Intraday Periodicity and Long Memory Property in High Frequency Data*

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Abstract

This paper examines the nature of long memory or self-similarity in temporally aggregated data of KOSPI and KRW-US \$, such as 10-min, 30-min, 1 hour and 1.5 hours. Apart from the commonly observed U-shaped pattern, inverse J-shaped patterns appear, due to market opening effects. The autocorrelations of absolute and squared normalized returns decay very slowly, and are associated with the long memory property. From empirical results from the FIGARCH$(1,d,1)$ model, the 10-min and aggregated intraday returns exhibit long memory in volatility. Finally, the long memory property is invariant to temporal aggregation data, supporting the theory of self-similarity in Korean financial data.

Keywords: Intraday periodicity; Volatility; Temporal aggregation; High frequency data; Long memory

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1. Introduction

Since the development of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, empirical studies have paid considerable attention to the origins of the long memory property in the volatility of financial time series.[1] In general, the presence or otherwise of the long memory property in volatility may simply be a spurious artifact of non-stationarities, due to structural changes or regime shifts.[2]

To avoid the problem of structural changes, some empirical studies that deal with low frequency data, such as daily frequency data, generally divide the sample data into two sub-samples, estimate semi-parametric long memory models using the sub-samples, and compare their results (Chung, Lin and Wu, 2000; Lamoureux and Lastrapes, 1990; Lobato and Savin, 1998). However, the use of daily frequency data cannot distinguish between real long memory and spurious long memory in volatility (Andersen and Bollerslev, 1998).

With the development of computer technology, the availability of higher frequencies allows temporal aggregation of the data and provides, for example, the ability to generate 10-, 20- and 30-minute interval data. The aggregated temporal data make it possible to reappraise the robustness of the empirical results previously obtained using low frequency data (Bollerslev and Wright, 2000). The real long memory property has a self-similarity feature that exhibits the same magnitude of the long memory parameter across sampling frequencies (Beran, 1994). Several empirical studies have examined whether the long memory property is invariant over multiple intraday frequencies data,

[1] The long memory property of financial time series refers to the presence of very slow hyperbolic decay in autocorrelations or fractionally integrated process (Baillie, 1996).

[2] Lamoreaux and Lastrapes (1990) point out that if exogenous deterministic structural changes are prevalent, this could give rise to persistence corresponding to the Integrated GARCH (IGARCH) process, in the sense that shocks to daily volatility are infinitely persistent.

and have found that the long memory property has self-similarity. This implies that the long memory property is not a spurious result stemming from structural changes in financial data (Anderson and Bollerslev, 1997a, 1997b; Baillie et al., 2004; Han, 2005, 2007; McMillan and Speight, 2006).

This paper considers an alternative explanation of the nature of the long memory property observed in volatility, using the high frequency data of the KOSPI, and of Korean won (KRW)-US \$ exchange rates. In this context, this paper has two purposes. First, we investigate intraday periodicity and persistence in the 10-min (ten minutes scale or frequency) intraday returns of Korean financial data. The high frequency returns are characterized by intraday periodicity, which is related to the trading day cycles that result from the Korean market features. Intraday periodicity, in the form of an inverse J-shaped pattern, suggests that volatility is high at the opening of trading, and low in the middle of the day and at closing time, because of market opening effects in the Korean financial markets.

Second, we examine the presence of long memory in the volatility of high frequency data, using the Fractionally Integrated GARCH (FIGARCH) model of Baillie, Bollerslev and Mikkelsen (1996). The presence or absence of long memory in temporally aggregated data may be associated with the identification of the real or the spurious long memory property in volatility. Although the Korean financial markets have experienced many exogenous shocks and multiple structural changes in the last decade, the temporal aggregation data examine the self-similarity feature that corresponds to the real long memory property, not those that result from exogenous shocks that correspond to the structural changes in Korean financial markets.

The remainder of this study is structured as follows. Section 2 discusses the basic properties of the intraday returns of Korean financial markets using the 10-min intraday returns of KOSPI and KRW-US \$. In particular, intraday periodicity is generated by average return patterns, and volatility persistence is characterized by autocorrelation functions. Section 3 discusses some of the important characteristics of the FIGARCH model. Section 4 presents the results of the long memory volatility feature over four different frequencies of 10-min, 30-min, 1-hour and 1.5-hour. The final section provides brief conclusions.

2. Characteristics of High Frequency Data

This section investigates the intriguing characteristics of intraday returns: intraday periodicity and volatility persistence. In this context, we consider the 10-min intraday returns for the KOSPI from January 2, 2003 through December 30, 2004, comprising 17,832 observations; and the KRW-US \$ from June 1, 2004 though May 30, 2006, consisting of 15,505 observations.[3] The dynamics of the sample 10-min intraday data are shown in Figures 1 (prices) and 2 (returns), respectively.

[3] The KOSPI data is obtained from the Korean Exchange (KRX), while the KRW-US \$ is sourced from the Delton. Co.

Figure 1. Dynamics of prices of 10-min data, (a) KOSPI, (b) KRW-US $

(a) (b)

