-movement in the regular leading CDS indices and then add to existent empirical literature on the large complex financial institutions (LCFIs). Using SVAR, the results show three important points: firstly, the correlation between the CDX index of North America and iTraxx indices of Europe are negative, taking into account the equity returns for all the large complex financial institutions. Secondly, this factor led shocks all over the LCFIs and CDX indices and shows a significant result for European, as opposed to United States banks. Thirdly, the remarkable effect that proposed the diffusion of the mechanism that brought banks to deteriorate and consequently raises the default risk is the effect of CDS market volatility on the equity return volatility of LCFIs. Fenech, et al. (2014) examine the co-movement in the empirical study of equity stocks in the pre- and debt-global financial crisis contexts of CDS spreads. The finding shows a negative co-movement in the debt-period of the global financial crisis, and this is strong to various equity indices. The finding is critical for investors that are engaged in random activities. Wang & Moore (2012) explore the case of the subprime crisis of the 38 developed and developing countries used to investigate the incorporation of the credit default swaps market with the United States market. They used the dynamic conditional correlation from the multivariate GARCH model, and the result exposes, specifically for developed markets, that the shocks of Lehman appear to be reinforced by the incorporation. The highest correlation for developed and developing markets is due to the fact of decreasing US interest rates that are the principal motivating factor, and the peak of the crisis indicates that the biggest world economy roughly conducted the CDS markets.

Taking into account the dynamic process, as our methodology will focus on it, we presented the studies done using the dynamic copula and a significant concern the variation of market co-movement and the dependence in varying period of the market. Recent studies show relevant issues for equity markets. Jondeau & Rockinger (2006) used dynamic copula to investigate the variations dependencies of financial time series over time, besides making other contributions. In this case, we are motivated plus in detail on the structure suggestions on the subject, due to the work of Fermanian & Wegkamp (2012) and Patton (2006a, 2006b) for the aim that is an illustration of the dynamic markets.

The mentioned studies above belong to the literature on the dependence structure of CDS market on financial derivatives and on the impact of credit default swaps on different financial assets. They used constant copulas and dynamic copulas and other methods. Then they achieve mixed findings, such as: negative co-movements in the post-period of the global financial crisis; and a positive dependence structure during the financial crisis and asymmetric tail dependence, indicating simultaneous losses. Nevertheless, we observe that researchers on dependence structure in the insurance sectors CDS indices, across countries and using different methods, are rare. Insurance credit default swaps does not have long history and the unavailability of data, the reason why there is no many studies in this specific area, and this attract our attention. Tamakoshia & Hamori (2014) did the one study using daily data from the UK, US and EU insurance sectors to assess the dependence structure in insurance CDS indices. He applied copula GARCH approach and showed significant increased dependencies during the financial crisis periods. It also revealed the Frank copula fitting well, with insignificant tail dependence discovered, indicating low systemic risks. We find the insufficiency of the results of the constant copula not able to capture the evolutions of dependence structure over time. It will be missing information during the process and can underestimate or overestimate the dependence structure over time. However, our method is different to the studies above in the limit of our knowledge we may be the first to use two regimes of residuals in the analysis of data in insurance CDS indices applied to Clayton and Gumbel copulas respectively lower and higher regimes. We used each regime separately by analysing the lowe regime of each pair of the market by constant and the time-varying Clayton copula, and the higher regime of each pair of the market with the constant and the time-varying Gumbel copula. This is different strategies to those used above to see how the dependence structure of insurance CDS indices evolves over time in the pair of lower and higher market regimes, separately, and the level of co-movement during this period of study of insurance credit default swaps.

III. Methodology

3.1 Basic Concept of Copulas

According to the basic concepts, we define copula as follows:

The n-dimensional distribution form a copula function, C, limited in the interval $[0,1]^n$ with the following condition that might be satisfied.

- A copula function is n- increasing.
- A copula function has margins C_j, with$j = 1, 2, \ldots, n$, $C_j(t) = t$ for each t in [0, 1].

We have two categories of copulas such as the elliptical copulas and the Archimedean copulas. But in this study, we concentrated on some non-Elliptical copulas, specifically the Clayton copula and the Gumbel copula, to determine the extreme dependence structure that appeared in the extreme events.

3.2 Copula GARCH approach

In the estimation of the copula parameters, we consider a two-step model approach likened to Patton (2006) who estimates: the copula parameters using the maximum likelihood method and the marginal distributions from univariate GJR-GARCH (m, n) models.

The GJR-GARCH (1, 1) model will be used in positive and negative shocks for marginal distributions given by:

$r_j = u_j + \varepsilon_j$ (3.2.1) $\varepsilon_j = \sigma_{j-1} e_j,$ $e_j \sim STK(\upsilon, \alpha)$ (3.2.2) With $E\left(\varepsilon_j^2\right) = \sigma_i$

Where r_j , u_j and ε_j: are respectively the return, the conditional mean that can include autoregressive terms and the random error term. The general model of GJR-GARCH is:

$$\sigma_j = \lambda_0 + \beta_1 \sigma_{j-1} + \lambda_1 \varepsilon_{j-1}^2 + \lambda_1^* \varepsilon_{j-1}^2 I_{j-1} \qquad (3.2.3)$$

Where I_j: the indication functions with the following condition: $I_{j-1} = 1$ if $\varepsilon_{j-1} < 0$ and $I_{j-1} = 0$ if $\varepsilon_{j-1} \geq 0$

In equation (3.2.3), if the coefficient $\lambda_1^* \geq 0$ it shows that the negative error terms have greater influence on future volatility.

3.3 Sklar's theorem

Sklar (1959) was the first to demonstrate the theorem, and revealed that a function of every joint distribution could be written as marginal distributions. For any distribution F of dimension p, with the distribution marginal F_j, the function copula will be given by:

$$F\left(z_1, \ldots, z_p\right) = c(F_1(z_1), \ldots, F_p\left(z_p\right)) \qquad (3.3.1)$$

We define $F_j\left(z_1, \ldots, z_p\right)$, $F_1(z_1)$ and $F_p(z_p)$ respectively, the joint distribution, the marginal distribution of variable z_1 , then the marginal distribution of variable z_p. With $j = 1, \ldots, p$, when the all marginal distribution is continuous, copula function will be given by:

$$c\left(\kappa_1, \ldots, \kappa_p\right) = F(F_1^{-1}(\kappa_1), \ldots, F_p^{-1}\left(\kappa_p\right)) \qquad (3.3.2)$$

then $z = F_1^{-1}(\kappa_1), \ldots, F_p^{-1}(\kappa_p)$, thus the copula density will be:

$$c\left(\kappa_1, \ldots, \kappa_p\right) = \frac{f(F_1^{-1}(\kappa_1), \ldots, F_p^{-1}\left(\kappa_p\right))}{\Pi_{j=1}^{p} f_j F_j^{-1}(\kappa_j)} \qquad (3.3.3)$$

3.4 Estimation function

We are using the standard estimation process that is semi-parametric, as known the copula is a function of some parameter $\varphi = \varphi_i$ with $j = 1, .. p$ and τ . The density of copula noted by C and arguments given by $t_1, \ldots, t_p$ is the derivative expressed by

$$C_{\varphi}(t_1, \dots, t_p) = \frac{\partial^p}{\partial u_{1,\dots,}\partial u_p} C(t_1, \dots, t_p) \tag{3.4.1}$$

The estimates values of the copula and the marginal distributions are generally estimated respectively by optimizing the log likelihood function, and then we have:

3.5 Maximum-likelihood estimation

The crucial part is to recognize how to compute and derive the generator derivatives. The conforming copula densities are described specifically by optimizing the log likelihood function.

$$\ell(\zeta, x) = \sum_{i=1}^{T} (\sum_{j=1}^{p} \ln\left(f_j(z_{j,t}; \delta_j)\right) + \ln(C(F_1(z_{1,t}), \dots, p(z_{p,t}); \gamma))) \tag{3.5.1}$$

Where $\zeta = (\delta, \gamma)$ represent the vector containing the marginal parameters $\delta = (\delta_1, \dots, \delta_p)$ and γ: the copula parameter.

