Communications for Statistical Applications and Methods
2014, Vol. 21, No. 4, 335–347

DOI: http://dx.doi.org/10.5351/CSAM.2014.21.4.335
Print ISSN 2287-7843 / Online ISSN 2383-4757

Time-Varying Comovement of KOSPI 200 Sector Indices Returns

Woohwan Kim[1,a]

[a]Financial Research & Implementation, Korea

Abstract

This paper employs dynamic conditional correlation (DCC) model to examine time-varying comovement in the Korean stock market with a focus on the financial industry. Analyzing the daily returns of KOSPI 200 eight sector indices from January 2008 to December 2013, we find that stock market correlations significantly increased during the GFC period. The Financial Sector had the highest correlation between the Constructions-Machinery Sector; however, the Consumer Discretionary and Consumer Staples sectors indicated a relatively lower correlation between the Financial Sector. In terms of model fitting, the DCC with t distribution model concludes as the best among the four alternatives based on BIC, and the estimated shape parameter of t distribution is less than 10, implicating a strong tail dependence between the sectors. We report little asymmetric effect in correlation dynamics between sectors; however, we find strong asymmetric effect in volatility dynamics for each sector return.

Keywords: Dynamic conditional correlation model, asymmetry, tail dependence, financial crisis, KOSPI 200 sector index.

1. Introduction

The dynamics of the comovement between assets and across sectors has been attracted significant attention from market participants, especially in the areas of asset allocation and portfolio risk management. Furthermore, there is a growing systemic concern on the magnified inter-linkages (spillover or contagion) between markets and/or sectors due to recent crises such as the Global Financial Crisis (GFC) and European Debt Crisis (EDC). Thus, it is important to examine how to evolve the comovement dynamics between financial returns employing sound econometric methods. One of main streams to characterize the comovement dynamics between returns is to model the time-varying conditional correlation using multivariate GARCH (MGARCH) models.

During the last decade various parametric MGARCH models are developed to model conditional second moment. Depending on the specifications of conditional volatility and covariance matrix, MGARCH models are categorized into three groups. The first group includes the VEC and diagonal VEC models of Bollerslev *et al.* (1988) and BEEK model of Engle and Kroner (1995), which are direct generalization of the univariate GARCH model into multivariate case. In the second group, the Constant Conditional Correlation (CCC) model of Bollerslev (1990) and Dynamic Conditional Correlation (DCC) model of Engle (2002) are the most well-known models, which isolate the conditional correlations from the conditional variance component. The last group is nonlinear extension of

This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government [NRF-2011-356-B00001].

[1] Director, Financial Research and Implementation (FRNI), 564-37 Yeonnam-dong, Mapo-gu, Seoul 121-867, Korea.
E-mail: jumnjump@gmail.com

Published online 31 July 2014 / journal homepage: http://csam.or.kr

univariate GARCH, known as the copula-GARCH model in literature. For a detailed account of the MGARCH literature, see the survey articles by Bauwens *et al.* (2006) and Silvennoinen and Teräsvirta (2009).

DCC models have empirical and theoretical advantages over other alternatives due to their simplicity and flexibility for modeling the dynamics of conditional correlation. The DCC models are able to inherently capture time-varying correlations, and can be estimated using a two-step procedure, which has resolved numerical difficulties associated with estimating the parameters in MGARCH models. In DCC approach, a multivariate problem is decomposed into a series of univariate problems, which leads lower estimation cost. The conventional DCC of Engle (2002) combines the standard univariate GARCH of Bollerslev (1986) with time varying conditional correlations based on the multivariate normal distribution. Similar to GARCH families, the DCC models are developed to capture empirical characteristics of financial returns such as tail dependence and correlation asymmetry. The former is achieved by applying multivariate distributions with heavy tail such as multivariate t and multivariate skewed t distributions. The latter is to directly extend the dynamic correlation specification by allowing for conditional asymmetries in underlying correlation dynamics.

Asymmetry in stock market volatility has been extensively examined within univariate GARCH models. The asymmetric effect, also known as leverage effect, refers to the generally negative correlation between an asset return and its changes of volatility. Among univariate GARCH models, EGARCH of Nelson (1991), and GJR-GARCH of Glosten *et al.* (1993), Asymmetric Power ARCH of Ding *et al.* (1993) models are widely applied to capture asymmetric effects. In the multivariate case, Cappiello *et al.* (2006) develop an asymmetric generalized DCC (ADCC) model, which is well suited to examine correlation dynamics among different asset classes and investigate the presence of asymmetric responses in conditional variances and correlations. Recently, Gjika and Horváth (2013) showed that the evidence of asymmetry in the conditional correlations among stock markets is limited, but has gained importance with the global financial crisis characterized by a series of joint negative shocks and increased turbulence. They find that the stock markets exhibit asymmetry in conditional variances and in the conditional correlations; however, asymmetries in conditional correlations are not as widespread as in the conditional variances. They also argue that the conditional variances and correlations are positively related suggesting that the diversification benefits decrease disproportionally during volatile periods. Thus, it is time and suggest issue to examine the significance of asymmetry in correlation dynamics using return data gone through recent crises.

This paper examines the dynamics co-movements between industrial sectors in the Korean stock market. We employ bivariate DCC models since our primary concern is co-movements between sectors, focused on financial industry, and it is difficult to get reliable estimators of DCC model without further modifications even in moderate dimensional case. We analyze the daily returns of eight sector indices; Constructions & Machinery, Shipbuilding & Transportation, Steels & Materials, Energy & Chemicals, IT, Financials, Consumer Staples and Consumer Discretionary, covered from 2nd January 2008 to 30th December 2013 with 1,495 observations, focused on the Financial Sector. Empirical results show stock market correlations significantly increased during GFC period. Specifically, Financials sector shows the highest correlation between Construction & Machinery and Steel & Materials sector, whereas Consumer Discretionary and Consumer Staples sectors have relatively lower correlation between Financials sector. In terms of model fitting, the dynamic conditional correlation model with multivariate t distribution shows the best fitting on the basis of BIC. The estimated shape parameter of multivariate t distribution is less than 10, implicating the strong tail dependence, which may lead the simultaneous break-down of two indices and eventually market malfunction. We also note that there are little asymmetric effect in the correlation dynamics between sectors; however, there are strong asymmetric effects in the volatility dynamics. Our findings coincide with those in Gjika and Horváth (2013), who showed that the asymmetries in the conditional correlations are not as widespread as in the conditional variances.