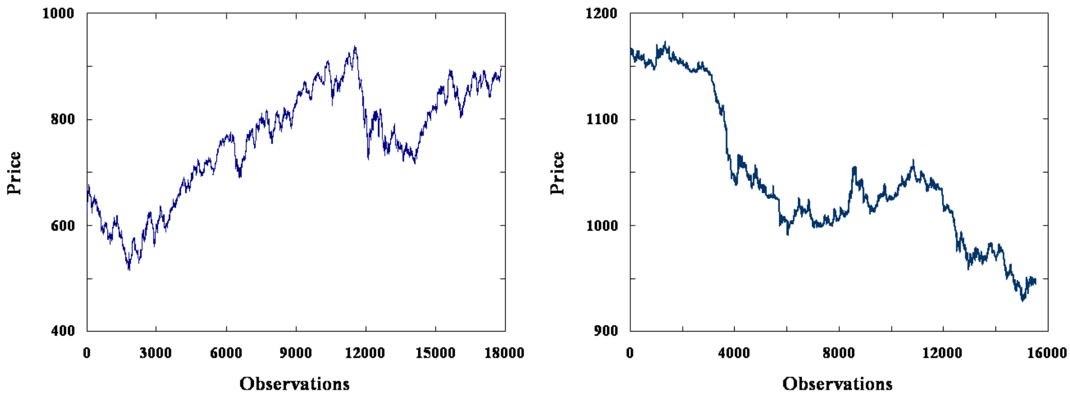
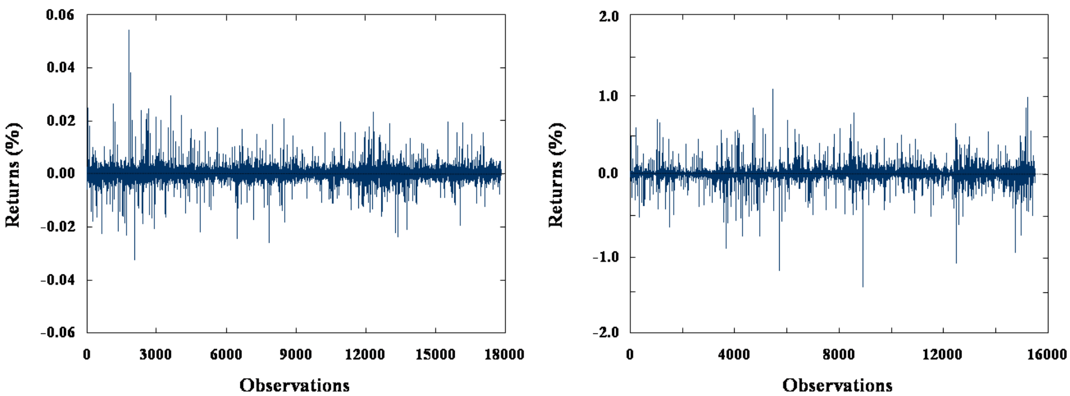


Figure 2. Dynamics of returns of 10-min data, (a) KOSPI, (b) KRW-US $

(a) (b)



Before considering the characteristics of intraday returns, we consider the distributional properties of the 10-min KOSPI and KRW-US $ return series. Table 1 summarizes the descriptive statistics of the two sample return series. Both return series show a similar picture of distributional properties. The mean values are indistinguishable from zero, and the corresponding standard deviation of the return series is much higher. However, the 10-min intraday returns of both sample series are clearly not normally distributed. For example, the values of the excess kurtosis and skewness are significantly different from zero, indicating that the distributions of both return series are skewed with fat-tails. Additionally, the high values of the Jarque-Bera (J-B) test statistics—94,678 in the case of KOSPI and 100,710 in the case of KRW-US $—reject the null hypothesis of normality at the 1% significance level.

Table 1. Descriptive statistics of 10-min return series

Statistics	KOSPI	KRW-US $
Mean (%)	0.002	-0.001
Standard deviation (%)	0.228	0.069
Minimum	-0.033	-0.014
Maximum	0.054	0.011
Skewness	1.053	-1.047
Excess kurtosis	48.99	58.61
Jarque-Bera	94,678***	100,710***

Notes: The Jarque-Bera (J-B) test statistics are distributed as $\chi^2(2)$ under the null hypothesis of normality. *** indicates the rejection of null hypothesis at a 1% significance level

2.1 Intraday Periodicity

In contrast to the lower frequency data, such as daily, weekly and monthly frequencies, the property of high frequency data shows an intraday periodicity of volatility, rather than of prices themselves (Dacorogna et al., 1993). The intraday periodicity, or U-shaped pattern, shows that, in major markets, trading activities are relatively heavy at the opening and closing of trading, and light in the middle of the day (Andersen and Bollerslev, 1997a, 1997b; Wood, McInish and Ord, 1985).

To examine the intraday periodicity, Figure 3 plots the average sample returns of 10-min intraday returns for the KOSPI and KRW-US \$. In the case of 10-min KOSPI returns, the initial 10-min interval from 9:00 to 9:10 a.m. (Korean standard time) shows large positive returns around 0.0975%, due to the impact of market opening effects, whereas the average returns across the day are centered on zero, and then increase towards the end of the trading day.

Unlike the case of KOSPI, the average returns of KRW-US \$ show large negative returns, approximately -0.99%, over the initial 10-min interval from 9:00 to 9:10 a.m., and they then increase towards the end of the trading day. It is commonly observed that low returns at opening and high returns near closing are due to trading activities. To sum up, there appears to be little evidence of any systematic and universal pattern in the average returns for the 10-min KOSPI and KRW-US \$ returns.

Unlike average returns, volatility fluctuates dramatically over the daily cycle. The average standard deviation over the 10-min interval (Figure 4) provides a picture of the behavior of market traders. From the average standard deviation of the 10-min KOSPI returns in Figure 4(a), the average standard deviation starts at nearly 0.99% in the initial 10-min interval (9:00 a.m.), then drops suddenly to the lowest level of 0.11% in the middle of the day (12:20 p.m.), and then closes to zero at closing time (14:50 p.m.). Apart from the commonly observed U-shaped pattern in developed markets, the average standard deviation of the KOSPI market shows an inverse J-shaped pattern across the 10-min intervals of every trading day.