3.6 Dynamic Archimedean Copulas

Patton (2006a) adjusted the theory of Engle (2002) for modeling the bivariate time-varying of Archimedean copulas based on an ARMA procedure. He assumed that over the sample the practical procedure of the copula remains static, while in Kendall's tau, the transformed copula parameters vary in the process of the evolution equation.

$$\delta_y = \Lambda(\varpi + \alpha_2 \delta_{y-1} + \alpha_1 \frac{1}{10} \sum_{j=1}^{10} |\kappa_{1,y-j} - \kappa_{2,y-j}|). \tag{3.6.1}$$

The logistic transformation is given by Λ and then $\Lambda(\mathrm{t}) = (1 + e^{-t})^{-1}$and is allowed to keep, at all times, the order of the parameters of the Clayton copulas, $\delta_y \in [0,1]$and $(\kappa_{1y}, \kappa_{2y})$, as are the observations at times y.

The dynamic process is restricted to bivariate application applied by Patton (2006a) through the absolute difference term $|\kappa_{1,y-j} - \kappa_{2,y-j}|$ called forcing variables. When there is impeccable positive dependence this absolute difference is close to zero, and entrains the parameter α_1 to be negative.

3.7 Type of Archimedean copula

3.7.1. Clayton copula

The Clayton copula is an asymmetric copula, displaying larger negative tail dependence than in the positive, and could be an improved choice. We obtain Archimedean Clayton copula given by the following expression:

$$C_{Clay}(t_1, \ldots, t_p) = \max((t_1^{-\delta} + \cdots + t_p^{-\delta} + n - 1)^{-1/\delta}, 0) \tag{3.7.1.1}$$

The Clayton copula has a generator function defined by $\varphi_{Clay}(t) = \frac{1}{\delta}(t^{-\delta} - 1)$ (3.7.1.2) with $\delta \in (0, \infty)$ named range of the accepted parameter, $\delta \in \Theta = [-1. \infty)/\{0\}$, $\delta > 0$. The bivariate Clayton copula and the bivariate density function of Clayton copula is given respectively as follow:

$$C_{Clay}(t, v) = (t^{-\delta} + v^{-\delta} - 1)^{\frac{-1}{\delta}} \tag{3.7.1.3}$$

$$C_{Clay}(t, v) = (1 + \delta)(t^{-\delta} + v^{-\delta} - 1)^{\frac{-1}{\delta - 2}}(tv)^{-\delta - 1} \tag{3.7.1.4}$$

The expression $\varphi'_\delta(u) = -u^{-\delta-1}$, will derive to obtain Kendall tau:

$$\tau = 1 + 4\int_0^1 \frac{\varphi_\delta(u)}{\varphi'_\delta(u)} du = \frac{\delta}{\delta + 2} \tag{3.7.1.5}$$

To find the tail dependence of Clayton copula, we apply $\varphi_\delta^{-1}(t) = (1 + \delta t)^{-1/\delta}$ in order to get

$$\lambda_{Lo} = \lim_{z \to \infty} \frac{\varphi_\delta^{-1}(2z)}{\varphi_\delta^{-1}(z)} = 2^{-1/\delta} \quad and \quad \lambda_{Up} = 2 - \lim_{z \to 0} \frac{1 - \varphi_\delta^{-1}(2z)}{1 - \varphi_\delta^{-1}(z)} = 0$$

The pair of variables (t, v) exhibits le lower tail dependence of the Clayton copula given by the following expression $\lambda_L = 2^{-1/\delta}$, (3.7.1.6)

With $\delta > 0$, agrees for lower tail dependence and zero upper tail dependence.

The log likelihood of Clayton copula function is given by:

$$\ell_{clayt}(t; v) = \sum_{y=1}^{T} \ln((1 + \delta)(t.v)^{-1-v}\left(t^{-\delta} + v^{-\delta} - 1)^{-2-\frac{1}{\delta}}\right), \tag{3.7.1.7}$$

The coefficients of dependency parameter, according to the evolution equations, employed in Patton (2006) are expressed by: $\vartheta_y = \Lambda\left(\varpi + \alpha_2\vartheta_{y-1} + \alpha_1 \frac{1}{10}\sum_{j=1}^{10}|t_{y-j} - v_{y-j}|\right)$, (3.7.1.8)

Where $\vartheta_y \in [0, \infty)$ is the level of dependence between t_y and v_y.

3.7.2. Gumbel copula

These Archimedean copulas are defined for $\delta \in \Theta = [1, \infty)$ and produced by generator $\varphi_\delta(u) = (-lnu)^\delta$.

The bivariate form is expressed by: $C_{GU}(t, v; \delta) = \exp\{-((-lnu)^\delta + \left(-lnv)^\delta\right)^{\frac{1}{\delta}}\}$, (3.7.2.1)

Gumbel copula exhibits the parameter $\delta > 1$ and has upper tail dependence. The density of the time-varying Gumbel copula is given by the following expression

$$C_{Gu}\left(\frac{t_y,v}{\delta_y,k_y}\right) = \frac{(-lnt_y)^{\delta_{y-1}}(-lnv_y)^{\delta_{y-1}}}{t_y v_y} exp\left\{-[(-lnt_y)^{\delta_{y-1}} + (-lnv_y)^{\delta_{y-1}}]^{\frac{1}{\delta_y}}\right\}\left\{-[(-lnt_y)^{\delta_{y-1}} + (-lnv_y)^{\delta_{y-1}}]^{(\frac{1-\delta_y}{\delta_y})^2}\right\} + (\delta_y - 1)[(-lnt_y)^{\delta_{y-1}} + (-lnv_y)^{\delta_{y-1}}]^{(\frac{1-\delta_y}{\delta_y})}, \quad (3.7.2.2)$$

With $\delta_y \in [1, \infty)$ represents the level of dependence between u_t and v_y, when $\delta_y = 1$ suggests that there is no dependence and, in another side, when $\delta_y \to \infty$ denotes an entirely dependent link. The expression of Kendall's tau and the tail dependence coefficients is given below: It is important to find $\varphi'_\delta(u) = -\frac{\delta}{y}(-lnt)^{\delta-1}$ in order to get the following formula of Kendall's tau. $\tau = 1 + 4\int_0^1 \frac{\varphi_\delta(u)}{\varphi'_\delta(u)} du$, and the Kendall's tau for the Gumbel copula became $\tau = \frac{\delta-1}{\delta}$. Then we obtain the tail dependence of Gumbel copula by: $\varphi_\delta^{-1}(u) = e^{-y^{1/\delta}}$ come from $\lambda_{Lo} = \lim_{z\to\infty} \frac{\varphi_\delta^{-1}(2z)}{\varphi_\delta^{-1}(z)} = 0$, and $\lambda_{Up} = 2 - \lim_{z\to 0} \frac{1-\varphi_\delta^{-1}(2z)}{1-\varphi_\delta^{-1}(z)} = 2 - 2^{1/\delta_y}$ (3.7.2.3)

It is important to specify that Gumbel copulas are simply a measure of positive dependence. Specifically, they simply insert between independence and co-monotonicity as follow $C_{Gu;1} = \Pi \ and\ C_{Gu;\infty} = M$.