The rest of this paper is organized as follows. Section 2 briefly explains the model specification and parameter estimation of DCC models. Section 3 presents the estimation results and summarizes our findings. Section 4 concludes.

2. DCC GARCH Models

Let r_t be the d-dimensional vector containing sector indices returns, which is given as

$$r_t = \mu_t + \varepsilon_t, \tag{2.1}$$

where μ_t denotes the conditional mean on the basis on the information up to time $t-1$, which is modeled as constant in this paper. The innovation ε_t is assumed to be a process with $E(\varepsilon_t|\mathcal{F}_{t-1}) = 0$ and $\mathrm{Var}(\varepsilon_t|\mathcal{F}_{t-1}) = \Sigma_t$, where $\mathcal{F}_{t-1}$ denotes the information set up to $t-1$. In DCC framework, the time varying conditional covariance matrix Σ_t is decomposed into

$$\Sigma_t = D_t \Gamma_t D_t, \tag{2.2}$$

where $D_t = D_t(\theta_1)$ is the diagonal matrix of time-varying volatilities from one of GARCH models, parameterized by a vector θ_1, with $\sigma_{i,t}$ on the ith diagonal. The conditional correlation matrix $\Gamma_t = \Gamma_t(\theta_1, \theta_2)$ contains the time varying correlations between two returns parameterized by two vectors θ_1 and θ_2.

The correlation matrix Γ_t of DCC(p, q) model of Engel (2002) is obtained by modeling a proxy process Q_t, given by

$$Q_t = \left(1 - \sum_{i=1}^{q} a_i - \sum_{j=1}^{p} b_j\right)\overline{Q} + \sum_{i=1}^{q} a_i z_{t-i} z'_{t-i} + \sum_{j=1}^{p} b_j Q_{t-j}, \tag{2.3}$$

where a_i and b_j are non-negative scalars, with the condition that $\sum_{i=1}^{q} a_i - \sum_{j=1}^{p} b_j < 1$ imposed to ensure stationarity and positive definiteness of Q_t, and $\overline{Q}$ is the sample covariance matrix of standardized errors z_t, *i.e.* $\overline{Q} = (1/T)\sum_{t=1}^{T} z_t z'_t$, where $z_t = D_t^{-1}(r_t - \mu_t)$. The correlation matrix is given as

$$\Gamma_t = \mathrm{diag}\,(Q_t^*)^{-\frac{1}{2}}\, Q_t \mathrm{diag}\,(Q_t^*)^{-\frac{1}{2}}, \tag{2.4}$$

where Q_t^* denotes the diagonal matrix of Q_t.

To allow asymmetric effects, the Q_t of ADCC(p, q, r) model by Cappiello *et al.* (2006) evolves according to

$$Q_t = \left(\overline{Q} - \sum_{i=1}^{q} a_i^2 \overline{Q} - \sum_{j=1}^{p} b_j^2 \overline{Q} - \sum_{k=1}^{r} g_k^2 \overline{N}\right) + \sum_{i=1}^{q} a_i^2 z_{t-i} z'_{t-i} + \sum_{j=1}^{p} b_j^2 Q_{t-j} + \sum_{k=1}^{r} g_k^2 \eta_{t-k} \eta'_{t-k}, \tag{2.5}$$

where $\eta_t = 1_{\{z_t<0\}} z_t$ with is a usual indicator function which takes on value 1 if the argument is true, *i.e.* $z_t < 0$, and 0 otherwise, and $\overline{N}$ is the sample covariance matrix of η_t, formally, $\overline{N} = (1/T)\sum_{t=1}^{T} \eta_t \eta'_t$. The a_i, b_j and g_k, totally denoted by parameter vector θ_2, are non-negative coefficients such that $\sum_{i=1}^{q} a_i^2 - \sum_{j=1}^{p} b_j^2 - \sum_{k=1}^{r} g_k^2 \delta < 1$, where δ denotes the maximum eigenvalue of $\overline{Q}^{-1/2}\,\overline{N}\,\overline{Q}^{-1/2}$, imposed to ensure positive definiteness. Cappiello *et al.* (2006) point out that this is guaranteed (necessary and sufficient condition) as long as $\sum_{i=1}^{q} a_i^2 - \sum_{j=1}^{p} b_j^2 - \sum_{k=1}^{r} g_k^2\delta < 1$.

The estimation of the parameters is done in two steps by quasi-maximum likelihood (QML), assuming that the innovations follow multivariate normal distribution. The log-likelihood of DCC model is given by

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left(d\log(2\pi) + \log|\Sigma_t| + \varepsilon_t'\Sigma_t^{-1}\varepsilon_t\right) \tag{2.6}$$

where $|\Sigma_t|$ denotes the determinant of the matrix Σ_t and θ is a parameter vector of DCC model. The idea of two-step approach is to separate the correlation parameters from variance parameters. The log-likelihood in (2.6) can be split into two parts, $L_v(\theta_1)$ and $L_c(\theta_1, \theta_2)$, and maximized sequentially. The log-likelihood in (2.6) is re-expressed as

$$L(\theta) = L_v(\theta_1) + L_c(\theta_1, \theta_2) \tag{2.7}$$

where $L_v(\theta_1)$ and $L_c(\theta_1, \theta_2)$ are respectively given as

$$L_v(\theta_1) = -\frac{1}{2}\sum_{t=1}^{T}\left(d\log(2\pi) + \log|D_t| + \varepsilon_t' D_t^{-1} D_t^{-1}\varepsilon_t\right), \tag{2.8}$$

$$L_c(\theta_1, \theta_2) = -\frac{1}{2}\sum_{t=1}^{T}\left(\log|\Gamma_t| + z_t'\Gamma_t^{-1}z_t - z_t'z_t\right). \tag{2.9}$$

In sequential approach, we estimate the parameters of the volatility model in the first step through to maximize the loglikelihood in formula (2.8). Once $\hat{\theta}_1$ is obtained $\overline{Q}$ is estimated as $(1/T)\sum_{t=1}^{T}\hat{z}_t\hat{z}_t'$, where $\hat{z}_t = \hat{D}_t^{-1}(r_t - \hat{\mu}_t)$. In the second step, the parameters of the correlation model are estimated via maximization of log-likelihood in formula (2.9) given $\hat{\theta}_1$ in the first step, *i.e.* $L_c(\hat{\theta}_1, \theta_2)$. This estimation technique is called as correlation targeting, similar to volatility targeting in univariate GARCH estimation.