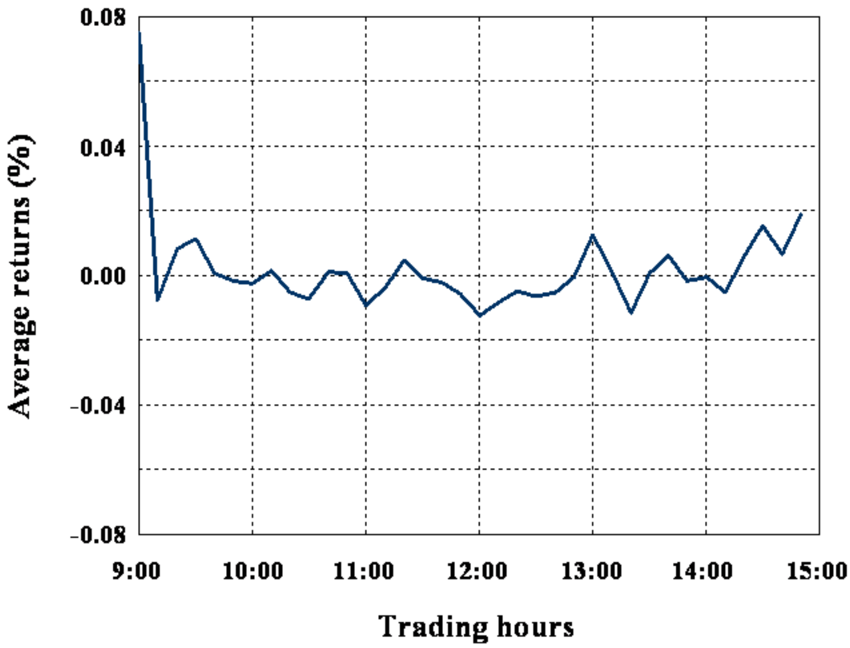
In the case of the KRW-US \$, the average standard deviation of the 10-min returns shows heavy trading activities in the initial 10-min interval, and light trading activities in the middle of the morning session. Before the close of the morning session a small spike occurs, and after the opening of the afternoon session the next spike occurs, as a result of the release of macroeconomic news in the market. In the middle of the afternoon session, trading activities decline again before the market closes for the day, and then rise slightly towards the end of the trading day. Thus, the intraday trading activities of KRW-US $ exhibit a double inverse J-shaped pattern due to the daily lunch break. This differs from the patterns of other major currencies such as DM-$, and JPY-$, which are distinctively characterized by the double U-shaped pattern in volatility (Andersen and Bollerslev, 1997b, 1998; Andersen, Bollerslev and Cai, 2000).

One important reason for the inverse J-shaped pattern is that a few 'day traders' close out all their positions at the end of each trading day, and reopen their positions the following morning (Admati and Pfledierer, 1988; Bertram, 2004). The rationale of these day traders is to avoid any overnight exposure risk in the markets. In the US and UK markets, trading activities at closing time are reinforced by a large number of intraday traders and, as a result, are equal to those occurring during the initial five-minute interval. In contrast to these developed markets, relatively little volatility associated with trading activities occurs at the Korean stock market's closing time, and larger volatility changes occur at opening time because of the impact of opening effects.

Figure 3. Intraday average returns of 10-min data, (a) KOSPI, (b) KRW-US $

During the initial 10-min interval, the average returns of the KOSPI market show large positive returns, whereas large negative returns are observed in the FX market. In the case of FX trading, there is a lunch break. No symmetrical and universal pattern appears across the trading day in the average returns of either market.

(a)



(b)

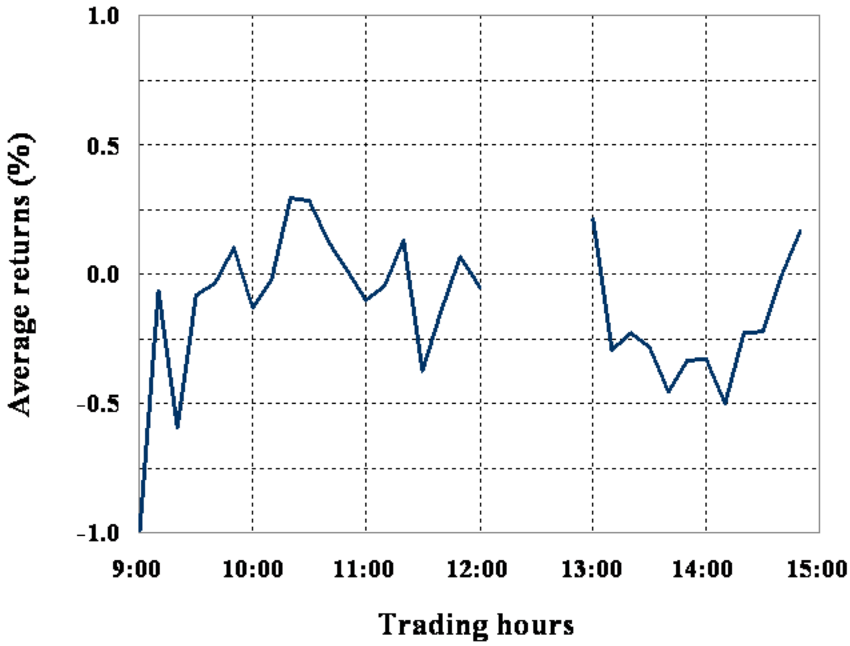
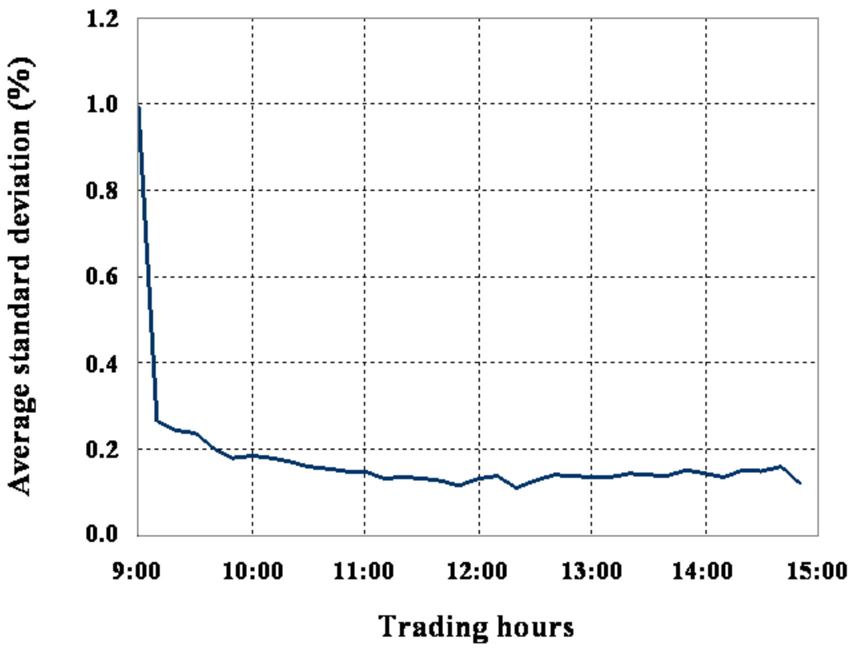