The dependences are expected to follow the ARMA (1, 10)-like process in the dynamics of the conditional Gumbel copula. The proposed time-varying Gumbel copulas used the dependence processes follow: $\delta_y = \Lambda(\varpi + \alpha_2\delta_{y-1} + \alpha_1\frac{1}{10}\sum_{j=1}^{10}|t_{y-j} - v_{y-j}|)$ (3.7.2.4)

3.8 Markov switching model

Let the general process expressed by the given formula: $x_i = \pi_{sta} + \varepsilon_i$ (3.8.1)

Where $sta = 1, \ldots, k$ and $\varepsilon_i \sim N(0, \sigma_{sta}^2)$.

Equation (3.22) is a simple case of a dynamic switching model, and then the intercept is switching states noted by an indicator variable sta. Thus, in the case of k states, will generate k values for π and σ^2. In this study we used the two states given by sta=1,2 generating the linear regression model under the general restrictions. We have the following model: $\begin{cases} x_i = \pi_1 + \varepsilon_i \\ x_i = \pi_2 + \varepsilon_i \end{cases}$

$where \quad \varepsilon_i \sim N(0, \sigma_1^2) \qquad \varepsilon_i \sim N(0, \sigma_2^2)$ (3.8.2)

We have two processes of dependent variables x_i that are represented in equation (3.8.1) for both states respectively 1 and 2. Where $\pi_1$and $\pi_2$represent respectively the expectation of the dependent variables then σ_1^2 and σ_2^2 the respective volatility innovative in states 1 and 2. Therefore $\pi_{sta} = \theta_0 + \theta_1 \pi_{sta}$ (3.8.3)

For more information about the Markov Switching regime model see in James, (1994).

4 EMPIRICAL AND INTERPRETATIONS OF RESULTS

4.1. Data Description

Our sample data is composed of 3865 daily observations of five years' insurance credit default swaps premiums of the United Kingdom, Eurozone and the United States from 1 January 2004 to 24 October 2018. We use the five years' CDS indices because they are usually exchanged in the indices market with maturity between 1 and 10 years. The full sample splited into three sub-sample periods, namely the pre-crisis period; the financial crisis period (characterising the 2008 global financial crisis) and the debt-crisis period. The data is obtained from Bloomberg Reuters.

Stage one, on 9 August 2007, started when the trust between banks vanished and they stopped doing business, and the banking system rushed by the Bank National of Paris (BNP) proclaimed in ending activities in three particular hedge funds of the US mortgage debt. The second stage started on 2 April 2009 - when the world leaders met at the G20 summit in London and was dedicated to the economic growth to help the International Monetary Fund and the overall institutions improving jobs and development and restructuring banks.

For this study, we examine the dependence structure and the level of co-movement in the pair of markets during the pre-crisis period, from 01 January 2004 to 08 August 2007. The financial crisis period starts from 09 August 2007 to 04 November 2009 and the Debt-crisis period from 05 November 2009 to 24 October 2018; and, finally, the entire sample from 01 January 2004 to 24 October 2018.

4.2 Data transformation

The transformation of the data has been done using the returns defined as follows:

$$r_i = \frac{P_i - P_{i-1}}{P_i} \quad (4.2.1)$$

where, $\boldsymbol{i} = 1, \ldots, t$ with r_i : being the returns of the CDS indices and x_i: denoting the raw time series of the daily five-years' CDS indices of UK, US and EU.

Markov switching approach of two regimes, is applied to find the higher and lower regime of residuals that is considered as the preliminary analysis of data and finally these residuals will be grouped in pair of lower regimes and in pair of higher regimes.

4.3 Descriptive statistics of log returns

Table 1: Summary of descriptive statistics of the daily insurance sector CDS -5 year's indices premiums.

Variables	RETEU	RETUK	RETUS
Mean	-0.000453	-0.000620	0.000327
Median	-0.000825	-0.000161	-0.000175
Std. Dev.	0.035518	0.033661	0.040201
Skewness	-0.062431	0.094279	-1.446992
Kurtosis	14.94711	8.920528	56.51798
Jarque-Bera	22988.54	5650.663	462600.1
Observations	3865	3865	3865

Note: Summary of the returns of data insurance credit default swaps indices for the crisis and debt-crisis sample covering the period 01/01/2004 to 24/10/2018 for a total of 3865 observations.

The results presented in Table 1 show the descriptive statistics of the dailly returns of insurance credit default swaps indices of five years premium, indicating that the standard deviation of the United States is higher follow by Eurozone for the simple reason that the financial crisis has more effect in the US and the EU. So, in this case, we assume a higher risk taken by insurance companies, then more default has to be seen here and expanded to the world. The skewness indices that measure an asymmetric distribution are non-positive in the US and EU, which means the presence of the longer left-hand tails of the distributions. The hypothesis of normality has been rejected by the test of Jarque-Bera for all levels of insurance sector CDS indices, confirming that the data in credit default swaps indices is not normally distributed. This finding is the same as in the study of Tamakoshia & Hamori (2014). But in contrast, the skewness of this study shows the distribution with long left tails.

See Appendix A, for Tables 2 and 3 that present the estimates parameters of the Markov switching model for the United States, United Kingdom and Eurozone, respectively, in the lower and the higher regimes.

In general, we observed that the mean parameters for US and EU are positive, showing that there is a positive relationship in the insurance credit default swaps market. Observing the parameters of both regimes during the specific period of Crisis and Debt-crisis carefully, we find the significant parameters showing the positive link of dependence in insurance CDS markets.

Tables 4 and 5 exhibit the results of the dependence constant parameters of the Clayton copula in the lower volatility regime as well as the dependence constant parameters of Gumbel copula in the higher volatility regime. The all extreme dependence parameters are significant for all periods. This finding indicates that these copulas fit the respective pair of both markets well, and specified that the different pair of markets insurance CDS indices co-move together during all periods of study. We also observe the higher dependence parameters displayed during Crisis and debt-crisis periods in all pairs of markets. The UK-EU pair of markets had the highest dependence parameters in both cases and revealed the highest correlation in the markets of UK and EU, which was influenced by the proximity of economic region, causing the higher extreme risk of transmission of insurance credit default swaps indices. These markets influence each other; meaning when one market suffers the risk of credit defaults; it brings other markets into the same situation.

Table 4: Estimates parameters of constant Clayton copulas in lower regime

	Param.	Pre-crisis 01/01/2004 08/08/2007	Crisis 09/08/2007 04/11/2009	Debt crisis 05/11/2009 24/10/2018	Entire sample 01/01/2004 24/10/2018
UK-US	θ	0.6467 (0.113)	0.7906 (0.212)	0.7789 (0.110)	0.3756(0.010)
UK-EU	θ	0.7154 (0.111)	0.8500 (0.121)	0.8302 (0.124)	1.1302(0.110)
US-EU	θ	0.6586 (0.122)	0.8103 (0.116)	0.7221 (0.112)	0.5511(0.010)

Notes: estimates parameters of constant Clayton copula with θ the dependence parameters and their standard errors in parentheses.

