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Dynamic Correlation Analysis of US Financial Crisis and Contagion: Evidence from Four OECD countries

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Abstract

By analyzing the dynamic conditional correlations (DCC) of the daily stock returns of four OECD countries with that of the US for the period of 2006-2010, we could find a process of increasing correlations (contagion) in the first phase of the US financial crisis and an additional increase of correlations (herding) during the second phase of the US financial crisis for the UK, Australia, and Switzerland. However, the impact of the US financial crisis on Japan was limited to the increase in correlation volatilities in the first phase. We also propose a new approach (DCCX-MGARCH) that allows simultaneous estimation of the DCC and their determinants, which can be used to identify channels of contagion. It is shown that an increase in VIX stock market index increases conditional correlations but an increase in the TED spread and relative stock market capitalization decrease conditional correlations of stock returns between four OECD countries and the US.

JEL classification: F31, G15

Keywords: DCCX-MGARCH, Dynamic conditional correlations, contagion, US financial crisis, VIX index, TED spread.

I. Introduction

At the beginning of the US financial crisis, which began with the failure of Lehmann Brothers in September 2008, some economists expected that the decoupling of financial markets could isolate the adverse impact of the US recession on the rest of the world. However, many studies report contagion of emerging markets (Beirne et al., 2008; Dooley and Hutchison, 2009; Kim and Kim, 2011) and advanced markets (Boyson et al., 2010; Christensen and Ronaldo, 2010; Chudick and Fratzscher, 2011) from the US financial crisis.

Even though identifying the nature of financial market contagion is extremely important, previous studies failed to reach a consensus on the existence of contagion with the earlier financial crisis episodes. Forbes and Rigobon (2002) argue that most of previous evidence of contagion (King and Wadhwani, 1990; Lee and Kim, 1993; Calvo and Reinhart, 1996) disappears when unconditional cross-market correlation coefficients are corrected for bias. However, Corsetti et al. (2005) show that Forbes and Rigobon's test is biased towards the null hypothesis of no contagion and report "some contagion, some interdependence." In other words, for proper investigation of stock market comovement (contagion), we need to consider heteroscedasticity and the dynamic nature of the correlations.

In this paper, we investigate the transmission of the recent US financial crisis to stock markets in four OECD countries. In particular, we are interested in (i) finding empirical evidence of contagion from the US stock market to those of the four OECD countries and (ii) analyzing two phases of crisis transmission, i.e., contagion and herding. Most importantly, we are interested in finding the channels of the transmission mechanism. To answer the first two questions, we use Engle's (2002) dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model. To answer the third question, we propose a new DCC-MGARCH type model with exogenous variables (DCCX-MGARCH). This methodology can estimate both the dynamic conditional correlation and the impact of explanatory variables simultaneously in one framework. The DCCX-MGARCH method can be useful in identifying the channels of contagion in the stock returns of four OECD countries (United Kingdom, Japan, Switzerland, and Australia) and that of the US. In other words, our DCCX-MGARCH model is different from previous models in that ours can directly estimate the effects of exogenous variables on the conditional correlations.

A number of variables can be considered important for the determination of dynamic conditional correlations of stock returns. We include the daily sovereign CDS spread, the VIX index, the relative stock market capitalization to the US, and the TED spread. We include the CDS spread as a measure of the sovereign risk of each country. The VIX implied volatility is a proxy for stock market uncertainty (Connolly et al., 2005), and it is a widely used measure of investor fear. The TED spread is the difference between the three-month LIBOR and the yield on the US Treasury bills with the same maturity. The TED spread is used as a measure for the level of financial stress in the interbank market. Brunnermeier (2009) shows that the TED spread provides a useful basis for gauging the severity of the liquidity crisis. Finally, the ratio of stock market capitalization relative to the US is included in the analysis as a measure of the financial independence from the US.

This paper is organized as follows. Section II reviews previous literature related to our research questions. In Section III, we estimate the dynamic conditional correlations of four OECD countries' stock return with the US stock return and provide empirical evidence of two phases (contagion and herding) of the US financial crisis on the conditional correlations of four OECD countries. Section IV investigates the determinants of conditional correlations using the DCCX-MGARCH model, and Section V concludes the paper.

II. Literature

Studies on stock market comovement (contagion) can be grouped into three different groups. The first group of studies (King and Wadhwani, 1990; Lee and Kim, 1993; Baig and Goldfajn, 1999) focuses on providing evidence of a significant increase in cross-country unconditional correlations of stock returns by employing a subsample analysis for a structural break, with a known structural break date. However, several studies (Forbes and Rigobon, 2002; Bordo and Murshid, 2001; Basu, 2002) argue that there is no significant increase in stock return correlations when they account for heteroscedasticity. Corsetti et al. (2005), Froot et al. (2001) and Basu (2002) confirm the existence of the contagion effect, making the evidence on the financial contagion inconclusive.