3. Empirical Analysis

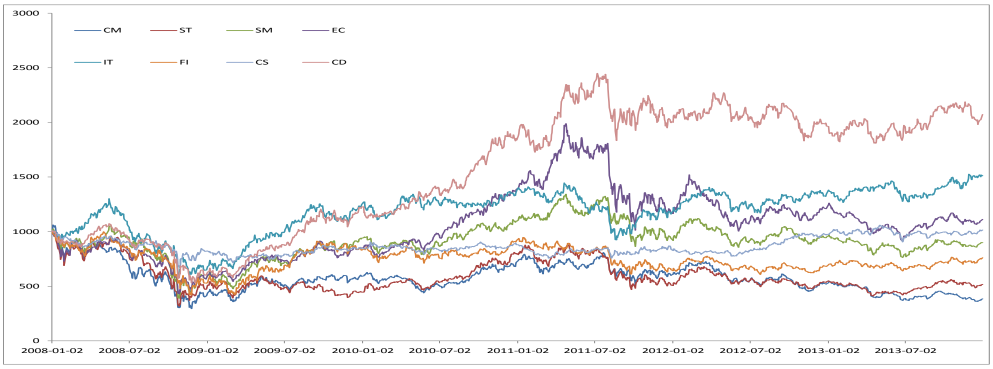
3.1. Data

The empirical data consists of the daily returns of KOSPI 200 eight sector indices; Construction & Machinery (CM), Shipbuilding & Transportation (ST), Steel & Materials (SM), Energy & Chemicals (EC), IT (IT), Financial (FI), Consumer Staples (CS) and Consumer Discretionary (CD), covered from 2nd January 2008 to 30th December 2013 with 1,495 observations. The KOSPI 200 sector indices are issued by Korea Stock Exchange (KRX) from 2nd January 2008, which are obtained from the following website *http://www.krx.co.kr*. The reference date of each index is 2nd January 2008, and reference value is 1,000.

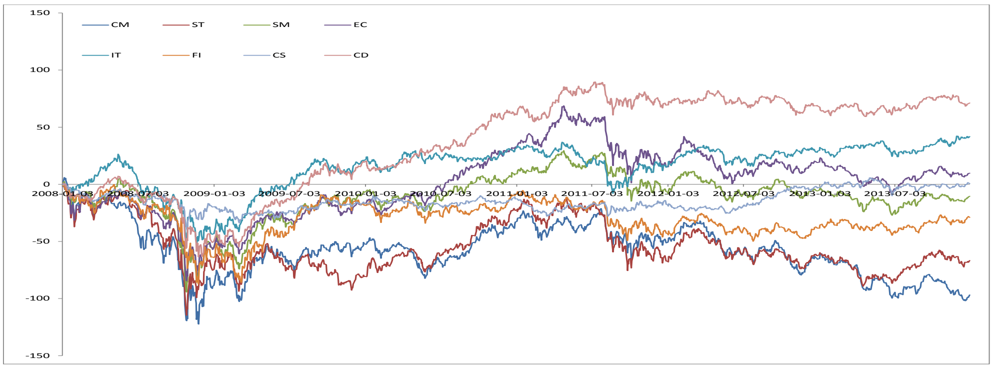
The continuous compound rate of sector return is calculated as

$$r_{i,t} = 100 \times \ln\frac{p_{i,t}}{p_{i,t-1}}, \tag{3.1}$$

where $p_{i,t}$ denotes the ith sector index at time t, for $i = 1, \ldots, d$.



(a) Sector indices



(b) Cumulative returns of sector indices

Figure 1: *Plot of sector indices*

Figure 1 depicts the time series plots of eight sector indices and cumulative returns. In panel (a), each index shows clear decreasing patterns during 2008, and then following increasing patterns from January of 2009 to the second quarter of 2011, except for CS sector which seems to remain almost same level around 870. We observe a downside spikes in August 2011, especially EC, CM, CD are evident. After this spike, EC, CM and CD sectors show relatively volatile dynamics until at the end of 2013; however, other indices are less volatile. As many studies point out, we observe the simultaneous break-down during GFC and EDC periods.

Specifically, the average degrees of minimum, mean and maximum of eight sector indices are 453.46, 935.37 and 1428.58, respectively. Specifically, the minimum values of index are ordered as CS (668.05), IT (581.85), CD (528.94), EC (429.5), FI (418.12), SM (389.36), ST (317.78) and CM (294.1). The average values of index are ordered as CD (1577.05), IT (1183.97), EC (1052.50), SM (910.63), CD (867.63), FI (744.26), ST (590.33) and CM (576.57). The maximum index values are ordered as CD (2449.21), EC (1988.06), IT (1525.68), SM (1343.08), CM (1061.13), CS (1058.81), ST (1002.67) and FI (1000). It is noticeable that the maximum degree of ST, FI, CS and CM sectors are almost same as its reference level, 1000, which indicates these four sectors show underperforms during last six years. In panel (b), the cumulative returns of each index are illustrated. Except for IT sector at the beginning of 2008, each return shows negative during GFC period and reaches its

Table 1: Summary statistics of sector indices returns

	CM	ST	SM	EC	IT	FI	CS	CD
Mean	−0.0640	−0.0441	−0.0072	0.0071	0.0276	−0.0183	0.0010	0.0488
SD	2.5131	2.4136	2.0368	2.0992	1.8239	2.0821	1.0479	1.7744
Skewness	−0.4171	−0.3517	−0.5070	−0.4071	−0.3060	−0.3395	−0.1210	−0.3364
Kurtosis	8.6867	7.5922	10.2603	8.6435	10.3585	9.3806	8.6405	8.4477
JB	2040.0***	1332.5***	3319.7***	2007.7***	3367.8***	2542.9***	1968.1***	1860.5***
LB(10)	18.48**	24.48***	23.68***	14.49	12.37	18.80**	50.10***	5.48
LB2(10)	1533.5***	1011.4***	1639.5***	1063.1***	703.2***	708.7***	627.5***	1029.9***