Table 5: Estimates parameters of constant Gumbel copula in higher regime

Param.	Pre-crisis 01/01/2004 08/08/2007	Crisis 09/08/2007 04/11/2009	Debt crisis 05/11/2009 24/10/2018	Entire sample 01/01/2004 24/10/2018

UK-US	θ	1.0688(0.3653)	2.6640(0.1325)	2.7311(0.2053)	1.2509(0.4532)
UK-EU	θ	1.6971(0.3211)	3.1261(0.2417)	2.7441(0.2613)	1.7977(0.3252)
US-EU	θ	1.4973(0.2854)	3.1057(0.4001)	2.1041(0.52110	1.3723(0.6211)

Notes: estimates parameters of constant Gumbel copula with θ the dependence parameter and their standard errors in parentheses.

Table 6 displays the estimated left tail dependence parameters of the time varying Clayton copula in lower regime of volatility. The results show larger parameters, ϖ, expressing the level of dependence in UK-US, UK-EU and in US-EU pair of markets. We notice great values of dependence parameters and significance in Crisis and Debt-crisis periods, implying the higher level of co-movement in the markets. We also notice the negative adjustment parameters expressed by α_1 in the pair of all periods. This shows the significance of variations in dependence over time.

The degree of persistence measured by α_2 is positive in all periods except in Pre-Crisis period of UK-US and US-EU pair of markets. Then, we notice that all parameters in Crisis and Debt-Crisis periods are significant, showing that the relationships influencing the extreme events of markets in insurance credit default swaps indices are highly interconnected. Therefore, when one market suffers the risk of credit default in insurance indices, it entrains the other market to suffer in the same order. Thus, we come to conclude, as shown in the case of constant copula, that there is higher risk of a contagion effect during a crisis period. This is sometimes due to the non-confidence of investors to take the right direction by avoiding the risk of loss in their business or due to regulations of contract in insurance credit default.

Table 7 represents the estimated time-varying Gumbel Copula showing the right tail dependence parameters in the higher regime of volatility. We observe that the results demonstrate a positive parameter of dependence in all periods and also the significance of all parameters during Crisis and Debt-Crisis times. This indicates the evidence that these markets co-move together in the extreme events insurance CDS indices. We also notice the negative adjustment parameters or forcing variables of all periods in the pair of UK-EU. The mean difference is negative imply the rising in tail dependence. In contrast in the pair of UK-US and US-EU markets, the mean difference is positive in Crisis period. This make sense in term of geographic distance separating the markets. The result displayed in this study are of the asymmetric dependence structure. In contrast, the finding of Poon, et al. (2004) finds no asymmetric tail dependence in his study.

Table 6: Estimates parameters of the time varying Clayton copula in lower regime

Country	param	Pre-crisis 01/01/2004 08/08/2007	Crisis 09/08/2007 04/11/2009	Debt crisis 05/11/2009 24/10/2018	Entire sample 01/01/2004 24/10/2018
UK-US	ϖ	1.0214 (0.818)	1.5341 (0.992)	1.1142(0.030)	0.9591(0.924)
	α_1	-1.9978 (7.050)	-0.7255 (0.060)	-0.8115(0.218)	-0.5596(0.337)
	α_2	-0.9933(0.306)	1.5325(0.974)	0.9801(0.186)	0.9317(0.069)
UK-EU	ϖ	1.0438(0.013)	1.7206(0.690)	1.1614(0.061)	1.0849(0.025)
	α_1	-0.7243 (05209)	-0.3640 (0.037)	-1.6013(0.506)	-0.4880(0.343)
	α_2	0.9947(0.802)	1.8651(0.889)	0.9575(0.165)	0.9645(0.122)
US-EU	ϖ	1.2131(0.397)	1.5501(0.266)	0.1435(0.015)	0.9438(0.016)
	α_1	-2.9665(0.917)	-0.1910(0.487)	-0.4625(0.112)	-0.3497(0.298)
	α_2	-0.9937(0.981)	1.9847(0.409)	0.9897(0.203)	0.9330(0.186)

Notes: estimated time varying parameters of Clayton copula in lower regime with ϖ, α_1 and α_2 the parameters of equation (3.7.1.8), the values in parentheses represent the standard errors.

Therefore, this result shows evidence of asymmetric tail dependence, proposing transmission of risks between the United States, United of Kingdom and Eurozone, and insurance credit default swaps indices during the period of distress, meaning that the systemic risk has an impact during the two crisis periods.

The conditional tail dependencies are very important to examine the joint extreme events affecting insurance credit default swaps indices during the period of higher risk of default, completing the insufficiency of the finding of the constant copulas. The degree of persistence expressed by the parameter α_2 is positive in Debt-Crisis and the financial Crisis for UK-EU pair of markets, indicating the positive relationship between the correlation parameters on time t and on time t+1. The higher volatility in the conditional correlation relates first to the lead up to the announcement of bankruptcy in the United States, whereas the second corresponds to the European Debt-Crisis. The crucial findings show that in the Crisis and Debt-Crisis periods the lower tail dependence is more persistent than the upper tail dependence in the selected pair of markets in this specific time.

Table 7: Estimates parameters of time-varying Gumbel copula in the higher regime

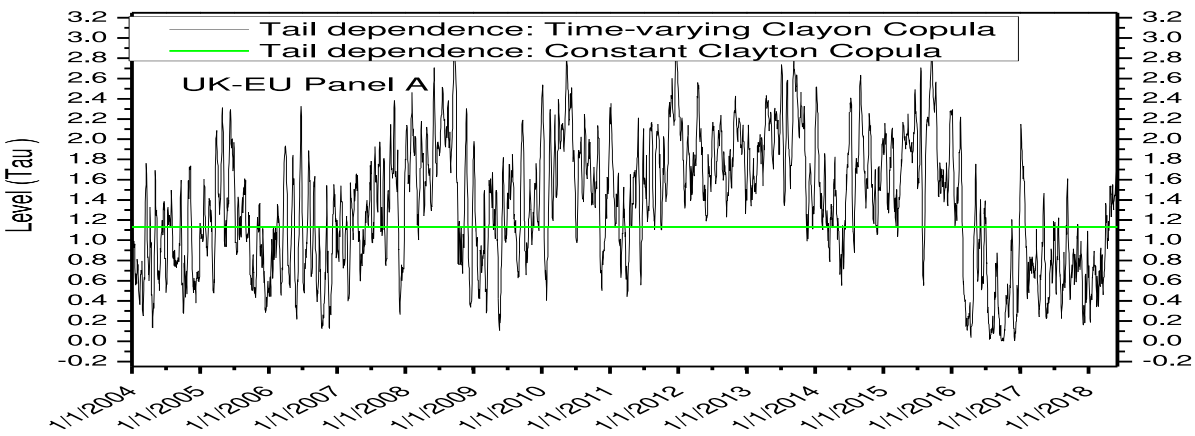
Country	para	Pre-crisis 01/01/2004 08/08/2007	Crisis 09/08/2007 04/11/2009	Debt crisis 05/11/2009 24/10/2018	Entire sample 01/01/2004 24/10/2018
UK-US	ϖ	0.8951(0.4001)	1.9851(0.9542)	0.9792(0.3100)	0.1607(0.2872)
	α_1	-1.1192(0.6432)	0.0618(0.0113)	-1.0300(0.4351)	-0.0717(0.1150)
	α_2	-0.0046(0.0101)	-1.2531(0.5212)	-0.0024(0.0012)	-3.2983(0.4086)
UK-EU	ϖ	1.9240(0.1636)	1.4127(0.1809)	0.9456(0.0618)	0.5110(0.1777)
	α_1	-0.8121(0.0713)	-0.5950(0.0407)	-0.0868(0.0203)	-0.2082(0.1048)
	α_2	-1.2964(0.066)	0.7952(0.0951)	1.3165(0.2101)	0.7501(0.1747)
US-EU	ϖ	0.6295(0.1659)	1.2699(0.2145)	0.6850(0.699)	0.8541(0.6307)
	α_1	-0.5622(0.4109)	-1.1115(0.7634)	0.1380(0.0551)	0.2448(0.3910)
	α_2	-1.5971(0.4565)	-0.0059(0.0021)	-1.3062(0.3350)	-0.9537(0.5193)

