The Dependence Structure in Credit Risk between Money and Derivatives Markets: A Time-Varying Conditional Copula Approach

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Abstract

This paper examines the dynamic dependence structure in credit risk between the money market and the derivatives market during 2004 to 2009. We use the TED spread to measure credit risk in the money market and the CDS index spread for the derivatives market. The dependence structure is measured by a time-varying student's *t* copula. The results show that the correlation between these two markets while fluctuating with a general upward trend prior to 2007 exhibited a noticeably higher correlation after 2007. This points towards evidence of credit contagion during the crisis. Meanwhile, three different phases are identified for the crisis period which sheds some light regarding the nature of the contagion mechanisms in these markets. Finally, the correlation between the two spreads fell in late 2008, although remained higher than the pre-crisis level. This is in part due to policy intervention that lowered the TED spread while the CDS spread remained higher, possibly due to the Eurozone sovereign debt crisis.

Keywords: TED, CDS, Copula, Contagion
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1. Introduction.

The TED spread, which is calculated as the difference between interest rates on three-month US T-bills and three-month Eurodollar Bills as represented by the London Interbank Offered Rate (LIBOR), remained as a forgotten part of the financial landscape until the recent financial crisis, when it started to receive an increased share of attention. That said, research on investigating the TED spread remains rather limited and mostly confined to using the spread as a measure of funding liquidity (see, for example, Lekkos, 2007; Beber et al., 2010; Brennan et al., 2012); while others have used the spread as a proxy for counterparty risk (see, for example, Cardarelli et al., 2011; Ng, 2012; Levich, 2012). Research that focuses on the dynamics of the TED spread is often through investigating the behaviour of Treasury rates and LIBOR rates. Tse and Booth (1996) employed the GARCH model to analyse volatility spillover between US Treasury and Eurodollar interest rates. Hammoudeh et al. (2011) examined possible asymmetric adjustment to the long-run equilibrium of the TED spread by investigating the co-movement of LIBOR and Treasury rates for three maturities.

In contrast, this paper investigates the nature of the TED spread as a measure of credit risk for the general economy. This is because the Treasury bill is the interest rate offered by the US government and is considered as risk free, while the LIBOR is the rate at which banks lend to each other. Thus, the spread of the two interest rates represents the risk of lending to commercial banks instead of lending to the government. In particular, we are interested in exploring the time-varying dependence structure between the TED spread and another widely used credit risk measure, the CDS spread, before and during the crisis period of 2007-2009. More specifically, we aim to investigate how credit risk from the money and derivatives markets, as measured by the above two spreads, is related and whether the subprime crisis resulted in increased cross-market linkages. Therefore, the purpose of this paper is to contribute to the literature on the dynamic co-movement between risk measures in the money market and derivatives market. This is achieved by applying the recently developed time-varying copula-GARCH model, where the marginal distributions are estimated by a univariate GJR-GARCH model and the joint distribution is captured by a time-varying student's *t* copula.

A copula is a function that joins one-dimensional distribution functions together to form multivariate distribution functions (Sklar, 1959). In other words, the joint distribution function can be written in terms of a copula and the marginal distribution functions. Thus, the copula contains all the information on the dependence structure of the random variables while the marginal distribution function contains all information of the margins. The use of a copula function removes the linear correlation restriction, that the joint distribution must be an elliptical distribution. Therefore, the copula provides a relatively straightforward way of modelling non-linear and non-normal joint distributions that might otherwise only be examined through simulation approaches.

The results of this paper can be summarised as follows: prior to the subprime crisis of 2007, the correlation structure between the money market and the derivatives market varies between positive and negative values indicating an uncertain co-movement relationship between these two markets. However, the correlation increased considerably and became more pronounced following the start of the financial crisis. The stronger and statistically significant increase in the conditional correlation coefficient between the money and derivatives markets, which reached a peak in 2008 during the crisis, points to evidence of credit contagion. This is consistent with the standard definition of financial contagion and provides strong support to the argument of Forbes and Rigobon (2002) that contagion exists if cross-market co-movement increases significantly after a shock.