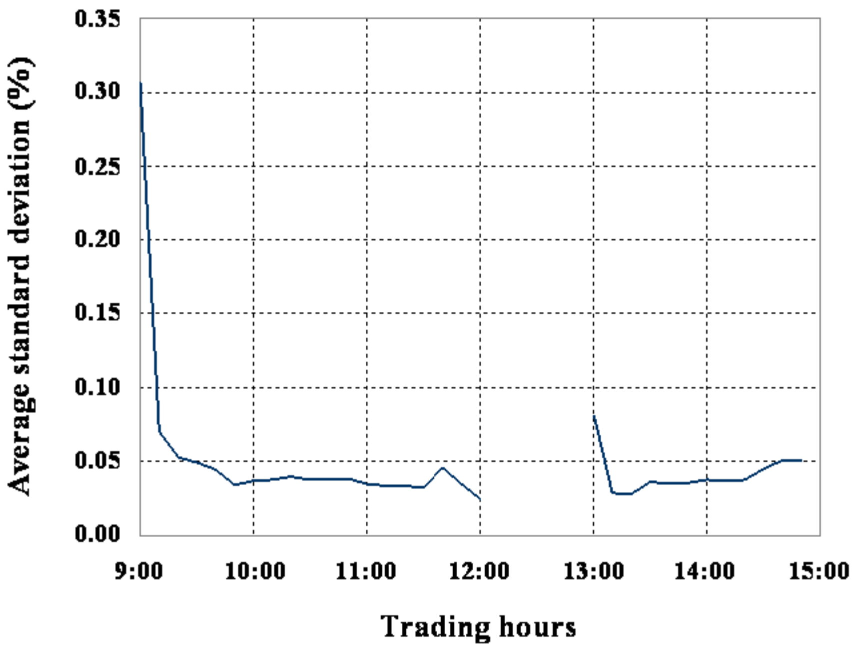
Figure 4. Average standard deviation for 10-min data, (a) KOSPI, (b) KRW-US $

The initial standard deviation of 10-min returns starts high in the morning, drops to the lowest level in the middle of day, and rises slightly again towards the close. The volatility of the KOSPI market exhibits a large inverse-J pattern, whereas two small inverse J-patterns before and after the lunch break are found in the KRW-US $ FX market.

(a)



(b)



2.2 Intraday Volatility Persistence

In this section, we demonstrate that the autocorrelations of 10-min return volatility die out at a slow rate, implying volatility persistence. To evaluate the volatility persistence, the autocorrelation functions of the 10-min returns, absolute returns and squared returns are extended with a two-sided 5% confidence band, in Figures 5 (KOSPI) and 6 (KRW-US $), respectively.[4] These two figures display the autocorrelation functions for up to 200 intervals, i.e., approximately five days (KOSPI) and six days (KRW-US $).

On the one hand, in the case of returns in Figure 5(a) and Figure 6(a), the first order autocorrelation exhibits small, positive but very significant value, but the next order autocorrelations die out very quickly. This may be due to the non-synchronous trading phenomenon. The overall pattern of higher order autocorrelations looks consistent with the realization of a white noise process. On the other hand, the autocorrelations for the absolute and squared returns display striking spike regular patterns. The strong intraday periodicity in the absolute returns and the squared returns induces the distorted U-shaped patterns in the sample autocorrelations, across each day. Even if the autocorrelations extend at the 200 lags of 10-min intervals, clear peaks never dissipate. As Figure 5(b) and Figure 6(b) show, the slowly declining U-shaped patterns occupy exactly the daily frequency in the KOSPI and KRW-US $ markets.[5]

[4] Volatility in this context can be interpreted as absolute returns and squared returns.
[5] The daily frequency of 10-min returns consists of 36 intervals in the KOSPI market as well as 31 intervals in the KRW-US $ FX market.