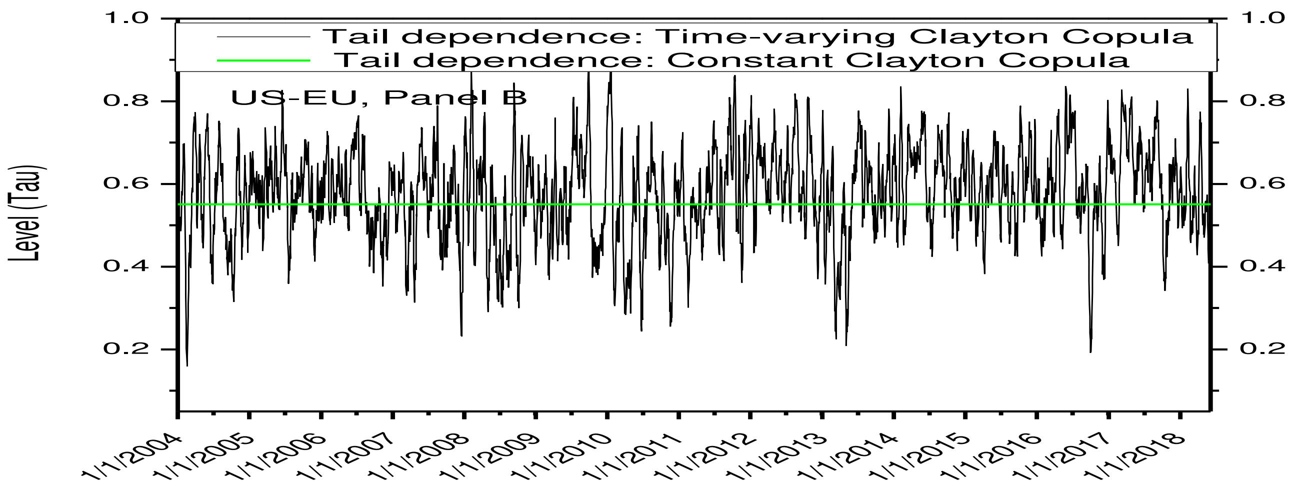
Notes: estimated time varying parameters of Gumbel copula in higher regime with ϖ, α_1 and α_2 the parameters of equation (3.7.2.4), the values in parentheses represent the standard errors.

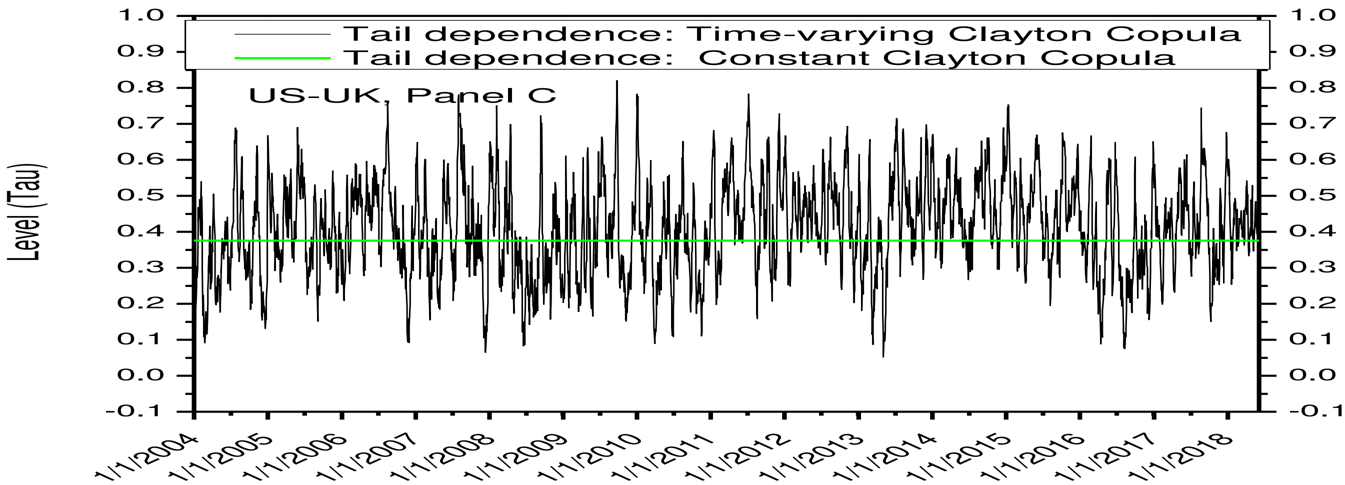
4.4 The Movement of the Tail Dependence in the lower Regime of Volatility

Figure 1 represents the tail dependence of the time varying Clayton copula in the lower regime of volatility for the entire sample. Panel A displays the evolution of the lower tail dependence in the UK-EU pair of markets with more fluctuations above the constant level of 1.11302 of dependence during the Crisis and Debt-Crisis periods. There was an extreme event that happened in the last semester of 2009 with the collapse or vanishing of three main investment banks in the US, namely: Lehman Brothers, Merrill Lynch and Bear Stearns. Panel B displayed remarkable periods of increase in fluctuations seen in Crisis and Debt-Crisis periods, and the evolution of dependence fluctuates more above than below the constant level of 0.5511 in these periods. Panel C shows higher fluctuations above the constant level of 0.3756 dependence.

The figure 1 represents estimation of conditional lower tail dependence of time varying Clayton copula in the lower regime of volatility for the entire sample.


Tail dependence: Time-varying Clayon Copula
Tail dependence: Constant Clayton Copula
UK-EU Panel A
Level (Tau)


Tail dependence: Time-varying Clayton Copula
Tail dependence: Constant Clayton Copula
US-EU, Panel B
Level (Tau)



In UK-EU, the increase starts from the beginning of the financial Crisis until the beginning of the Debt-Crisis where the evolution of dependence over time seems higher and fluctuates above the constant level. In some ways, this may have been due to the real estate bubble distressing the United States' housing prices that peaked in the first quarter of 2006; or it may be due toward the credit crisis causing the break of the housing bubble. The main financial crisis knockout of the world in the economy sector and other sectors then led to: difficulties in procuring mortgage loans in the United States; numerous European banks involved in troubles; and the crisis entraining to earlier cooperation among the economies of European countries.

4.5 The Movement of the Tail Dependence in the higher Regime of Volatility

Figure 2, See Appendix A it shows the evolution of the insurance credit default swaps in the upper tail dependence of Gumbel copula and the constant dependence. The movement of the upper tail dependence parameters of UK-EU pair of markets over time is fairly unpredictable: certain periods are important to be mentioned - as we can see in panel D, the pair of markets fluctuate up and down around the constant dependence of 1.7977. Specifically, during the financial crisis and Debt-crisis the market was more volatile above the constant level of dependence. The tail dependence for the US-EU pair of the market in Panel E shows the evolution of parameter over time and how it fluctuates below and above the constant level of 1.3723. Panel F demonstrates more fluctuations of the evolution of tail dependence above than below the constant level of 1.2509 of dependence during the starting of the financial Crisis until the period of debt-Crisis.