The second group of studies (Hamao et al., 1990; Kanas, 1998; Kim et al., 2006; Chiang et al., 2007; Ng, 2000, Beirne et al., 2008; Frank and Hesse, 2009) utilizes a multivariate GARCH model to account for heteroscedasticity and the dynamic nature of the correlations. First of all, Hamao et al. (1990) utilizes the ARCH family of statistical models and report a price volatility spillover effect among three major international stock markets. In a similar vein, Kanas (1998), using the EGARCH model, shows reciprocal spillover effects in the European equity markets, and Ng (2000), using multivariate GARCH model, shows that Pacific-Basin stock markets are driven by a regional shock from Japan and a global shock from the US. On the other hand, Connolly et al. (2005) and Kim et al. (2006) investigate the international stock-bond return relation and report that stock market uncertainty has important cross-market pricing influences. Furthermore, Chiang et al. (2007) investigate the financial contagion of Asian markets during the Asian financial crisis using dynamic correlations analysis and report evidence of contagion in this area. Finally, Frank and Hesse (2009) use a multivariate GARCH model to investigate the extent of comovements of financial variables across markets and report that inter-linkages between funding stress and equity markets in advanced economies and emerging market financial indicators increase sharply during specific crisis moments. Our methodology can be classified into this second group since we use the multivariate GARCH model to estimate dynamic conditional correlations between the stock returns of the four OECD countries with that of the US.

The third group of studies (Bracker et al., 1999; Johnson and Soenen, 2003; Connoly et al., 2007; Baele et al., 2009; Norden and Weber, 2009) have tried to find determinants of stock market comovements. While Bracker et al. (1999) show that measures of bilateral import dependence and the size deferential across markets are important determinants of stock market integration, Johnson and Soenen (2003) report that a high share of trade with the US has a strong positive impact on stock market comovements but that increased bilateral exchange rate volatility and a higher ratio of stock market capitalization relative to US contribute to lower comovement in Americas. On the other hand, Connolly et al. (2007) find that cross-country stock return comovements tend to be stronger following high implied volatility days. Finally, Norden and Weber (2009) investigate the comovement of credit-default swap, bond and stock markets during 2000-2002 and they report that stock returns lead CDS and positive stock returns are associated with negative CDS spread changes. While the third group of studies identified a number of fundamentals that determine the comovements of stock markets, they failed to establish a relationship between dynamic conditional correlations and those fundamentals.

In our analysis of the DCCX-MGARCH model, we simultaneously estimate dynamic conditional correlations and the impact of exogenous variables over time, which can be used to identify channels of contagion.

III. The dynamic conditional correlation model

3.1. The DCC-MGARCH Model

We use the dynamic conditional correlation (DCC) estimator proposed by Engle (2002). The DCC model is a flexible yet parsimonious parametric model that has been widely employed.

Let $y_t = [\Delta s_{1,t}\ \Delta s_{2,t}]'$ be a 2×1 vector of the log of stock market index ($s_{i,t}$) in a conditional mean equation. A VAR representation of the conditional mean equation can be written as in Equation (1):

$$A(L)\ y_t = e_t, \quad where \quad e_t \sim N(0, H_t)\ \forall\ t = 1, ...T \qquad (1),$$

where $A(L)$ is a polynomial matrix in the lag operator L and $e_t = [\varepsilon_{1t,} \varepsilon_{2t}]'$ is a vector of innovations with a conditional variance-covariance matrix $H_t = \{h_i\}_t\ \forall\, i = 1\ and\ 2$. The GARCH component of the framework can be rewritten as $H_t = D_t R_t D_t$, where $D_t = diag\,(\sqrt{h_{i,i,t}})$, and $R_t = \{\rho_{ij}\}_t$ is the time-varying correlation matrix containing conditional correlation coefficients. The elements in D_t follow the univariate GARCH (*P, Q*) processes in the following manner:

$$h_{i,t} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} \varepsilon_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{i,t-q} \quad \forall i = 1, 2 \qquad (2).$$

The second component of the framework consists of a specific DCC(*M, N*) structure, which can be expressed as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad (3),$$

where $Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\bar{Q} + \sum_{m=1}^{M} \alpha_m (\varepsilon_{t-m} \varepsilon'_{t-m}) + \sum_{n=1}^{N} \beta_n Q_{t-n}$,

$\bar{Q}$ is the unconditional correlation matrix of $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$, $Q_t^* = diag\{\sqrt{q_{i,i}}\}$ is a 2×2 diagonal matrix containing the square root of diagonal elements in Q_t, and α and β are nonnegative scalars that satisfy $\alpha + \beta \prec 1$.

