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Information Transmission Effects between Large and Small Capitalization Indices in Tokyo Stock Exchange

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Abstract

This paper explores the information transmission effects by examining the mean and volatility spillovers between large- and small-cap stock indices in Tokyo Stock Exchange. A systematic VAR model and the bivariate VC-GJR-GARCH model (Tse and Tsui, 2002) are used to investigate the mean and volatility spillovers, respectively. The empirical results exhibit that there are no strong evidences for any mean spillovers between large- and small-cap stock indices, which is consistent with Reyes (2001). For the volatility spillovers, bidirectional information transmissions between large- and small-cap stock indices are observed. In the further research, the volatility of large-cap stock index is only affected by the positive shocks of small-cap stock index. However, the volatility of small-cap stock index is significantly affected by both positive and negative shocks of large-cap stock index. These results may provide some implications for predicting the short-term dynamics of volatility for large- and small-cap stock indices.

Keywords: Information transmission, VAR, Bivariate VC-GJR-GARCH, Tokyo Stock Exchange.

JEL Classification: G14, G15, G18

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1. Introduction

Interdependences among international stock markets, size-sorted portfolios and stock indices represent certain kind of information transmissions. Adequately understanding the complicated transmission behaviors in financial markets possibly bring about additional information and it may be beneficial for the prediction of asset price and the decisions of investment. This is why the subject of information transmissions has attracted momentous attention of many researchers and market participants.

An integrated investigation of the linkages and interactions across major international stock markets is essential for investors to carry out multinational trading and hedging strategies successfully. Likewise, the short-term dynamics and reciprocal actions among individual firms and capitalized indices in a specific stock market definitely play crucial determinants of profitable investing strategies. Lo and MacKinlay (1990) found the evidence of unidirectional lead-lag relations among the returns of size-sorted portfolios in US stock market, which the returns of portfolios consisting of large capitalization (large-cap) stocks tend to dominate those of small capitalization (small-cap) stocks but not vice versa. Kanas (2004, 2005) used Cross Correlation Function and the Cointegration approach (ARDL method) respectively to test the lead-lag effect of returns for ten sized-sorted equity portfolios in the UK stock market. Consistent with the result of Lo and MacKinlay (1990), a significant lead-lag effect was found in the mean from large- to small-cap portfolios, but not for those of equal-cap portfolios. They concluded that these asymmetric phenomena were attributed to the lagged information transmission between large- and small-cap portfolios. Such evidences provide some implications for trading strategies and the explanations of profitability of contrarian strategy.

The process of information can be observed not only from price movement but volatility of returns. The transmission process of volatility deserves meticulous study because it also represents a source of information (Ross, 1989; Andersen, 1996). In the literatures, volatility spillovers among size-sorted portfolios have been widely investigated in different equity markets (e.g. Conrad et al., 1991; Reyes, 2001; Kanas, 2004). The process of volatility transmission, identical to the effect on mean returns, appear the asymmetric pattern, which shocks to large-cap firms (large-cap stock index) will transmit to small-cap ones (small-cap stock index) but not vice versa. Moreover, Grieb and Reyes (2002) provided some evidence of Granger-causal transmission of information to the correlation between large- and small-cap stock indices in the UK. They found that the correlation of large-cap and small-cap stock indices will be affected by the information of large-cap stock index positively, but negatively by the information of small-cap stock index. An examination of the volatility spillovers process also enhances the understanding of information transmissions among financial markets.

This study concentrates on the issue of information transmission effects between large- and small-cap stock indices in Tokyo Stock Exchange (TSE). The asymmetric transmission effects on mean and volatility are reexamined by using TOPIX new index series[1]. Three capitalization-weighted stock indices data, including TOPIX Core 30, TOPIX Large 70 and TOPIX Small, used in the study are from the TOPIX new index series of TSE. TOPIX Core 30 and Large 70 are regarded as the large-cap stock index, and TOPIX Small is the small-cap stock index. These three stock indices are briefly described in Section III. For the first errand, we adopt VAR approach to test the mean spillover effect between the returns of large- and small-cap stock indices. The second purpose of this study is to employ a time-varying correlation GARCH (denote as VC-GARCH) model (Tse and Tsui, 2002) to examine the volatility spillover effects between the returns of large- and small-cap stock indices in TSE. Reyes (2001) adopted a bivariate EGACRH model to examine volatility spillover effects between large- and small-cap stock indices of TSE. An asymmetric volatility spillover effect from large-cap stock returns to small-cap returns was found, but not vice versa. Similar to the results of Kato and Schallheim (1985), he also found that the correlation between large- and small-cap stock indices returns is not constant, which rationalize us to adopt the VC-GARCH model to investigate the information transmission effects among different capitalized stock indices in Tokyo stock market[2]. Furthermore, in order to capture the leverage effect found in the returns of these stock indices, we adopt the asymmetric volatility specification of GJR model (Glosten, Jagannathan and Runkle, 1993) in the bivariate VC-GARCH model.