Furthermore, three different phases are identified for the dependence structure during the crisis. The first phase shows a dramatic increase in cross-market correlation due to the spread of credit deterioration soon after the start of the financial crisis. The second phase shows a continued high correlation. This period starts from the end of 2007 to late 2008. The last phase shows a decrease in cross-market correlation between the money market and the derivatives market, although it remains higher than the pre-crisis period. Notably, while the TED spread falls following government intervention, the CDS spread remain higher, this, we argue, is in part due to the Eurozone debt crisis.

The rest of the paper is organised as follows. Section 2 briefly discusses the copula-GARCH model. Section 3 introduces the data while Section 4 presents the empirical results. The last section summarises and concludes.

2. The Copula-GARCH Model.

We use a two-step method similar to Patton (2006) to estimate the copula parameters. That is, we first estimate the marginal distributions from univariate GJR-GARCH models. Then we estimated the copula parameters through the method of maximum likelihood.

2.1. The Marginal Distributions

Given the potential for asymmetry between positive and negative shocks we consider the GJR-GARCH(1,1) model for the marginal distributions, which can be expressed as:

$$r_t = \mu + \varepsilon_t \text{ and } E(\varepsilon_t^2) = h_t \tag{1}$$

where r_t is the asset return, μ the conditional mean that may include, for example, autoregressive terms and ε_t the random error term. The GJR-GARCH model is then given by:

$$h_t = \alpha_0 + \beta_1 h_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \alpha_1^* \varepsilon_{t-1}^2 I_{t-1}, \tag{2}$$

where $I_{t-1} = \begin{cases} 1 \text{ if } \varepsilon_{t-1} < 0 \\ 0 \text{ if } \varepsilon_{t-1} \geq 0 \end{cases}$. From the above model, we know if $\alpha_1^* \geq 0$, then negative error terms have a larger effect on future volatility.

Furthermore, the Hansen (1994) skewed student's *t* distribution is used as the distribution for the innovations. The skewed *t* distribution is close to a student's *t* distribution. However, it allows the distribution to be asymmetric while maintaining the assumption of a zero mean and unit variance. It is conditional upon historical information provided by the previous values of realisations. The skewed *t* distribution is defined as:

$$d(z|\eta,\lambda)=\begin{cases} bc(1+\frac{1}{\eta-2}(\frac{bz+a}{1-\lambda})^2)^{-\frac{\eta+1}{2}} & if\ z<-a/b \\ bc(1+\frac{1}{\eta-2}(\frac{bz+a}{1+\lambda})^2)^{-\frac{\eta+1}{2}} & if\ z\geq -a/b \end{cases} \tag{3}$$

where $a \equiv 4\lambda c\frac{\eta-2}{\eta-1}$, $b \equiv 1+3\lambda^2-a^2$, $c \equiv \frac{\Gamma(\frac{\eta+1}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}$. η and λ denote the degrees of freedom and the asymmetry parameter and $2<\eta<\infty$ and $-1<\lambda<1$. From the above model, we know that if $\lambda>0$, then the density of the distribution is skewed to the right.

2.2 The Copula Function

The dependence structure between the returns of the TED and CDS spreads is captured by the time-varying student's *t* copula, which allows us to capture the tail dependence between the two returns. The student's *t* copula function can be expressed as

$$C_t^{v,\rho}(x,y)=\int_{-\infty}^{t_v^{-1}(x)}\int_{-\infty}^{t_v^{-1}(y)}\frac{1}{2\pi(1-\rho^2)^{\frac{1}{2}}}\ \{1+\frac{(s^2-2\rho st+t^2)}{v(1-\rho^2)}\}^{-(v+2)/2}dsdt \tag{4}$$

where ρ is the correlation coefficient, and $t_v^{-1}(u)$ is the inverse of the standard t distribution with degree of freedom v.

For the student's *t* copula, we specify that the time-varying parameter ρ_t evolves over time as in the Dynamic Conditional Correlation model of Engle (2002):

$$\rho_t = D_t^{-1}R_tD_t^{-1}$$

$$R_t=(1-\theta_1-\theta_2)\Psi+\theta_1\xi_{t-1}\xi_{t-1}^T+\theta_2\mathrm{R}_{t-1} \tag{5}$$

where D_t is a square matrix with zeros as off-diagonal elements and square root of R_t as diagonal elements. θ_1 and θ_2 are non-negative numbers satisfying $\theta_1+\theta_2\leq 1$. R_t is the covariance matrix of the vector of standardised residuals ξ_{t-1} and Ψ is the sample unconditional covariance.

