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Return and Volatility Spillovers between Japanese and Chinese Stock Markets：An Analysis of Overlapping Trading Hours with High-frequency Data*

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Abstract

In this paper we analyze return and volatility spillovers during overlapping trading hours between China (Shanghai Composite Index) and Japan (Nikkei 225 Index) using intraday high-frequency data. We first adjusted the 5-min. returns for intraday periodicity with Flexible Fourier Form (FFF). Then these data are used to estimate a FIAPARCH model the standard residuals of which are then employed to test for causality in mean and in variance with a cross-correlation function (CCF) approach. The results indicate a unidirectional influence from China to Japan both in terms of return and volatility. Further, volatility spillover arises with some delay after a return spillover.

JEL Classification Number: G10, G14, G15

Key words: intraday return and volatility spillover effects, high-frequency data, intraday periodicity, CCF approach, Flexible Fourier Form

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1. Introduction

The purpose of this paper is to shed light on the intraday return and volatility spillovers between Chinese[1] and Japanese stock markets.[2] China's real GDP has overtaken that of Japan in 2011 and it seems worthwhile to explore the interactions between these two markets.

There are a large number of studies on international stock market interdependence. Many report the existence of return and/or volatility spillover effects between countries or a unidirectional effect from a larger market (such as the U.S.) to a smaller market (Hamao, Masulis and Ng (1990), Jeon and von Furstenberg (1990), Cheung and Mak (1992), Masih and Masih (1999), Darrat and Zhong (2005), Mukherjee and Mishra (2010), among others). However, there exist many papers which point out that the Chinese stock market is not influenced by price movements in other international markets, such as the U.S., the U.K., German, or Japanese markets (Huang, Yang and Hu (2000), Groenewold, Tang and Wu (2004), Chen and Liu (2008), Hirayama and Tsutsui (2009), Nishimura and Men (2010), etc.). This result of China's relative independence despite its economic size is an interesting puzzle which we will explore in this paper using a new dataset and methodology.

In the first place, most empirical analyses of international stock price interactions have thus far utilized daily data, but this paper employs stock price data observed at a 5-minute frequency[3]. Technological innovations in communication and computers have led to ever faster transmission of information and execution of financial transactions. Stock markets that are efficient should reflect new information from abroad very rapidly. Thus, it is important to analyze high-frequency data to explore how fast the spillover occurs.

In the second place, since we are focusing on China and Japan, it is crucial to use high-frequency data because these two markets have overlapping trading hours. The time difference between the two countries is a mere one hour which implies a daily span is too

[1] By 'China' we mean the mainland China in this paper. Thus, Hong Kong, Macao and Taiwan are excluded from the analysis.

[2] The share of market capitalization of the Shanghai Stock Exchange in the world total as reported by the World Federation of Exchanges (WFE) rose from 0.66% in 2005 to 4.94% in 2010. If Shenzhen Stock Exchange is added to Shanghai, the combined share rose from 0.93% in 2005 to 7.33% in 2010. At the end of 2010, the market capitalization of the Tokyo Stock Exchange, the single largest in Asia, stood at 3.83 trillion US dollars with a 6.97% share in the world total.The data source is *WFE Annual Report*.

[3] Studies exploring return and/or volatility spillover with high-frequency data have focused on European and American markets with overlapping trading hours are: Jeong (1999), Égert and Kočenda (2007), Černy and Koblas (2008), and Harju and Hussain (2008).

long to capture mutual influences. If we use daily closing prices from these markets[4], we can probably measure the effect of Tokyo on Shanghai, but the reverse effect from Shanghai to Tokyo is based on a 23-hour lag which would include effects from the intervening markets such as European and American markets. Consequently, it would be natural and appropriate to utilize intraday high-frequency data during overlapping trading hours to capture the spillovers between China and Japan.

Hirayama and Tsutsui (2009) also use high-frequency (minute-by-minute) data to analyze interactions between Chinese and Japanese stock markets. Compared with their work, this paper has two merits. The first is that this paper analyzes both return and volatility spillovers, while Hirayama and Tsutsui (2009) only focus on the former. Volatility is a very important concept in modern financial markets and it has become a standard practice to estimate volatility spillovers in studying co-movements between international stock markets (Hamao, Masulis, and Ng (1990)).[5] Whether volatility spillover effects can be verified as in the case of return spillovers is an interesting question to answer.[6]

Secondly, while Hirayama and Tsutsui (2009) conduct empirical analyses without dealing with intraday periodicity in stock prices, this paper attempts to purge the data of intraday periodic patterns by applying Flexible Fourier Form (FFF) to intraday data as proposed by Gallant (1981). Andersen and Bollerslev (1997, 1998b) also employ this method to treat intraday periodicity. As Andersen and Bollerslev (1997, 1998b) and many others have shown, estimating volatility without seasonally adjusted intraday data is subject to a statistical bias in estimation. Thus, it is interesting to compare our result with that of Hirayama and Tsutsui (2009) regarding the return spillover effects.