In this paper, our key element of interest in R_t is $\rho_{1,2,t} = q_{1,2,t} / \sqrt{q_{1,1,t} q_{2,2,t}}$, which represents the conditional correlation between US stock returns and other OECD countries' stock returns. The log-likelihood function for this model can be expressed as follows:

$$L = [-1/2 \sum_{t=1}^{T} (n \log(2\pi) + \log |D_t|^2 + \varepsilon_t^{'} D_t^{-2} \varepsilon_t)] + [-1/2 \sum_{t=1}^{T} (\log |R_t| + \varepsilon_t^{'} R_t^{-1} \varepsilon_t + \varepsilon_t^{'} \varepsilon_t)] \quad (4)$$

Engle (2002) proposes a two-step approach for estimating the DCC model.

3.2. Estimation of the DCC-MGARCH model

3.2.1. Data and summary statistics

We collected daily stock market indices, the TED spread[1], the stock market volatility index (VIX), and stock market capitalization from DataStream. CDS spreads were from Bloomberg, Inc. To investigate the dynamic correlation coefficient of four OECD countries during the US financial crisis, our sample covers from the 1st of September 2006 to the 22nd of July 2010. Table 1 shows the summary statistics for stock market returns of four OECD countries, and Figure 1 plots the daily stock return of the five countries.

[Table 1 about here]

From the first panel of Table 1, we can see that the average daily stock market returns are negative for all the countries for the whole sample period (before the US financial crisis and thereafter). The UK recorded the largest average negative return (loss) of 0.069% while Switzerland recorded the smallest average daily loss of 0.0365%. From the JB statistics, we can reject that all daily return series have normal distributions. In addition to this, ARCH (5) test statistics reject the null hypnosis of homoscedasticity for all countries, and Ljung-Box Q

[1] The data appendix has the detailed definitions and sources of each time series.

test statistics reject the null hypothesis of no serial correlation for the United Kingdom, Japan, and Australia.

Figure 1 shows the daily stock market returns of the five OECD countries. From Figure 1,

[Figure 1 about here]

we can see that stock return volatility is highest in Australia (standard error of 2.548) and lowest in Switzerland (standard error of 1.675) and that all five countries' stock return volatility increase significantly after Lehmann Brothers' failure. Table 2 reports the summary statistics for the conditional correlation coefficients estimated by DCC-GARCH model defined in

[Table 2 about here]

Equation (2). From Table 2, we can see that the mean value of DCC is highest in the United Kingdom (as high as 0.5481) and lowest in Japan (as low as -0.0007).

3.3.2. Estimates of the DCC-GARCH model

Table 3 reports the estimates of the return and conditional variance equations. From

[Table 3 about here]

Table 3, we can see that the AR(1) term in the mean equation is significantly negative for all five countries, and this is consistent with Antoniou et al. (2005) in terms of the presence of positive feedback trading in advanced markets. The effects of the US stock returns on OECD stock returns are highly significant, positive, and consistently large in magnitude, ranging from 0.371 (Switzerland) to 0.826 (Australia). The coefficients for the lagged variance and shock-squared terms in the variance equation are significant, and this is consistent with time-varying volatility and confirms the appropriateness of the GARCH (1,1) specification. Note that the sum of the estimated coefficients (a+b) is quite close to unity, implying that the volatility displays a highly persistent fashion. One advantage of using the model is the fact that four possible pair-wise correlation coefficients for the five index returns in the sample can be estimated in a single system equation. From Table 3, we can see that the hypothesis that all estimated coefficients of the US return (γ_2) are zero in the mean equation and all estimated coefficients of the US volatility (b) in the variance equation are zero can be rejected, and this validates our GARCH (1,1) model specifications.

3.3.3. Estimates of DCC for stock return data

Figure 2 shows estimates of DCC between the stock returns of the US and those of the United Kingdom, Japan, Australia, and Switzerland during the period of September 2006 - July 2010. First of all, we can see that DCCs increase sharply after Lehmann Brothers' failures (third quarter of 2008) and reach their highest level at the end of 2008. Even though the United Kingdom, Australia, and Switzerland were hit hard, recording large and positive correlations, the stock returns of Japan show very low correlations with the US before the crisis (as low as -0.07). After Lehmann Brothers' failure, the correlations became significantly higher and persisted at higher levels for the UK, Australia, and Switzerland, ranging from 0.35 to 0.62. Those estimates of stock return correlations are much higher than the estimates of Asian markets (Chiang et al., 2007).

However, the correlations of Japan increased as high as 0.217 after the crisis, but decayed thereafter. Our study provides evidence of contagion[2] effects in OECD stock markets in the early phase of the recent US financial crisis and then herding behavior in the latter phase. However, the impact of the US financial crisis has had a limited impact on Japan,

[2] Contagion describes the spread of shocks from one market to another with a significant increase in correlations between markets while herding is the simultaneous behavior of investors across different markets with high correlation coefficients in all markets.

i.e., the US financial crisis has increased the stock return correlations of Japan, but this has been a temporary impact.