3. Data and Summary Statistics.

Daily data for the TED spread are calculated as the difference between three-month US Treasury Bill and three-month Eurodollar bill as represented by LIBOR, while the CDS data chosen is the DataStream CDS index spread for the UK bank sector to represent the overall condition of banks in the credit derivatives market. The data are obtained from Thomson DataStream for the period 1 January 2004 to 31 December 2009 with summary statistics for the level and first-difference (return) in Table 1.

Since a rise in the correlation between two risky assets is often considered as the key symptom of contagion (De Gregorio and Valdés, 2001; Baig and Goldfajn, 2002), it is necessary to compare the correlation between the two spreads during the various phases of the crisis period. Similar to other studies, such as Dungey (2009) and Celık (2012), we define the period after 17 July 2007 as the crisis period, as this is the announcement day of Bear Stearns hedge funds failure. Figure 1 plots the TED and CDS original and return series for the period 1 January 2004 to 31 December 2009. We can see that both spreads started to increase from mid-2007 onwards, which indicates potential credit contagion arising from the subprime meltdown.

3.1 TED Spreads Dynamics

A review of the dynamics of TED spreads provides anecdotal evidence that the TED spread reflects the health of the general economy. From 2004 to early 2007, the TED spread was as low as 11 basis points. This occurs when banks are considered strong and in good financial health. In such circumstance, banks would have faith in lending to each other and at a higher rate of interest than paid on government bills. In contrast, the TED spread reached 400 basis points in early October 2008 after a series of bank and other financial institution bankruptcies. On 10th October 2008, the TED spread hit a new high of 501 basis points, reflecting the breakdown in the interbank market.

Since LIBOR is a primary benchmark rate that is estimated by large global banks operating in London financial markets for short term interest rates around the world, the TED spread responds closely to financial policy. As the TED spread is an important indicator of the health of financial markets, governments were keen on taking measures to adjust the spread back to its historical level. After the financial crisis began, banks and financial institutions were unwilling to lend money to each other, thus the priority of governments was to restart the interbank market.

As such, a series of government bailouts were implemented to stabilise the financial system. In the US, the government announced the TARP (Troubled Asset Relief Program) on 3 October 2008, followed by the 2008 British bank rescue packages, along with bank rescue packages and government interventions in other Western European countries. An immediate effect of these programmes can be seen as the TED spread dropped from about 400 to 200 in late 2008, and continued to drop below 100 in 2009 due to a less tight funding constraint and much greater confidence between banks' lending to each other.

3.2 CDS Spreads Dynamics

In some contrast, the CDS spread shows a different pattern, although with some general similarities. For example, on 17 September 2008, very shortly after the Lehman failure, the Scottish Banking Group HBOS agreed to an emergency acquisition by Lloyds TSB. As such, the CDS index spread subsided while on the same day the TED spread exceeded 300 bps, breaking the record from the Black Monday crash of 1987, as banks started seeking cash to shore up finances. The CDS spread then continued to drop from early October onward, as a direct result of the GAPS (UK Government Asset Protection Scheme) and other related insurance schemes (e.g., the guarantee scheme for asset backed securities, GSABS). However, the drop is very immediate and short-lived. While the TED spread reach its highest point in 2008, after the failure of Lehman, and started to fall back to the normal level, the CDS spread continuous to fluctuate at a high level, at an average of 150 basis points.

The difference between the market behaviour of the two spreads may arise from government policy undertaken in the period after the financial crisis. The British bank rescue plan differs from the US TARP, in that the UK government aims to purchase shares of banks while TARP aimed at tackling the immediate funding shortfall. As such, the bank rescue package transfers the default risk onto the government's balance sheet. We can see drops in the CDS index spread for a short period due to the fact that the potential default risk has been transferred. However, in the long-run, risk is put back onto banks since many have exposure to European counties that are facing fiscal problems as a result of their bank rescue packages and the substantial increase in sovereign default risk. For example, according to the Wall Street Journal, UK banks have $193 billion of exposure to Ireland. Many international bond mutual funds also have sizeable exposure to sovereign debt of Portugal, Ireland, Greece and Spain. Therefore, investors have to pay more as fears grow over UK banks' exposure to the Eurozone debt crisis. This also serves to illustrate that although governments had introduced asset protection schemes, the market still took the view that risk remained high.

