Dynamic Linkages in Credit Risk: Modelling the Time-Varying Correlation between the Money and Derivatives Markets over the Crisis Period

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Abstract

This paper examines the dynamic linkages 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 CDS index spread for the derivatives market. The linkages are measured by a DCC-GJR-GARCH model. The results show that the correlation between the TED spread and the CDS index spread fluctuated around zero prior to the crisis. While the correlation increased before the crisis, it moved notably higher during the crisis. Finally, the correlation fell in early 2009 but persisted at a level between 0.05 and 0.1, higher than the pre-crisis period.

Keywords: Credit Risk, CDS, TED Spread

JEL: G12, C22

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This paper examines the dynamic linkages 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 CDS index spread for the derivatives market. The linkages are measured by a DCC-GJR-GARCH model. The results show that the correlation between the TED spread and the CDS index spread fluctuated around zero prior to the crisis. While the correlation increased before the crisis, it moved notably higher during the crisis. Finally, the correlation fell in early 2009 but persisted at a level between 0.05 and 0.1, higher than the pre-crisis period.

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1. Introduction.

The TED spread is the difference between interest rates on Treasury Bills and Eurodollar Bills. In simple terms, the TED spread 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). In the general economy, the TED spread can be used as an indicator of credit risk. 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. An increase in the TED spread suggests that lenders believe the default risk in interbank loans has increased and thus prefer to invest in safer T-bills, which offer better credit quality. When such possible default risk is higher, banks also tighten the constraints on lending money to other counterparties by demanding a higher return on their money. Similarly, a decrease in TED spread indicates the risk of default is considered to be decreasing and equally of loosened constraints in inter-bank lending.

The CDS (credit default swap) has been used as a tool against default risk and has become an increasingly popular tool in the derivatives market. Generally speaking, a credit default swap is a financial instrument that provides its buyer a secure recovery payment when default happens, while the buyer has to offer a regular payment to the seller in exchange for the protection from default. By doing this, the buyer transfers the default risk to the seller. The CDS spread is the premium paid by the protection buyer and can be used as a direct proxy for credit risk as it indicates how much the buyer is willing to pay for the credit protection against a default.

This study examines the dynamic relationship between these two measures that represent credit risk in the money market and the derivatives market respectively. In particular, we are interested in the time-varying nature of these credit risk measurements prior to and during the crisis period of 2007-2009. Thus, the purpose of this paper is to contribute to the literature on the dynamic co-movement between risk measurements in the money market and derivatives market. This is done by applying the recently developed dynamic conditional correlation generalised autoregressive heteroscedasticity (DCC-GARCH) model.

Our results suggest that the correlation coefficient between the two spreads varies between positive and negative values prior to 2007 indicating an uncertain pattern for the linkage. The financial crisis that started in 2007 however tightened the two markets with a significant increase in dependence. As the CDS spread can be used as a proxy for the credit constraint,[1] while the TED spread is often recognised as the funding constraint, the result shows that before the financial crisis, the credit and funding constraints weakened the relationship between TED spread and CDS index. However, the financial crisis enhanced such a relationship, as the credit constraint limited banks ability to lend funds. This is also consistent with the financial contagion effect and provides support to Forbes and Rigobon's (2002) argument that contagion exists if cross-market comovement increases significantly after a shock.[2]

The rest of the paper is organised as follows. Section 2 briefly discusses the dynamic conditional correlation model, while Section 3 introduces the data and presents the empirical results. Section 4 summarises and concludes.

2. The Dynamic Conditional Correlation (DCC) Model.

[1] For a discussion regarding the role of CDS's with regard to credit constraints, see, for example, Ashcraft and Santos (2009) and Jarrow (2010). In general, the CDS spread proxies for credit risk, but an increase in the spread could reduce a firm's ability to issue new debt and hence, in that sense, constrained.

[2] In a related but distinct paper, Anderson (2011) reports increased correlations in industry-level CDS correlations due to contagion effects primarily arising from liquidity and default risk.

