Intraday dynamics in long memory volatility relationships between the Japanese and Korean stock markets

Sang Hoon Kang[a]
Department of Business Administration
Pusan National University

Ron McIver[b]
School of Commerce
University of South Australia

Seong-Min Yoon[c]
Department of Economics
Pusan National University

Abstract

We use bivariate GARCH-DCC and FIGARCH-DCC models to investigate intraday long memory volatility spillovers between the Japanese (TOPIX) and Korean (KOSPI 200) markets, based on analysis of two sets of 30-min. and a one-hour interval data. Our empirical results identify strong dynamic volatility correlation and long memory volatility transmission between TOPIX and KOSPI 200 intraday returns. Additionally, we find the bivariate FIGARCH-DCC model provides superior forecasting performance to alternative univariate and bivariate GARCH model specifications. We conclude that the bivariate FIGARCH-DCC model provides a useful structure for modeling and forecasting long memory spillover effects in the volatility of intraday returns.

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Key words: Intraday spillover effect, Long memory, GARCH-DCC, FIGARCH-DCC, TOPIX, KOSPI 200

a Associate Professor, Department of Business Administration, Pusan National University, E-mail: sanghoonkang@pusan.ac.kr.
b Lecturer, School of Commerce, University of South Australia, Adelaide, 5000, SA, Australia, E-mail: ronald.mciver@unisa.edu.au.
c Author for Correspondence; Professor, Department of Economics, Pusan National University, Jangjeon2-Dong, Geumjeong-Gu, Busan, 609-735, Korea; E-mail: smyoon@pusan.ac.kr.

1. Introduction

The volatility of financial asset prices often exhibits persistence or long memory, whereby autocorrelations of absolute and squared time series returns are characterized by very slow decay. This long memory characteristic is crucial in asset risk management, investment portfolios, and the pricing of derivative securities, as its presence is closely connected to the predictability of volatility (Poon and Granger, 2003).

Based on the fractionally integrated process of Granger (1980) and Hosking (1981), Baillie, Bollerslev and Mikkelsen (1996) extend the standard GARCH model to allow for these long memory properties in conditional variances. The fractionally integrated GARCH (FIGARCH) model approach allows for fractional orders of integration, $I(d)$, d being between zero and one, and estimates a process intermediate to that of the GARCH and IGARCH processes. The FIGARCH model also provides superior value-at-risk and out-of-sample forecasts to the stationary GARCH model (Caporin, 2008; Tang and Shieh, 2006; Kang, Kang and Yoon, 2009; Kambououdis, 2009; Kasman, Kasman and Torun, 2009).

Understanding cross-market price and volatility spillover effects is another issue of interest, particularly in studies of financial market integration. Financial spillover effects are important concepts for international portfolio and risk managers when building optimal risky portfolios (Kenourgios, Samitas and Paltalidis, 2011; Syllignakis and Kouretas, 2011; Roboreod, 2014). The dynamics of price spillover effects provide price predictions and an opportunity for exploitable trading strategies, which provide evidence against market efficiency (Pati and Rajib, 2011; Dimpfi and Jung, 2012). Additionally, information about volatility spillover effects may be useful in applications that rely on estimates of conditional volatility, such as option pricing, portfolio optimization, management of value-at-risk, and risk hedging (Arouri, Jouini and Nguyen, 2011, 2012; Aragó and Salvador, 2011).

Recent econometric studies have developed advanced techniques to capture spillover effects, in the form of multivariate generalized autoregressive conditional heteroskedasticity (multivariate GARCH) models (Bauwens, Laurent and Rombouts, 2006; Wang and Wu, 2012; Chang, McAleer and Tansuchat, 2012; Gjika and Horáth, 2013; Zhang, Li and Yu, 2013; Lean and Teng, 2013, others). However, as they have utilized low-frequency data, precluding the capture of uncovered intraday information transmission between financial markets, these previous studies have been limited in their ability to detect spillover effects. With developments in information technology (IT), researchers can more easily access and analyze high-frequency data, which provides more reliable information for examining the spillover effect over short time periods.

In this paper, we focus on the issue of price and volatility spillovers between the Tokyo Stock Price Index (TOPIX) and Korea's Composite Stock Price Index 200 (KOSPI 200). To do so, we apply the bivariate GARCH and FIGARCH models, using a dynamic conditional constant (DCC) approach, to two intraday data sets. These data sets are based on 30-minute and one-hour intervals. This provides important insights into intraday long memory volatility spillover effects between the two markets.

This paper differs from the extant literature in the following ways. First is through exploration of the intraday volatility spillover between the TOPIX and KOSPI 200 markets. Second is in use of high frequency data to consider linkages through long memory volatility spillover effects between these equity markets. Finally, this study analyzes the forecasting results of univariate and multivariate GARCH-type models over multiple forecasting horizons—one, five, and 20 trading days—in order to assess if any model displays superior performance.

The rest of this paper is organized as follows. Section 2 briefly discusses the literature on financial market spillover effects. Section 3 provides descriptive statistics for the 30-min intraday data. Section 4 discusses the econometric methodologies used in this study. Section 5 provides results. Conclusions are discussed in Section 6.

2. Literature Review

An extensive empirical literature evaluates inter-market information transmission or volatility spillovers (Hamao, Masulis and Ng, 1990; Koutmos and Booth, 1995; Kanas, 1998; In et al., 2001). Such volatility spillovers are usually attributed to cross-market hedging and changes in shared information, which may simultaneously alter expectations across markets (Arouri, Jouini and Nguyen, 2011, 2012; Aragó and

Salvador, 2011). In addition, the existence of volatility spillovers provides evidence of market contagion; that is, a shock increases volatility not only in its own asset or market, but also in other assets or markets (Chiang, Jeon and Li, 2007; Poshakwale and Aquino, 2008; Dean, Faff and Loudon, 2010; Zhao, 2010; Ding and Pu, 2012).

