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Information Transmission between Large and Small Stocks in the Korean Stock Market

Sang Hoon Kang, Seong-Min Yoon

***Abstract*—**Little attention has been paid to information transmission between the portfolios of large stocks and small stocks in the Korean stock market. This study investigates the return and volatility transmission mechanisms between large and small stocks in the Korea Exchange (KRX). This study also explores whether bad news in the large stock market leads to a volatility of the small stock market that is larger than the good news volatility of the large stock market. By employing the Granger causality test, we found unidirectional return transmissions from the large stocks to medium and small stocks. This evidence indicates that pat information about the large stocks has a better ability to predict the returns of the medium and small stocks in the Korean stock market. Moreover, by using the asymmetric GARCH-BEKK model, we observed the unidirectional relationship of asymmetric volatility transmission from large stocks to the medium and small stocks. This finding suggests that volatility in the medium and small stocks following a negative shock in the large stocks is larger than that following a positive shock in the large stocks.

***Keywords*—**Asymmetric GARCH-BEKK model, Asymmetric volatility transmission, Causality, Korean stock market, Spillover effect

I. Introduction

INFORMATION transmission mechanisms of returns and volatility between large and small stocks have drawn the attention of academics and practitioners because they both play crucial roles in arbitrage trading strategies, portfolio management, and risk management. In short, (1) the dynamics of return spillover effects provide returns predictions and an opportunity for an exploitable trading strategy, which represents evidence against market efficiency; (2) the knowledge of return spillover effects may be useful for asset allocation or asset selection; and (3) information about volatility spillover effects may be useful for applications that rely on estimates of conditional volatility, such as option pricing, portfolio optimization, management of value-at-risk, and risk hedging.

Earlier empirical studies have documented the cross-correlation in returns between large and small stocks [1-6]. Moreover, a number of these studies supported asymmetric cross-correlation in returns between large and small stocks, that is, price changes in large stocks tend to lead those of small stocks, but small stocks do not lead large stocks due to transaction costs [7], signal quality [8] and asymmetric trading patterns between large and small stocks [9-10].

Academic interest has also been directed to the investigation of asymmetric volatility spillovers between large and small stocks. In fact, volatility shocks to large stocks have a strong influence on the future volatility of small stocks, but volatility shocks to small stocks have little impact on the future volatility of large stocks. Note that since volatility is often related to the rate of information flow [11], the asymmetry volatility spillover between large and small stocks suggests that the prices of large stocks respond to new information immediately, but that the prices of small stocks delay reaction when news arrives [12]. In contrast to asymmetric volatility spillover, Hasan and Francis [13] argued that symmetric volatility spillover effect is activated both from large stocks to small stocks, and from small stocks to large stocks.

Subsequent studies have investigated transmission mechanisms of returns and volatiles between large and small stocks at the same time. On the one hand, Harris and Pisedtasalasai [14] found that there are significant spillover effects in both returns and volatility from the portfolios of larger stocks to the portfolios of smaller stocks in the UK. This finding implies that market-wide information is first incorporated into the prices of large stocks before being impounded into the prices of small stocks. Alsubaie and Najand [15] also found that the volatility of small stocks can be predicted by observing the volatility of large stocks in the Saudi stock market.

On the other hand, Pardo and Torró [16] added evidence against the hypothesis of asymmetric volatility spillover from large to small stocks. They found that in the Spanish Stock Exchange, volatility shocks to small stocks are important in predicting the future dynamics of smaller stocks, but the reverse is only true for the negative shocks coming from large stocks. Karmakar [17] investigated how negative volatility shocks are transmitted between the large and small stocks in India. They found a distant asymmetry in the predictability of returns, but also found symmetric volatility spillover between large and small stocks.

As mentioned above, it can be concluded that there is a strong return spillover from the market portfolio of large stocks to the portfolio of small stocks, but the evidence of volatility spillover is mixed with inconclusive results. In this context, the primary aim of this paper was to re-examine the volatility linkages among the market portfolios of differently size stocks in Korea using a Granger-causality test and a bivariate GARCH model.

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The main contribution of this paper is twofold. First, this study investigates the return and volatility transmission mechanisms between large and small stocks in the Korea Exchange (KRX) using data from daily Korea Composite Stock Price Index (KOSPI) large-cap, medium-cap and small-cap stocks. Scant attention has been paid to information transmission between the portfolio of large stocks and that of small stocks in the Korean stock market. The causality of information transmission might provide price predictability between large and small stocks and improve a new hedging strategy for portfolio management in the Korean stock market.