This paper is organized as follows. In the next section the data to be used is explained and its intraday characteristics are summarized. Then, the intraday periodicity is removed by applying the FFF. The third section estimates FIAPARCH (Fractionally Integrated APARCH) model to characterize the volatility generating mechanism. We derive

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[4] In fact Shanghai closes exactly one hour after Tokyo's closing.

[5] The stock investors are paying increasing attention to volatility as well as returns. This is probably the background for Nikkei, Inc., the publisher of the Nikkei Stock Average Index, to introduce a new Nikkei Stock Average Volatility Index on Nov. 19, 2010 and to start updating this Index every 15 seconds from January 2012.

[6] Another important issue is whether the speed of transmission may differ between the two. To investigate this problem, we explicitly test for the lags in spillovers by using cross-correlation function (CCF) approach proposed by Cheung and Ng (1996).

standardized residuals from this model and then compute cross-correlation functions with these residuals. The fourth section concludes the paper.

2. Statistical Methodology and Intraday Periodicity

2.1 Data

We have collected data on Nikkei 225 Index (abbreviated as NKY) for Japan and on Shanghai Composite Index (henceforth referred to as SHCOMP) for China for the period from Jan. 2, 2008 to Nov. 30, 2010.[7] We retrieved stock prices at 5-minute intervals and computed a logged difference multiplied by 100. As one uses higher-frequency data, one obtains more data points, but it comes at a cost of increased market microstructure noise such as the bid-ask bounces. Taking this tradeoff into account, Andersen *et al.* (2001), Koopman, Jungbacker, and Hol (2005), and Watanabe (2007) recommend using 5-min. observations.[8] In the case of NKY, furthermore, there is a peculiar system of updating special quotes[9] at 5-min. intervals which was first reported by Tsutsui *et al.* (2007). If one were working with minute-by-minute data, this would appear as a spike in auto-correlation functions at 5-min intervals. With 5-min. intervals, this problem becomes irrelevant.

The trading hours of the Tokyo Stock Exchange is 09:00-11:00 for the morning session and 12:30-15:00 for the afternoon session. Those of Shanghai are, in Japanese Standard Time, 10:30-12:30 for the morning session and 14:00-16:00 for the afternoon session (Fig. 1). Therefore, there are two overlapping periods (windows) during which the two stock exchanges are open simultaneously: 30 min. period for 10:30-11:00 in the morning and 60-min. period for 14:00-15:00 in the afternoon every day. We use observations during these two windows in the computation of cross-correlation functions below. In this case there are 11,988 observations on 5-min. returns. When either Tokyo or Shanghai Stock

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[7] China has two major stock exchanges: one in Shanghai and the other in Shenzhen. The Shenzhen Composite Index is also available to us. The market capitalization of the main board of Shanghai at the end of 2010 stands at 18.5 trillion RMB which is far greater than that of Shenzhen at 4.4 trillion RMB. The volume and value of market turnover for 2010 is 3.4 trillion shares and 34.7 trillion RMB for Shanghai and is 1.2 trillion shares and 14.0 trillion RMB for Shenzhen. Since Shanghai is a much greater market than Shenzhen, we chose Shanghai to represent the entire Chinese market. In addition, the simple correlation coefficient between the two market indexes is extremely high (0.94 even using min.-by-min. returns according to Hirayama and Tsutsui (2009)), implying that it is not necessary to take Shenzhen into account. The data source for the above is the respective website of the two exchanges and their *Fact Books*. The figures are total for A and B shares.

[8] See also fn. 19.

[9] When the next transaction price is likely to exceed a certain pre-set band, a special quote is invoked and the order matching is temporarily suspended. This constitutes an announcement to inform the market participants of a large price jump.

Exchange is closed due to a national holiday, we excluded this date from the analysis. However, when we deseasonalize the intraday data and when we estimate volatility measures by a FIAPARCH model in Section 3, we use all the available observations during the entire trading hours. Overnight returns and returns during the lunch break are not included in the analysis. Consequently, there are 54 observations per day for Tokyo and 48 for Shanghai. With 712 trading days in Tokyo and 707 in Shanghai, the total sample size amounts to 38,358 and 33,936 respectively. The data source is Nikkei, Inc. for NKY and TickData.com for SHCOMP.