Recently, empirical studies have analyzed the impact of the 2008 global financial crisis (GFC) on information transmission amongst equity markets. Syllignakis and Kouretas (2011) capture contagion effects between US and German stock returns and CEE stock returns during the GFC using the DCC approach. Hwang et al. (2013) examine patterns of crisis spillover between stock returns of ten emerging economies and those of the US using an EGARCH-DCC model. This allows them to identify distinct patterns in dynamic correlations associated with crisis spillover for sub-groups from a ten country sample. These include: contagion, herding, and post-crisis adjustment; contagion and herding; and simple contagion. Dimitriou, Kenourgios and Simos (2013), using a FIAPARCH-DCC model, provide evidence of decoupling of some BRICS' markets during the GFC, followed by increased post-GFC coupling between the US and BRICS' markets.

Few studies have focused on spillover effects in intraday returns. Wu, Li and Zhang (2004) find bi-directional volatility spillovers between intraday US and UK futures markets. Chiang, Yu and Wu (2009), using both ten-min. and 30-min. interval returns, find a positive dynamic conditional correlation between the DJIA spot and Nasdaq futures markets. Pati and Rajib (2011) suggested that five-min. intraday futures prices lead spot prices and so futures markets make the major contribution to price discovery in the Indian market. Kang, Cheong and Yoon (2013) and Kim and Ryu (2014) identify intraday bi-directional volatility spillover effects between the Korean spot and futures markets using the asymmetric GARCH-BEKK model.

3. Data and descriptive statistics

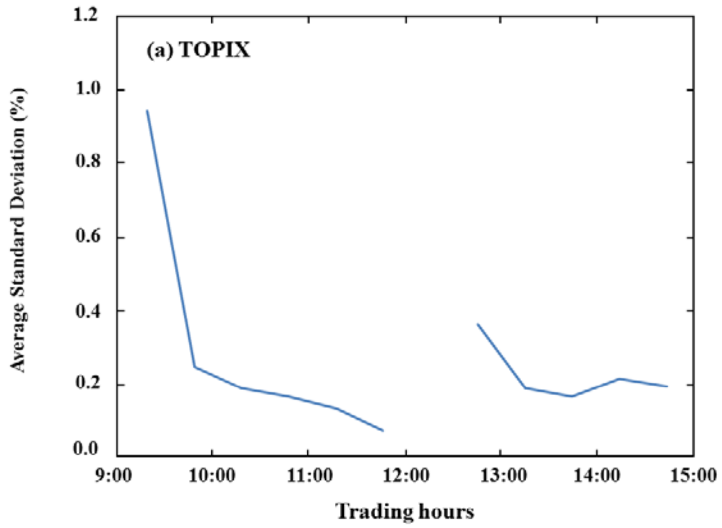
This study considers two sets of high frequency intraday price data, based on 30-min. and one-hour time intervals, for both the TOPIX and KOSPI 200 markets. The data sets cover the period from January 4 2011 to December 28 2012, and were obtained from the SIRCA database. The high-frequency price series were converted into logarithmic return series for each of the sample indices; that is, $r_{i,t} = \ln\left(P_{i,t} / P_{i,t-1}\right) \times 100$, where $r_{i,t}$ denotes the continuously compounded percentage returns for index i at time t and $P_{i,t}$ denotes the price level of index i at time t.

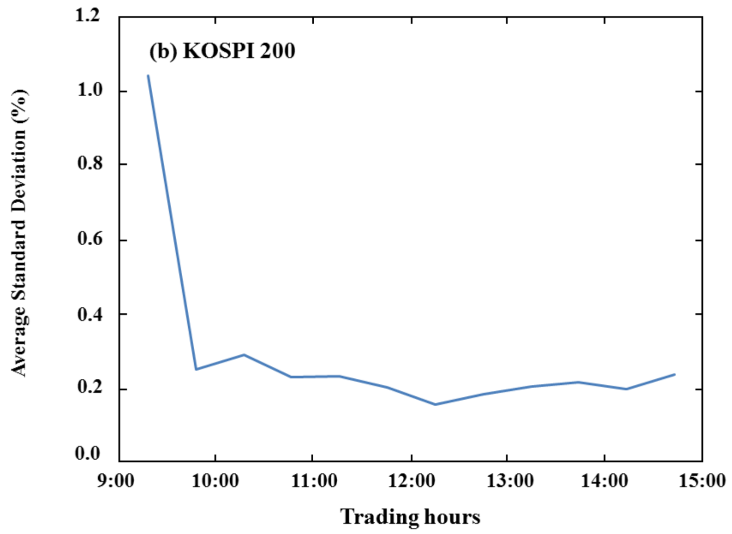
The TOPIX and KOSPI 200 equity markets have a homogenous trading period with a 9:00 am opening and a 3:00 pm closing. However, the TOPIX trading day consists of two sessions, a morning session (9:00 am to 11:30 am) and an afternoon session (12:30 pm to 3:00 pm), whereas the KOSPI 200 market trades over the full 9:00 am to 3:00 pm period. We therefore remove lunch-break observations (11:30 a.m. to 12:30 p.m.) to match trading time intervals between the two markets.

Figure 1 shows average standard deviations of returns (volatility) across the 30-min. intervals. Average volatility for the TOPIX is higher at the opening of both the morning and afternoon sessions, declining significantly during the remainder of each session. For the TOPIX, volatility starts at about 0.9% at the beginning of the morning session and is just under half of this level for the opening of the afternoon session. This results in two distinct inverted J-shape patterns over the trading day.

In the KOSPI 200 market, volatility starts at about 1.03 % in the initial 30-min interval and then drops to its lowest level by mid-day, rising slightly towards the close. Daily trading activities show an inverted J-shaped pattern across the 30-min intervals for every trading day as a result of the market opening effects. A similar pattern in intraday series can be also founded in Andersen, Bollerslev and Cai (2000), Wu, Li and Zhang (2005), Haniff and Pok (2010), and Kang, Cheong and Yoon (2013).