Second, this study also examines how asymmetric volatility responds to news in cross markets using an asymmetric bivariate GARCH model. In particular, we explore whether bad news in the large stock market leads to larger volatility of the small stock market than does good news volatility of the large stock market. A good understanding of the asymmetric volatility response to news is an important ingredient for designing trading and hedging strategies and optimizing portfolios.

The rest of this paper is organized as follows. Section 2 presents the econometric methodology. Section 3 provides descriptive statistics of the sample data. Section 4 discusses the empirical results. Section 5 presents our conclusions.

II. Methodology

A. Cointegration Test And Granger Causality Test

Cointegration is an econometric property of time series variables. If two or more time series are themselves non-stationary, but their linear combination is stationary, then the series are said to be co-integrated. In practice, cointegration is a means for correctly testing those hypotheses concerning the relationship between two series with unit roots. In the literature, the Johansen cointegration test [18] is the most popular approach for testing cointegration. The cointegration test is based on the maximum likelihood estimators of a vector autoregressive (VAR) process.The likelihood ratio-test statistic for the hypothesis of the at most r co-integrated relationship and the at least $m = n - r$ common trend is given by:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \tag{1}$$

$$\lambda_{\max} = -T \ln\left(1 - \hat{\lambda}_{r+1}\right) \tag{2}$$

where is the trace statistic, is the eigen-max statistic, denotes the smallest estimated eigen-values, and is the sample size. The null hypothesis tested in is no cointegration. In fact, for bivariate cointegration tests, up to two null hypotheses can be tested. If the null that is rejected, at least one cointegrating vector may exist, and the second hypothesis that is subsequently tested.

The Granger (1969) causality test is often used to check the statistical causation among financial markets. The following bivariate regressions are used to test for causality between the two time series data:

$$x_t = a_0 + a_1 x_{t-1} + \cdots + a_k x_{t-k} + b_1 y_{t-1} + \cdots + b_n y_{t-n} + \varepsilon_{xt}, \tag{3}$$

$$y_t = a'_0 + a'_1 y_{t-1} + \cdots + a'_n y_{t-n} + b'_1 x_{t-1} + \cdots + b'_k x_{t-k} + \varepsilon_{yt}, \tag{4}$$

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The null hypothesis (does not strictly Granger-cause) is rejected if the coefficients on the lag values of in Equation (3) are jointly significantly different from zero, i.e., . Bi-directional causality exists if the null hypothesis, that does not strictly Granger-cause , is also rejected.

B. Bivariate GARCH Model

Much attention has focused on how news from one market affects the volatility process of another market. In this study, we analyze the volatility spillover effects between three KOSPI size sub-indices by using a bivariate framework of the BEKK parameterization [19]. In this model, the variance-covariance matrix of equations depends on the squares and cross products of innovation ε_t, which is derived from the following mean equation:

$$R_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t), \tag{5}$$

where is the vector of returns at time for each market.The vector of random errors,represents the innovation for each market at time with its corresponding conditional variance-covariance matrix.The market information available at time is represented by.

This bivariate structure thus facilitates the measurement of the effects of innovations in the mean returns of one market on its own lagged returns and those of the lagged returns of the other market. The standard BEKK parameterization for the bivariate GARCH model is written as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \quad (6)$$

where H_t is a 2×2 matrix of conditional variance-covariance at time t, and C is a 2×2 lower triangular matrix with three parameters. A is a 2×2 square matrix of coefficients and measures the extent to which conditional variances are correlated past squared errors. B is a 2×2 squared matrix of coefficients and shows the extent to which current levels of conditional variances are related to past conditional variances.

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

where the parameters of Equation (7) reveal how market shocks and volatility are transmitted over time.The off-diagonal elements of matrices and capture cross-market effects, such as shock spillover (and) and volatility spillover (and).

The standard BEKK model implies that only the magnitude of past return innovations is important in determining current conditional variances and covariances. However, it has been well observed that volatility responds asymmetrically to positive and negative innovations of equal magnitude, i.e., volatility tends to rise more in response to negative shocks (bad news) than to positive shocks (good news) [20-22].