3.3.4. Two phases of the US financial crisis

As shown in Figure 2, the pair-wise conditional correlation coefficients between the stock returns of OECD countries are persistently higher and more volatile after Lehmann Brothers' failure (September 15th, 2008). At the same time, it seems clear that conditional correlation coefficients of Japan returned to the pre-crisis level after almost a year. For this reason, we want to look into the time series behavior of correlation coefficients and identify the impact of external shocks on their movements and volatility. We use two dummy variables for different sub-samples to investigate the dynamic patterns of correlation coefficients.

The model is given as follows:

$$\rho_{ij,t} = \sum_{p=1}^{p} \phi_p \rho_{ij,t-p} + \sum_{k=1}^{2} \alpha_k DM_{k,t} + e_{ij,t} \tag{7}$$

where $\rho_{ij,t}$ is the pair-wise correlation coefficient between the stock returns of the US and those of the UK, Japan, Australia, and Switzerland. The lag length in Equation (7) is determined by the AIC criterion. DM_1 is a dummy for the first phase of the crisis period (9/15/2008-9/14/2009), and DM_2 is a dummy for the second phase of the crisis period (9/15/2009-7/21/2010). Since our pre-tests using ARCH-LM statistics (Table 1) find significant heteroscedasticity in all cases, the conditional variance equation is assumed to follow a GARCH (1,1) specification with two dummy variables:

$$h_{ij,t} = C_0 + A_1 h_{ij,t-1} + B_1 e^2_{ij,t} + \sum_{k=1}^{2} d_k DM_{k,t} \tag{8}$$

As the model implies, the significance of the estimated coefficients of the dummy variables indicates structural changes in the mean and/or variance shifts of the correlation coefficients due to external shocks during the different phases of the crisis. The maximum likelihood estimation of Models (7) and (8) are reported in Table 4.

[Table 4 about here]

To verify the validity of our model, we tested whether or not the estimated coefficients of dummy variables are zero in the mean and variance equations using the likelihood ratio tests, and we can reject the hypotheses of zero restrictions on dummy variables in the mean and variance equations. From Table 4, we can see that all estimates of $DM_{1,t}$ and $DM_{2,t}$ in the mean equation are significant and positive, except for Japan. This implies that the correlation during the early phase of the crisis is significantly higher than that of the pre-crisis period, and there are additional increases in correlations during the second phase of the crisis. This finding is consistent with the comovement paths shown in Figure 2 and support the herding behavior hypothesis in the early and second phase of the crisis. The herding phenomenon will nullify the benefit of holding a diversified international portfolio in the region. All of the lagged variance and shock-squared terms are highly significant, displaying a clustering phenomenon. From the lower part of Table 4, the coefficients for $DM_{1,t}$ are positive for all four countries while the coefficients for $DM_{2,t}$ are significant only for the United Kingdom. This evidence suggests that the correlation coefficients can vary greatly, and this variability could last for a prolonged period time for the United Kingdom but only a certain period of time for Australia, Japan, and Switzerland. It is interesting that correlation coefficients for Japan do not show any structural break during the different phases of crisis, but Japan only show increased correlation variability during the first phase of the crisis.

IV. Determinants of DCC for stock market returns

4.1. The DCCX-MGARCH Model

We propose a DCCX-MGARCH type model, where the conditional correlation coefficient is determined by exogenous variables.

$$h_{12,t} = \rho(X_t)\sqrt{h_{1,1,t}\ h_{2,2,t}}, \qquad (5)$$

where $-1 \prec \rho(X_t) \prec 1$ is a monotonic increasing function of X_t, a $K \times 1$ vector of economic fundamental variables that affects the size of the conditional correlation. This approach is useful for identifying the propagation channel of stock returns comovements. We propose the following parameterization for such a conditional correlation function:

$$\rho(X_t) = 2\left[\frac{\exp(\theta' X_t)}{1+\exp(\theta' X_t)}\right] - 1, \qquad (6)$$

where $\theta = [\theta_1, \theta_2, ..., \theta_k]'$ *and* $X_t = [x_1, x_2, ..., x_k]'$.

For exogenous variables that are supposed to determine the dynamic conditional correlations, we include the daily sovereign CDS spread, the VIX index, relative stock market capitalization to the US, and the TED spread. We include CDS spreads since Jorion and Zhang (2007) show that credit event information is captured in CDS spread and Bystrom (2005) and Norden and Weber (2009) find that positive stock returns are negatively associated with CDS spread changes. The VIX index is included since Giot (2005) showed that the VIX index and stock return have negative relationship. While Andersson et al. (2007) suggest that periods of elevated stock market uncertainty lead to decoupling between stock and bond prices, Cai et al. (2009) show that higher correlations emerge between countries when both countries experience higher stock market volatility. We include the TED spread since Brunnermeier (2009) shows that the TED spread provides a useful basis for gauging the severity of the liquidity crisis. Finally, we include the ratio of stock market capitalization relative to the US since Johnson and Soenen (2003) show that a higher ratio of stock market capitalization relative to the US contributes to lower comovement.