Note: SD denotes standard deviation. JB and LB(10) stand for the Jarque-Bera and Ljung-Box Q statistic with order = 10, respectively. The former is for the normality test and the latter is for the autocorrelation test. The LB2 is Ljung-Box statistic using squared returns to examine autocorrelation in second order (variance). The *** denotes the statistically significant at 1% significance level. In each column, we abbreviate Construction & Machinery (CM), Shipbuilding & Transportation (ST), Steel & Materials (SM), Energy & Chemicals (EC), IT (IT), Financial (FI), Consumer Staples (CS) and Consumer Discretionary (CD).

lowest level at the end of October or November 2008. After GFC, the cumulative return of each index shows clear increasing pattern, lasting almost 30 months until the middle of 2011. Especially, EC, SM and CD reach its highest level on April or July of 2011. Generally speaking, CD, IT and EC sectors show relatively better performance, whereas CM, ST and FI sectors keep negative returns during full-sample period. Specifically, the average cumulative returns are ordered as CD (37%), IT (15%), EC (1%), SM (−11%), CS (−15%), FI (−31%), ST (−55%) and CM (−58%). In summary, CD, IT and EC sectors outperform, whereas SM, CS, FI, ST and CM sectors underperform during last six years.

Table 1 provides the summary statistics of sector indices returns. The average of each mean return is −0.0061, and that of standard deviation is 1.9739. The CD has the highest mean (0.0488) and CM has the lowest mean (−0.0640). In terms of standard deviation, the CM has the highest standard deviation (2.5131), which is beyond double compared to that of the lowest, CS (1.0479). As is typical for many indices returns, we can see negative skewness and strong excess kurtosis, implicating non-normality. The Jarque-Bera (JB) normality test confirms the non-normality of each return series at the 1% significance level. In addition, we test the presence of autocorrelation in return and squared return using Ljung-Box statistics. The null hypotheses of no autocorrelation are rejected in all cases of squared return series at the 1% significance level, which implicates the strong ARCH effect. However, test results on autocorrelation in return are not unanimous. Specifically, there is significant autocorrelation in case of ST, SM and CS (1% level), CM and FI (1% level), whereas EC, IT and CD sectors are statistically insignificant.

Table 2 provides the static (or unconditional) pair-wise correlations between sectors. We confirm a strong correlation between all pairs of eight sector returns, whose average degree is 0.65. The highest (lowest) correlation is 0.80 (0.45) between CM and ST (EC and CS). In general, CM (CS) has relatively high (low) correlation, average value of each correlation is 0.70 (0.50). Focused on the Financial Sector, the highest correlation is 0.72 (between CM), the lowest correlation is 0.62 (between EC), and the average correlation between Financial and other sectors is about 0.65.

3.2. GARCH results

The conditional volatility of individual return is modeled employing one of GARCH families. As Cappiello *et al.* (2006) showed, the univariate models have to be properly specified in order to estimate the conditional correlations consistently. After having estimated the conditional variances, we fit the pairwise DCC models on standardized residuals. We consider the following models: standard GARCH(1, 1) of Bollerslev (1986), Absolute Value GARCH (AVGARCH) model of Taylor (1986),

Table 2: Static correlation coefficients

	CM	ST	SM	EC	IT	FI	CS	CD
CM	1							
ST	0.7994	1						
SM	0.7664	0.7682	1					
EC	0.7739	0.7845	0.7972	1				
IT	0.6696	0.6738	0.6877	0.7002	1			
FI	0.7168	0.6518	0.6513	0.6174	0.6351	1		
CS	0.4803	0.4774	0.5271	0.4518	0.5040	0.5742	1	
CD	0.6764	0.6535	0.6718	0.7086	0.7317	0.6241	0.4720	1

Note: All pair-wise correlations are statistically significant at the 1% significance level.

Table 3: Univariate GARCH(1, 1) models

Model	Formula
GARCH	$\sigma_t^2 = w + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$
AVGARCH	$\sigma_t^2 = w + \alpha_1\lvert\varepsilon_{t-1}\rvert + \beta_1\sigma_{t-1}^2$
EGARCH	$\ln\left(\sigma_t^2\right) = w + (\alpha_1\varepsilon_{t-1} + \gamma(\lvert\varepsilon_{t-1}\rvert - E\lvert\varepsilon_{t-1}\rvert)) + \beta_1 \ln\left(\sigma_{t-1}^2\right)$
GJR-GARCH	$\sigma_t^2 = w + \alpha_1 (\lvert\varepsilon_{t-1}\rvert - \gamma\varepsilon_{t-1})^2 + \beta_1\sigma_{t-1}^2$
TGARCH	$\sigma_t = w + \alpha_1 (\lvert\varepsilon_{t-1}\rvert - \gamma\varepsilon_{t-1}) + \beta_1\sigma_{t-1}$
APGARCH	$\sigma_t^\delta = w + \alpha_1 (\lvert\varepsilon_{t-1}\rvert - \gamma\varepsilon_{t-1})^\delta + \beta_1\sigma_{t-1}^2$

Note: In terms of APARCH model, the GARCH is a special case of APARCH model when $\gamma = 0$ and $\delta = 2$, AVGARACH is $\gamma = 0$ and $\delta = 1$, and GJR-GARCH is $\delta = 2$, and TGARCH is an APARCH model when $\delta = 1$.

Table 4: BIC of various GARCH models

	CM	ST	SM	EC	IT	FI	CS	CD
GARCH	4.2906	4.3041	3.9110	3.9296	3.7431	3.9364	2.7600	3.7465
AVGARCH	4.3049	4.3159	3.9131	3.9397	3.7496	3.9343	2.7672	3.7554
EGARCH	4.2683	4.2834	**3.8908**	3.9157	3.7261	3.9101	2.7548	3.7449
GJR-GARCH	**4.2631**	**4.2830**	3.8926	**3.9134**	**3.7221**	3.9108	**2.7500**	**3.7392**
TGARCH	4.2685	4.2842	3.8917	3.9180	3.7280	**3.9085**	2.7550	3.7451
APARCH	4.2678	4.2868	3.8955	3.9183	3.7270	3.9125	2.7547	3.7441

Exponential GARCH (EGARCH) of Nelson (1991), GJR-GARCH model of Glosten *et al.* (1993), Threshold GARCH (TGARCH) model of Zakoian (1994) and Asymmetric Power ARCH (APARCH) model of Ding *et al.* (1993). Table 3 shows the conditional variance specifications of various GARCH models considered in this paper.