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[1] The introduction of TOPIX new index series refers to the Guidebook of Tokyo Stock Exchange.

[2] Grieb and Reyes (2002) employed a bivariate LEGARCH(1,1) to consider the time-varying correlation between the large- and small-cap stock indices returns.

For the VAR analysis, we use Generalized Method of Moment (GMM) to estimate the coefficients and follow Newey and West (1987, 1994) method to consider heteroscedasticity and autocorrelation when calculating the variance-covariance matrix. The statistical inferences based on the robust Wald test demonstrate that the null hypotheses are not significantly rejected (except for the mean spillover from large- to small-cap indices of Core 30 index v.s Large 70 index), indicating that there is no strong evidence of unidirectional or bidirectional mean spillover effect between large- and small-cap stock indices. This result is consistent with the conclusion of Reyes (2001). For the examination of volatility spillover effect, the empirical results show that there are bidirectional volatility spillovers whether the large-cap stock index is proxied by Core 30 index or Large 70 index. This indicates that shocks on small-cap stock index will be transmitted to large-cap stock index in the form of second moment. The results are dissimilar with the conclusions of existing literatures. In our further research, an interesting finding is that the volatility of large-cap stock index is only significantly decreased by the positive shocks of small-cap stock index. However, the volatility of small-cap stock index is significantly increased by both positive and negative shocks of large-cap stock index.

The structure of this article is organized as follows. Section II provides the description of the bivariate time-varying correlation GJR-GARCH model in testing the volatility spillover effect. Section III presents the data description and preliminary analysis. Section IV reports the empirical findings and final section is the concluding remarks.

2. Bivariate time-varying correlation GJR-GARCH model for volatility spillover effect

To model the dynamic relationship and investigate the volatility spillover effect between different capitalized stock indices, the VC-MGARCH(1,1), proposed by Tse and Tsui (2002), is employed to consider the time-varying correlations among the research targets. Moreover, the combination of GJR-GARCH and VC-MGARCH is explicitly incorporated the potential for asymmetry in the conditional variance equation, as suggested by Engle and Ng (1993). Hence, the specifications of the bivariate VC-GJR-MGARCH(1,1) model for examining volatility spillover effects are described as follows:

$$R_t = \mu + \phi(L)R_t + u_t \quad u_t \mid \Omega_{t-1} \sim N(0, D_t \Gamma_t D_t) \tag{1}$$

where $R_t = (r_{1,t} \quad r_{2,t})'$, $\mu = (\mu_1 \quad \mu_2)'$, and $u_t = (u_{1,t} \quad u_{2,t})'$. Note that $r_{1,t}$ and $r_{2,t}$ denote the returns series of large- and small-cap stock indices. Ω_{t-1} is the information set at time t-1. D_t denotes the 2×2 diagonal matrix where the *i*th diagonal element is $\sigma_{i,t}$. Thus, $\varepsilon_t = D_t^{-1} u_t$ is the standardized residual and is assumed to be serially independently distributed with zero mean and conditional variance matrix $\Gamma_t = \{\rho_{ij,t}\}$. The conditional variance Γ_t is also the conditional correlation of R_t. $\phi(L)$ denotes a 2×1 coefficient matrix whose two elements are $\phi_1(L)$ and $\phi_2(L)$, where $\phi_{i,p}(L) = \phi_{i,1}L - \cdots - \varphi_{i,p}L^p$ for i=1,2. In order to examine the volatility spillover effects, the conditional variance equation is set as

$$D_t^2 = \text{diag}\{\omega_i\} + \text{diag}\{\alpha_i + \gamma_i I_{it}^-\} \quad u_{t-1}u_{t-1}' + \text{diag}\{\beta_i\} \quad D_{t-1}^2 + \text{diag}\{\delta_i\} \quad v_{t-1}v_{t-1}' \tag{2}$$

where $\omega_i > 0,\ \alpha_i > 0,\ \beta_i > 0$, and $\alpha_i + \beta_i < 1$ for $i = 1,2$. $I_{it}^- = 1$ if $u_{it} < 0$ and $I_{it}^- = 0$ otherwise. A significant γ_i indicates that there is a leverage effect existed in the underlying asset. The term $v_{t-1}v_{t-1}'$ is set for examining the volatility spillover effects, where $v_{t-1} = (u_{2,t-1} \quad u_{1,t-1})'$. For instance, if δ_1 is significantly different from zero, then volatility of index 2 will spill over to that of index 1. The structure of conditional correlation is specified as

$$\Gamma_t = (\iota\iota' - \text{diag}\{\theta_1\} - \text{diag}\{\theta_2\}) \quad \Gamma + \text{diag}\{\theta_1\} \quad \Gamma_{t-1} + \text{diag}\{\theta_2\} \quad \Psi_{t-1} \tag{3}$$