Figure 1. Average standard deviations for 30-min intraday data





Note: Trading activities clearly exhibit a double inverted J-shaped pattern for the TOPIX market and a single inverted J-shaped pattern for the KOSPI 200 market.

Table 1 shows descriptive statistics and results for unit root tests for the two sets of TOPIX and KOSPI 200 intraday return series. As shown in Panel A of Table 1, both sets of intraday return series (30-min. and 1-hour) display similar descriptive statistics. This includes all return series displaying a leptokurtic distribution with a higher peak and a fatter tail than the case of a normal distribution, as evidenced in the skewness, excess kurtosis, and Jarque-Bera (J-B) test results. Additionally, calculated values of the Ljung-Box statistic, $Q^2(5)$, for the squared return series are extremely high, indicating rejection of the null hypothesis of no serial correlation. Thus, the return series display ARCH-type dependencies, confirming the appropriateness of a GARCH-type model formulation in analyzing intraday volatility.

Table 1. Descriptive statistics and results of unit root tests

	TOPIX		KOSPI 200	
	30-min	1-hour	30-min	1-hour
Panel A: Descriptive statistics				
Mean	-0.0103	-0.0019	-0.0069	-0.0012
Std. Dev.	3.5309	0.4801	4.0055	0.5330
Maximum	3.7669	4.7195	3.6324	3.5996
Minimum	-6.1185	-6.8100	-5.5663	-5.7299
Skewness	-1.7599	-1.3550	-1.6812	-1.2817
Kurtosis	56.265	40.732	41.808	24.662
J-B	615860***	168750.7***	344920***	56110.5***
$Q^2(5)$	263.53***	923.13***	222.37***	125.97***
Panel B: Results of unit root tests				
ADF	-65.906***	-49.676***	-68.640***	-49.810***
PP	-65.784***	-49.758***	-68.674***	-49.828***
KPSS	0.2285	0.2103	0.0605	0.0616

Notes: The J-B (Jarque-Bera) test was used for the null hypothesis of normality in the sample return distribution. The Ljung-Box statistic, $Q^2(5)$, was used to check for the presence of serial correlation in squared returns up to the 10th order. MacKinnon's 1% critical value is –3.435 for the ADF and PP tests. *** indicates the rejection of the null hypothesis at the 1% level of significance.

Panel B of Table 1 provides the results of two types of unit root test for stationarity of the individual return series: standard parametric augmented Dickey-Fuller (ADF) tests; and non-parametric Phillips-Peron (PP) tests. Large negative values for the ADF and PP test for each series support rejection of the null hypothesis of a unit root at the one per cent level of significance. Thus, each of the intraday return series may be regarded as stationary.

To examine the presence of long memory property in both 30-min. and one-hour intraday returns, we use three long-memory tests. The first is Lo's (1991) modified R/S analysis. The second and third are two semi-parametric estimators of the long-memory parameter, the log-periodogram regression (GPH) of Geweke and Porter-Hudak (1983) and the Gaussian semi-parametric (GSP) of Robinson and Henry (1999). [1]

Table 2 summarizes the results of the long memory tests for all absolute and squared (as a proxy for volatility) intraday return series for the TOPIX and KOSPI 200 time series, respectively. The results of Lo's R/S test, presented in Panel A of Table 2, displays strong evidence of persistence for both 30-min. and one-hour intraday returns. Similarly, Panels B and C of Table 2 report the estimation results for the semi-parametric GSP and GPH tests. Note that the results of the GPH and GSP tests for long memory are sensitive to the size of the bandwidth. In order to ensure the robustness of the GSP and GPH tests, the GPH test was implemented with different bandwidths: $m = T^{0.5}$ and $m = T^{0.6}$, and the GSP test statistic was also estimated with diverse bandwidths: $m = T/4$, $m = T/16$, $m = T/64$.

The estimated long memory results for the GSP and GPH tests support rejection of the null hypothesis of short memory in volatility for each set of intraday returns. On the whole, the volatilities of both 30-min. and one-hour intraday returns seem to be well-matched to being modelled as fractionally integrated processes. This supports exploring use of the FIGARCH model to identify the long-memory property in the intraday volatility process for both equity markets.

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[1] In the case of Lo's modified R/S test, the Hurst exponent (H) is calculated using the R/S statistic. If $H = 0.5$, then this exponent indicates a random walk process indicating short memory. If $0 \le H < 0.5$, it suggests that the series is anti-persistent process (i.e., a long-range negative dependence). Finally, if $0.5 < H \le 1$, the series is a persistent process. To test for the statistical significance of the H estimates, we use the t-statistic, where the null hypothesis is $H_0 : H = 0.5$ and the alternative hypothesis is $H_1 : H \ne 0.5$. In the case of the GSP and GPH methods, test is of the null hypothesis $H_0 : d = 0$ versus $H_1 : d \ne 0$ using the t-test statistic. If $d = 0$, the series is a random walk or has a short-memory process. If $-0.5 < d < 0$, it is an anti-persistent process. If $0 < d < 0.5$, the series displays long memory. Finally, if $0.5 < d < 1$, the series is non-stationary.