The best model is chosen based on Bayesian information criterion (BIC). The parameter estimation is conducted by using *rugarch* package, which is available in R. The BIC of various GARCH models is presented in Table 4, and the best model for each return is underlined with bold style. The GJR-GARCH(1, 1) is chosen as the best model based on BIC for modeling conditional variance of each sector return, except for two cases; SM (EGARCH, TGRACH and GJR-GARCH ordered by BIC) and FI (TGARCH, EGARCH and GJR-GARCH). Even GJR-GARCH model is not best candidate in all cases, it is suitable to describe the time-varying volatility of each sector return allowing to asymmetric effect in time-varying volatility dynamics.

The GJR-GARCH(1, 1) estimation results are given in Table 5. We find that there is a strong persistence in time-varying volatility dynamics, since the sum of and is close to unity. In addition, we note that there is strong asymmetric (leverage) effect in each return, especially in cases of Finance, IT and CD sectors. The CM and ST sectors show relatively moderate leverage effects, which are significant at 10% significance levels. The SM and CS sectors have no significant leverage effects

Table 5: GJR-GARCH(1, 1) estimation results

	CM	ST	SM	EC	IT	FI	CS	CD
w	0.0941***	0.0680***	0.0435***	0.0555***	0.0234**	0.0219***	0.0276***	0.0546**
	(0.0258)	(0.0215)	(0.0182)	(0.0187)	(0.0092)	(0.0065)	(0.0112)	(0.0250)
α_1	0.0453**	0.0368**	0.0299	0.0554***	0.0218***	0.0211***	0.0345*	0.0489***
	(0.0199)	(0.0185)	(0.0310)	(0.0137)	(0.0044)	(0.0032)	(0.0199)	(0.0110)
β_1	0.9092***	0.9321***	0.9338***	0.9125***	0.9473***	0.9522***	0.9211***	0.9221***
	(0.0127)	(0.0149)	(0.0128)	(0.0101)	(0.0101)	(0.0057)	(0.0217)	(0.0183)
γ_1	0.7124*	0.6408*	0.8219	0.4825**	0.9999***	0.9999***	0.6422	0.3956***
	(0.3739)	(0.3452)	(0.9241)	(0.1634)	(0.0002)	(0.0002)	(0.4439)	(0.1465)

Note: Standard errors reported in parentheses. ***, ** and * denote the statistically significant at 1%, 5% and 10% significance levels, respectively.

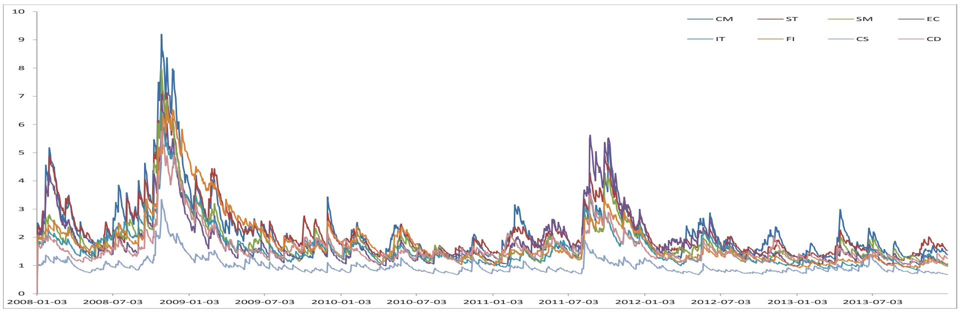


Figure 2: *Volatility plots of sector indices returns (Note: The conditional volatility is obtained from the GJR-GARCH(1, 1) model.)*

based on GJR-GARCH model, however the SM sector shows significant leverage effect if EGARCH model is applied. Therefore, we conclude that there is a significant asymmetric effect in each sector return.

The plot of time-varying volatility of each sector return is presented in Figure 2 employing GJR-GARCH(1, 1) model. The volatility of each return shows similar pattern during our sample period, whereas the absolute magnitudes of volatility are quite different. The volatility of each return reaches its highest level at the end of October 2008, when is the middle of GFC. Precisely, the maximum of all sectors occurs on 27th or 28th October 2008, except for Financial sector, which occurs on 7th, November 2008. The maximum degrees of each volatility are CM (9.20%), SM (7.98%), ST (7.59%), EC (7.07%), FI (6.53%), IT (6.46%), CD (5.76%) and CS (3.34%). After GFC period, the volatility of each return decreases and seems to be stabilized. There is another sharp increase in third quarter of 2011, which is clearly related to EDC. The average degree of each time-varying volatility is 1.77%, specifically CM (2.20%), ST(2.19%), FI (1.86%), EC (1.85%), SM (1.81%), IT (1.61%), CD (1.63%) and CS (0.98%). In summary, the volatility of CM and ST sector shows relatively higher than other sectors, and FI, EC and SM are the second highest sectors. The CS sector has the lowest volatility. It is noticeable that these results are consistent with standard deviation given in Table 1.