4. Empirical Results

Bae et al. (2003) found that contagion is an event that is characterised by nonlinear changes in market association. However, neither the linear correlation or the more advanced VAR or VECM, or even the recent multivariate GARCH models have considered the nonlinearity of the contagion phenomenon (Wen et al., 2012). Therefore, in this paper, we verify the contagion effect by applying the copula method.

The estimation process for copula parameters is performed in two steps: first, estimation of the conditional marginal distributions is performed through the univariate GARCH model; second, the copula parameters are estimated. To capture asymmetric, fat-tailed and non-normal features observed in the unconditional distribution of the two return series, we consider an ARMA-GJR-GARCH model. This model is justified by first considering a test for the presence of GARCH effects. This is achieved by applying the Breusch-Godfrey test, which is used to examine higher orders of autocorrelation in returns and volatilities. To account for the positive skewness observed for the return series, we consider the skewed *t* distribution for innovation. The choice of skewed *t* distribution is justified by a Kolmogorov-Smirnov (KS) test, which assess the null hypothesis that the errors are from a given distribution. We have considered a range of distributions for innovations, including the normal, student's *t*, skewed student's *t* and Generalised Error Distribution. The KS test suggests the skewed student's *t* has the lowest *p*-value and hence is preferred.[1]

Therefore, the models for the conditional marginal distributions can be written as a ARMA(1,1)-GJR-GARCH(1,1)-ST model, which have the following forms:

$$\mathrm{R}_{\mathrm{i,t}} = \alpha_1 + \varepsilon_{\mathrm{i,t}} + \beta_1 \mathrm{R}_{\mathrm{i,t-1}} + \gamma_1 \varepsilon_{\mathrm{i,t-1}}$$

$$\mathrm{h}_{\mathrm{i,t}} = \mathrm{g}_1 + \mathrm{m}_1 \mathrm{h}_{\mathrm{i,t-1}} + \mathrm{n}_1 \varepsilon^2_{\mathrm{i,t-1}} + \phi_1 \mathrm{S}_{\mathrm{t-1}} \varepsilon^2_{\mathrm{i,t-1}} \tag{6}$$

where *i* indexes the TED and CDS return respectively and where:

$$\mathrm{S}_{\mathrm{t-1}} = \begin{cases} 0 \text{ if } \varepsilon_{\mathrm{t-1}} < 0 \\ 1 \text{ if } \varepsilon_{\mathrm{t-1}} \geq 0 \end{cases}, \ \varepsilon_{\mathrm{TED,t-1}} \sim \mathrm{ST}(\mathrm{z_i} | \eta, \lambda).$$

In this model, all the lags are specified to be one, as Brooks (2002) states that a GARCH model with lag one can sufficiently describe volatility clustering in asset returns. The estimation results are presented in Table 2. We find that both TED returns and CDS returns

[1] Results available upon request.

exhibit a similar pattern. Both have a positive autocorrelation parameter and a negative moving average parameter. Both have similar ARCH and GARCH parameters, although the asymmetric variance parameter is only significant for the TED return series. With respect to the distribution, the skewness parameter is insignificant for both series with -0.038 for TED and 0.041 for CDS, while the tail parameter, which represents the degrees of freedom, is significant for both series.

The conditional marginal densities generated by the above GARCH models are then used to estimate the copula function. A goodness-of-fit test is implemented on ten copulas to determine the best fitting copula for the dependence structure. Table 3 presents the results for the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). As can be seen, the time-varying student's *t* copula has the lowest AIC and BIC value and is clearly superior to other copulas in describing the dynamic dependence structure between CDS returns and TED returns.[2]

Figure 2 shows the conditional correlation estimated by the time-varying student's *t* copula for the period 1 Jan 2004 to 31 Dec 2009. From 2004 to 2007, the correlations between the two markets are very weak and oscillated around zero. Although there appears to be a general upward trend, the correlations vary between positive and negative values, which suggest an uncertain co-movement relationship between the two indices. That is, there is a possible gentle upward trend but in the interval of [-0.1 0.1]. However, it is apparent that correlations between the returns increase considerably and are more pronounced following the start of the financial crisis in 2007. The conditional correlation coefficients show substantial time-variation and reach a peak in 2008, supporting the argument of Forbes and Rigobon (2002) that contagion may exist if cross-market co-movement increases significantly after a shock. To more formally identify a change in the conditional correlation coefficient