where $\theta_1 \geq 0,\ \theta_2 \geq 0$, and $\theta_1 + \theta_2 \leq 1$. ι denotes a vector of ones and is the element-by-element multiplication. $\Gamma = \{\rho_{ij}\}$ is a time-invariant 2×2 positive definite matrix with unit diagonal elements and $\Psi_{t-1} = \{\psi_{ij,t-1}\}$ is a 2×2 matrix whose elements are functions of the lagged observation of R_t. For a bivariate case considered in Tse and Tsui (2002), $\psi_{ij,t-1}$ is specified as

$$\psi_{ij,t-1} = \frac{\sum_{h=1}^{2} \varepsilon_{i,t-h}\varepsilon_{j,t-h}}{\sqrt{\sum_{h=1}^{2} \varepsilon_{i,t-h}^{2} \sum_{h=1}^{2} \varepsilon_{j,t-h}^{2}}} \quad \text{for} \quad i, j = 1, 2 \text{ and } i \neq j \tag{4}$$

where $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the standardized residuals. Under the assumption of normality, the conditional log-likelihood

$$L(R_t \mid \Theta) = \sum_{t=1}^{T} \left[-\frac{1}{2} \ln\left|D_t \Gamma_t D_t\right| - \frac{1}{2} \varepsilon_t' \Gamma_t^{-1} \varepsilon_t \right]$$

$$= \sum_{t=1}^{T} \left[-\frac{1}{2} \ln\left|D_t \Gamma_t D_t\right| - \frac{1}{2} u_t' D_t^{-1} \Gamma_t^{-1} D_t^{-1} u_t \right] \tag{5}$$

where $\Theta = \{\omega_1, \omega_2, \alpha_1, \alpha_2, \beta_1, \beta_2, \gamma_1, \gamma_2, \delta_1, \delta_2, \rho_{12}, \theta_1, \theta_2\}$ is the parameter vector of the model, and the BFGS numerically algorithm in WinRats 6.0 was used to maximize Eq.(5).

3. Data description and preliminary analysis

The three capitalization-weighted stock indices data, including TOPIX Core 30, TOPIX Large 70 and TOPIX Small, used in the study are from the TOPIX new index series of Tokyo Stock Exchange (TSE). These capitalization-weighted stock indices were developed with a base index value of 1000 as of April 1, 1998[3], and the empirical data are obtained from the Bloomberg database. The sample period for this study covers nearly thirteen years, from 4 January 1993 to 17 October 2005, totaling 3151 daily observations for each stock index price series. The trends of all stock indices are plotted in Figure 1. For the series of return rates we use the first difference of log index-prices, i.e. ri,t = ln(pi,t / pi,t-1), where pi,t and pi,t-1 represent the closing price index of i at time t and t-1 respectively.

The TOPIX Core 30 is a super-large capitalization index, which contains the most liquid stocks with the largest market capitalization on the 1st section of TSE. The TOPIX Large 70 consists of the remaining 70 TSE

[3] The detailed introduction TOPIX can refer the "New Index Series Guidebook" of Tokyo Stock Exchange.

1st section stocks, excluding the TOPIX Core 30 components, within the TOPIX 100 components. Both indices are most liquid among all indices in TOPIX. For these reasons, TOPIX Core 30 and Large 70 are treated as the Large-Cap index in this study. The TOPIX Small is a small capitalization index, which excludes the 500 most liquid and non-eligible stocks in the 1st section of TSE. Hence, it is chosen as the proxy for the Small-Cap index.

Basic statistics of these daily return series are reported in Table1. Most of the return series in the sample have significant skewness and kurtosis, which indicate that their empirical distributions have heavy tails and it contributes to the rejection of the hypothesis of normality when using the Jarque- Bera test (1987). In this regard, we employ robust standard errors of the parameter estimates. For the serial correlations of return and square-return, Ljung-Box Q statistics with 12 lags demonstrate significant autocorrelations, which indicate that these return series exhibit conditional heteroscedasticity. Hence, fitting a GARCH-type model to capture the patterns of second moments is an appropriate specification.

For the unit root test, three unit roots tests, namely, ADF (1981), KPSS (1992), and ERS (1996) test, are adopted to examine the stationarity of the returns of the three stock indices. The null hypotheses of ADF and ERS test are unit roots; however, the null of KPSS test is not unit roots. Moreover, the test statistics here contains interception term and time trend, respectively. The results reported in Panel B of Table 1 show that all unit roots tests indicate the stock indices returns of Core 30 and Large 70 are stationary except the KPSS test of the Small-cap index. However, ADF and ERS tests reject the null of unit roots for Small-cap index. Hence, the return of Small-cap index is regarded as a stationary series.