3.3. Correlation dynamics

Table 6 provides the estimation results of DCC(1, 1) and ADCC(1, 1, 1) models with multivariate normal and multivariate t distributions, which are obtained by using rmgarch package in R. It is clearly that the correlation dynamic is quite persistent, since is close to unity regardless of model

Table 6: DCC(1, 1) and ADCC(1, 1, 1) estimation results

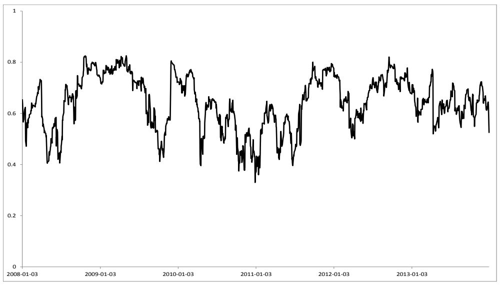
Model		FI-CM	FI-ST	FI-SM	FI-EC	FI-IT	FI-CS	FI-CD
DCC	a_1	0.0274***	0.0489***	0.0405***	0.0561***	0.0401***	0.0663***	0.0653***
		(0.008)	(0.013)	(0.012)	(0.018)	(0.013)	(0.012)	(0.015)
	b_1	0.9605***	0.9428***	0.9499***	0.9306***	0.9265***	0.8860***	0.9016***
		(0.011)	(0.017)	(0.017)	(0.025)	(0.030)	(0.020)	(0.026)
	BIC	7.625	7.732	7.341	7.377	7.224	6.318	7.278
DCC-t	a_1	0.0356***	0.0474***	0.0509***	0.0695***	0.0417***	0.0674***	0.0582***
		(0.009)	(0.010)	(0.011)	(0.019)	(0.013)	(0.012)	(0.012)
	b_1	0.9509***	0.9448***	0.9344***	0.9103***	0.9290***	0.8825***	0.9174***
		(0.014)	(0.012)	(0.016)	(0.027)	(0.029)	(0.021)	(0.020)
	ν	8.7710***	8.7344***	8.2536***	8.8385***	10.2405***	9.2627***	8.7977***
		(1.079)	(1.086)	(0.955)	(1.102)	(1.456)	(1.188)	(1.085)
	BIC	**7.576**	**7.681**	**7.284**	**7.332**	**7.192**	**6.274**	**7.235**
ADCC	a_1	0.0247***	0.0442***	0.0366***	0.0480***	0.0367***	0.0635***	0.0627***
		(0.007)	(0.013)	(0.009)	(0.013)	(0.014)	(0.016)	(0.020)
	b_1	0.9600***	0.9420***	0.9491***	0.9311***	0.9277***	0.8872***	0.9027***
		(0.012)	(0.018)	(0.018)	(0.022)	(0.029)	(0.021)	(0.028)
	g_1	0.0086	0.0126	0.0129	0.0242	0.0076	0.0064	0.0050
		(0.104)	(0.017)	(0.017)	(0.019)	(0.017)	(0.023)	(0.023)
	BIC	7.629	7.737	7.345	7.380	7.228	6.323	7.282
ADCC-t	a_1	0.0311***	0.0386***	0.0423***	0.0537***	0.0373***	0.0600***	0.0497***
		(0.008)	(0.009)	(0.009)	(0.014)	(0.014)	(0.016)	(0.015)
	b_1	0.9488***	0.9441***	0.9334***	0.9151***	0.9304***	0.8859***	0.9210***
		(0.015)	(0.015)	(0.015)	(0.021)	(0.028)	(0.021)	(0.020)
	g_1	0.0161	0.0234	0.0274	0.0408**	0.0099	0.0168	0.0167
		(0.014)	(0.015)	(0.019)	(0.020)	(0.016)	(0.023)	(0.019)
	ν	8.9441***	8.9102***	8.4575***	9.1101***	10.3669***	9.3354***	8.8586***
		(1.117)	(1.115)	(1.024)	(1.161)	(1.530)	(1.184)	(1.100)
	BIC	7.580	7.684	7.287	7.333	7.198	6.278	7.239

Note: Robust standard errors reported in parentheses. The *** and ** denote the statistical significance at 1% and 5% significance levels, respectively.

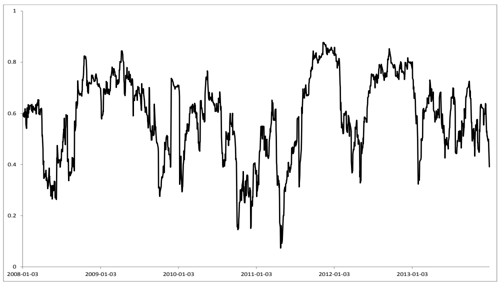
specifications. In each pair, the dynamic conditional correlation model with t distribution shows the best fitting. The parameter estimate of multivariate t distribution, known as degree of freedom in literature and denoted by in Table 6, is below 10 in both DCC and ADCC models. This result indicates there is strong tail dependence between sectors, which possibly leads the simultaneous break-down of stock market. The parameter controls tail dependence between variables, the smaller indicates the stronger tail dependence. It is regarded there is strong tail dependence when is less than 20 in literature.

It is noticeable that there are little asymmetric effects in the correlation dynamics between the sectors, except for the pair of FI and EC. Our findings are consistent with Gjika and Horváth (2013), who point out that the asymmetries in the conditional correlations are not as widespread as in the conditional variances, in general. They analyze four stock indices of the Czech Republic, Hungary, Poland and the euro area (STOXX50), and find that the asymmetric effect in the conditional correlation is present only for the Hungary-Poland pair.

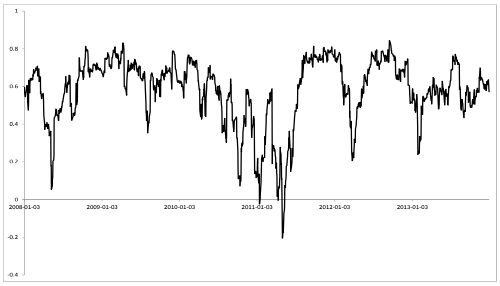
Figure 3 illustrates the time varying conditional correlation between Financials and other seven sectors, employing DCC with t distribution model. The minimum of dynamic correlation are 0.33 (FI-CM), 0.07 (FI-ST), −0.20 (FI-SM), −0.39 (FI-EC), 0.19 (FI-IT), −0.07 (FI-CS) and −0.24 (FI-CD). The average degrees of dynamic correlation are 0.64 (FI-CM), 0.59 (FI-ST), 0.58 (FI-SM), 0.55 (FI-EC), 0.57 (FI-IT), 0.51 (FI-CS) and 0.51 (FI-CD). Whereas, the maximum of dynamic correlation show similar, ranged from 0.83 to 0.88.