To circumvent this problem, Kroner and Ng [20] extended the GJR-GARCH approach of Glosten, Jagannathan and Runkle [21] to a multivariate setting capturing the asymmetric response to news on volatility. The asymmetric GARCH-BEKK model is written as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\eta_{t-1}\eta'D, \quad (8)$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \begin{bmatrix} \eta_{1,t-1}^2 & \eta_{1,t-1}\eta_{2,t-1} \\ \eta_{2,t-1}\eta_{1,t-1} & \eta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}, \quad (9)$$

where $\eta_{t-1} = \begin{bmatrix} \max\left(0, -\varepsilon_{1,t-1}\right) \\ \max\left(0, -\varepsilon_{2,t-1}\right) \end{bmatrix}$, D is a 2×2 squared matrix of parameters and captures any asymmetry in variances and covariance through the definition of.If the off-diagonal coefficient is positive and significant, the bad news volatility of the large stock market (small stock market) causes a larger volatility of the small stock market (large stock market) than does the good news volatility of the large stock market (small stock market).

The parameters of the bivariate GARCH model can be estimated by the maximum likelihood estimation method optimized with the Berndt, Hall, Hall and Hausman (BHHH) algorithm. The conditional log likelihood function $L(\theta)$ is expressed as:

$$L(\theta) = -T\log 2\pi - 0.5\sum_{t=1}^{T}\log\left|H_t(\theta)\right| - 0.5\sum_{t=1}^{T}\varepsilon_t(\theta)' H_t^{-1}\varepsilon_t(\theta), \quad (10)$$

where T is number of observations and θ denotes the vector of all the unknown parameters.

III. Data and Descriptive Statistics

The data series is comprised of three daily market indices of the Korea Exchange (KRX), namely, the KOSPI large-cap, KOSPI medium-cap (hereafter the mid-cap) and KOSPI small-cap. The KRX produces KOSPI subindices by grouping the listed companies into large-cap, mid-cap and small-cap by the size of their market capitalization.[1] The sample period covers from January 2, 2002 to December 30, 2010.[2] Figure 1 shows the identical movement of the three sample index prices.

The return series of the two prices are computed by calculating, where denotes the continuously compounded returns for indices at time , and denotes the closing price of indices at time.The three return series clearly show volatility clustering as presented in Figure 2.

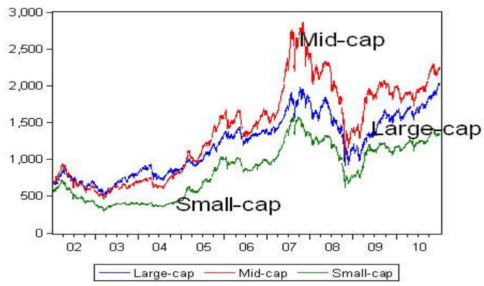

Fig. 1 Daily price indices (January 2, 2002 ~ December 30, 2010)

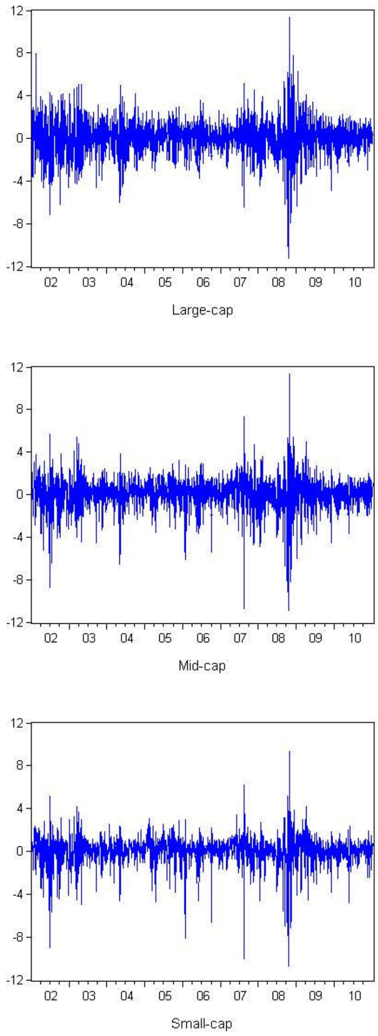

Fig. 2 Daily returns series(January 2, 2002 ~ December 30, 2010)

The highest mean return is observed for the mid-cap followed by the large-cap and the small-cap. But the highest standard deviation is for the large-cap followed by the mid-cap and the small-cap, respectively. The measures of skewness indicate that all return series are negatively skewed. Also, the excess kurtosis measures show that all three return series are leptokurtic. This evidence implies that the distribution of three return series is not normally distributed, which is also supported by the Jarque-Bera normality test.