Figure 5. Correlograms for the 10-min KOSPI returns

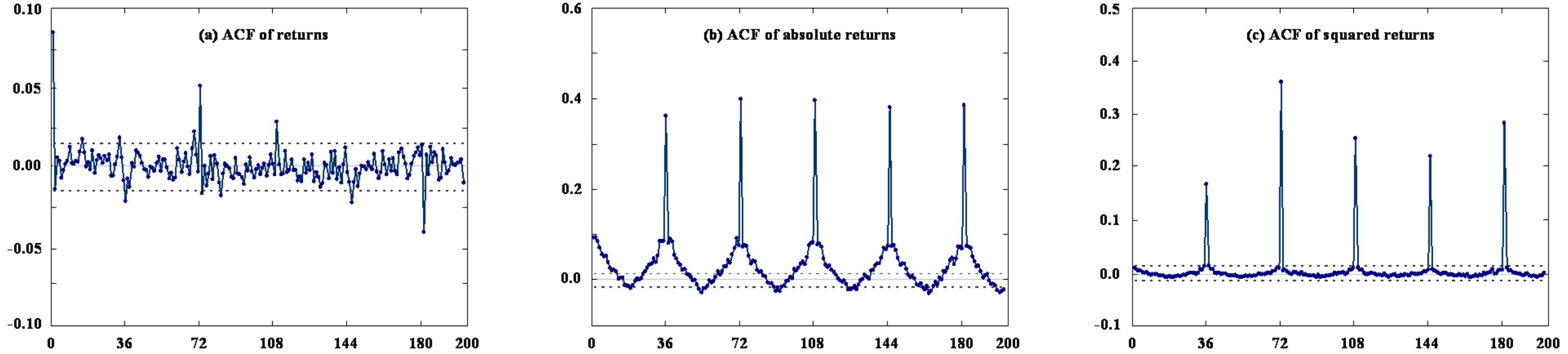
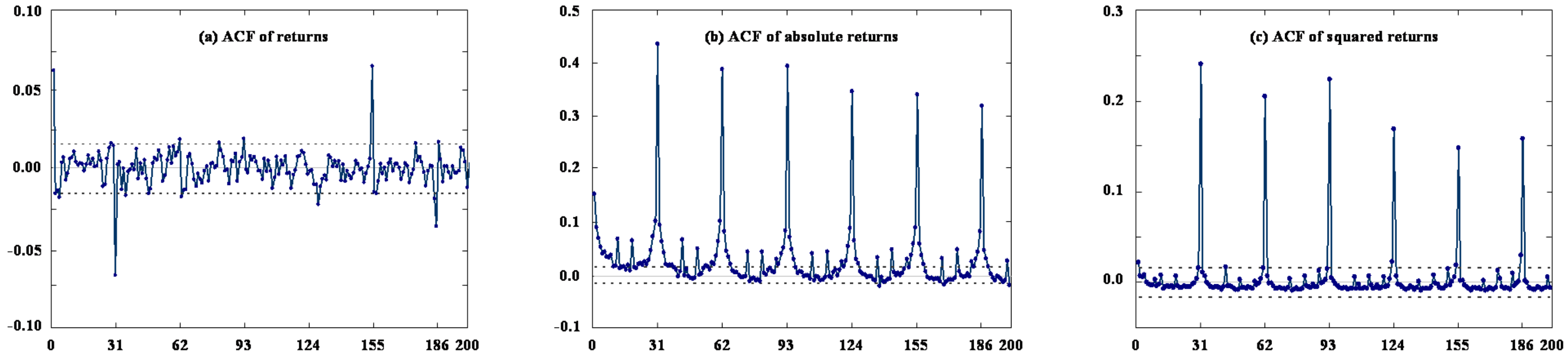


Figure 6. Correlograms for the 10-min KRW-US $ returns



The distinct U-shaped patterns observed have a strong impact on the autocorrelation patterns of intraday returns. The standard ARCH, GARCH and volatility models, originally designed to capture volatility persistence but not suitable for modeling such patterns, are masked by the distant intraday periodicity (Bollerslev, Cai and Song, 2000). They cannot accommodate the strong regular cyclical U-patterns described in Figure 5 (b), (c) and Figure 6 (b), (c). Thus, the negligible intraday periodicity may result in a distortion in the estimates of GARCH class models.

To remove this pattern in the autocorrelations, several approaches have been applied to the high frequency data returns (Anderson and Bollerslev, 1997b; Baillie and Bollerslev, 1991; Dacorogna et al., 1993; McMillan and Speight, 2006; Müller et al., 1990;).[8] We follow the approach of McMillan and Speight (2006), which filters the sample data in order to normalize the data by its standard deviation for each of the relevant 36 10-minute intervals that comprise the trading day. We calculate the normalized returns $\left(R^{s}_{n,t}\right)$ via the following transformation:

$$R^{s}_{t,n} = \frac{R_{n,t} - \left\langle R_{t,n} \right\rangle}{\sigma\left(R_{t,n}\right)}, \tag{1}$$

where $\langle \ldots \rangle$ and $\sigma(\ldots)$ denote average and standard deviation over time interval n ($n = 1,2,\ldots,36$ in the case of KOSPI; $n = 1,2,\ldots,31$ in the case of KRW-US \$) on day t (496 in the case of KOSPI; 502 in the case of KRW-US $).

[8] Andersen and Bollerslev (1997b) introduced the flexible Fourier form approach, using the average absolute returns. Baillie and Bollerslev (1991) suggested a simple dummy variable for each intra-day interval, while Müller et al. (1990) and Dacorogna et al. (1993) suggested using time scale transformations in the exchange rate intraday data. These approaches require a large number of additional parameters to be estimated at high frequencies data. This section, in this context, focuses on the more general and simple approach of removing the U-shaped pattern in the autocorrelation function of intraday returns. The approach of McMillan and Speight (2006) provides the simple normalization by average absolute returns adopted here.