4.3. Estimation

The estimation results for Equation 6 are reported in Table 5. First, it is shown that increased

[Table 5 about here]

TED spread decreases conditional correlations for all four countries under consideration. Increased TED spread implies a worsened liquidity situation or "fear" (Lashgari, 2000: Cheung et al., 2010) in the world capital market, and this, in turn, decreases the comovements of stock returns among four OECD countries and that of the US. Second, it is shown that the VIX index of a sovereign country has a significant positive effect on the conditional correlations for three countries under investigation. This implies that uncertainty in one countries' stock market may spread to the US or vice versa. This is consistent with Cai et al. (2009) and previous estimates of conditional variance function in Table 3. In Table 3, all estimates of b in variance equations are positive and significant, implying that there are significant volatility spillover effects in those countries. Third, the estimated coefficient of the ratio of stock market capitalization to the US is negative and significant for all four countries, and this finding is consistent with Johnson and Soenen (2003). A higher ratio of stock market capitalization relative to the US implies a higher level of independence from the US stock market, and this can decrease the conditional correlations of stock returns.

Finally, increased sovereign risk measured by the CDS spread increases the conditional correlations for the UK and Australia. This finding is consistent with Bystrom (2005), who found that an increase in stock price volatility is positively correlated with the CDS spread. In other words, increased CDS spread increases stock price volatility, and this increased stock return volatility in the UK and Australia can increase stock return correlations. However, estimated coefficient of CDS spread for Switzerland has an unexpected negative sign.

We can see that most of dummy variables are significant in Table 5 (dummy variables are not included for Switzerland since its CDS spread data does not cover a whole range of analysis). While dummy variables for both phases are significant and positive for the United Kingdom and Australia, it is shown that those of Japan are negative and significant only for the second phase of the crisis.

V. Conclusions

This paper investigated the relationship between the stock returns of four OECD markets and that of the US. To examine stock market contagion and herding behavior, we employed dynamic multivariate GARCH model to estimate dynamic conditional correlations using the daily stock return data for the 2006-2010 period. Based on the estimated dynamic conditional correlations between four OECD countries and the US, we analyzed the dynamic behavior of stock market interactions by dividing the whole sample period into three sub-sample periods (pre-crisis, first phase of the crisis, and second phase of the crisis). During the first phase of the crisis, we identified a process of increasing correlations and an additional increase of correlations during the second phase caused by herding behavior in the United Kingdom, Australia, and Switzerland. However, the impact of the US financial crisis on Japan was limited to the increase in correlation volatilities in the first phase, and this disappeared during the second phase of the crisis, leaving the correlations of the Japan pre-crisis level. Finally, we proposed a new approach that allows simultaneous estimation of the conditional correlation coefficients and determinants of conditional correlations over time and that can be used to identify channels of contagion. It is shown that an increase in the VIX stock market index increases conditional correlations while increases in TED spreads and relative stock market capitalization decrease the conditional correlations of the four OECD countries with the US.

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Data Appendix

Stock Index

Item	Description	Datastream Code
US Index	S&P 500 Composit	S&PCOMP(PI)
UK Index	UK-DS Market	TOTMUK$(PI)
Swiss Index	Swiss-DS Market	TOTMKSW(PI)
Australia Index	Australia-DS Market	TOTMAU$(PI)
Japan Index	Japan-DS Market	TOTMJP$(PI)

Volatility Index

Item	Description	Bloomberg Source
US	Volatility Index for S&P 500	VIX
UK	Volatility Index for FTSE 100	VFTSE
Swiss	Volatility Index for SMI	VSMI
Australia	Volatility Index for S&P/ASX	SPAVIX
Japan	Volatility Index for Nikkei225	VXJ

TED Spread

Item	Description	Datastream Code
TED US	LIBOR – US Treasury Bill 3M	BOELI3M – FRTBS3M
TED UK	LIBOR – UK Interbank 3M	BOELI3M – LDNIB3M
TED Swiss	LIBOR – Swiss Interbank 3M	BOELI3M – SWIBK3M
TED Australia	LIBOR – Australian Deposit 3M	BOELI3M – GSAUD3M
TED Japan	LIBOR – Japan Interbank 3M	BOELI3M – JPIBO3M