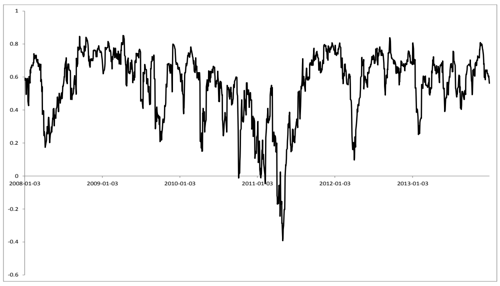
(a) FI-CM



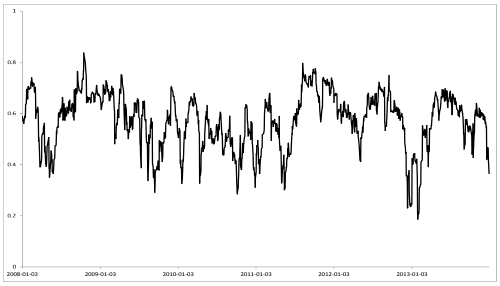
(b) FI-ST



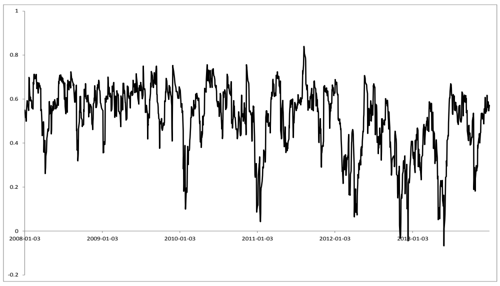
(c) FI-SM



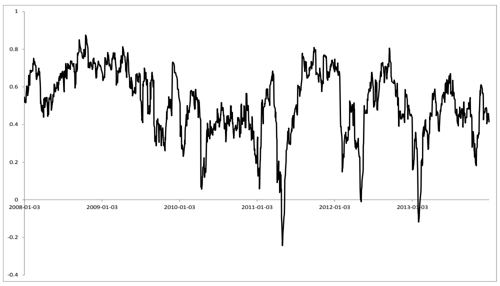
(d) FI-EC



(e) FI-IT



(f) FI-CS



(g) FI-CD

Figure 3: *The dynamics of conditional correlations (Note: The dynamic conditional correlations are obtained from the DCC*$(1,1)$ *with t distribution model.)*

Now we discuss the pair-wise correlation dynamic focused on the Financial Sector. At first, the correlation between FI and CM shows positive correlation during full-sample period with minimum 0.33 (29th December 2010), average 0.64 and maximum 0.83 (4th May 2009). The correlation is increasing in the middle of 2008, lasting this higher level almost 18 months, affected by GFC shock. Other periods with higher correlation are observed in the early of 2010 (lasting 2 months), and the late of 2011 (lasting 6 months). These second higher correlation period is possibly caused by EDC. As we know, Korean Financial Sector suffers from default of Project Finance in Construction sector, thus the correlation between FI and CM is strongly positive and has the highest degree than any other pairs.

The correlation dynamics between FI and ST shows positive correlation during full-sample period with minimum 0.07 (26th April 2011), average 0.59 and maximum 0.88 (11th November 2011), and reaches its level at the end of 2008 and 2012 and in the middle of 2013. There is clear decreasing period in the middle of 2009. The Shipping industry is one of the most affected sectors suffering from global economic downturn triggered by GFC in 2008. Thus, it seems natural that the correlation between FI and ST is strong and positive during last six years.

The correlation between FI and SM has minimum −0.20 (2nd May 2011), average 0.58 and maximum 0.84 (17th September 2012). The correlation between them shows sharp increase in April 2008, and then keeps this degree until April 2010, almost lasting two years. Another high increase is observed in the mid of 2011, lasting this higher level almost eight months. The former increase is related to GFC and the latter results from EDC. It is noticeable that there is a usual negative spike on 2nd May 2011.The overall dynamics between FI and EC also seems similar to that of FI and SM, which has minimum −0.39 (2nd May 2011), average 0.55 and maximum 0.85 (10th April 2009).

The correlation dynamics between FI and IT shows positive correlation during full-sample period with minimum 0.19 (30th January 2013), average 0.57 and maximum 0.84 (17th October 2008). The dynamics of these two sectors seem quite volatile, *i.e.* continuously repeating up and down with some spikes.

The correlation dynamics between Financials and Consumer Stationary is also remarkable. The minimum correlation is −0.07 (30th May 2013), average 0.51 and maximum 0.84 (10th August 2011). The dynamics seems to keep its mean level 0.5 during sample period with irregular downward spikes, observed in January 2010 and 2011, April and December 2012, and May 2013. The correlation dynamics between Finance and Consumer Discretionary has the minimum correlation is −0.24 (2nd May 2011), average 0.51 and maximum 0.84 (17th August 2008), and also shows several decreasing spikes in the April of 2011 and 2012. Whereas, there are five increasing periods, observed in the early of 2008 and 2013, in the middle of 2008, 2011 and 2012. Unlike CM and SM sectors, CS and CD sectors seem less correlated with Financial Sector, since these sectors are closely related to living materials, thus they show relatively little correlation with Financial Sector.

To summarize, the stock market correlations increased during GFC and EDC periods. The correlations of FI-CM and FI-SM have the highest strength, whereas those between FI-CD and FI-CS are relatively lower degree. These results are consistent with unconditional correlations given in Table 2, and also coincide with our prior knowledge based on Korean economic outlook.