We could see that more information had been missed during Crisis and Debt-Crisis if we concluded using constant copulas only. There is fluctuation in this value, which meant the time-varying dependence explained the behaviour of dependence rather than the constant copula: this finding is robust when looking for the evolution of the dependence structure over time

5 Conditional Tail Dependencies

The tail dependencies are a highly valuable tool to investigate the combined extreme events distressing financial returns during the higher instability periods or a market crash.
Figure 1 and 2 exhibit the time-varying of the conditional lower and upper tail dependencies.

Table 8: Estimates parameters (Tau) for Clayton Copula

Clayton	Pre-crisis	Crisis	Debt crisis	Full sample
UK-EU	0.4004	05807	0.5375	0.5316
US-EU	0.1525	0.3809	0.2926	0.2843
UK-US	0.0940	0.2393	0.1675	0.1579

Table 9: Estimates parameters (Tau) for Gumbel Copula

Gumbel	Pre-crisis	Crisis	Debt crisis	Full sample
UK-EU	0.2934	0.6178	0.5426	0.5295
US-EU	0.2808	0.4087	0.3503	0.3428
UK-US	0.2504	0.3364	0.2654	0.2596

Kendall's Tau explains the non-parametric dependence measures and is sovereign of marginal distributions: they are extremely powerful measures of dependence structures associated to insurance CDS. We are more focused on the findings of the Crisis period and the results of the Debt-Crisis until the end period of our sample observations. Table 8 and 9 presented the results of the tail dependence Tau of the lower and higher regimes; and we find that the all Tau parameters are positive, showing the chance of moving together in their business. The higher tail dependence has been seen in Crisis and Debt-Crisis for both regimes.

The pair of market dependence is higher for the UK-EU for both regimes sometimes due to the distance separating their countries and the economic link between the United Kingdom and the Eurozone. It is followed by the US-EU and finally by the UK-US pairs. This easily explains that the link between the markets of the UK-EU is more correlated than that of the US and EU, and so far, than that of the UK and US.

5. THE CONCLUSIONS OF THE STUDY

5.1 discussion of the results

We studied the dependence structure of insurance CDS indices 5-years premium of the United Kingdom, the United States and the Eurozone markets in two regimes of volatilities separately. We applied the lower regime using Clayton copula and the higher regime using Gumbel copula for the period from 01 January 2004 to 24 November 2018. The Markov switching model was applied to extract residuals of two regimes of volatilities used for analysis. This model displayed the positive mean parameters showing the positive link of dependence in the insurance credit default swaps market of the US and EU. The main results show in the descriptive statistics an asymmetric distribution, due to the negative skewness values found for all the markets. These results confirm the non-normality distribution and justify the presence of a long left tail. The financial crisis did have more effect on insurance CDS indices during this period, and therefore the higher standard deviation in US, EU and EU, maybe is due to the higher-risk taken by the insurance companies during crisis period and affected the all sample.

The dependence parameters of both regimes show the extreme parameters of the constant copulas significant for all periods. This finding indicates that these copulas fit well the pair of markets and justify the co-movement between the extreme markets. The higher dependence parameters are displayed in all pairs of markets in crisis period, followed by the debt crisis period, indicating that insurance CDS are more connected and produce a transmission of risk in their markets during the distress period. The highest dependence parameters in both regimes of the UK-EU pair of markets reveal the highest correlation in the market of the UK and EU, influenced by the distance, limiting their economic region. This relationship between both markets, the EU and the UK causes the higher extreme risk of transmission of insurance credit default swaps indices. Therefore, the markets are influenced by each other, which means when one market suffers the risk of credit defaults, it brings other markets into a similar situation.

The time-varying Clayton and Gumbel copulas show a higher level of co-movement in the markets in crisis and debt crisis periods. The results show larger parameters ϖ expressing the level of dependence in the pair of markets in crisis and debt-crisis. The time-varying Clayton copula captures the lower tail dependence and taking into account the period of market stress; we notice that all the parameters in crisis and debt crisis period are significant. This result shows that the relationship influencing the extreme events of markets in insurance credit default swaps indices are highly interconnected. Consequently we conclude, as in the case of constant copula that, there is a higher risk of contagion effect in crisis period. In the higher regime of volatility, we observe a significance for all parameters in crisis and debt crisis showing the evidence that these markets co-move together in the right extreme events insurance CDS indices.

The difference with the Tamakoshia & Hamori (2014) study is seen in the level of variations and adjustment, and also in the dependence structure over time. Putting more attention on the stress period, we find a negative level of variations or negative adjustment parameters in all periods of lower regime, and in the UK-EU pair of higher regimes. This result shows that smaller mean-difference guides to a rising in tail dependence and greater the coefficient of mean-difference leads to a diminution in tail dependence. Therefore, a positive level of persistence is being seen during crisis and debt-crisis in all pairs of markets of lower regime and in UK -EU of higher regime.

The evidence of asymmetric tail dependence structure demonstrates the transmission of risks between the US, UK and EU in the insurance credit default swaps indices during crisis period.
The conditional tail dependence is very important to examine the extreme events. The higher volatility in the conditional correlation relates first to the lead up to the announcement of bankruptcy in the United States, whereas the second corresponds to the European debt-crisis.

The graph in all panels explains the fluctuations of markets and the level of dependence over time. We noticed the over estimation and the under estimation of dependence during the study period comparing to the finding of Tamakoshia & Hamori (2014). This finding is robust when looking for the evolution of the dependence structure over time, and brings strategies to investors in their project when the distress period happens.

The tails dependencies tau are positive for both regimes showing the chance of the countries of interest to move together in their business. The higher tail dependence has been seen in crisis and post-crisis. The pair of market UK-EU shows higher tau in both regimes, sometimes is due to the distance separating the countries and the economic link between the United Kingdom and the Eurozone. This explains easily that the link between the markets of UK-EU is more correlated than that of the US and EU and so far, than that of the UK and US.

5.2 Implication and recommendation

The implication of our results is crucial to investors and risk managers on the strategies of their business interest and understanding of the behaviour of insurance CDS during shock times. The findings show that the insurance CDS indices still need more information about how the risk default will be reduced in the future research. Therefore, we recommend a study in insurance CDS to evaluate the level of risk contagion and causality that has been seen during crisis and debt crisis periods

References

Abid, F. & Naifar, N., 2005. The impact of stock returns volatility on credit default swap rates: A copula study. *Internatioanl Journal of Theoretical and Applied Finance,* 8(8), pp. 1135-1155.

Arouri, M., Hammoudeh, S., Jawadi, F. & Nguyen, D. K., 2014. Financial linkages between US sector credit default swaps markets. *International Financial Markets,Institutions & Money,* Volume 33, pp. 223-243.

Brechmann, E. C., Hendrich, K. & Czado, C., 2013. Conditional copula simulation for systemic risk stress testing. *Insurance: Mathematics and Economics,* Volume 53, pp. 722-732.

Chen, Y.-H., Wang, K. & Tu, A. H., 2008. Dependence structure between the credit default swap return and the kurtosis of the equity return distribution: Evidence from Japan. *International Financial Markets, Institutions and Money,* Volume 18, p. 259–271.

Creal, D. D. & Tsay, R. S., 2015. High dimensional dynamic stochastic copula models. *Journal of Econometrics,* Volume 189, pp. 335-345.

Da Silva, P. P., Rebelo, P. T. & Afonso, C., 2014. Tail Dependence of Financial Stocks and CDS Markets – Evidence Using Copula Methods and Simulation-Based Inference. *Open-assessment,* Volume 8, pp. 1-27.