===== Figure 1 =====

2.2 Properties of Intraday Data

We characterize the properties of the intraday 5-min. returns in this subsection. Specifically, we focus on means of 54 or 48 5-min absolute returns ($\left|r_{t(i)}\right|$)[10], averaged across 712 or 707 days of trading, in order to capture the intraday patterns in volatility (Fig. 2). The graph for NKY exhibits a slightly W-shaped pattern which is not as stark as those described by Andersen, Bollerslev, and Cai (2000), because we omit returns during the lunch break.[11] The intraday volatility for SHCOMP, however, does not display a W-shaped pattern at all. The volatility diminishes unambiguously toward the closing of each session in Shanghai.

===== Figure 2 =====

The lines in Figure 3 indicate autocorrelation functions up to 10-day lags (namely, 540 lags for NKY, and 480 lags for SHCOMP). These charts clearly exhibit a regular intraday periodicity which is quite stable over the past several days. Within a day the volatility pattern is U-shaped in Shanghai, but is somewhat W-shaped in Tokyo. One should note that these autocorrelations are all highly statistically significant (the 5% critical value is depicted in these charts by a dotted line). Another feature is that ACFs decline very gradually over the 10-day period, suggesting that the volatility follows a long-memory

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[10] Following Andersen and Bollerslev (1997, 1998b), Andersen, Bollerslev and Cai (2000) and many others, we compute mean absolute returns as a proxy for intraday volatility.

[11] If the return over a lunch break is included in the analysis, the spike in the middle of the day becomes much higher, giving rise to a much clearer W-shaped pattern.

process.

===== Figure 3 =====

2.3 Removing Intraday Periodicity

As Andersen and Bollerslev (1997, 1998b) and others have shown, applying empirical analyses to high-frequency intraday data without treating the periodicity properly results in biases in estimated volatility. Thus, we apply a Flexible Fourier Form (FFF) proposed by Gallant (1981) to the raw data as Andersen and Bollerslev (1997, 1998b) have adopted. Details are relegated to the Appendix. Henceforth, the raw intraday return is denoted by $r_{t(i)}$ and the adjusted return by $\tilde{r}_{t(i)}$.

Figure 4 plots the mean intraday volatility of the adjusted series. The results exhibit no intraday cyclical patterns, indicating that the adjusted returns, $\tilde{r}_{t(i)}$, via FFF are suitable for estimation. We should be wary, however, of high autocorrelations which dampen very slowly (Fig. 5). This is a typical symptom of a long-memory process, thus we consider a fractional integration when we estimate a volatility model in the next section.

===== Figure 4 =====

===== Figure 5 =====

The basic statistical properties of the adjusted returns are displayed in Table 1. The means of intraday returns are both negative, which imply a declining market in the two stock markets. However, they are not significantly different from zero. The standard deviation of SHCOMP is greater than that of NKY at 1% significance, indicating a higher riskiness in Shanghai than in Tokyo during this period. The skewness and kurtosis both differ significantly from the values implied by a normal distribution (0 and 3 respectively). A large value for kurtosis means the distribution of intraday returns have fatter tails than the normal distribution.

LB(10) is a test for the absence of serial correlation from the first order through tenth order lag which was proposed by Ljung and Box (1978). The two volatility measures have both very high values of *LB*(10). *LB*(500), not shown here, is also highly significant at 1% level, implying that the intraday volatility has a long-memory property.

===== **Table 1** =====

3. A Causality-in-mean and Causality-in-variance Test Using the CCF Approach

3.1 The Empirical Methods

In this section, we apply a two-step procedure developed by Cheung and Ng (1996). Step one: we estimate appropriate volatility model for each univariate time series to obtain their standardized residuals. Step two: the CCF of standardized residuals and squared standardized residuals are used to detect causality in mean and causality in variance between Japanese and Chinese stock markets.