In estimating the DCC model, we first estimate univariate GARCH models for both series. The standardised residuals from this first step are then used in the estimate of the covariance matrix. Given the potential for asymmetry between positive and negative shocks we consider the GJR-GARCH (1,1) model, which can be expressed as:

$$E(\varepsilon_t^2) = h_t$$

$$h_t = \alpha_0 + \beta_1 h_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \alpha_1^* \varepsilon_{t-1}^2 I_{t-1} \quad (1)$$

where $I_{t-1} = \begin{cases} 1 \; if \; \varepsilon_{t-1} < 0 \\ 0 \; if \; \varepsilon_{t-1} \geq 0 \end{cases}$ and the residuals ε_t are obtained from a conditional mean model. From the above model, we know if $\alpha_1^* \geq 0$, then the negative error terms have stronger effect on the future value of volatility.

In order to model the time-varying correlation between the two-series we consider dynamic conditional correlation (DCC) model of Tse and Tsui (2002), we also consider the similar model of Engle (2002), which produces qualitatively near identical results. Tse and Tsui (2002) proposed a dynamic conditional correlation model which adopts past conditional correlation and residuals to provide a description of future correlations. In this model, the covariance matrix is defined as:

$$H_t = D_t R_t D_t \quad (2)$$

where $D_t = diag\left(h_{11t}^{\frac{1}{2}}, \ldots, h_{NNt}^{\frac{1}{2}}\right) = \begin{bmatrix} 1 & \cdots & \rho_{1N} \\ \vdots & \ddots & \vdots \\ \rho_{N1} & \cdots & 1 \end{bmatrix}$ and the conditional correlation R_t is defined as:

$$R_t = (1 - \theta_1 - \theta_2)R + \theta_1 \Psi_{t-1} + \theta_2 \mathrm{R}_{\mathrm{t-1}} \quad (3)$$

where θ_1 and θ_2 are non-negative numbers satisfying $\theta_1 + \theta_2 < 1$ and Ψ_{t-1} represents the information from period $t-1$ and is a symmetric matrix whose diagonal elements are equal to 1.

3. Data and Empirical Results.

3.1. Data and Summary Statistics

Daily data for the TED spread are calculated as the difference between 3-month US Treasury Bills and 3-month Eurodollar bills. The Data are obtained from Thomson Datastream for the period 1 Jan 2004 to 31 Dec 2009. The TED spread is obtained in basis points, with summary statistics in Table 1. 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 by government bills. By contrast, the TED spread reach 400 basis points in early Oct 2008 after a series of bankruptcies of banks and financial institutions. On 10 Oct 2008, the TED spread hit a new high of 501 basis points, reflecting the breakdown in interbank market. We choose the Datastream CDS index spread for the UK Bank Sector to represent the overall condition for banks in the credit derivatives market in the UK. As noted, the summary statistics are also presented in Table 1.

Figure 1 plots the TED and CDS original and return series.[3] Both the TED spread and CDS spread can both used to assess credit risk and we can see the increase in both spreads from mid-2007 onwards. We can also see that while the TED spread reaches its highest point in 2008, after the failure of Lehman, and then reduces back to a normal level, the CDS spread continues to fluctuate at an unusually high level. The difference between the market behaviour of the two spreads may arise from government policy taken place in the period after the financial crisis. As the TED spread is an important indicator to the health of the 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

[3] The return series is defined as the percentage change.

the priority of governments was to restart the interbank market. As such the US government introduced TARP (Troubled Asset Relief Program), while in the UK, the government introduced GAPS (Government Asset Protection Scheme), along with other related insurance schemes (e.g., the guarantee scheme for asset backed securities, GSABS). The purpose of the GAPS programme was to insure banks against bad loan losses for up to 90% of the loss. The effect of these programmes served to reduce the TED spread and to move towards more normal conditions in the inter-bank market. However, the CDS spread shows a different pattern. It continued to fluctuate at a high level, at an average of 150 basis points. This serves to illustrate that although governments had introduced asset protection schemes, the market still took the view that risk remained high.

3.2. Estimation Results

As noted, the estimation process for dynamics correlations is performed in two steps: first, estimate the univariate GARCH models; second, estimate the DCC parameters. Thus, for the first step we estimate univariate ARMA(1,1)-GJR-GARCH models, the specification of which is defined in equation (1). We considered a range of distributions for the innovations, including the normal, student *t*, skewed *t* and Generalized Error Distribution. The results reported in Table 2 are from the skewed *t* distribution, which had the lowest *p*-value across the distributions for the Kolmogorov-Smirnov (KS) test, which was used to assess the null that the errors are from a given distribution and hence the adequacy of the model.