Table 2. Results of the long memory tests for intraday absolute and squared returns

	TOPIX		KOSPI 200	
	30-min	1-hour	30-min	1-hour
Panel A: Lo's modified R/S test				
Absolute return				
$(q=1)$	2.2572***	2.1213***	6.1847***	5.1074***
$(q=5)$	2.2996***	2.2834***	5.4616***	5.4058***
Squared return				
$(q=1)$	2.4848***	2.4555***	4.0486***	3.8816***
$(q=5)$	2.0605***	1.7968*	3.9128***	3.9595***
Panel B: GSP Robinson (1995) test				
Absolute return				
$m=T/4$	0.2324 (0.0139)***	0.1729 (0.0187)***	0.2387 (0.0138)***	0.1611 (0.0187)***
$m=T/16$	0.5191 (0.0277)***	0.4631 (0.0375)***	0.4433 (0.0277)***	0.4516 (0.0375)***
Squared return				
$m=T/4$	0.2168 (0.0139)***	0.1961 (0.0187)***	0.1206 (0.0138)***	0.0832 (0.0187)***
$m=T/16$	0.5651 (0.0277)***	0.3227 (0.0375)***	0.2730 (0.0277)***	0.3004 (0.0375)***
Panel C: GPH (1983) test				
Absolute return				
$m=T^{0.5}$	0.1874 (0.0131)***	0.1836 (0.0180)***	0.0636 (0.0131)***	0.1848 (0.0180)***
$m=T^{0.6}$	0.4819 (0.0519)***	0.4125 (0.0634)***	0.4751 (0.0519)***	0.4685 (0.0634)***
Squared return				
$m=T^{0.5}$	0.1380 (0.0131)***	0.1884 (0.0180)***	0.1628 (0.0131)***	0.0995 (0.0180)***
$m=T^{0.6}$	0.3476 (0.0519)***	0.2273 (0.0634)***	0.2937 (0.0519)***	0.4190 (0.0634)***

Note: The critical values of the Hurst-Mandelbrot R/S test and Lo's modified R/S analysis are 2.098 at the 1% significance level. The numbers in parentheses are the standard deviation of the estimates. "q" in Lo's modified R/S test is the number of lag of autocorrelation. (m) denotes the bandwidth for the GSP and the GPH tests. ** and *** indicate the significance at the 5% and1% levels, respectively.

4. Methodology

4.1. Fractional integrated GARCH (FIGARCH) model

We assume that the return-generating process can be described by an AR(1) model in which the dynamics of current stock returns are explained by their lagged returns. The AR (1) model is defined as follows

$$r_{i,t} = \mu + \psi_1 r_{i,t-1} + \varepsilon_{i,t} \ , \ t \in \mathrm{N}$$

with

$$\varepsilon_t = z_t \sqrt{h_t} \ , \quad z_t \sim N(0,1) \tag{1}$$

where $|\mu| \in [0, \infty)$, $|\psi_1| < 1$, and the innovations $\{z_t\}$ are an independently and identically distributed (i.i.d) process. The conditional variance h_t is positive with probability one and is a measurable function of the variance-covariance matrix, $\sum_{t-1}$.

The standard GARCH (p, q) model of Bollerslev (1986) is as follows:

$$h_{i,t}^2 = \omega + \alpha(L)\varepsilon_{i,t}^2 + \beta(L)h_{i,t}^2, \tag{2}$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, L denotes the lag or backshift operator, $\alpha(L) \equiv \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q$, and $\beta(L) \equiv \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p$. In Equation (2), the persistence of conditional variances is measured by the sum $(\alpha + \beta)$. A common empirical finding is that the sum $(\alpha + \beta)$ is quite close to one, thereby implying that shocks are infinitely persistent, which corresponds to the integrated GARCH (IGARCH) process of Engle and Bollerslev (1986).

Baillie, Bollerslev and Mikkelsen (1996) developed the fractional IGARCH (FIGARCH) model, which nests the GARCH and IGARCH models. The FIGARCH model allows for fractional orders of integration between zero and one, and thus captures the presence of long memory behavior in the conditional variance. The FIGARCH(p, d, q) model can be presented as follows

$$\phi(L)(1-L)^d \varepsilon_{i,t}^2 = \omega + [1 - \beta(L)](\varepsilon_{i,t}^2 - h_{i,t}^2) \tag{3}$$

where the long memory parameter d satisfies the condition $0 \leq d \leq 1$, $\phi(L)$ and $\beta(L)$ are finite order lag polynomials with roots assumed to lie outside the unit circle, and the fractional differencing operator $(1-L)^d$ is defined as

$$(1-L)^d = 1 - dL + \frac{1}{2!}d(1-L)L^2 - \frac{1}{3!}d(d_1-1)(d-3)L^3 + \cdots \tag{4}$$

The conditional variance process or the ARCH(∞)representation of the FIGARCH model is given by

$$h_{i,t}^2 = \omega + \beta(L)h_{i,t}^2 + [1-\beta(L)]\varepsilon_{i,t}^2 - \phi(L)(1-L)^d \varepsilon_{i,t}^2 = \omega[1-\beta(L)]^{-1} + \varphi(L)\varepsilon_{i,t}^2 \tag{5}$$

where $\varphi(L) = \sum_{i=1}^{\infty} \varphi_i L^i$ and $\varphi(1) = 1$for every d. The FIGARCH model provides greater flexibility for modeling the conditional variance, because it accommodates the covariance stationary GARCH model (when $d = 0$) and the IGARCH model (when $d = 1$) as special cases. In the FIGARCH model the persistence of shocks to the conditional variance, or degree of long memory, is measured by the fractional differencing parameter d. Thus, the attraction of the FIGARCH model is that, for $0 < d < 1$, it is sufficiently flexible to allow for an intermediate range of persistence (Baillie, Bollerslev and Mikkelsen, 1996).