[2] The use of these criteria as appropriate goodness-of-fit tests is motivated by the work of Patton (2004), Chan et al. (2008), Zhang et al (2009) and Nafiar (2012).

and hence the contagion effect, a simple t-statistic test is carried out. Here, we test whether the mean of the conditional correlation coefficient statistically differs between the crisis and pre-crisis periods. The null of the t-statistic is $H_0: \rho^{pre-crisis} = \rho^{crisis}$, where ρ^{crisis} is the average of the conditional correlation coefficients in the crisis period and $\rho^{pre-crisis}$ is the value for the pre-crisis period. The value of the t-statistic is -30.4. This result, therefore, supports the view that we can reject the null hypothesis that the two correlations have the same mean value and indeed the negative value indicates a higher correlation in the crisis period. Hence, this provides evidence in support of the contagion effect. Furthermore, while the correlation narrowed in early 2009, it nonetheless persisted at the level between 0.05 and 0.1 and above the pre-crisis level.

4.1. Discussion of Results

As suggested by the empirical results, three different phases can be identified for the dependence structure during the crisis period of 2007 - 2009. The first phase shows a dramatic increase in cross-market correlation due to the spread of credit deterioration after the start of the financial crisis. Assuming that investors hold positions from both the TED and CDS spreads, credit contagion happens when default risk is significantly raised in one market, where investors suffer heavy losses, and this affects the second market. For example, the huge increase in default risk in the CDS market increased the cost of insuring against default. Hence, investors that suffer losses end up selling their positions in other markets. In an illiquid market such as the LIBOR market, this affects other investors who hold similar positions and are therefore forced to sell their positions. This then drives up the TED spread due to the reduced cash-flow in the LIBOR market.

As can be seen, credit concern is a major part of the story. Typically, the TED spread is used to capture counterparty risk in the overall banking sector. However, as the US

Treasury bill is considered to be risk free, the TED spread may also reflect liquidity or flight-to-quality risk. Investors who lose confident in the banking system will choose other safer investments, such as Treasury bills. This drives the Eurodollar rate up and the T-bill rate down. Where the majority of investors act simultaneously this results in an increase in the CDS and TED spread at the same time.

The second phase shows a continued high correlation. This period begins from the end of 2007 and ends in late 2008. The continued high correlation can be explained by herding behaviour as the crisis grew. That is, given the increased uncertainty about the fundamental value of financial assets during the financial crisis, investors are likely to follow investment choices made by others. Any public news about one market may be interpreted as information regarding the entire economy. Therefore, high correlations persist in this phase.

The last phase shows a decrease in cross-market correlation between the money and derivatives market. During this period, banks remained hesitant in lending to each other without knowing each other's balance sheet given the large number of bad assets hiding in banks' balance sheets which could trigger another default. This period starts from late 2008, when a series of monetary policy actions were announced, such as the TARP by the U.S. government in October 2008 or the 2008 UK bank rescue package and bank rescue packages initialised by several other Western European countries, such as Belgium, France, Germany, Ireland, Luxembourg and the Netherlands, which aimed to restore market confidence by providing a range of loans and interbank lending. Since these packages injected funds into banks' balance sheets, it relieved the funding constraints between banks and brought the TED spread down. Indeed, as direct result the TED spread starts to drop from its highest level in October 2008.

On the other hand, the bank rescue plans did not bring the CDS index spread back to normal levels. The CDS spread continued to fluctuate at a high level, at an average of 150 basis points. This may because that the British bank rescue plan differs from the TARP, in that the UK government aimed to purchase shares in the banks while the American programme was aimed at tackling the immediate funding shortfall. Therefore, the bank rescue package actually transfers the default risk onto government balance sheets. Nonetheless, we can see a drop in the CDS index spread given the fact that the potential default risk has been transferred. In the long-run, however, the risk is put back onto the banks since many have exposure to those European counties that are facing fiscal problems as a result of the bank rescue packages and the substantial increased sovereign default risk. That is, the contagion risk is back. Investors have to pay more as fears grow over UK banks' exposure to the Eurozone debt crisis. The correlation therefore fell as government intervention led to a decrease in the TED spread such that the funding constraint became less tight, while the CDS spread remained relatively high as default risk remained. This finding is especially important for policy makers due to the instability of financial contagion. For the UK CDS market, the contagion risk remains through the increase in Eurozone sovereign default risk. Therefore, policy makers should seek ways to close contagion channels and decrease potential instability in the financial system.