Figure 7. Correlograms for the 10-min normalized KOSPI returns

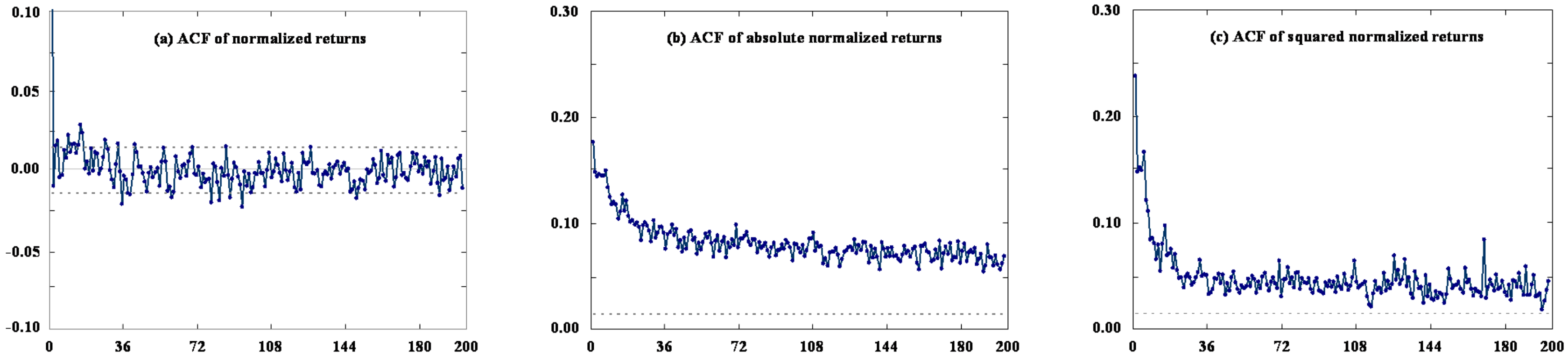


Figure 8. Correlograms for the 10-min normalized KRW-US $ returns

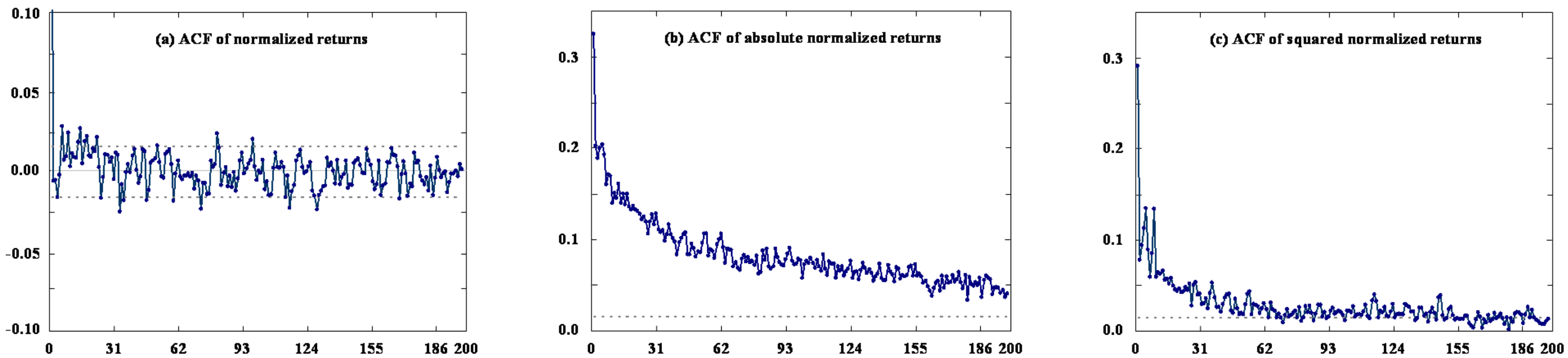


Figure 7 and Figure 8 display the autocorrelations of the returns, absolute returns and squared returns for the normalized 10-min data. After adjusting for intraday periodicity, the autocorrelations of intraday returns no longer exhibit the regular U-shaped pattern. It is clear that the strong intraday periodicity has been removed in the autocorrelations of the absolute and squared normalized returns.

Nevertheless, the extreme persistence of autocorrelations remains above the 5% significance band in Figure 7 (b), (c) and Figure 8 (b), (c). This fact is associated with the long memory property in these data. Thus, the volatility processes of intraday returns may have a long memory property in Korean financial markets.

Table 2. Descriptive statistics and independence test for normalized returns

Series	Obs.	Mean	Standard deviation	Skewness	Excess kurtosis	$Q_2(24)$
(a) Summary statistics for KOSPI normalized returns						
10-min	17,832	-0.0004	1.002	-0.36	5.27	4,643.01**
30-min	5,944	-0.0004	0.648	-0.79	6.92	433.28**
1-hour	2,972	-0.0004	0.475	-0.72	5.19	310.01**
1.5-hour	1,984	0.0009	0.389	-0.34	1.95	303.38**
(b) Summary statistics for KRW-US $ normalized returns						
10-min	15,505	0.0000	1.000	0.40	10.92	3,277.34**
30-min	5,014	0.0009	0.658	0.49	10.42	318.45**
1-hour	2,509	0.0014	0.467	0.26	5.03	271.57**
1.5-hour	1,506	0.0003	0.375	0.25	5.70	199.40**

Notes: $Q_2(24)$ is the Box-Pierce test statistic for the squared return series at lag up to 24. ** indicates the rejection of the null hypothesis of independence at the 5% significance level.

To facilitate the temporal aggregation analysis, the 10-min intraday return data of both markets are subsequently aggregated by summation, such as 30-min, 1-hour and 1.5-hour intraday returns. Table 2 presents descriptive statistics for the normalized returns of the different time scales data. For all temporal aggregation data, the normalized returns are skewed and have a very significant large excess kurtosis, implying that the distribution of normalized returns has higher peaks and fatter-tails than the normal one, regardless of time scales. In addition, the Box-Pierce test statistics for squared returns ($Q_2(24)$) reject the null hypothesis of independence, indicating that there is significant dependence in the conditional variance.

3. Methodology

3.1 Model Specification

We used the FIGARCH model of Baillie, Bollerslev and Mikkelsen (1996) to investigate the presence of long memory volatility properties in the sample data. A MA(1)-FIGARCH$(1,d,1)$ model can be given by the following equations:

$$R_{t,n}^{s} = \mu + \varepsilon_{t,n} + \theta_1 \varepsilon_{t,n-1}, \tag{2}$$

$$\varepsilon_{t,n} = z_{t,n}\sigma_{t,n},\ z_{t,n} \sim N(0,1), \tag{3}$$

$$\sigma_{t,n}^{2} = \omega + \beta_1 \sigma_{t,n-1}^{2}\left[1 - \beta_1 L - (1-\phi_1 L)(1-L)^{d}\right]\varepsilon_{t,n}^{2}, \tag{4}$$

where ω, β_1, ϕ_1, and d are the parameters to be estimated, and $0 \le d \le 1$ is the fractional differencing parameter, which measures the long memory property in the conditional variance. The FIGARCH process has impulse response weights,

$\sigma_t^2 = \omega/(1-\beta_1) + \lambda(L)\varepsilon_{t,n}^2$ where $\lambda(L) = \sum_{k=0}^{\infty} \lambda_k L^k$. For $\log k$, $\lambda_k \approx k^{d-1}$ indicates a long memory process, or Hurst effect of hyperbolic decay.[9]

To understand the long memory dynamics, we calculated the cumulative impulse response functions for the three different models, GARCH, IGARCH and FIGARCH. The cumulative impulse response function analyzes the effect and propagation of volatility shocks. Figure 9 plots the cumulative impulse response functions of the 10-min KOSPI and KRW-US \$ returns for the GARCH(1,1), the IGARCH(1,1,1) and the FIGARCH $(1, d, 1)$ models. While the IGARCH (1,1,1) model of both markets shows infinite persistence in its impulse weights, the weights of the GARCH model decay at a rapid exponential rate. In contrast to the other two models, the FIGARCH model of both markets shows the eventually slow hyperbolic rate of decay of the impulse response functions. Thus, the FIGARCH model appears to be most appropriate to capture the long memory property in both markets.