4.2. Bivariate FIGARCH-DCC model

In order to evaluate the volatility spillovers, we apply a bivariate FIGARCH model to the two sets of intraday market returns. The structure of conditional correlations is modelled by using the DCC approach of Engle (2002), allowing investigation of the time-varying correlations between the two markets while ensuring positive definiteness in the variance-covariance matrix (H_t) under the simple conditions imposed on specific parameters. Parameterization of the FIGARCH-DCC model allows direct inference of the time-varying correlations between intraday TOPIX and KOSPI 200 market returns, and dealing with a relatively large number of variables in the system without having a numerical convergence problem at the estimation stage. In the multivariate case which we use, the variance-covariance matrix of residuals is defined as follows:

$$H_t = D_t R_t D_t \tag{6}$$

where D_t is an (2×2) diagonal matrix of time-varying conditional standard deviation of the residuals, obtained from taking the square root of the conditional variance modelled by univariate AR(1)-GARCH(1,1) and AR(1)-FIGARCH models, respectively. R_t is a matrix of time-varying conditional correlations, given by:

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{7}$$

That is

$$R_t = \begin{bmatrix} \frac{1}{\sqrt{q_{11}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{11}}} \end{bmatrix} \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{q_{11}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{22}}} \end{bmatrix}$$

The covariance matrix $Q_t = \lfloor q_{ij,t} \rfloor$ of the standardized residual vector $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \dots)'$ is denoted as:

$$Q_t = (1 - \alpha_{dcc} - \beta_{dcc})\bar{Q} + \alpha_{dcc}(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + \beta_{dcc} Q_{t-1} \tag{8}$$

with α_{dcc}, $\beta_{dcc} > 0$ and $\alpha_{dcc} + \beta_{dcc} < 1$. $\bar{Q}_t = \{\bar{q}_{ij,t}\}$ denotes the unconditional covariance matrix of ε_t. The coefficients, α_{dcc} and β_{dcc}, are the estimated parameters depicting the conditional correlation process. diag $\{Q_t\} = \sqrt{q_{11,t}}$ is a diagonal matrix containing the square root of the i th diagonal elements of Q_t. The dynamic correlation can be expressed as:

$$\rho_{12,t} = \frac{(1 - \alpha_{dcc} - \beta_{dcc})\bar{q}_{12} + \alpha_{dcc}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{dcc} q_{12,t-1}}{\sqrt{\left[(1 - \alpha_{dcc} - \beta_{dcc})\bar{q}_{11} + \alpha_{dcc}\varepsilon_{1,t-1}^2 + \beta_{dcc} q_{11,t-1}\right]\left[(1 - \alpha_{dcc} - \beta_{dcc}) q_{22} + \alpha_{dcc}\varepsilon_{2,t-1}^2 + \beta_{dcc} q_{22,t-1}\right]}} \tag{9}$$

Significance of α_{dcc} and β_{dcc} implies that the estimators obtained from the DCC-GARCH and DCC-FIGACH model are dynamic and time-varying. α_{dcc} indicates the short-run volatility impact, implying the persistency of the standardized residuals from the previous period. β_{dcc} measures the lingering effect of the impact of a shock on conditional correlations, which indicates persistence in the conditional correlation process. $\rho_{ij,t}$ indicates the direction and strength of correlation. If the estimated $\rho_{ij,t}$ is positive, the correlation between return series is positive and vice-a-versa (see Engle 2002 for further details).

We estimate the DCC model using the quasi-maximum likelihood (QML) estimation method proposed by Bollerslev and Wooldridge (1992), in which the log-likelihood can be expressed as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left[k\log(2\pi) + 2\log|D_t| + \log|R_t| + \varepsilon' R_t^{-1}\varepsilon_t\right] \tag{10}$$

The DCC model's design allows for two-stage estimation of the conditional covariance matrix H_t. In the first stage, we fit a univariate GARCH-type model to each set of intraday returns, then the estimates of $h_{ii,t}$ are obtained. In the second stage, we transform the return series using their estimated standard deviation, the result from the first stage, with this information being used to estimate the parameters of the conditional correlation.

5. Empirical results

5.1. Estimates of univariate GARCH type models

Tables 3 and 4 report the estimation results of the univariate GARCH and FIGARCH specifications with Student-*t* distributions used to capture long memory in the volatility of intraday returns. All specifications are estimated using the OxMetrics package (results for GARCH-type models with normal distribution are available by request from the corresponding author). This section also compares the performance of the GARCH and FIGARCH models with regard to the capture of long memory in both 30-min. and one-hour intraday volatility.

Table 3 indicates that all estimated parameters of the standard GARCH model are significant for both 30-min. and one-hour intraday returns. The sum of ARCH and

GARCH terms are quite close to unity, implying that the volatility is highly persistent in both sets of intraday returns. Diagnostic tests ($Q^2(5)$ and ARCH (5)) show that the GARCH models with Student-t distribution are well specified, as standardized residuals are not subject to both serial correlation and ARCH effects.

Table 3. Estimation results and diagnostic tests for univariate GARCH (1,1) models

	TOPIX		KOSPI 200	
	30-min	1-hour	30-min	1-hour
Panel A: estimation results				
Const (m)	-0.0335	-0.0058	0.0562	0.0053
	(0.0199)*	(0.0041)	(0.0277)**	(0.0052)
AR(1)	0.0475	0.0413	0.0674	0.0905
	(0.0103)***	(0.0280)***	(0.0114)***	(0.0144)***
Const (v)	0.2335	0.0084	0.2022	0.0475
	(0.1237)*	(0.0009)***	(0.1668)	(0.0503)
ARCH	0.1106	0.0194	0.0295	0.2899
	(0.0581)*	(0.0023)***	(0.0209)	(0.2847)
GARCH	0.9851	0.9392	0.9867	0.9745
	(0.0033)***	(0.00058)***	(0.0027)***	(0.0042)***
Student-*df*	2.0111	2.0028	2.1134	2.0202
	(0.0052)***	(0.0003)***	(0.0720)***	(0.0193)***
Log-likelihood	-11057.3	-721.521	-12143.3	-1115.59
Panel B: diagnostic tests				
AIC	4.265779	0.515038	4.684504	0.793629
Hannan-Quinn	4.268431	0.520347	4.687156	0.798938
$Q^2(5)$	1.2566	2.9346	4.5508	9.009
	[0.7394]	[0.4018]	[0.2077]	[0.0291]
ARCH (5)	0.2505	0.5775	0.9464	1.4747
	[0.9397]	[0.7173]	[0.4495]	[0.8310]

Notes: Const (m) and Const (v) are the constants of the mean and variance processes, respectively. $Q^2(5)$ is the empirical statistics of Ljung-Box test applied to squared standardized residuals. P-values are in brackets. Student-t values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and1% levels, respectively.