3.1.1 Volatility Model

Models to analyze volatility in economic/financial time series are broadly divided into two groups. The first is the ARCH (Autoregressive Conditional Heteroskedasticity) model first proposed by Engle (1982). The second is the SV (Stochastic Volatility) model.[12] Due to its ease of estimation, the ARCH model has been extended in many directions. We adopt, in this paper, a FIAPARCH（Fractionally Integrated APARCH） model proposed by Chung (1999) which is an extension of APARCH (Asymmetric Power ARCH) model suggested by Ding, Granger and Engle (1993). The APARCH model is suited to capture asymmetric effects in a volatility process. Fractional integration describes a long-memory process, which is often the case with many volatility measures.[13]

The AR(k)-FIAPARCH($1,d,1$) model to be used in estimation is written as follows:

$$\tilde{r}_{t(i)} = c + \sum_{h=1}^{k} \phi_h \tilde{r}_{t(i-h)} + \varepsilon_{t(i)}\,,\ \ \varepsilon_{t(i)} = \sigma_{t(i)} z_{t(i)}\,,\ \ z_{t(i)} \sim i.i.d. \quad E(z_{t(i)}) = 0 \quad Var(z_{t(i)}) = 1 \tag{1}$$

$$\sigma_{t(i)}^{\delta} = \sigma^2 (1-\beta) + (1 - \beta L - (1-\alpha L)(1-L)^d)((|\,\varepsilon_{t(i)}\,| - \gamma \varepsilon_{t(i)})^{\delta} - \sigma^2) + \beta \sigma_{t(i-1)}^{\delta} \tag{2}$$

Equation (1) is a return equation which is specified as an AutoRegressive (AR) model. ϕ

[12] The ARCH-type models are explained in detail by Bollerslev, Engle and Nelson (1994) and Xekalaki and Degiannakis (2010). The SV models are treated by Shephard (2005).

[13] Chung (1999) improves structural problems inherent in a FIGARCH model of Baillie, Bollerslev, and Mikkelsen (1996) and in a FIAPARCH model of Tse (1998). The reader is referred to Laurent and Perets (2002) and Xekalaki and Degiannakis (2010) for details. Note in passing that Xekalaki and Degiannakis (2010) label Chung's model FIAPARCHC in order to distinguish it from Tse's model.

are parameters of the autoregressive terms, $\varepsilon_{t(i)}$ is an error term, $z_{t(i)}$ is an *i.i.d.* random variable with mean 0 and variance 1.[14] Equation (2) is a variance equation which is a FIAPARCH model as formulated by Chung (1999). σ^2 is the unconditional variance of $\varepsilon_{t(i)}$, and *L* is the lag operator such that $L^k y_t = y_{t-k} (k = 0,1,\cdots)$. The notable feature of this model is parameter *d*, which critically determines whether the variable in question has a long-memory property. If $d = 0$, the volatility follows a short-memory process, and if $0 < d < 1$, it follows a long-memory process. With $d < 0.5$, it is a stationary, and with $d \geq 0.5$, it is a non-stationary long-memory process.

There might arise an asymmetric effect on volatility, depending upon whether the stock price rises or falls. In our FIAPARCH model, this asymmetry can be captured by γ. If $\gamma = 0$, there is no asymmetric effect, and if $\gamma > 0$, an unexpected decline in stock price (a negative $\varepsilon_{t(i)}$) increases volatility.

While the variance is specified as $\sigma^2_{t(i)}$ in most ARCH models, in our APARCH specification above, $\sigma^{\delta}_{t(i)}$ is formulated. The power δ of this term is also estimated as one of the parameters.[15]

3.1.2 The CCF approach

The residuals of an estimated FIAPARCH model are standardized by $\hat{z}_{t(i)} = \hat{\varepsilon}_{t(i)} / \hat{\sigma}_{t(i)}$ which are then applied to the CCF approach of Cheung and Ng (1996). The CCF approach enables us to obtain information on the lag structure in causal relationships as well as on the causality in mean and causality in variance. Namely, return and volatility spillover effects can be tested at the same time. This approach does not require a normality assumption, because the test statistics are known to follow a standard normal distribution asymptotically (Hamori 2003, p. 2).

For the sake of exposition let us denote the standard residuals for Japan as $\hat{z}_{Jpn,t(i)}$ and those for China as $\hat{z}_{Chn,t(i)}$. The sample cross-correlation function at a *k*-th lag between $\hat{z}_{Jpn,t(i)}$ and $\hat{z}_{Chn,t(i)}$ is defined as follows:

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[14] Since the standardized residuals of equation (1) do not follow a normal distribution, we used Quasi-Maximum Likelihood (QML) method to estimate parameters of the AR-FIAPARCH model. See Sec. 2.2 of Xekalaki and Degiannakis (2010) for details of QML.

[15] An APARCH model incorporates seven special cases of an ARCH-type model which helps us to identify one of them by restricting certain parameters. For example, if $\delta = 2, \gamma = 0$, the APARCH model is reduced to a conventional GARCH model. See Appendix A of Ding, Granger and Engle (1993) for details.

$$\rho_{JpnChn}(k) = Cov_{JpnChn}(k) \Big/ \sqrt{Var_{Jpn} \times Var_{Chn}} \tag{3}$$

where Var_{Jpn} and Var_{Chn} is the variance of $\hat{z}_{Jpn,t(i)}$ and $\hat{z}_{Chn,t(i)}$ respectively and $Cov_{uv}(k)$ is a sample cross-covariance with a *k*-th lag.