In addition, we also examine the null hypothesis of a white-noise process for sample returns using the Ljung-Box test statistics of the returns $LB(20)$ and the squared returns $LB^2(20)$, with a lag of 20. The results of the Ljung-Box test rejected the null hypothesis of no serial correlation, indicating that there is strong evidence of serial dependence in the returns and the squared returns. Such a feature (non-normality and serial correlation) allow us to employ a GARCH model.

TABLE I
DESCRIPTIVE STATISTICS OF SAMPLE RETURNS

Statistics	Large-cap	Mid -cap	Small-cap
Mean	0.049	0.054	0.039
Std. dev.	1.646	1.578	1.326
Skewness	-0.379	-0.952	-1.494
Kurtosis	7.452	9.896	12.83
J-B	1899.2*	4763.8*	9830.2*
$LB(20)$	27.57*	72.56*	190.3*
$LB^2(20)$	1556.2*	2040.0*	1073.8*

Notes: The J-B corresponds to the test statistic for the null hypothesis of normality in sample returns distribution. The Ljung-Box statistics, $LB(20)$ and $LB^2(20)$ checks for the serial correlation of the returns and the squared returns up to the 20th order. * indicates the rejection of the null hypothesis at the 1% significance level.

Table II provides the results of ADF and PP unit root tests for the log price series and the return series. The null hypothesis of the ADF and PP tests is that a time series contains a unit root. As shown in Table 2, the calculated values of both the ADF and PP test statistic indicate that the log price series contain a single unit root at the l% significance level, implying that the log prices series are non-stationary. However, in the case of return series, both of these statistics reject the null hypothesis of a unit root at the l% significance level, implying that the return series are stationary in all samples.

TABLE II
UNIT ROOT TEST FOR LOG PRICE AND RETURNS

	Log price			Returns		
	Large	Medium	Small	Large	Medium	Small
ADF [prob.]	-0.941 [0.776]	-0.866 [0.799]	-0.429 [0.902]	-46.85 [0.000]	-42.55 [0.000]	-40.31 [0.000]
PP [prob.]	-0.849 [0.804]	-0.877 [0.796]	-0.487 [0.891]	-47.02 [0.000]	-42.71 [0.000]	-40.61 [0.000]

Note: Mackinnon's (1991) 1% critical value is –3.435 for the ADF and PP tests.

IV. EMPIRICAL RESULTS

A. Co integration Test and Causality Test

Table IV shows the results of the Johansen cointegration test for two pair-wise sets, namely, the large-cap vs. the mid-cap and the large-cap vs. the small-cap. The null hypothesis that two indices are not co integrated $(r = 0)$ against the alternative of one co integrating vector $(r > 0)$ is not rejected because the $\lambda_{trace}(r=0)$ and $\lambda_{max}(r=0)$ statistics do not exceed their critical values at the 5% significant level for each pair-wise sets. Thus, we conclude that there is no evidence of a cointegration relationship between the large-cap and the mid-cap and between the large-cap and the small-cap. In other words, there is no long-run relationship between the three markets.

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TABLE III
JOHANSEN COINTEGRATION TEST

Null hypothesis	Trace statistic	0.05 Critical value	Max-Eigen statistic	0.05 Critical value
Large-cap vs. Mid-cap				
$r=0$	6.503	15.41	5.619	14.07
$r\leq 0$	0.884	3.76	0.884	3.76
Large-cap vs. Small-cap				
$r=0$	8.721	15.41	8.487	14.07
$r\leq 0$	0.234	3.76	0.234	3.76

Notes: A one-sided test of the null hypothesis showed that the variables are not cointegrated. The reported critical values are the Osterwald-Lenum (1992) critical values.

Furthermore, we examine the causality relationship of returns between the three index returns by employing the Granger causality test in Table 4. The optimal lag length is chosen by the Akaike information criterion (AIC). The causality test results between the large-cap and the mid-cap (small-cap) clearly reject the null hypothesis that the large-cap returns do not Granger-cause the mid-cap (small-cap) returns at the 5% significant level, but the reverse causality is insignificant. The results indicate that past information about the large-cap stocks has a better ability to predict the turns of the mid-cap (small-cap) than that of the mid-cap to predict the return of the large-cap. This means that there is a unidirectional returns transmission from the large-cap market and the mid-cap (small-cap) market.