The estimation results for the FIGARCH model, reported in Table 4, suggest that the FIGARCH model captures the long memory property in the volatility processes of both 30-min and 1-hour intraday returns. In fact, the long memory parameters (d) are significant at l% level, suggesting that both intraday volatility processes are persistent over time. With respect to diagnostic tests, the lower values of both information criteria

(AIC and Hannan-Quinn) show the superiority of FIGARCH model relative to the GARCH model. Similar to the GARCH cases, the FIGARCH model is well specified to capture the long memory property in the conditional variances of intraday returns due to insignificance of diagnostic tests $Q^2(5)$ and ARCH (5).

Table 4. Estimation results and diagnostic tests for univariate FIGARCH (1,1) models

	TOPIX		KOSPI 200	
	30-min	1-hour	30-min	1-hour
Panel A: estimation results				
Const (m)	-0.0348	-0.0068	0.0580	0.0038
	(0.0201)*	(0.0041)*	(0.0280)***	(0.0051)
AR(1)	0.0621	0.0325	0.1003	0.0928
	(0.0103)***	(0.0107)***	(0.0127)***	(0.0144)***
Const (ν)	0.1900	0.0685	0.4742	0.0086
	(0.0473)***	(0.0208)***	(0.1119)***	(0.0058)
ARCH	0.5419	0.1940	0.7070	0.1739
	(0.0403)***	(0.0452)***	(0.0230)***	(0.0888)**
GARCH	0.9072	0.8361	0.9045	0.9493
	(0.0175)***	(0.0416)***	(0.0137)***	(0.0294)***
d-Figarch	0.5752	0.6474	0.4125	0.8487
	(0.0623)***	(0.0842)***	(0.0468)***	(0.0879)***
Student-*df*	2.0912	2.1104	2.3743	2.2646
	(0.0162)***	(0.0249)***	(0.0376)***	(0.0351)***
Log-likelihood	-11057.3	-720.159	-12126	-1114.52
Panel B: diagnostic tests				
AIC	4.264676	0.513368	4.678224	0.791886
Hannan-Quinn	4.267770	0.517919	4.681318	0.796435
$Q^2(5)$	1.4793	2.3836	6.4082	6.8620
	[0.6870]	[0.4966]	[0.0933]	[0.0764]
ARCH (5)	0.2981	0.4805	1.3659	1.4403
	[0.9141]	[0.7911]	[0.2338]	[0.2065]

Notes: Const (m) and Const (ν) are the constants of the mean and variance processes, respectively. $Q^2(5)$ is the empirical statistics of Ljung-Box test applied to squared standardized residuals. P-values are brackets. Student-t values are reported in parentheses. *, ** and *** indicate the significance at the 10%, 5% and1% levels, respectively.

Overall, the FIGARCH model most accurately represents the long-memory property in the conditional variance of both sets of intraday returns. The presence of long memory in intraday volatility implies dependencies between distant observations over short time intervals. These dependencies may be used in predicting future values of volatility, providing evidence against weak-form market efficiency.

5.2 Estimate of bivariate GARCH-type models

This subsection considers volatility spillover effects between two market intraday returns (30-min and 1-hour), using bivariate GARCH-type models. Tables 5 and 6 report estimates from bivariate GARCH(1,1)-DCC and bivariate FIGARCH$(1,d,1)$-DCC models based on Student-t distributions.

Table 5. Estimation results and diagnostic tests for bivariate GARCH (1,1) models

	30-min		1-hour	
	TOPIX	KOSPI 200	TOPIX	KOSPI 200
Panel A: estimation results				
Const (m)	-0.0248	0.0416	-0.0036	0.0025
	(0.0207)	(0.0265)	(0.0042)	(0.0052)
AR(1)	0.0638	0.0714	0.0464	0.0847
	(0.0100)***	(0.0109)***	(0.0107)***	(0.0127)***
Const (ν)	0.3013	0.2042	0.0497	0.0388
	(0.1105)***	(0.1132)*	(0.1732)	(0.1469)***
ARCH	0.0190	0.0342	0.1631	0.2711
	(0.0072)***	(0.0156)**	(0.5586)	(0.9710)
GARCH	0.9841	0.9869	0.9678	0.9703
	(0.0028)***	(0.0024)***	(0.0062)***	(0.0092)***
Student-*df*	2.1013 (0.0372)***		2.0277 (0.0956)***	
Log-likelihood	-22005.6		-1033.91	
Panel B: Dynamic conditional correlation				
Average CORij	0.3425 (0.0449)***		0.5393 (0.0233)***	
α_{dcc}	0.0011 (0.0005)**		0.0543 (0.0914)	
β_{dcc}	0.9984 (0.0006)***		0.9214 (0.1087)***	
Panel C: diagnostic tests				
$Q^2(5)$	0.7088	2.8919	0.8700	7.4330
	[0.9824]	[0.7166]	[0.9723]	[0.1903]
AIC	0.007805		0.011570	
Hannan-Quinn	0.014877		0.023706	
Hosking (5)	13.819 [0.9998]		12.075 [0.8432]	
McLeod-Li (5)	13.846 [0.9998]		12.084 [0.8429]	

Notes: Const (m) and Const (ν) are the constants of the mean and variance processes, respectively. $Q^2(5)$ is the empirical statistics of Ljung-Box test applied to squared standardized residuals. P-values are brackets. Student-t values are reported in parentheses. Hosking (1980) and McLeod and Li (1983) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardize residuals (5 lags). *, ** and *** indicate significance at the 10%, 5% and1% levels, respectively.