Table 1 Preliminary analysis of Core 30, Large 70 and Small-cap indices returns

Panel A. Summary statistics			
	Core 30 Index	Large 70 Index	Small-cap Index
Mean (%)	-0.0007	0.004	-0.004
Std. Dev.	1.454	1.238	1.105
Skewness	0.074*	0.056	-0.333***
Excess kurtosis	2.679***	2.245***	4.130**
Maximum (%)	7.816	7.142	5.893
Minimum (%)	-7.603	-6.044	-7.526

J-B		945.511***	663.436***	2298.072***
Q(12)		46.211***	37.364***	102.244***
$Q^2(12)$		398.614***	457.464***	372.167***
Panel B. Unit-root tests				
Test statistics				
ADF	t_μ	-25.594 (5)***	-27.539 (4)***	-47.772 (0)***
	t_τ	-27.593 (5)***	-27.535 (4)***	-47.791 (0)***
KPSS	η_μ	0.092 (5)	0.084 (4)	0.421 (0)*
	η_τ	0.079 (5)	0.087 (4)	0.193 (0)**
ERS	DF-GLS_μ	-25.343 (5)***	-27.321 (4)	-47.688 (0)***
	DF-$GLS_{\mu,\tau}$	-25.345 (5)***	-27.172 (4)	-47.341 (0)***

Note:

1. * 、** and *** denote significantly at the 10% 、5% and 1% level.
2. J-B test statistics are based on Jarque and Bera (1987) and are asymptotically chi-square-distributed with 2 degrees of freedom.
3. μ and τ denotes the test statistics including interception and time trend, respectively. The numbers inside the parentheses are optimal lags.

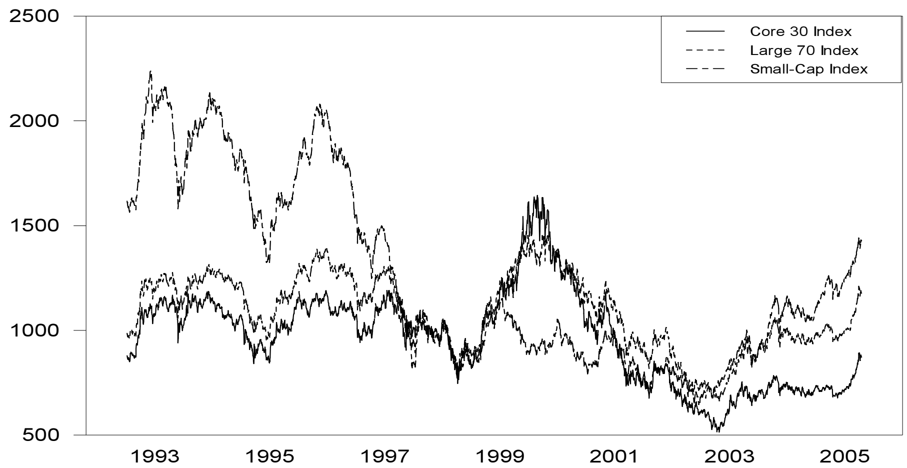


Figure 1 Trends of Core 30, Large 70 and Small-cap Stock Indices

4. Empirical results

4.1 Testing for constant correlation and asymmetric effect on volatility

The empirical result of Kato and Schallheim (1985) indicated that there might be the January and June seasonality effect in the correlation among Japanese stock returns. Moreover, Reyes (2001) found a June effect in the conditional correlation between large-cap and small-cap stocks in the TSE. Consequently, the constant correlation test proposed by Tse (2000) is implemented in this section. He developed two test statistics (IM and LM tests) to detect that the correlation coefficients among specific assets hold constant or not. The null hypothesis is constant and the alternative is dynamic. As noted in conclusions of Tse (2000), the IM test will suffer from the non-normality of financial data; oppositely, the LM test has immunity against the stylized fact of financial data. Hence, this study adopts the LM test of Tse (2000) to examine the constant correlation hypothesis between the Core 30 and Small-Cap stock indices, and also the Large 70 and Small-Cap indices. Moreover, a large number of observations in this paper can avoid over-rejecting the null hypothesis in smaller samples.

Table 2 Constant correlation test of large- and small-Cap stock indices

	Core 30 Index vs. Small-cap Index		Large 70 Index vs. Small-cap Index	
Parameter	Core 30	Small-Cap	Large 70	Small-Cap
ω	0.039 (0.008)***	0.062 (0.011)***	0.055 (0.009)***	0.082 (0.012)***
α	0.093 (0.009)***	0.139 (0.015)***	0.089 (0.008)***	0.147 (0.014)***
β	0.890 (0.011)***	0.816 (0.019)***	0.874 (0.012)***	0.791 (0.019)***
ρ	0.759 (0.007)***		0.836 (0.005)***	
LM-correlation	0.008 (0.002)***		0.003 (0.001)*	
$Q^2(12)$	15.808	6.841	7.151	5.911
Engle-Ng Diagnostics				
Sign Bias Test	0.031 (0.094)	0.192 (0.108)*	-0.011 (0.095)	0.203 (0.114)*
Negative Sign Test	-0.055 (0.046)	-0.030 (0.066)	-0.013 (0.055)	-0.029 (0.070)
Positive Size Bias Test	-0.028 (0.045)	-0.076 (0.072)	-0.068 (0.054)	-0.082 (0.076)
Joint Test	5.316	14.924***	2.662	14.927***
Log-likelihood	-8591.682		-7608.437	

Note:

1. *, ** and *** denote significantly at the 10%、5% and 1% level, respectively.
2. Standard errors are in parentheses.
3. Q(12) and $Q^2(12)$ are Ljung-Box Q test for serial correlation in the standardized residuals and squared standardized residuals with 12 lags, respectively.
4. LM-correlation denotes the LM test for the constant correlation proposed by Tse (2000).
5. The Joint test is distributed at chi-squared with 3 degrees of freedom.