CDS Spread

Item	Description	Bloomberg Source
CDS US	US CDS Spread	CMA New York
CDS UK	UK CDS Spread	CMA New York
CDS Swiss	Swiss CDS Spread	CMA New York
CDS Australia	Australia CDS Spread	CMA New York
CDS Japan	Japan CDS Spread	CMA New York

Table 1. Descriptive statistics for stock market returns (2006/09/01-2010/07/21)

A.Entire Period

	US	UK	Japan	Australia	Switzerland
Daily stock market returns ($\Delta s_{i,t}$)					
Mean	-0.0441	-0.069	-0.0559	-0.0584	-0.0365
Std. Error	1.9838	2.2531	1.7939	2.5481	1.6751
Normality Test					
Skewness	-0.1375	0.0205	-0.0074	-0.821**	0.173**
Kurtosis	5.336**	4.616**	3.8664**	4.8765**	3.715**
JB statistic	811.53**	605.68**	424.82**	752.34**	6982.6**
Heteroscedasticity test					
ARCH(5) LM test	161.29**	191.393**	116.792**	307.490**	120.752**
Autocorrelations test					
Ljung-Box Q	68.53**	52.620**	55.611**	23.219	65.720**

Note: Double asterisks (**) denote significance at 1% critical level and single asterisk (*) at 5% critical level respectively.

B.Pre-Crisis Period

	US	UK	Japan	Australia	Switzerland
Daily stock market returns ($\Delta s_{i,t}$)					
Mean	-0.0167	-0.03478	-0.0424	0.005498	-0.003388
Std. Error	1.0874	1.3116	1.3115	1.6685	0.9917
Normality Test					
Skewness	-0.382**	-0.1804	-0.347**	-0.377**	-0.221*
Kurtosis	2.0656**	2.2960 **	1.801**	2.243**	3.117**
Jarque-Bera	107.510**	119.739**	82.563**	124.108**	219.687**
Heteroscedasticity test					
ARCH(5) LM test	7.39**	14.92**	14.09**	19.80**	12.69**
Autocorrelations test					
Ljung-Box Q	37.05*	30.16	37.28*	10.59	22.90

Note: Double asterisks (**) denote significance at 1% critical level and single asterisk (*) at 5% critical level respectively.

C.Post-Crisis Period

	US	UK	Japan	Australia	Switzerland
Daily stock market returns ($\Delta s_{i,t}$)					
Mean	-0.01795	-0.02381	-0.02948	-0.000634	-0.0070
Std. Error	2.1920	2.4634	1.8482	2.7278	1.8272
Normality Test					
Skewness	-0.153	-0.0269	0.050	-0.973**	10.149
Kurtosis	4.696**	4.200**	4.649**	5.098**	3.242**
Jarque-Bera statistic	445.775**	335.135**	435.143**	599.137**	213.303**
Heteroscedasticity test					
ARCH(5) LM test	24.71**	26.33**	39.58**	50.96**	20.47**
Autocorrelations test					
Ljung-Box Q	44.00**	43.41**	42.28**	20.98	55.92**

Note: Double asterisks (**) denote significance at 1% critical level and single asterisk (*) at 5% critical level respectively.

Table 2: Summary statistics of estimated DCCs of 5 OECD countries: Equation (5)

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}}$$

Entire Period

	US-UK	US-Japan	US-Australia	US-Switzerland
Mean	**0.5481**	**-0.0007**	**0.2707**	**0.4813**
Std. Error	0.0259	0.0369	0.0368	0.0383
Skewness	1.0437 **	2.174 **	0.6241 **	1.8894 **
Kurtosis	2.5225 **	5.6123 **	0.3809 **	4.7100 **
Jarque-Bera statistic	304.65 **	1432.31 **	48.4007 **	1036.197 **

Note: Double asterisks (**) denote significance at 1% critical level and single asterisk (*) denote significance at 5% critical level.

Pre-Crisis Period

	US-UK	US-Japan	US-Australia	US-Switzerland
Mean	**0.5298**	**-0.02491**	**0.2260**	**0.4605**
Std. Error	0.01618	0.02469	0.02162	0.01815
Skewness	-1.6699**	0.4548**	-0.1471	-0.6070**
Kurtosis	4.9780**	3.6973**	0.8967**	0.4881*
Jarque-Bera statistic	796.5491**	227.2236**	19.7411**	37.9653**

Note: Double asterisks (**) denote significance at 1% critical level and single asterisk (*) denote significance at 5% critical level.

Post-Crisis Period

	US-UK	US-Japan	US-Australia	US-Switzerland
Mean	**0.5638**	**-0.004604**	**0.2848**	**0.4981**
Std. Error	0.02990	0.05496	0.04221	0.04897
Skewness	1.2510**	1.7403**	0.7839**	1.3541**
Kurtosis	2.2670**	3.0890**	-0.08467	2.9252**
Jarque-Bera statistic	229.4058**	435.8264**	49.6082**	319.8108**

Note: Double asterisks (**) denote significance at 1% critical level and single asterisk (*) denote significance at 5% critical level.