Panel A of Table 5 presents the estimation results of the bivariate GARCH-DCC model between TOPIX and KOSPI 200 intraday returns. The estimation results in Panel A indicate similarity in the estimates for the univariate GARCH models in both markets. For example, the sum of ARCH and GARCH terms are very close to unity, implying volatility persistence or volatility clustering in both 30-min. and one-hour intraday returns. In addition, Panel A of Table 6 reports the estimations of bivariate FIGARCH-DCC model based on the Student-t distribution for the two sets of intraday returns. The fractional integrated coefficient (*d*) is highly significant for both 30-min. and one-hour intraday returns, revealing a high level of persistence in conditional variances. The KOSPI 200 market displays higher persistence for both 30-min. and one-hour intraday return intervals.

Panel B of Tables 5 and 6 present estimates of the dynamic conditional correlation model (DCC). The ARCH effect (α_{dcc}) is positive and significant for both intraday returns, underlying the importance of shocks between the TOPIX and KOSPI 200 markets. For the GARCH effects (β_{dcc}), the parameters are significant and very close to one for both sets of intraday returns, confirming a high level of volatility persistence between the TOPIX and KOSPI 200 markets. Overall, the parameters (*d*), α_{dcc} and β_{dcc} indicate the significance of the dynamic and time-varying long memory estimates from the FIGARCH model. In particular, the average conditional correlations between the TOPIX and KOSPI 200 markets are all positive and significant at the one per cent level, indicating bidirectional causality between TOPIX and KOSPI 200 market intraday returns. This bidirectional causal relationship between the two intraday returns becomes stronger as the time interval increases from 30-min. to one-hour.

According to the diagnostic tests (Panel C of Tables 5 and 6), the Ljung-Box $Q^2(5)$ test statistics for the squared standardized residuals do not support rejection of the null hypothesis of no serial correlation, providing evidence of no misspecification in the GARCH and FIGARCH models. Additionally, the Hosking and Mcleod and Li test results suggest acceptance of the null hypothesis of no serial correlation in the bivariate models, and so there is no evidence of statistical misspecification in the bivariate GARCH-DCC and FIGARCH-DCC models. Lower values for both the AIC and

Hannan-Quinn information criteria indicate the superiority of the bivariate FIGARCH-DCC model compared to the bivariate GARCH-DCC model.

Table 6. Estimation results and diagnostic tests for bivariate FIGARCH $(1,d,1)$ models

	30-min		1-hour	
	TOPIX	KOSPI 200	TOPIX	KOSPI 200
Panel A: estimation results				
Const (m)	-0.0222	0.0463	-0.0046	0.0014
	(0.0210)***	(0.0269)*	(0.0042)	(0.0048)
AR(1)	0.0797	0.0980	0.0454	0.0857
	(0.0107)***	(0.0116)***	(0.0112)***	(0.0129)***
Const (ν)	0.8234	0.6573	0.0375	0.0058
	(0.1909)***	(0.1678)***	(0.0089)***	(0.0049)
ARCH	0.6907	0.7432	0.3244	0.9657
	(0.0362)***	(0.0321)***	(0.0811)***	(0.0249)***
GARCH	0.8071	0.8890	0.7226	0.1088
	(0.0186)***	(0.0167)***	(0.0613)***	(0.0975)
d-Figarch	0.1896	0.3686	0.4073	0.9530
	(0.0766)**	(0.0465)***	(0.1408)***	(0.0972)***
Student-*df*	2.3474 (0.0428)***		2.2664 (0.0327)***	
Log-likelihood	-22022.6		-1034.23	
Panel B: Dynamic conditional correlation				
Average CORij	0.4915 (0.0123)***		0.5425 (0.0226)***	
α_{dcc}	0.0329 (0.0144)**		0.0153 (0.0169)	
Beta	0.5415 (0.1739)***		0.9221 (0.1136)***	
Panel C: diagnostic tests				
$Q^2(5)$	0.3913	5.0890	0.5384	6.3286
	[0.9955]	[0.4051]	[0.9906]	[0.2755]
AIC	0.007035		0.010156	
Hannan-Quinn	0.013224		0.020775	
Hosking (5)	13.829 [0.9998]		9.5421[0.9458]	
McLeod-Li (5)	13.857 [0.9998]		9.5531[0.9455]	

Notes: Const(m) and Const (ν) are the constants of the mean and variance processes, respectively. $Q^2(5)$ is the empirical statistics of Ljung-Box test applied to squared standardized residuals. P-values are brackets. Student-t values are reported in parentheses. Hosking (1980) and McLeod and Li (1983) multivariate Portmanteau statistics test the null hypothesis of no serial correlation in squared standardize residuals (5 lags). *, ** and *** indicate significance at the 10%, 5% and1% levels, respectively.

5.3. Forecasting evaluations

This section evaluates the forecasting performance of the two competing GARCH-class models: univariate and bivariate GARCH and FIGARCH models. To assess the predictive accuracy of these volatility models, we use two forecasting evaluation criteria (loss functions). These are the root mean square error (*RMSE*) and the mean absolute error (*MAE*). For the univariate case, these criteria are respectively defined as:

$$MAE = \frac{1}{T}\sum_{i=1}^{T}\left|\sigma_{f,t}^{2} - \sigma_{a,t}^{2}\right|$$

$$MSE = \frac{1}{T}\sum_{i=1}^{T}(\sigma_{f,t}^{2} - \sigma_{a,t}^{2})^{2} \qquad (11)$$

where T is number of forecasting data points. $\sigma_{a,t}^{2}$ is the realized volatility and $\sigma_{f,t}^{2}$ is the volatility forecast obtained from a GARCH-class model. A rolling forecasting methodology is used to implement the one-, five-, and twenty-day out-of-sample forecasts of the GARCH-type models considered.