5. Conclusion.

This paper has examined the dynamic dependence structure between the TED spread and the CDS spread by applying a time-varying student's *t* copula. The results from this model suggest that the correlation between these two markets while fluctuating with a general upward trend prior to 2007, exhibited a noticeably higher correlation after 2007, which points to the evidence of credit contagion during the subprime crisis. Meanwhile, three different phases are identified for the crisis period which shed some light on the nature of contagion mechanisms in financial markets. After early 2008, the correlation fell but persisted at a level of around 0.05, higher than the pre-crisis period. In particular, while the TED spread fell following government intervention, the CDS remains higher, in part due to the onset of the Eurozone sovereign debt crisis. Hence, it would appear that the credit contagion may be back.

The key contribution and implication of the results presented here demonstrate the nature of the time-varying correlation and contagion between the TED and CDS spreads and thus the nature of economic risk as measured by the money and derivatives market. In particular, the results support the contagion view of Forbes and Rigobon (2002), with an increase in correlation following a negative shock. Furthermore, in the specific case here, the results show that although government intervention has reduced the TED spread and initially reduced the CDS spread, while interest rates remained lower, market risk remained and so the CDS spread rose again. This led to a lower correlation but still historically high.

References

Bae, K., Karolyi, G. and Stulz, R. (2003) 'A New Approach to Measuring Financial Contagion', *Review of Financial Studies,* 16(3), 717-763.

Baig, T. and Goldfajn, I. (2002) 'Monetary Policy in the Aftermath of Currency Crises: The Case of Asia', *Review of International Economics,* 10(1), 92-112.

Beber, A., Breedon, F. and Buraschi, A. (2010) 'Differences in Beliefs and Currency Risk Premiums', *Journal of Financial Economics,* 98(3), 415-438.

Brennan, M., Chordia, T., Subrahmanyam, A. and Tong, Q. (2012) 'Sell-Order Liquidity and the Cross-Section of Expected Stock Returns', *Journal of Financial Economics,* 105(3), 523-541.

Brooks, C. (2008) *Introductory Econometrics for Finance* (2nd Edition), Cambridge University Press, Cambridge.

Cardarelli, R., Elekdag, S. and Lall, S. (2011) 'Financial Stress and Economic Contractions', *Journal of Financial Stability,* 7(2), 78-97.

Celık, S. (2012) 'The More Contagion Effect on Emerging Markets: The Evidence of DCC-GARCH Model', *Economic Modelling,* 29(5), 1946-1959.

Chen, Y., Tu, A. and Wang, K. (2008) 'Dependence Structure between the Credit Default Swap Return and the Kurtosis of the Equity Return Distribution: Evidence from Japan', *Journal of International Financial Markets, Institutions & Money,* 18(3), 259-271.

De Gregorio, J. and Valdés, R. (2001) 'Crisis Transmission: Evidence from the Debt, Tequila, and Asian Flu Crises', *The World Bank Economic Review,* 15(2), 289-314.

Dungey, M. (2009) 'The Tsunami : Measures of Contagion in the 2007-2008 Credit Crunch', *CESifo Forum,* 9(4), 33-43.

Engle, R. (2002) 'Dynamic Conditional Correlation', *Journal of Business and Economic Statistics,* 20(3), 339-350.

Forbes, K. and Rigobon, R. (2002) 'No Contagion, Only Interdependence: Measuring Stock Market Comovements', *The Journal of Finance,* 57(5), 2223-2261.

Hammoudeh, S., Chen, L. and Yuan, Y. (2011) 'Asymmetric Convergence and Risk Shift in the TED Spreads', *The North American Journal of Economics and Finance,* 22(3), 277-297.

Hansen, B. (1994) 'Autoregressive Conditional Density Estimation', *International Economic Review,* 35(3), 705-730.

Lekkos, I. (2007) 'Modelling Multiple Term Structures of Defaultable Bonds with Common and Idiosyncratic State Variables', *Journal of Empirical Finance,* 14(5), 783-817.