The test statistic LM-correlation is asymptotically distributed as a χ 2 with 1 degree of freedom under the null of constant correlation. The results of constant correlation test of large-cap and small-cap stock indices are reported in Table 2. It can be seen that the constant correlation hypothesis is rejected under at 1% and 10% significant level for the pairs of "Core 30 Index vs. Small-Cap Index" and "Large 70 Index vs. Small-Cap Index". Moreover, the Q-statistics provide the adequacy of second moment modeling for both asset returns. Hence, the results here support us to adopt a time-varying correlation model to characterize the dynamic relationship between large-cap and small-cap stock indices.

As for the asymmetric effects on volatility, four test statistics proposed by Engle and Ng (1993) are used to check for the misspecifications on conditional variance equation. The results show that the sign bias test and joint test of small-cap index are significant at 10% and 1% level, respectively. Consequently, the conditional variance equation of the bivariate time-varying correlation GARCH model is modified with the GJR-GARCH specification in order to seize the stylized fact of volatility asymmetry.

4.2 Mean spillovers between large- and small-capitalized stock indices

Several studies provide empirical evidence on first-moment (mean) interactions among national stock markets and size-based portfolios (Koutmos & Booth, 1995; Booth et al., 1997; Liu et al., 1997; Kanas, 2004, 2005). In this section, a systematic VAR model is adopted to examine the mean spillovers between large- and small-capitalized stock indices in TSE. For illustration, consider the following bivariate VAR model

$$\begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{6}$$

where $r_{1,t}$ and $r_{2,t}$ denote the large- and small-cap stock indices returns, respectively. The large-cap indices are proxied by Core 30 index and Large 70 index, respectively. For the error variables, $E(\varepsilon_{1,t}) = E(\varepsilon_{2,t}) = 0$, and $E(\varepsilon_{1,t}, \varepsilon_{2,t+s}) = 0$ for $s \neq 0$, and $E(\varepsilon_{1t}, \varepsilon_{2t}) = \Sigma$, where $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$. In order to handle the dynamic relationships of underlying returns appropriately, a VAR model with two lags is determined based on the Schwarz information criteria (SBC). Hence, $\Phi_{ij}(L) = 1 - \varphi_{ij,1}L - \varphi_{ij,2}L^2$ (i,j = 1,2), where L is the lag operator and $\varphi_{ij,1}$, $\varphi_{ij,2}$ are the coefficients). Under the model specification above, we can establish the hypotheses to test whether the mean spillover effects between large- and small-cap stock indices exist in TSE. Two sets of null hypothesis are constructed, that is, $\varphi_{12,1} = \varphi_{12,2} = 0$ and $\varphi_{21,1} = \varphi_{21,2} = 0$. If the first null hypothesis is rejected significantly, it suggests that the current returns of large-cap stock index are affected by the lag returns of small-cap stock index. This indicates that the mean returns of small-cap index spill over to the large-cap index. Similarly, if the second null hypothesis is rejected significantly, it means that the current returns of small-cap index will be influenced by the past returns of large-cap index.

The testing approach has two steps. First, the GMM is used to estimate the coefficients of the VAR model. Based on the Newey and West (1987, 1994), the phenomena of heteroscedasticity and autocorrelation are considered in the variance-covariance matrix of the four coefficients vectors $\theta^1 = \left(\varphi_{11,1}, \varphi_{11,2}, \varphi_{12,1}, \varphi_{12,2}\right)$ and $\theta^2 = \left(\varphi_{21,1}, \varphi_{21,2}, \varphi_{22,1}, \varphi_{22,2}\right)$, which stand for the large- and small-cap indices returns. The variance-covariance matrices of θ^1 and θ^2 are given by:

$$\hat{\Omega}^i = E\left[(\hat{\theta}^i - \theta^i)(\hat{\theta}^i - \theta^i)'\right] \quad i=1,2 \tag{7}$$

The robust Wald test statistic (RW) for the previous null hypotheses which no mean spillovers between the large- and small-cap indices returns is given by:

$$RW = (R^i\hat{\theta}^i)'\left[R^i\hat{\Omega}^i(R^i)'\right]^{-1}(R^i\hat{\theta}^i) \quad i=1,2 \tag{8}$$

The statistic RW has a chi-squared distribution with 2 degrees of freedom. The restriction matrices are $R^1 = [0\ 0\ 1\ 0, 0\ 0\ 0\ 1]$ and $R^2 = [1\ 0\ 0\ 0, 0\ 1\ 0\ 0]$, which test for the mean spillovers from small-cap to large-cap indices and from large-cap to small-cap indices respectively.