Dias, A. & Embrechts, P., 2010. Modeling exchange rate dependence dynamics at different time horizons. *Journal of International Money and Finance,* Volume 29, pp. 1687-1705.

Embrechts, P. & Hofert, M., 2013. A note on generalized inverses. *Mathematical meth. operation research,* Volume 77, pp. 423-432.

Embrechts, P., Neslehova, J. & Wuthrich, M. V., 2009. Additivity properties for Value-at-Risk under Archimedean dependence and heavy-tailedness. *Insurance: Mathematics and Economics,* Volume 44, p. 164–169.

Engle, R., 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business and Economic Statistics,* 20(3), pp. 339-350.

Fenech, J.-P., Vosgha, H. & Shafik, S., 2014. Modelling the dependence structures of Australian iTraxx CDS index. *Applied Economics,* 46(4), pp. 420-431.

Fermanian, J.-D. & Wegkamp, M. H., 2012. The time dependent copulas. *Journal of Multivariate Analysis,* Volume 110, pp. 19-29.

Forte, S. & Lovreta, L., 2015. Time varying credit risk discovery in the stock and and CDS markets: Evidence from quiet and crisis times. *European Financial management,* 21(3), pp. 430-461.

Fung, H.-G., Wen, M.-M. & Zhang, G., 2012. How does the use of credit default swaps affect firm risk and value? Evidence from US life and property/casualty insurance companies. *Financial Management,* pp. 979-1007.

Gatfaoui, H., 2010. Investigating the dependence structure between credit default swap spreads and the U.S. financial market. *Annual Finance,* Volume 511-535, p. 6.

Giovanni , . C. & Christos , I., 2012. An empirical analysis of the impact of the credit default swap index market on large complex financial institutions. *International Review of Financial Analysis,* Volume 25, pp. 117-130.

James , D. H., 1994. *Time Series Analysis.* One of Princeton University Press's Notable Centenary Titles ed. s.l.:s.n.

Joe, H., 1997. *Multivariate Models and Dependence Concepts.* S.I ed. s.l.:Chapman & Hall.

Jondeau, E. & Rockinger, M., 2006. The copula-Garch model of conditional dependences: An international stock market application. *Journal International Money Finance,* 25(5), pp. 827-853.

Kim, K. & Jung, S. S., 2014. Empirical Analysis of Structural Change in Credit Default Swap Volatility. *chaos solitons & Fractals,* Volume 60, pp. 56-67.

Naifar, N., 2011. Modelling dependence structure with Archimedean copulas and applications to the iTraxx CDS index. *Journal of Computational and Applied Mathematics,* Volume 235, p. 2459–2466.

Patton, A., 2006a. Estimation of multivariate models for time series of possibly different lengths. *Journal Applied Economics,* 21(2), pp. 147-173.

Patton, A., 2006b. Modelling Asymmetric Exchange rate dependence. *International Economic review,* 47(2), pp. 527-556.

Patton, A., 2006. Modelling asymmetric exchange rate dependence. *International Economic Review,* 47(2), pp. 527-556.

Poon, S.-H., Rockinger, M. & Tawn, J., 2004. Extreme value dependence in financial markets: Diagnostics, models, and financial implications. *Review Financial Study,* 17(2), pp. 581-610.

Reboredo, J. C. & Ugolini, A., 2015. A vine-copula conditional value-at-risk approach to systemic sovereign debt risk for the financial sector. *North American Journal of Economics and Finance,* Volume 32, pp. 98-123.

Sklar, A., 1959. Fonctions de répartitions à n dimensions et leur marges. *Journal of statistics,* Volume 8, pp. 229-231.

Tamakoshia, G. & Hamori, S., 2014. The conditional dependence structure of insurance sector credit default swap indices. *North American Journal of Economics and Finance,* Volume 30, pp. 122-132.

Wang, K., Chen, Y.-H. & Huang, S.-W., 2011. The dynamic dependence between the Chinese market and other international stock markets: A time-varying copula approach. *International Review of Economics and Finance,* Volume 20, pp. 654-664.

Wang, P. & Moore, T., 2012. Integration of credit default swap markets during the US subprime crisis: Dynamic Correlation Analysis. *International financial institutions and money,* 22(1), pp. 1-15.

Wu, W. & Mc Millan, D. G., 2014. The dependence structure in credit risk between money and derivatives markets. *Managerial Finance,* 40(8), pp. 758 - 769.

Appendix A

Table 2: Estimates parameters of Markov Switching model in lower regime

Country	param	Pre-crisis 01/01/2004 08/08/2007	Crisis 09/08/2007 04/11/2009	Debt crisis 05/11/2009 24/10/2018	Entire sample 01/01/2004 24/10/2018
US	θ_0	0.0061(0.0033)	0.0621(0.0203)	0.0722(0.0230)	0.0030 (0.0025)
	δ	0.2283(0.0718)	0.1661(0.0661)	0.1965(0.0000)	0.1806 (0.0341)
UK	θ_0	-0.002(0.0008)	-0.0025(0.0014)	-0.0116(0.0022)	0.0007(0.0024)
	δ	-0.2220(0.0454)	0.2595(0.0494)	-0.2253(0.0435)	-0.0133(0.0386)
EU	θ_0	0.0019(0.0007)	0.0030(0.0012)	0.0043(0.0006)	0.0014(0.0022)
	δ	-0.0642(0.0385)	0.1846(0.0742)	0.1688(0.0239)	0.1270(0.0367)

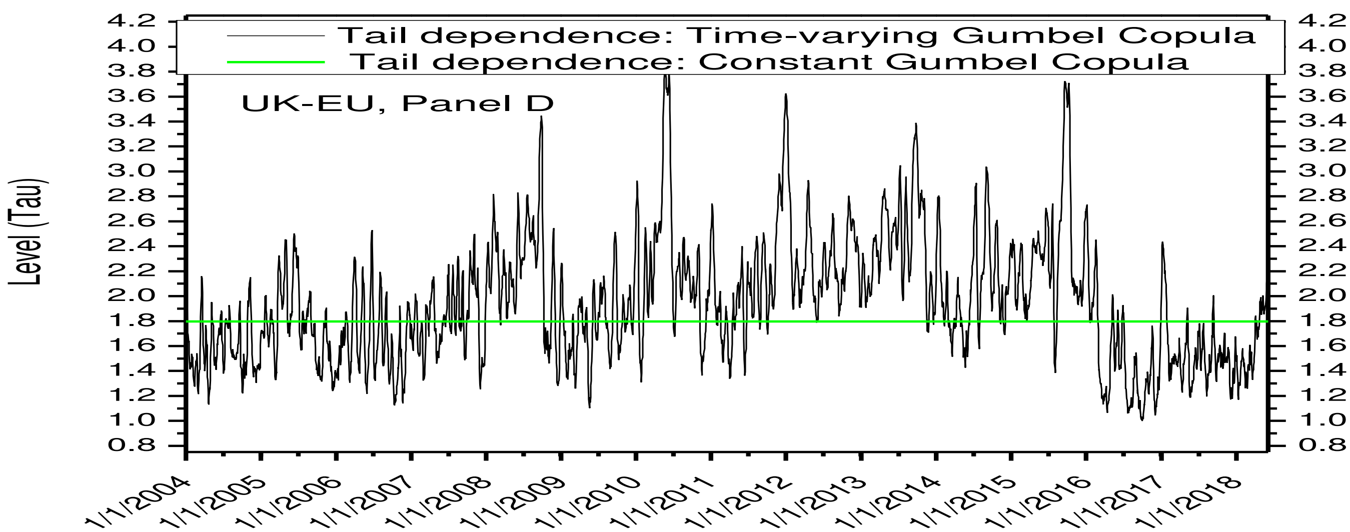
Notes: this table estimated the parameters of Markov switching approach in regime one (lower regime), with θ_0 the intercept and θ_1 the coefficient of lag1.