Table 3: Estimation results from the DCC-GARCH model (2006/09/01-2010/07/21)

	UK		Japan		Australia		Switzerland		US	
Return equation: $\Delta s_{i,t} = \gamma_{i,0} + \gamma_{i,1}\,\Delta s_{i,t-1} + \gamma_2\,\Delta s_{US,t-1} + \varepsilon_{i,t}$										
γ_0	0.077*	(0.037)	-.0001*	(0.029)	0.128*	(0.037)	0.070*	(0.037)	0.072*	(0.037)
γ_1	-0.230*	(0.020)	-0.134*	(0.021)	-0.157*	(0.021)	-.197*	(0.019)	-.089*	(0.031)
γ_2	0.497*	(0.033)	0.462*	(0.025)	0.826*	(0.035)	0.371*	(0.022)	--	--
Variance equation: $h_{ij,t} = c_i + a_i\,h_{ij,t-1} + b_i\,\varepsilon^2_{i,t-1}$										
c	0.029**	(0.006)	0.046*	(0.014)	0.137*	(0.044)	0.096*	(0.022)	0.022**	(0.005)
a	0.929**	(0.001	0.891*	(0.014)	0.843*	(0.019)	0.927*	(0.010)	0.899*	(0.012)
b	0.063**	(0.007)	0.087*	(0.011)	0.139*	(0.019)	0.063*	(0.011)	0.093*	(0.011)
-Log Likelihood					7454.53					
LR-test ($\gamma_2 = 0$ for all countries)					Chi-squared (4) = 708.94***					
LR-test (b = 0 for all countries)					Chi-squared (5) = 36935.3***					
LR-test (b = $\gamma_2 = 0$ for all countries)					Chi-squared (9) = 40849.54***					

Notes: Values in parentheses are standard errors. Double asterisks (**) and single asterisk (*) indicate significance at the 1% and 5% critical levels, respectively.

Table 4: Test of changes in DCC during different phases of US financial crisis

	UK		Japan		Australia		Switzerland	
Mean equation: $\rho_{ij,t} = \sum_{p=1}^{p} \phi_p \rho_{ij,t-p} + \sum_{k=1}^{2} \alpha_k DM_{k,t} + e_{ij,t}$								
Con.	0.071**	(.0001)	-0.002**	(.0003)	.0121**	(.0001)	0.0313**	(0.001)
ρ_{t-1}	0.869**	(.0002)	0.908**	(.0104)	0.946**	(.0007)	0.932**	(.0005)
$DM_{1,t}$	0.005**	(.0005)	0.0004	(.0009)	0.004**	(.0009)	0.0002*	(.0009)
$DM_{2,t}$	0.001**	(.0004)	0.0004	(.0006)	0.001**	(.0001)	.0012**	(.0005)
Variance equation: $h_{ij,t} = C_0 + A_1 h_{ij,t-1} + B_1 e^2_{ij,t} + \sum_{k=1}^{2} d_k DM_{k,t}$								
C_0	1.34e-6**	(2.24e-7)	2.22e-6**	4.76e-7	1.12e-6**	3.26e-7	4.77e-6**	5.69e-7
h_{t-1}	0.679**	(0.018)	.824**	(.010)	0.783**	(0.008)	0.734**	(0.019)
ε^2_{t-1}	0.377**	(0.022)	.182**	(0.013)	0.287**	(0.003)	0.210**	(0.025)
$DM_{1,t}$	9.88e-6**	(3.36e-6)	1.2e-5**	(1.7e-6)	1.18e-5**	(3.6e-6)	2.68e-5**	(6.6e-6)
$DM_{2,t}$	4.16e-6**	(1.18e-6)	1.16e-6	(9.83e-7)	-3.78e-7	(4.81e-7)	1.54e-7	(8.55e-7)

LR test
H_0 : DM_1=DM_2=0 in mean equation, Chi-squared (8)=71.71***
H_0 : DM_1=DM_2=0 in variance equation, Chi-squared (8)=19019782.54***
H_0 : DM_1=DM_2=0 in mean and variance equation, Chi-squared (16)=43866124.01***

Notes: Values in parentheses are standard errors. Double asterisks (**) and single asterisk (*) indicate significance at the 1% and 5% critical levels, respectively.