3.2 Model Density and Estimation

Under the assumption of conditional Gaussian (or normal) errors, the most common approach for estimating ARCH class models is to maximize the following conditional likelihood function:

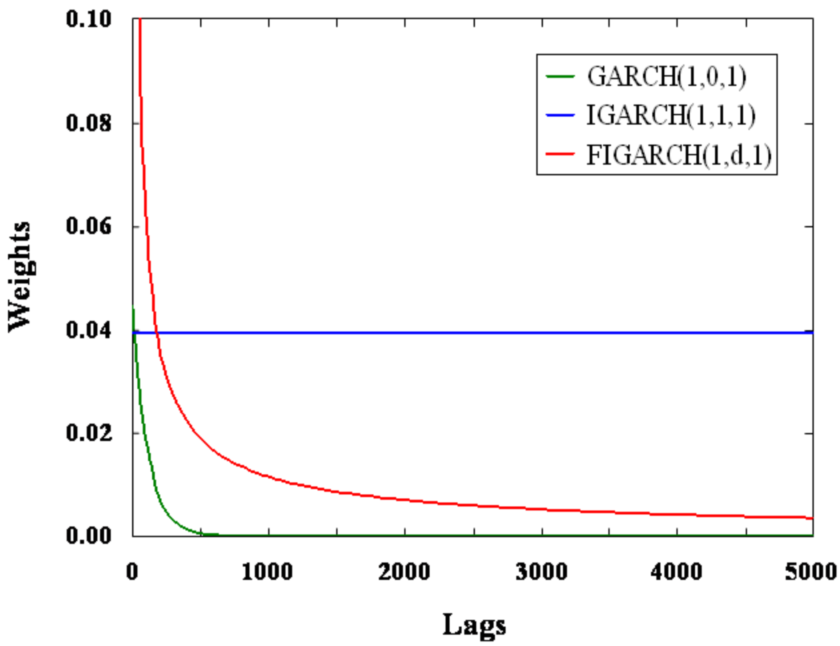
$$\log(L_{Norm}) = -\frac{1}{2} T \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left[\log(\sigma_{t,n}^2) + \frac{\varepsilon_{t,n}^2}{\sigma_{t,n}^2} \right]. \tag{5}$$

[9] For more details, see Baille, Bollerslev and Mikkelsen (1996).

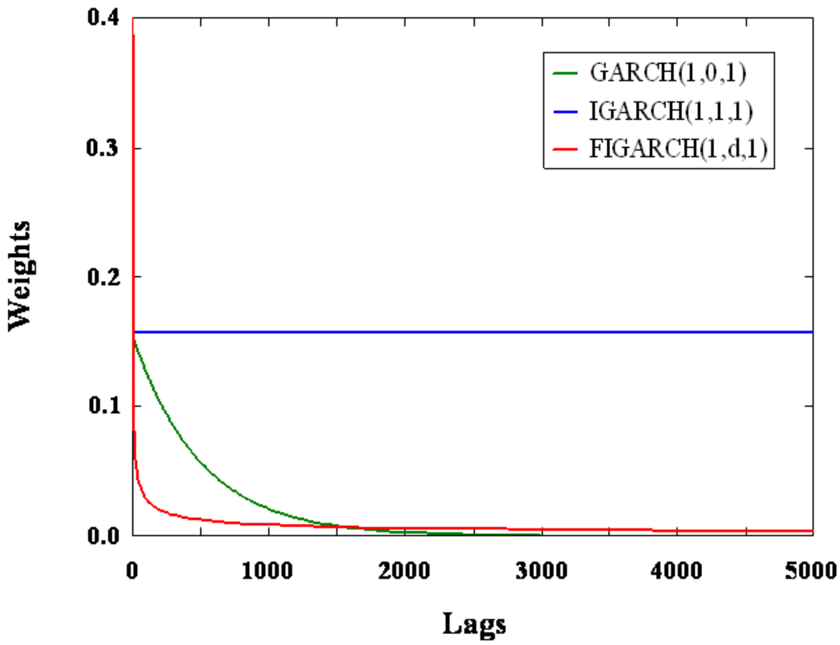
Figure 9. Cumulative impulse response functions of (a) KOSPI and (b) KRW-US $

These figures present the cumulative impulse response functions for the conditional variances for estimated GARCH $(1,1)$, IGARCH $(1,1,1)$ and FIGARCH $(1,d,1)$ models for the 10-min KOSPI and KRW-US $ returns, respectively.

(a)



(b)



Since high frequency data in many applications are not well described by the conditional normal distribution in Equation (5), our subsequent inference is consequently based on the Quasi Maximum Likelihood Estimation (QMLE) technique of Bollerslev and Wooldridge (1992).

$$T^{1/2}\left(\hat{\theta}_T - \theta_0\right) \rightarrow N\left\{\ 0,\ A(\theta_0)^{-1} B(\theta_0) A(\theta_0)^{-1} \right\}, \tag{6}$$

where $\hat{\theta}_T$ based on T observations is consistent and asymptotically normally distributed, θ_0 denotes the true parameter values and $A(\cdot)$ and $B(\cdot)$ represent the Hessian and outer product gradients, respectively.

4. Empirical Results

In this section, we investigate the self-similarity feature over multiple frequencies, such as 10-min, 30-min, 1-hour and 1.5-hour data. Table 3 reports the estimation results of the FIGARCH$(1,d,1)$ model for the KOSPI and KRW-US \$, respectively.[10] To check the relevance of the model specification, this table also provides a set of diagnostic statistics. In particular, the Box-Pierce statistics $Q_2(24)$ for the squared standardized residuals are statistically insignificant in all cases, implying that the conditional variance equation is correctly specified over various frequency return series. In addition, the values of the ARCH (5) test statistic reject the null hypothesis of no-ARCH effect in the residuals from the FIGARCH model.