TABLE IV
PAIRWISE GRANGER CAUSALITY TESTS

Null hypothesis	lags	Test values	
		F-value	P-value
Large-cap vs. Mid-cap			
$(Large) \neq> (Medium)$	2	3.136**	0.043
$(Medium) \neq> (Large)$		0.269	0.764
Large-cap vs. Small-cap			
$(Large) \neq> (Small)$	4	4.250**	0.002
$(Small) \neq> (Large)$		1.703	0.147

Notes: The symbol "$\neq>$" means "does not Granger-cause." The optimal lag structure is determined by AIC (Alaike Information Criterion). ** indicates rejection of the null hypothesis at the 5% significance level.

B. Volatility Spillover between the Three Markets

In order to examine the volatility spillover effect, we employ the symmetric and asymmetric GARCH (1,1) models based on the BEKK framework. We first investigate the volatility spillover based on a symmetric BEKK model and then examine the asymmetric volatility based on an asymmetric BEKK model. The estimation results of the symmetric and asymmetric BEKK models are reported in Table 5 and Table 6, respectively.

As mentioned earlier, the diagonal elements in matrix A capture the own past shock effect, while the diagonal elements in matrix B measure the own past volatility effect. From Table 5, the diagonal parameters (a_{11}, a_{22}, b_{11}, b_{22}) are statistically significant, indicating the presence of strong ARCH and GARCH effects, i.e., own past shocks and volatility affects the conditional variance of each pair-wise set. More specifically, past shocks have played a greater role in the volatility of the mid-cap (small-cap) than in the volatility of the large-cap ($a_{22}>a_{11}$), while the past volatility has played a greater role in the present volatility of the large-cap than in the present volatility of the mid-cap (small-cap) ($b_{22}>b_{11}$).

TABLE V
ESTIMATION RESULTS OF THE SYMMETRIC GARCH-BEKK MODEL

	Large-cap vs. Mid-cap		Large-cap vs.Small-cap	
Variable	Coef.	S.E.	Coef.	S.E.
Panel A: Estimation results of symmetric GARCH-BEEK model				
c_{11}	0.141*	(0.036)	0.152*	(0.028)
c_{21}	0.308*	(0.053)	0.194*	(0.064)
c_{22}	-0.185 *	(0.040)	0.271*	(0.037)
a_{11}	0.122*	(0.034)	0.190*	(0.027)
a_{12}	-0.131 *	(0.043)	-0.070*	(0.008)
a_{21}	0.181*	(0.041)	0.152*	(0.040)
a_{22}	0.533*	(0.004)	0.636*	(0.039)
b_{11}	1.023*	(0.015)	0.987*	(0.012)
b_{12}	0.109*	(0.024)	0.079*	(0.016)
b_{21}	-0.084 *	(0.022)	-0.056*	(0.021)
b_{22}	0.779*	(0.036)	0.738*	(0.029)
Panel B: Diagnostic tests				
$LB_1(20)$	26.32 [0.155]		22.52 [0.312]	
$LB_2(20)$	23.23 [0.277]		17.95 [0.590]	
$LB_1^2(20)$	13.56 [0.852]		22.52 [0.956]	
$LB_2^2(20)$	9.503 [0.976]		10.57 [0.957]	
Log-likelihood	-6477.37		-6535.14	

Notes: P-values are in brackets and standard errors are in parenthesis. The $LB_i(20)$ and $LB_i^2(20)$ test statistic checks for the serial correlation of standard residuals and squared standardized residuals. *indicate significance at the 1% level.

The off-diagonal elements of matrices and capture cross-market effects such as shock spillover and volatility spillover effects between the large-cap and the mid-cap and between the large-cap and the small-cap.We find evidence of bidirectional shock spillover effect between the large-cap and the mid-cap (small-cap),because of the significance of the cross market coefficients and. In fact, past shocks in the large-cap have a significant but negative effect on the present volatility for both the mid-cap and small-cap, whereas past shocks in both the mid-cap and small-cap have a positive influence on the present volatility in the large-cap. In addition, we identify a bidirectional volatility spillover effect between the large-cap and the mid-cap (small-cap), because of the significance of cross market coefficients and. These findings indicate that common information leads to market linkage between the three KOSPI sub-indices.