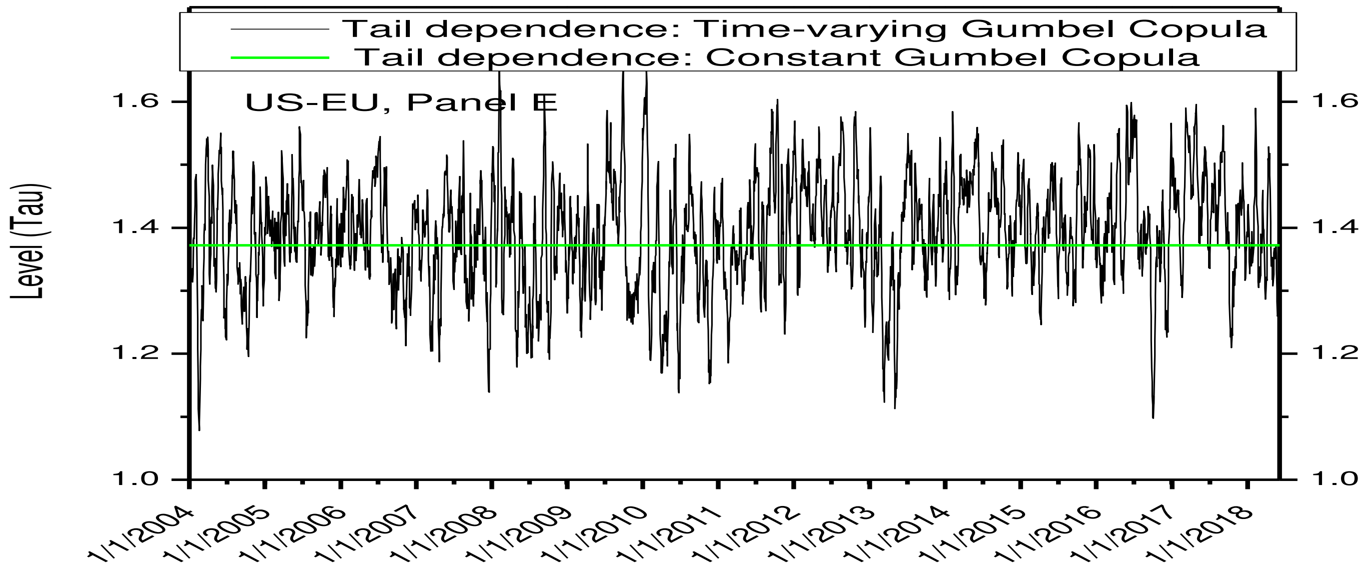
Table 3: Estimates parameters of Markov Switching model in higher regime

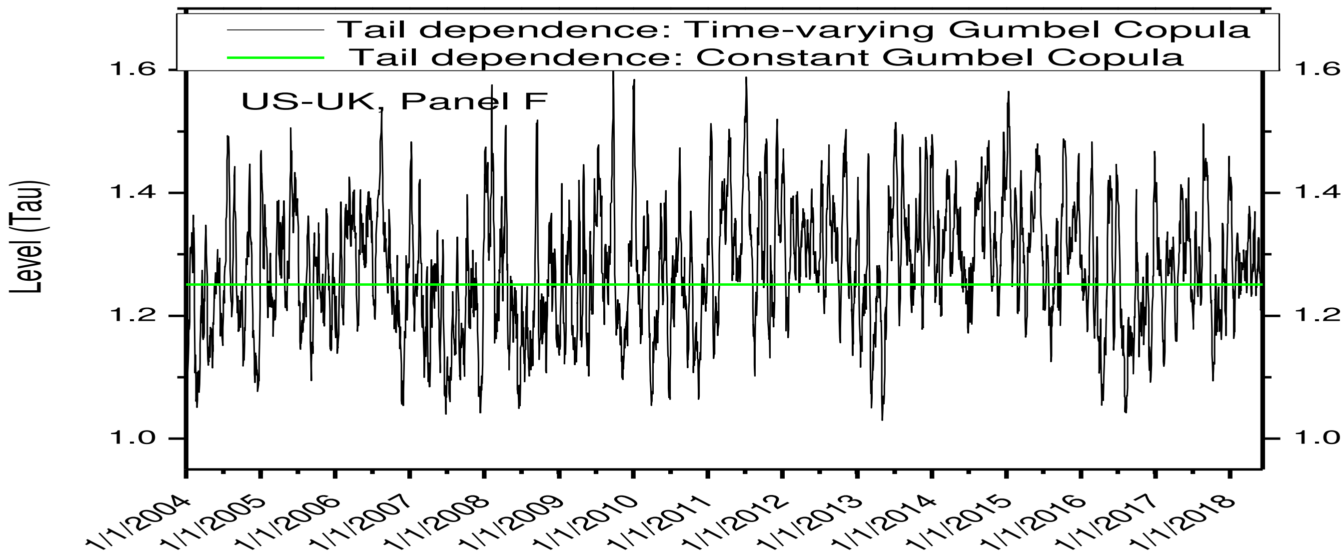
Country	param	Pre-crisis 01/01/2004 08/08/2007	Crisis 09/08/2007 04/11/2009	Debt crisis 05/11/2009 24/10/2018	Entire sample 01/01/2004 24/10/2018
US	θ_0	0.0019(0.0005)	0.0039(0.0009)	0.0014(0.0004)	0.0016 (0.0003)
	δ	0.0856(0.0381)	0.3350(0.593)	0.1139(0.0185)	0.1667(0.0195)
UK	θ_0	0.0004(0.0037)	-0.0026(0.0003)	-0.0017(0.0005)	-0.0011(0.0004)
	δ	0.0122(0.0754)	0.2547(0.0513)	0.0963(0.0286)	0.0275(0.0241)
EU	θ_0	0.0025(0.0054)	0.0096(0.0016)	0.0008(0.0002)	0.0009 (0.0005)
	δ	0.0811(0.0816)	0.2842(0.0014)	0.0701(0.0146)	0.1362(0.0199)

Notes: this table presented the estimates parameters of Markov switching approach in regime two (higher regime), with θ_0 the intercept and θ_1 the coefficient of lag1.

The figure 2 represents conditional upper tail dependence of the time varying Gumbel copula in the higher regime of volatility for the entire sample.




Tail dependence: Time-varying Gumbel Copula
Tail dependence: Constant Gumbel Copula
US-EU, Panel E
Level (Tau)
1.6
1.4
1.2
1.0
1/1/2004
1/1/2005
1/1/2006
1/1/2007
1/1/2008
1/1/2009
1/1/2010
1/1/2011
1/1/2012
1/1/2013
1/1/2014
1/1/2015
1/1/2016
1/1/2017
1/1/2018


Tail dependence: Time-varying Gumbel Copula
Tail dependence: Constant Gumbel Copula
US-UK, Panel F
Level (Tau)
1.6
1.4
1.2
1.0
1/1/2004
1/1/2005
1/1/2006
1/1/2007
1/1/2008
1/1/2009
1/1/2010
1/1/2011
1/1/2012
1/1/2013
1/1/2014
1/1/2015
1/1/2016
1/1/2017
1/1/2018