Similarly, forecasting error statistics related to the bivariate GARCH-type models are:

$$MAE_{xy} = \frac{1}{T}\sum_{i=1}^{T}\left|Cov(x,y)_{f,t} - Cov(x,y)_{a,t}\right|$$

$$MSE_{xy} = \frac{1}{T}\sum_{i=1}^{T}\left(Cov(x,y)_{f,t} - Cov(x,y)_{a,t}\right)^{2} \qquad (12)$$

where $Cov(x,y)_{a,t}$ is the actual covariance of market index intraday returns (x=TOPIX and y=KOSPI 200), and $Cov(x,y)_{f,t}$ is the covariance forecasts estimated from the bivariate volatility models.

Table 7 reports the forecasting performance of the univariate GARCH-type models for the two intraday data sets. Given its lower values for each of the two forecasting error functions, the FIGARCH model with Student-t distribution provides more accurate volatility predictions than the GARCH models for both 30-min. and one-hour intraday data over all forecasting horizons. This implies that these long memory volatility models are superior for modelling intraday volatility, consistent with Kang et al. (2009) who find superior forecasting ability for FIGARCH models in crude oil markets.

Similarly, the forecasting results for the bivariate model, reported in Table 8, show that the DCC-FIGARCH model has the lowest error functions for both 30-min. and one-hour pairs of intraday returns. In particular, for longer horizon forecasts, the long memory volatility (FIGARCH) model produces forecasts of the covariance matrix that are statistically more accurate than those produced by the short volatility (GARCH) model. These findings indicate that the ability of DCC-FIGARCH model to incorporate long memory and cross-market volatility spill overs contributes to improved forecasting and of the intraday volatility process. Several empirical studies suggest that such predictive powers assists investors in solving optimal portfolio design, risk hedging and asset allocation issues (Ferreira and Lopez, 2005; Chkili et al., 2012; Harris and Nguyen, 2013).

Table 7. Empirical forecast evaluations for one-, five- and 20-day forecasting horizons

	GARCH		FIGARCH	
	RMSE	*MAE*	*RMSE*	*MAE*
Panel A: 30-min intraday returns				
1-day horizon				
TOPIX	249.535	238.461	**54.6524**	**52.2437**
KOSPI 200	37.2311	36.1347	**6.61549**	**6.16746**
5-day horizon				
TOPIX	245.618	243.652	**59.6442**	**56.1992**
KOSPI 200	38.6230	37.2856	**10.1655**	**7.82163**
20-day horizon				
TOPIX	212.125	209.625	**66.6559**	**56.6010**
KOSPI 200	38.2057	37.0776	**9.51294**	**7.86489**
Panel B: 1- hour intraday returns				
1-day horizon				
TOPIX	23.8840	22.0385	**0.64164**	**0.60226**
KOSPI 200	2.32630	2.14685	**0.28924**	**0.25709**
5-day horizon				
TOPIX	22.6512	22.6392	**0.60503**	**0.58198**
KOSPI 200	2.05825	2.05087	**0.28002**	**0.27270**
20-day horizon				
TOPIX	19.8494	19.7449	**0.62739**	**0.52312**
KOSPI 200	2.20756	2.19568	**0.27591**	**0.26784**

Note: the lowest values in bond face indicate the best-performing model.

Table 8. Covariance forecasts for one-, five- and 20-day forecasting horizons

	RMSE	*MAE*	*RMSE*	*MAE*
Panel A: 30-min intraday returns				
1-day horizon	12.9404	12.5618	**4.48566**	**4.15320**
5-day horizon	16.3690	14.3679	**11.2644**	**6.75348**
20-day horizon	17.1313	13.5076	**13.4340**	**5.83151**
Panel B: 1-hour intraday returns				
1-day horizon	1.10148	1.02280	**0.12374**	**0.13871**
5-day horizon	1.09867	1.08066	**0.22901**	**0.17642**
20-day horizon	5.18324	1.04370	**0.45382**	**0.14285**

Note: the lowest values in bond face indicate the best-performing model.

6. Conclusions

In this paper, we have examined the issues of price and volatility spillovers between two important Asian equity markets, the Tokyo Stock Price Index (TOPIX) and Korea's Composite Stock Price Index 200 (KOSPI 200). In doing so the contributions of this paper are a focus on intraday rather than longer-term volatility spillovers, and thus also in the associated use of intraday 30-minute and one-hour interval return data. Analysis is based on results from univariate and bivariate GARCH-DCC and FIGARCH-DCC models. This has allowed us to provide insights into intraday long memory volatility in TOPIX and KOSPI 200 returns, intraday long memory spillover effects between these sets of market returns, and the performance of alternative specifications of GARCH and GARCH-DCC models.

We identify the presence of long memory in return volatility in both the TOPIX and KOSPI 200 returns, which is suggestive of evidence against weak-form market efficiency. Following this we find that the long memory volatility process in one market positively influences that of its counterpart in real time; that is, the existence of financial spillover effects in volatility between the TOPIX and KOSPI 200. Thus, intraday traders should account for the identified positive long memory volatility relationship between these two markets, even over short time intervals, in assessing investment and portfolio risk.

Finally, we provide analysis of the forecasting performance of the two competing GARCH-class models: univariate and bivariate GARCH and FIGARCH models. We assess the predictive accuracy of these models through use of the root mean square error (RMSE) and the mean absolute error (MAE) (as loss functions). We find the FIGARCH model with Student-t distribution provides more accurate volatility predictions than the GARCH models for both 30-min. and one-hour intraday data over all forecasting horizons. Similarly, we find that the bivariate FIGARCH-DCC model has the lowest error functions for both 30-min. and one-hour pairs of intraday returns. This reflects that the long memory volatility FIGARCH-style models produce forecasts for the covariance matrix that are statistically more accurate than those produced by the short volatility GARCH-style models. This implies that long memory volatility models based on the FIGARCH specification are superior for modelling intraday volatility and forecasting long memory spillover effects in the volatility of intraday returns.

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