Levich, R. (2012) 'FX Counterparty Risk and Trading Activity in Currency Forward and Futures Markets', *Review of Financial Economics,* 21(3), 102-110.

Naifar, N. (2012) 'Modeling the Dependence Structure between Default Risk Premium, Equity Return Volatility and the Jump Risk: Evidence from a Financial Crisis', *Economic Modelling,* 29(2), 119-131.

Ng, E. (2012) 'Forecasting US Recessions with Various Risk Factors and Dynamic Probit Models', *Journal of Macroeconomics,* 34(1), 112-125.

Patton, A. (2004) 'On the Out-of-Sample Importance of Skewness and Asymmetric Dependence for Asset Allocation', *Journal of Financial Econometrics,* 2(1), 130-168.

Patton, A. (2006) 'Estimation of Multivariate Models for Time Series of Possibly Different Lengths', *Journal of Applied Econometrics,* 21(2), 147-173.

Sklar, A. (1959) 'Fonctions de Répartition à n Dimensions et Leurs Marges', *Publications de l'Institut de Statistique de I'Université de Paris,* 8(1), 229-231.

Tse, Y. and Booth, G. (1996) 'Common Volatility and Volatility Spillovers between U.S. and Eurodollar Interest Rates: Evidence from the Futures Market', *Journal of Economics and Business,* 48(3), 299-312.

Wen, X., Wei, Y. and Huang, D. (2012) 'Measuring Contagion between Energy Market and Stock Market during Financial Crisis: A Copula Approach', *Energy Economics,* 34(5), 1435-1446.

Zhang, S., Paya, I. and Peel, D. (2009) 'Linkages between Shanghai and Hong Kong Stock Indices', *Applied Financial Economics,* 19(23), 1847-1857.

Table 1 Summary Statistics

	Mean	Max	Min	S. Dev.	Skewness	Kurtosis	J.B.
TED	70.5	501	10.94	66.67	2.64	12.51	7722.09
CDS	57.64	235.21	4.63	64.62	0.89	2.3	236.81
R.TED	0.95	143.48	-66.18	14.07	2.11	20.9	22051.4
R.CDS	0.24	71.58	-47.61	5.56	1.39	31.12	52077.7

Note: The table shows summary statistics of TED spread and CDS index and their returns. The sample period covers 1 Jan 2004 to 31 Dec 2009 and has 1565 daily observations.

Table 2 Result of the Univariate Conditional Marginal Model

	TED		CDS	
	Coefficient	Std.Error	Coefficient	Std.Error
CST-M(α)	0.1172	0.1659	-0.0418	0.0844
AR(β)	0.3061**	0.0516	0.3461**	0.1446
MA(γ)	-0.4582**	0.0446	-0.2464*	0.1365
CST-V(g)	3.1122**	1.5113	0.5098*	0.2265
ARCH(m)	0.1641**	0.0528	0.2341**	0.0703
GARCH(n)	0.8138**	0.0458	0.8259**	0.0475
GJR(ϕ)	0.1249**	0.0620	-0.0087	0.0537
Asymmetry(η)	-0.0384	0.0308	0.0405	0.0288
Tail(λ)	3.4620**	0.3247	2.8620**	0.2468
	statistics	*p*-value	statistics	*p*-value
LM (1)	0.0224	0.88	2.27e-06	0.99
LM (2)	0.2319	0.89	0.0046	0.99
Box Pierce Q^2(5)	3.7510	0.29	1.1766	0.76
Box Pierce Q^2(10)	6.9476	0.54	4.6216	0.80
Log likelihood	-5759.5		-4200.81	

*Note: **indicates significant at 5% level, *indicates significant at 10% level. LM(.) refers to a test for series correlation in the errors, with the lag length in parentheses.*

Table 3 Log-likelihood of Copula Estimation

Whole Sample	Negative LL	AIC	BIC
Time-varying			
Time-varying Student's *t* copula	-4.8040	-9.6067	-9.6033
Time-varying Gaussian copula	-2.4267	-4.8495	-4.8392
Time-varying Clayton copula	-1.81	-3.6187	-3.6153
Static			
Student's t copula	-2.2420	-4.4814	-4.4746
Normal copula	-2.0533	-4.1052	-4.1018
Plackett copula	-2.0030	-4.0048	-4.0013
Frank copula	-1.9691	-3.9370	-3.9336
Clayton's copula	-0.5360	-1.0708	-1.0673
Gumbel copula	5.5211	11.0435	11.0469
Rotated Gumbel copula	10.6669	21.3351	21.3385