Table 5: Estimation of DCCX

$$\rho(X_t)=2\left[\frac{\exp(\theta' X_t)}{1+\exp(\theta' X_t)}\right]-1,\ \theta=[\theta_0,\theta_1,\theta_2,\theta_3,\theta_4]'$$

	UK		Japan		Australia		Switzerland	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
θ_0	1.298**	(.087)	0.131**	(0.044)	0.027	(0.079)	1.211**	(0.028)
θ_1	0.004**	(.0001)	0.0004	(.0001)	0.0015**	(.0002)	-.0001	(.0008)
θ_2	-.037**	(0.005)	-0.019**	(0.003)	-0.141**	(0.009)	1.992**	(0.668)
θ_3	-0.829*	(0.333)	-.3633*	(0.161)	-0.351	(0.765)	-.012	(0.009)
θ_4	0.005**	(.0006)	0.0028**	(.0003)	0.0012*	(.0006)	0.004**	(.0006)
DM_1	0.268**	(.0006)	-0.012	(0.012)	0.437**	(0.017)	--[3]	--
DM_2	0.306**	(0.019)	-0.135**	(0.015)	0.317**	(0.022)	--[3]	--
Log Likelihood	923.12		1018.62		597.11		600.01	

Notes:
1. Values in parentheses are standard errors. Double asterisks (**) and single asterisk (*) indicate significance at the 1% and 5% critical levels, respectively.
2. X_0 is a constant, X_1 is the CDS spread, X_2 is the TED spread, X_3 is the relative stock market capitalization of four OECD countries relative to US and X_4 is the VIX index for stock market.
3. Switzerland does not have sufficient observations of CDS spread data to utilize dummy variables.

Figure 1. Daily stock market returns of the five OECD countries

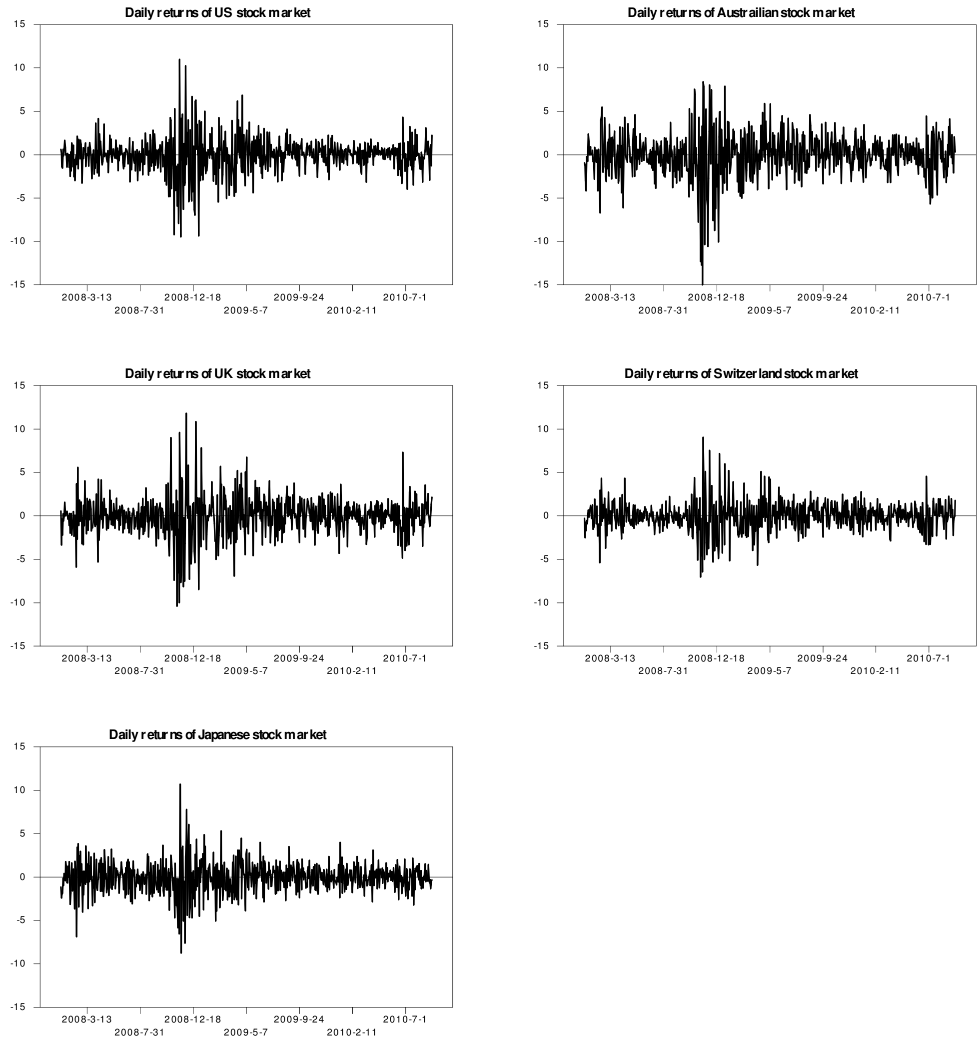

Figure 2. Estimates of DCCs among US and four OECD countries