[10] We also estimate the FIGARCH model with the daily data over the period from October 1998 to December 2005. Note that the estimates results are very similar to other previous studies that support the presence of long memory in the volatility of KOSPI and KRW-US \$ (Han, 2003; So et al., 2006). To save space, we do not present these results here.

The estimated values of long memory parameter d over different sampling frequencies are found to be significantly different from zero, indicating that the long memory property is prevalent in the volatility of KOSPI and KRW-US \$ intraday returns. For the temporally aggregated returns, the results of the robust Wald test reject the validity of the stationary GARCH $(d = 0)$ model null hypothesis, and support the long memory FIGARCH model in Korean financial markets.

In addition, the estimates of d are relatively stable and consistent across the various normalized intraday returns related to each of the sampling frequencies (0.284~0.408 in the case of KOSPI and 0.349~0.480 in the case of KRW-US \$) that refer to the self-similarity feature or the real long memory property. Thus, the nature of the long memory property is a self-similar process, indicating that the long memory property is an intrinsic feature of the system, rather than a result of exogenous shocks associated with regime shifts or leading to possible structural changes in Korean financial markets.[11] As a result, our empirical analysis supports the theory of self-similarity advocated by Baillie, Cecen and Han (2000), Baillie et al. (2004) and McMillan and Speight (2006).

[11] There is an interesting question concerning the KRW-US \$ return volatility related to central intervention operations during the currency crisis of 1997. Han (2005) found that the long memory in the volatility appears due to exogenous shocks or multiple beaks associated with the currency crisis in the Korean FX market. However, after the currency, the Korean FX market was liberalized, and abolished the daily exchange rate margin. As a result, in the given sample period, the Korean FX market had become more closely related with other FX markets (JPY-\$ and DM-\$).

Table 3. Estimation results of FIGARCH $(1,d,1)$ models

Model: $R^{s}_{t,n} = \mu + \varepsilon_{t,n} + \theta_1 \varepsilon_{t,n-1}$, $\varepsilon_{t,n} = z_{t,n}\sigma_{t,n}$, $z_{t,n} \sim N(0,1)$, $\sigma^2_{t,n} = \omega + \beta_1 \sigma^2_{t,n-1}\left[1-\beta_1 L - (1-\phi_1 L)(1-L)^d\right]\varepsilon^2_{t,n}$

	KOSPI				KRW-US $			
Intervals	10-min	30-min	1 hour	1.5 hour	10-min	30-min	1 hour	1.5 hour
μ	0.0129	0.006	0.006	0.008	-0.003	-0.006	0.006	0.005
	(0.006)**	(0.007)	(0.008)	(0.008)	(0.005)	(0.007)	(0.008)	(0.008)
ω	0.051	0.026	0.006	0.004	0.017	0.014	0.066	0.011
	(0.006)**	(0.014)**	(0.004)	(0.003)	(0.001)**	(0.005)**	(0.003)**	(0.011)
ϕ_1	0.625	0.517	0.727	0.663	0.695	0.530	0.689	0.309
	(0.021)**	(0.188)**	(0.098)**	(0.101)**	(0.015)**	(0.094)**	(0.109)**	(0.047)**
ϕ_1	0.431	0.307	0.487	0.312	0.495	0.267	0.538	0.127
	(0.018)**	(0.177)**	(0.086)**	(0.083)**	(0.014)**	(0.081)**	(0.117)**	(0.042)**
d	0.284	0.301	0.369	0.408	0.480	0.454	0.398	0.349
	(0.016)**	(0.048)**	(0.099)**	(0.098)**	(0.019)**	(0.066)**	(0.086)**	(0.089)**
$\log(L)$	-23908.89	-5458.31	-1807.73	-849.20	-19118.73	-4250.86	-1384.17	-527.80
Skewness	-0.197	-0.541	-0.600	-0.174	0.362	0.286	0.051	0.116
Excess kurtosis	1.185	2.842	2.733	1.247	5.622	3.753	3.418	3.856
$Q_2(24)$	18.33	16.39	19.96	17.96	16.19	16.90	13.16	17.09
ARCH (5)	0.905	1.095	1.240	0.822	0.737	0.281	0.558	0.317
$W_{d=0}$	315.06**	39.32**	13.89**	17.33**	638.22**	47.31**	21.42**	15.37**

Notes: $\log(L)$ is the maximized value of the log likelihood function, and QMLE asymptotic standard errors are presented in parentheses. The $Q_2(24)$ statistics are the Box-Pierce test statistics for 24 degrees of freedom to test for serial correlation in the squared standardized residuals. ARCH (5) represents the F-statistics of ARCH test statistic with lag 5. The ARCH test, skewness and excess kurtosis are based on the standardized residuals. W is the robust Wald statistic for testing the null hypothesis GARCH specification against the alternative FIGARCH. ** indicates the rejection of the t-statistics at a 5% significance level.

5. Conclusions

This paper has analyzed the intraday volatility dynamics and the nature of long memory in the Korean stock market index (KOSPI) and FX rates (KRW-US \$). In this context, we investigated the characteristics of the high frequency data, and focused on the intraday periodicity and the persistence of volatility.

Apart from the commonly observed U-shaped pattern in major financial markets, we observed that the intraday periodicity of volatility exhibits an inverse J-shaped pattern, because of market opening effects in the Korean financial markets. To remove such intraday periodicity, we normalized our sample return data, and found that the autocorrelations of absolute and squared normalized returns decay very slowly, and are associated with the long memory property in the volatility of KOSPI and KRW-US \$ returns.

The estimate of the long memory parameters from the FIGARCH model is statistically significant, implying that the volatility process of the high frequency returns is characterized by the long memory property. In particular, estimating the long memory parameter is invariant to different data sampling frequencies, supporting the view that the dynamics of high frequency returns have self-similarity, and that the long memory property is an inherent feature of the data generation process in Korean financial markets.

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