Table 2 presents the estimation results of ARMA(1,1)-GJR-GARCH-ST of the two univariate conditional models. We find that both TED returns and CDS returns 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 degree of freedom, is significant for both series.

The DCC model proposed by Tse and Tsui (2002), where the model of the dependency parameter p_t is:

$$p_t = (1 - \theta_1 - \theta_2)p + \theta_1 \Psi_{t-1} + \theta_2 \mathrm{p}_{\mathrm{t-1}} \tag{4}$$

where θ_1 and θ_2 are non-negative numbers satisfying $\theta_1 + \theta_2 < 1$ and $\Psi_t = \frac{\sum_{i=o}^{n-1} z_{1,t-i} z_{2,t-i}}{\sqrt{\sum_{i=0}^{n-1} z_{1,t-i}^2 \sum_{i=0}^{n-1} z_{2,t-i}^2}}$.

The result of the DCC estimation can be found in Table 3. Our results reveal a large degree of persistence in the conditional correlation process, with alpha+beta very close to one. Figure 2 shows that the time-varying conditional correlation between the TED spread and CDS spread increased over the period 2007-2009. 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 comovement relationship between the two indices. That is, there is a possible upward trend but in the interval of [-0.1 0.1]. During 2007 and after the beginning of the financial crisis, there is a significant rise in the conditional correlation between these two indices. The correlation increases up to 0.2 and then fluctuates widely. 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. This finding is consistent with research that demonstrates that the dependence of financial indices will become enhanced in a crisis.

The result showing the increase in correlation confirms the role of contagion within the credit market and that the funding and credit constraints are tightened together as the credit constraint limited banks ability to lend funds on a large scale before 2008. This behaviour is consistent with the general economic condition, in which the credit risk of the counterparty became more important than previously. The increase in the correlation between the TED spread and the CDS spread arose as banks became more reluctant to lend to each other increasing the rate on loans as default risk also rose. The correlation later 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.

4. Conclusion

In this paper we have examined the dynamic linkages between TED spread and CDS spread using the DCC-GJR-BVGARCH model. 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. This is consistent with the view that the dependence between financial assets will increase during a crisis. After early 2008, the correlation fell but persisted at a level of between 0.05 and 0.1, higher than the pre-crisis period. The decrease in the correlation may have arisen as government intervention reduced funding constraints between banks and the inter-bank rate. However, credit risk and the risk of default remained high, thus, the CDS price continued to fluctuate at a higher level.

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Table 1 Summary Statistics

	Mean	Max	Min	S. Dev.	Skewness	Kurtosis	J.B.
TED	70.50	501.00	10.94	66.67	2.64	12.51	7722.09
CDS	57.64	235.21	4.63	64.62	0.89	2.30	236.81
R.TED	0.95	143.48	-66.18	14.07	2.11	20.90	22051.37
R.CDS	0.24	71.58	-47.61	5.56	1.39	31.12	52077.68

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 GJR-GARCH Model

	TED		CDS	
	Coefficient	Std.Error	Coefficient	Std.Error
Cst(M)	0.1172	0.1659	-0.0418	0.0844
AR(1)	0.3061**	0.0516	0.3461**	0.1446
MA(1)	-0.4582**	0.0446	-0.2464*	0.1365
Cst(V)	3.1123**	1.5113	0.5098**	0.2265
ARCH(Alpha1)	0.1641**	0.0528	0.2341**	0.0703
GARCH(Beta1)	0.8138**	0.0458	0.8259**	0.0475
GJR(Gamma1)	0.1249**	0.0620	-0.0087	0.0537
Asymmetry	-0.0384	0.0308	0.0405	0.0288
Tail	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	-5759.50		-4200.81	

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

Table 3 DCC Estimation

	Coefficient	Std.Error	t-value	t-prob
Rho	0.0076	0.1335	0.06	0.95
Alpha	0.0066	0.0033	1.99	0.05
Beta	0.9905	0.0082	120.90	0.00
degree of freedom	3.8894	0.1701	22.87	0.00
Log-likelihood	-10003.30			