Table 3 Robust Wald test for the mean spillover effects

RW test for H_0 :	Core 30 Index vs. Small-cap Index	Large 70 Index vs. Small-cap Index
$\varphi_{12,1} = \varphi_{12,2} = 0$	2.502	1.777
$\varphi_{21,1} = \varphi_{21,2} = 0$	4.631*	0.231

Note：Critical values of χ^2 (2) at 10% and 5% significant level are 4.605 and 5.991, respectively.
* denotes significantly at 10% level.

The empirical results of mean spillover effects are presented in Table 3. For the two pairs of stock indices, the RW test statistics are both not statistically significant, which indicate that there are no mean spillover effects from small-cap to large-cap index. Moreover, for the pair of Core 30 vs. Small-cap index, the RW test statistic is statistically significant at 10% level. However, RW test statistic is no longer significant for the pair of Large 70 vs. Small-cap index. Consequently, we do not find strong evidences to show that there are mean spillover effects existed between large- and small-cap stock indices. The result is supported by Reyes (2001), which used JLG and JSM stock indices with bivariate AR(1)-GACRH(1,1) model.

4.3 Volatility spillovers between large- and small-capitalized stock indices

The VC-GJR-GARCH, as opposed to the constant-correlation GARCH model, allows for an asymmetric response of conditional variances to past returns, known as the 'leverage effect' (Nelson, 1991) and also the time-varying correlation. To capture departures from normality as shown in Table 1, statistical inferences are based on robust t-statistics (Bollerslev and Wooldbridge, 1992). The estimation results are provided in Table 4. First, we notice that a positive and statistically significant γ_i indicates leverage effects exist in these returns series. It can be seen that the estimates of θ_1 and θ_2 are statistically significant at the 1% level, and the persistence of volatility and correlation, measured by $\alpha_i+\beta_i$ and $\theta_1 + \theta_2$, are quite high for the two pair data sets. Moreover, a null hypothesis of $\theta_1 = \theta_2 = 0$ is constructed to test the time-varying correlation setting. The likelihood ratio statistic LR, which tests for the restriction $H_0:\theta_1=\theta_2=0$, shows the rejection of constant correlation hypothesis. The time-varying correlations of "Core 30 vs. Small-cap" and "Large 70 vs. Small-cap" are plotted in Figure 2(a) and (b). As shown in Table 4 and Figure 2, Small-cap index has higher correlation with Large 70 index and relative low correlation with Core 30 index.

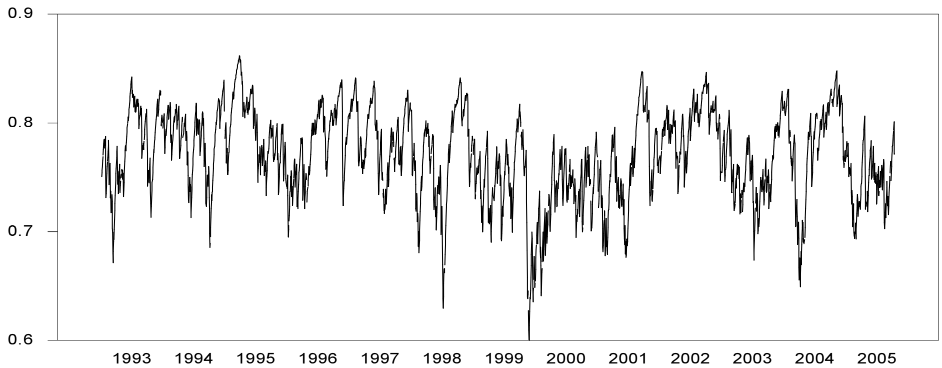
The inspiration for examining the volatility spillover effect directly come from Ross (1989), who observes that the volatility of price change will shed light on the process by which information is transmitted across firm of different market value.