TABLE VI
ESTIMATION RESULTS OF THE ASYMMETRIC GARCH-BEKK MODEL

	Large-cap vs. Mid-cap		Large-cap vs. Small-cap	
Variable	Coef.	S.E.	Coef.	S.E.
Panel A: Estimation results of asymmetric GARCH-BEEK model				
c_{11}	0.089*	(0.031)	0.180*	(0.031)
c_{21}	0.332*	(0.034)	0.110*	(0.056)
c_{22}	0.000	(0.637)	-0.220*	(0.022)
a_{11}	0.012	(0.032)	0.098*	(0.030)
a_{12}	-0.307*	(0.036)	-0.185*	(0.025)
a_{21}	0.256*	(0.032)	0.143*	(0.044)
a_{22}	0.556*	(0.040)	0.652*	(0.036)
b_{11}	1.051*	(0.012)	0.979*	(0.015)
b_{12}	0.146*	(0.021)	0.072*	(0.013)
b_{21}	-0.140*	(0.021)	-0.072*	(0.028)
b_{22}	0.715*	(0.032)	0.714*	(0.022)
d_{11}	0.376*	(0.051)	0.383*	(0.037)
d_{12}	0.393*	(0.060)	0.443*	(0.044)
d_{21}	-0.058	(0.060)	-0.029	(0.045)
d_{22}	0.070	(0.076)	-0.022	(0.083)
Panel B: Diagnostic tests				
$LB_1(20)$	27.83 [0.113]		23.04 [0.287]	
$LB_2(20)$	31.81 [0.045]		31.26 [0.052]	
$LB_1^2(20)$	10.71 [0.953]		25.05 [0.200]	
$LB_2^2(20)$	14.30 [0.814]		31.26 [0.052]	
log-likelihood	-6416.63		-6453.12	

Notes: P-values are in brackets and standard errors are in parenthesis. The $LB_i(20)$ and $LB_i^2(20)$ test statistic checks for the serial correlation of standard residuals and squared standardized residuals. *indicate significance at the 1% level.

Table VI shows the estimated results of the asymmetric volatility spillover effect between the large-cap and the mid-cap and between the large-cap and the mid-cap. We find evidence of an asymmetric response to negative shocks (bad news) of the own market of the large-cap because of the significance of diagonal coefficient d_{11}. However, there is no asymmetric response to negative shocks of the own market for the mid-cap and the small-cap because of the insignificance of coefficient d_{22}.

In addition, the cross-market asymmetric response is evident from the large-cap to both the mid-cap and small-cap due to the significance of coefficient d_{12}. This means that bad news in the large-cap market leads to a larger volatility in the mid-cap and small-cap markets than does good news in the large-cap market. However, we find no evidence of a cross-market asymmetric response in volatility of the large-cap market following a negative shock in the mid-cap and small-cap markets as the cross-coefficient d_{21} is insignificant.

Note that the Ljung-Box Q-statistics for both standardized, $LB_i(20)$, and squared standardized residuals, $LB_i^2(20)$, are reported below in Tables 5 and 6, respectively. We can see that there is no serial correlation in the standardized and squared standardized residuals, indicating the appropriateness of the symmetric and asymmetric BEKK models.

V. CONCLUSION

This paper investigates the return and volatility spillover effects between the KOSPI large and KOSPI medium stocks and between the KOSPI large and KOSPI small stocks in Korea. In particular, we consider the symmetric and asymmetric volatility transmissions between the three KOSPI sub indices.

By employing the Granger causality test, we found unidirectional return transmissions from the large stocks to medium and small stocks. This evidence indicates that pat information about the KOSPI large stocks has a better ability to predict the returns of the KOSPI medium stocks and the KOSPI small stocks than that of either the KOSPI medium stocks or the KOSPI small stocks to predict the return of the KOSPI large stocks.

With regard to volatility spillover, we first considered symmetric volatility spillover using the standard BEKK model. Our empirical results show a bi-directional volatility spillover from the KOSPI large market to the KOSPI medium and small markets, indicating that common shocks or information lead to market linkage between the three KOSPI sub indices. In addition, by using the asymmetric GARCH-BEKK model, we observed the unidirectional relationship of asymmetric volatility transmission from the large stocks to the medium and small stocks. This finding suggests that volatility in the medium and small stocks following a negative shock in the large stocks is larger than that following a positive shock in the large stocks.

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