Figure 1 TED Spread and CDS Spread Daily Index and Their Returns from 1 Jan 2004 to 31 Dec 2009

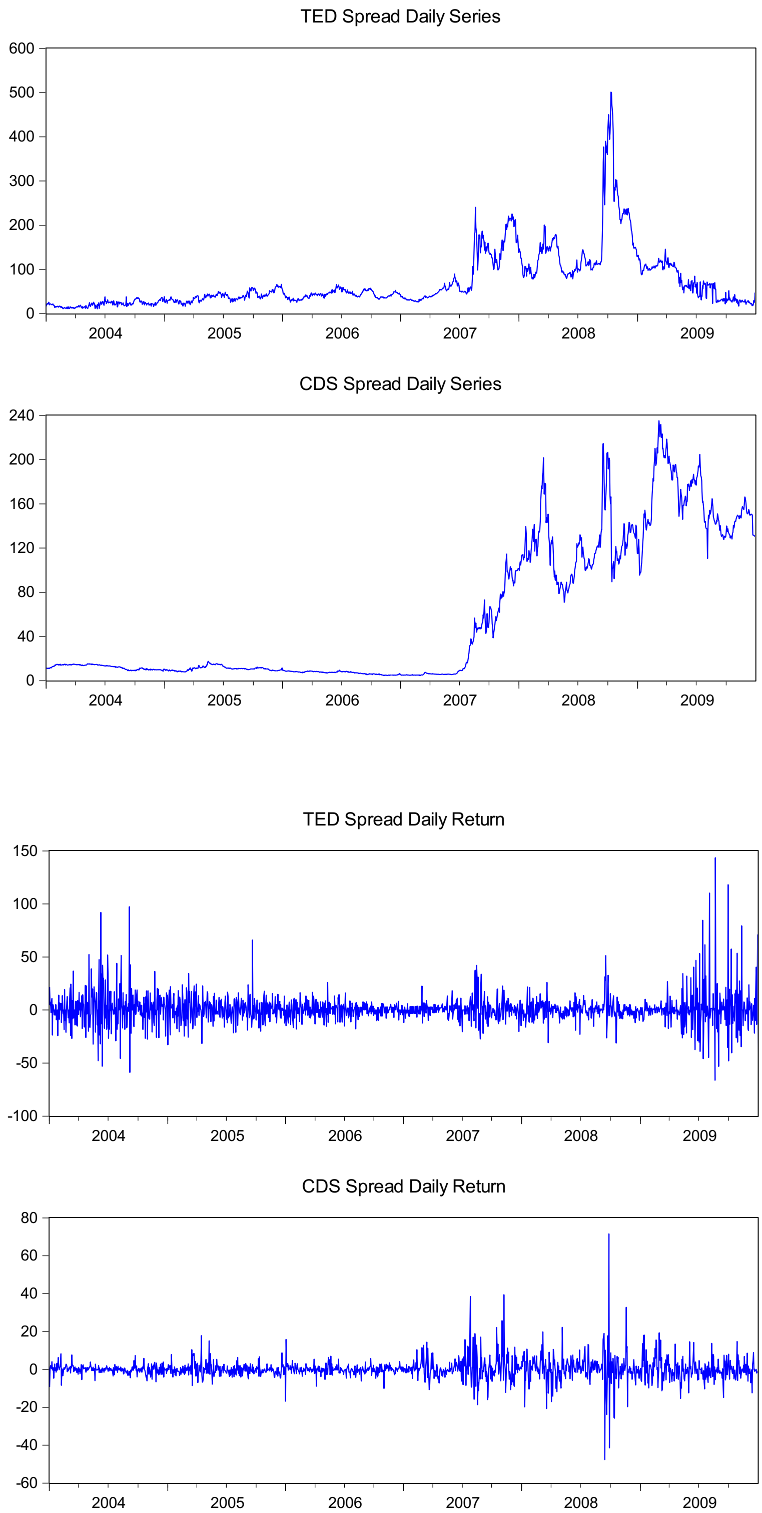

Figure 2. Conditional Correlation Estimation for Time-varying Student's *t* Copula - 2004 to 2009