Next, we examine how much the correlation between sectors are changed in relation to market turmoil, by regressing the conditional correlations on a constant and a dummy variable for each GFC and EDC period. At first, to quantify the impact of GFC, we generate two dummy variables, one is for short-run and the other is for long-run perspective. The short-run GFC dummy takes a value of one from 30th December 2008 onwards (247 observations), zero from 4th January 2010 to 30th December 2009 (253 observations). In addition, the long-run GFC dummy takes one from 30th December 2008

Table 7: Regression Results

Dummy Variables		FI-CM	FI-ST	FI-SM	FI-EC	FI-IT	FI-CS	FI-CD
Short-run GFC	c	0.6891***	0.6332***	0.6731***	0.6298***	0.5757***	0.6029***	0.5970***
	ϕ_{SR-GFC}	−0.0498***	−0.0765***	−0.0986***	−0.0368***	0.0323***	−0.0192**	0.0659***
Long-run GFC	c	0.6406***	0.5775***	0.5908***	0.5474***	0.5647***	0.5010***	0.4852***
	ϕ_{LR-GFC}	−0.0012	−0.0030	−0.0341***	0.0456***	0.0432***	0.0826***	0.1777***
EDC	c	0.6609***	0.6284***	0.6065***	0.6126***	0.5721***	0.4125***	0.4614***
	ϕ_{EDC}	−0.0651***	−0.0964***	−0.1062***	−0.1716***	−0.0203***	0.1247***	−0.0093***

Note: The *** and ** denote the statistical significance at 1% and 5% significance levels, respectively.

onwards (247 observations), zero from 4th January 2010 to 30th December 2013 (1247 observations). Similarly, we introduce dummy variable for EDC, which takes one from the 4th January 2010 to 29th December 2011 (499 observations), zero from 2nd January 2012 to 30th December 2013(495 observations).

Table 7 presents our regression results. Firstly, we discuss GFC impact in short-run sense. The slope coefficients, denoted by in Table 7, of FI-IT (0.0323) and FI-CD (0.5970) are positive and statistically significant at 1% level, which indicates that the correlations of these pairs are relatively higher during GFC period compared to those of Post-GFC. On contrary, all remaining pairs show negative slope coefficients and significant at 1% level, which means that the correlations are increased after GFC. The magnitude by which correlations are decreased varies between −0.02 and −0.10 during GFC period. Our regression results provide interesting insight on the impact of GFC on return volatility and correlation. As we see in the Figure 2, the volatility of each sector return show a huge spike due to GFC shock, which leads to significantly high volatility level during GFC. However, the correlation dynamics shows too complicated to decide whether the correlation is increased or not because of GFC shock.

Moving to long-run perspective, the slope coefficients (in Table 7), except for three pairs (FI-CM, FI-ST and FI-SM), are positive and statistically significant at 1% level indicating that the sector correlations have remained at high levels during GFC period. The magnitude of correlation increasing varies between 0.05 and 0.18. The two pairs (FI-CM and FI-ST) with negative slope coefficient are statistically insignificant, and furthermore, these two pairs have the strongest correlation with Financials during whole sample period, so GFC seems less effect on these pairs. The FI-SM has negative slope coefficient with statistically significant at 1% level, which may result from the huge downside spike in May 2008, see Figure 3 panel (c).

Now we discuss the impact from EDC on correlation strength. Except for FI-CS, all pairs have negative slope coefficients (in Table 7) with statistically significance at 1% level. The magnitude by which correlations are increased varies between −0.03 and −0.17. We argue that this insignificance partly result from the huge downward spikes in the correlation dynamics during EDC period. The only pair with positive with significance is FI-CS, which may relate to trading volume of CS sector between Korean and Euro economy.

To conclude, regression results confirm that sector correlations significantly increased during GFC period. Especially, we note that two pairs of FI-IT and FI-CD show significant increase in correlation strength due to GFC both short- and long-run senses. In addition, we find that EDC seems not to be a critical shock to increase correlation magnitude between sectors in Korean market.

4. Conclusion

This paper examines the dynamics of return co-movements between industrial sectors in Korean stock market by employing four Dynamic Conditional Correlation (DCC) models allowing for asymmetry and tail region dependence in correlation dynamics. Focused on Financial Sector, we analyze the characteristics on the time-varying correlation between eight sector indices; Constructions & Machinery, Shipbuilding & Transportation, Steels & Materials, Energy & Chemicals, IT, Financials, Consumer Staples and Consumer Discretionary, covered from 2nd January 2008 to 30th December 2013 with 1,495 observations.

Empirical results show that stock market correlations significantly increased over time, especially during GFC period. In terms of model fitting, the dynamic conditional correlation model with t distribution shows the best alternative to describe dynamic correlation of KOSPI 200 sector returns. We also note there are little asymmetric effects in the correlation dynamics between the sectors, whereas there are strong asymmetric effects in the volatility dynamics of each sector return. Our findings are consistent with Gjika and Horváth (2013), who point out that the asymmetries in the conditional correlations are not as widespread as in the conditional variances, in general. In addition, Financial Sector show the highest correlation between Constructions & Machinery sector, whereas Consumer Discretionary and Consumer Staples sectors have relatively lower correlation between Financial Sector.

References

Bauwens, L., Laurent, S. and Rombouts, J. V. K. (2006). Multivariate GARCH models: A survey, *Journal of Applied Econometrics*, **21**, 79–109.

Bollerslev, T. (1986). Generalized autoregressive conditional Heteroskedasticity, *Journal of Econometrics*, **31**, 307–327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model, *Review of Economics and Statistics*, **72**, 498–505.

Bollerslev, T., Engle, R. F. and Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances, *The Journal of Political Economy*, **96**, 116–131.

Cappiello, L., Engle, R. F. and Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns, *Journal of Financial Econometrics*, **4**, 537–572.

Ding, Z. C., Granger, W. J. and Engle, R. F. (1993). A long memory property of stock market returns and a new model, *Journal of Empirical Finance*, **1**, 83–106.

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate GARCH models, *Journal of Business and Economic Statistics*, **20**, 339–350.

Engle, R. F. and Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH, *Econometric Theory*, **11**, 122–150.

Gjika, D. and Horváth, R. (2013). Stock market comovements in central Europe: Evidence from the Asymmetric DCC Model, *Economic Modelling*, **33**, 55–64.

Glosten, L. R., Jagannathan, R. and Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance*, **48**, 1779–1801.

Nelson, D. B. (1991). Conditional Heteroskedasticity in asset returns: A new approach, *Econometrica*, **59**, 347–370.

Silvennoinen, A. and Teräsvirta, T. (2009). *Multivariate GARCH Models, Handbook of Financial Time Series*, Springer, New York, 201–229.

Taylor, S. J. (1986). *Modelling Financial Time Series*, John Wiley & Sons, New York.

Zakoian, J.-M. (1994). Threshold Heteroskedastic models, *Journal of Economic Dynamics and Control*, **18**, 931–955.

Received May 21, 2014; Revised June 27, 2014; Accepted June 30, 2014