Figure 1 TED spread and CDS Spread Daily Index and their Return from 1 Jan 2004 to 31 Dec 2009

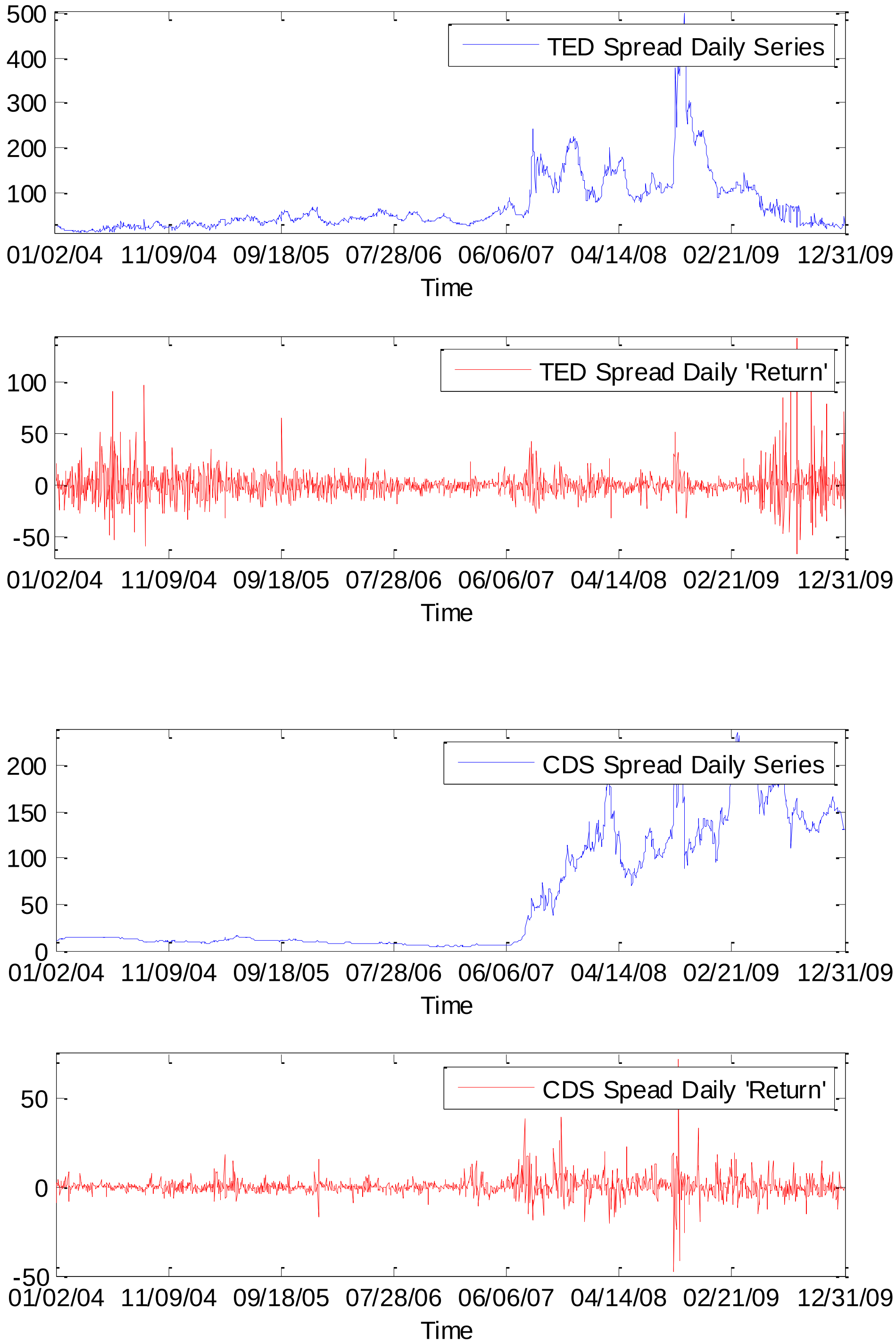

Figure 2 Time-varying Conditional Correlation estimated by DCC model