Table 4 Volatility spillovers among Large- and Small-cap stock indices

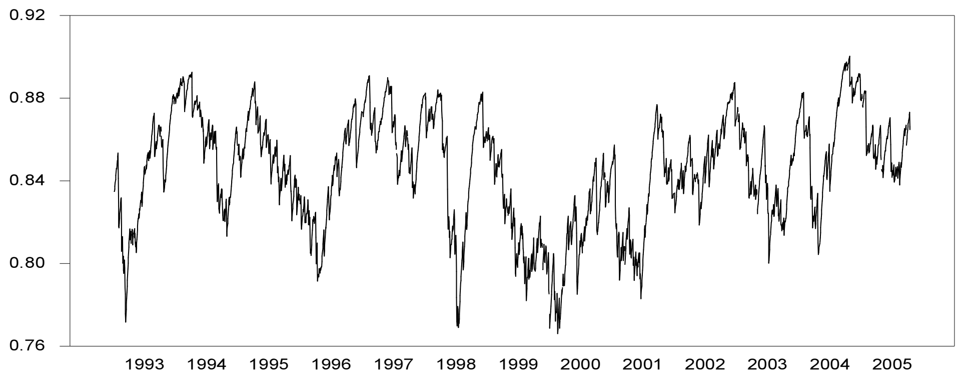
	Core 30 Index vs. Small-cap Index		Large 70 Index vs. Small-cap Index	
Parameter	Core 30 (i =1)	Small-Cap (i =2)	Large 70 (i =1)	Small-Cap (i =2)
μ_i	0.025 (0.014)*	0.011 (0.009)	0.022 (0.010)**	0.009 (0.008)
ϕ_{i1}	0.088 (0.010)***	0.180 (0.012)***	0.055 (0.010)***	0.166 (0.009)***
ϕ_{i2}	-0.028 (0.011)**	0.066 (0.011)***	-0.006 (0.010)	0.074 (0.009)**
ω_i	0.032 (0.004)***	0.037 (0.003)***	0.040 (0.001)***	0.042 (0.001)***
α_i	0.080 (0.008)***	0.044 (0.007)***	0.084 (0.001)***	0.033 (0.002)***
β_i	0.892 (0.008)***	0.841 (0.009)***	0.878 (0.001)***	0.825 (0.001)***
γ_i	0.042 (0.003)***	0.097 (0.007)***	0.037 (0.003)***	0.099 (0.004)***
δ_i	-0.010 (0.004)**	0.022 (0.002)***	-0.009 (0.002)***	0.046 (0.001)***
ρ_{12}	0.820 (0.008)***		0.886 (0.004)***	
θ_1	0.943 (0.006)***		0.970 (0.002)***	
θ_2	0.020 (0.002)***		0.009 (0.0007)***	
Log-likelihood	-8408.545		-7410.785	
	$H_0:\theta_1=\theta_2=0$			
LR(2)	57.007***		36.045***	
	Diagnostics on standardized residuals			
Q(12)	12.293	13.654	14.546	15.068
$Q^2(12)$	14.859	5.474	6.370	6.141

Note：1. *, ** and *** denote significantly at the 10%, 5% and 1% level.
2. Standard errors are in parentheses.
3. LR(2) is the likelihood ratio statistic distributed at chi-squared with 2 degrees of freedom.
4. Q(12) and $Q^2(12)$ are Ljung-Box Q test for serial correlation in the squared standardized residuals with 12 lags, respectively.

Bidirectional spillover can be observed by the statistically significant parameter δ_i in Table 4. This suggests there is information being transmitted in the form of volatility from the large-cap index to small-cap index and also from small-cap index to large-cap index. This result is contradicted with the report by Lo and MacKinlay (1990) and Conrad et al. (1991), who report shocks to large-cap firms spill over to the conditional variance of small-cap firms, but shocks to small-cap firms have no impact on the mean or the variance of the returns of larger-cap firms. Although the bidirectional volatility spillovers existed between large- and small-cap indices, we can see that the responses on the variance are distinct. Shocks to large-cap index increase the variance of small-cap index; on the contrary, shocks to small-cap index decrease the variance of large-cap index. Moreover, the increasing and decreasing magnitudes of the variances are asymmetric. Shocks from large-cap index will give rise to a greater impact of small-cap index. The results suggest that just as the volatility of small-cap index can be predicted by shocks to larger-cap index, the volatility of larger-cap index can also be predicted by shocks to smaller-cap index. However, the volatility spillover effect from larger to smaller firms is more obvious and influential than that from smaller to larger firms.



Figre 2(a) Time-varying Correlation between Core 30 and Small-cap **Indices**



Figre 2(b) Time-varying Correlation between Large 70 and Small-cap **Indices**

4.4 Asymmetric volatility transmission between large- and small-capitalized stock indices

In this short section, we further investigate the volatility spillover effects by dividing the shocks into two categories, i.e. good news and bad news. Positive shocks are referred to good news; on the contrary, negative shocks are regarded as bad news. Hence, we modify the specification of conditional variance to as follows

$$D_t^2 = \mathrm{diag}\{\omega_i\} + \mathrm{diag}\{\alpha_i + \gamma_i I_{it}^-\} \quad u_{t-1}u'_{t-1} + \mathrm{diag}\{\beta_i\} \quad D_{t-1}^2 + \mathrm{diag}\{\delta_i^g I_{it}^g + \delta_i^b I_{it}^b\} \quad v_{t-1}v'_{t-1} \qquad (9)$$

where $I_{it}^g = 1$ if $u_{it} > 0$ and $I_{it}^b = 1$ if $u_{it} < 0$ for i=1, 2. If δ_1^g (δ_2^g) is significantly different from zero, this implies that the good news of small-cap (large-cap) index will spill over to large-cap (small-cap) index. Similarly, significant estimates of δ_1^b (δ_2^b) indicate that the bad news of small-cap (large-cap) index will affect the volatility of large-cap (small-cap) index.

As reported in Table 5, the estimates (except for δ_i^g and δ_i^b) are approximately the same as in Table 4. For the estimates of equation (9), δ_2^g and δ_2^b are all statistically significant and it reveals that both good and bad news from large-cap index significantly cause a positive increase in volatility of small-cap index. The increase of volatility induced by bad news tends to have greater impact than that induced by good news. For the large-cap index, there is an interesting finding that good news from small-cap index has significant influence to decrease the volatility of large-cap index since only the parameter of δ_i^g is statistically significant. However, bad news from small-cap index does not impact the volatility of large-cap index. The empirical results hold constant whether the large-cap index is proxied by Core 30 or Large 70 index.

Table 5 Asymmetric Volatility spillovers among Large- and Small-cap stock indices

	Core 30 Index vs. Small-cap Index		Large 70 Index vs. Small-cap Index	
Parameter	Core 30 (i =1)	Small-Cap (i =2)	Large 70 (i =1)	Small-Cap (i =2)
μ_i	0.024 (0.013)*	0.011 (0.008)	0.017 (0.010)	0.006 (0.009)
ϕ_{i1}	0.089 (0.011)***	0.181 (0.012)***	0.058 (0.010)***	0.167 (0.010)***
ϕ_{i2}	-0.031 (0.011)***	0.063 (0.011)***	-0.008 (0.010)	0.071 (0.010)***
ω_i	0.032 (0.002)***	0.036 (0.003)***	0.038 (0.002)***	0.040 (0.002)***
α_i	0.085 (0.003)***	0.042 (0.002)***	0.089 (0.002)***	0.037 (0.009)***
β_i	0.895 (0.003)***	0.842 (0.006)***	0.883 (0.002)***	0.830 (0.004)***
γ_i	0.027 (0.003)***	0.097 (0.004)***	0.028 (0.005)**	0.078 (0.006)***
δ_i^g	-0.030 (0.005)***	0.021 (0.002)***	-0.028 (0.005)***	0.033 (0.006)***
δ_i^b	0.007 (0.006)	0.023 (0.002) ***	0.001 (0.005)	0.066 (0.006) ***
ρ_{12}	0.820 (0.010)***		0.882 (0.005)***	
θ_1	0.944 (0.008)***		0.967 (0.004)***	
θ_2	0.020 (0.002)***		0.009 (0.001)***	
Log-likelihood	-8406.343		-7406.570	
	$H_0: \theta_1 = \theta_2 = 0$			
LR(2)	56.633***		35.087***	
	Diagnostics on standardized residuals			
Q(12)	11.791	13.660	13.844	15.275
$Q^2(12)$	15.811	5.532	6.526	6.179

Note：1. *, ** and *** denote significantly at the 10%, 5% and 1% level.
2. Standard errors are in parentheses.
3. LR(2) is the likelihood ratio statistic distributed at chi-squared with 2 degrees of freedom.
4. Q(12) and $Q^2(12)$ are Ljung-Box Q test for serial correlation in the squared standardized residuals with 12 lags, respectively.

A related article by Kroner and Ng (1991) observed that bad news from portfolio of large-firms spills over to portfolio of small-firms, but not vice versa. Our results suggest that good news from both large- and small-cap index transmits to each other; even so, the responses of their volatility are opposite. Consequently, it should be pointed out that the information asymmetries are found for good and bad news in the predictability of the volatility between large- and small-cap stock indices. For bad news, it is consistent with the literature4 that only small-cap index is affected by large-cap index. For good news, the asymmetry refers to the reverse behaviors on their volatility.

5. Conclusions

This study examines the information transmission effects by examining the mean and volatility spillovers between large-cap stock index (Core 30 and Large 70 index) and small-cap stock index (Small-cap index) in Tokyo Stock Exchange. The examination of the mean and volatility spillovers is respectively carried out with a systematic VAR model and the bivariate VC-GJR-GARCH model (Tse and Tsui, 2002).

The empirical results exhibit that there are no strong evidences for any mean spillovers between large- and small-cap stock indices, which is consistent with Reyes (2001). For the volatility spillovers, bidirectional information transmissions between large- and small-cap stock indices are observed. This is dissimilar with the finding of Lo and MacKinlay (1990) and Conrad et al. (1991) for US data sets. In our further research, we divide the shocks into two categories, i.e. positive shocks (good news) and negative shocks (bad news). The most interesting aspect of the empirical evidence is that the volatility of large-cap index is only significantly affected and decreased by the good news from small-cap index whether the large-cap index is proxied by Core 30 index or Large 70 index. However, bad news of small-cap index does not significantly impact the volatility of large-cap index. Moreover, the volatility of small-cap index is significantly increased by both good and bad news of large-cap index. These results may provide some implications for predicting the short-term dynamics of volatility for large- and small-cap stock indices.

[4] Lo and MacKinlay (1990) and Conrad et al. (1991) did not consider information quality, that is, positive shocks (good news) and negative shocks (bad news). Hence, the asymmetric information transmission indicated that a volatility "surprise" to larger firms can be used to predict the volatility of small firms, but not vice versa.

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