Now we can define a test statistic, $CCF(k)$, at lag *k*:

$$CCF(k) = \sqrt{T \times n}\rho_{xy}(k) \quad . \tag{4}$$

Cheung and Ng (1996) proved that the test statistic of (4) follows an asymptotically standard normal distribution as the sample size, *T*, approaches infinity. By testing the null hypothesis, H_0:*CCF*(*k*)=0 (no causality) against the alternative hypothesis, H_1:*CCF* (*k*)$\neq 0$ (causality exists), we can infer the presence or absence of causality at lag *k* between two return series. To be specific, when we cannot reject the null for k>0, we infer causality from Japan to China. In the case of k<0, non-rejection of the null implies causality from China to Japan.

The above is a test of causality in mean. The causality in variance is tested by first squaring the two standardized residuals, $\hat{z}^2_{Jpn,t(i)}$ and $\hat{z}^2_{Chn,t(i)}$, and then by applying the same procedures as above to these squared residuals.

3.2 Empirical Results

3.2.1 Estimation Results of the AR-FIAPARCH Model

The estimation results of AR-FIAPARCH model are summarized in Table 2.[16] The parameter, *d*, is greater than 0 and less than 0.5 at a 1% significance level in both China and Japan, which implies that the two intraday volatility measures follow a stationary long-memory process.

The parameter, γ, to capture the asymmetric response of volatility is positive at a 1% significance level. Volatility tends to increase more in the case of stock price declines. This result is consistent with past research on Chinese and Japanese stock markets such as Watanabe (2007), Men, Nishimura and Li (2007), among others. The null of $\delta = 2$ cannot be rejected either in China or Japan.

[16] The lag order of the AR part was determined by the minimum AIC achieved by *k*=24 for both NKY and SHCOMP after varying the parameter between 1 and 30. However, these 24 coefficients on the lagged independent variables in the AR part are not shown in the Table to save space.

We examine the appropriateness of our specification by focusing on the serial correlation of standardized residuals, $\hat{z}_{t(i)} = \hat{\varepsilon}_{t(i)} / \hat{\sigma}_{t(i)}$, and their squares, $\hat{z}^2_{t(i)}$. The Ljung-Box statistics, $LB(10)$ and $LB(30)$ in Table 2, test the null hypothesis that the autocorrelation coefficients from lag 1 to 10 or 30 are all zero. The results indicate that the null cannot be rejected at a 10% level, justifying our model specification.

===== Table 2 =====

3.2.2 Causality Tests by the CCF Approach

We now proceed to test causality in mean and causality in variance by using the standardized residuals obtained above in the FIAPARCH model. We can shed light on the return and volatility spillover effects between China and Japan.

The estimation results are shown in Table 3. Since the common trading hours is 30 min. in the morning and 60 min. in the afternoon, we tested lags up to sixth order (30 min.). Tests on causality in mean are displayed on the left-hand side of Table 3. The results indicate there is no causality from past values of NKY to SHCOMP. However, SHCOMP has a significant effect on NKY with 1- or 2- period lag at a 1% or a 10% significance level respectively. The 5-min return in Tokyo responds to a return in Shanghai with a 5- to 10-min. delay. Utilizing min.-by-min. returns of Shanghai and Tokyo, Hirayama and Tsutsui (2009) found that Tokyo completes responding to Shanghai within about 10 minutes. Our result is quite consistent with their finding.

The tests on causality in variance are exhibited on the right-hand side of Table 3. As in the case of causality tests in mean, NKY has no discernible effect on SHCOMP, but SHCOMP has a slight, albeit with a three-period lag (15 min.), effect on NKY at a 5% level. Thus, volatility spillover also runs from China to Japan as in the return spillover effects.

Finally, we should note that the spillover effects are both positive: a rise in return or volatility in China leads to a similar rise in Japan.

===== Table 3 =====

4. Conclusions

Despite ample evidence on mutual return/volatility spillovers between major economies, the Chinese market has been an exception in that it is not affected by other markets. Therefore, we regard this finding an important and interesting issue worth investigating in depth. Even more importantly, we would like to explore its underlying causes. One of our new contributions to the literature is the use of high-frequency (5-min.) data to focus on this issue. Since China and Japan are geographically close, they share one and a half hours of simultaneous trading on a given day. It is natural as well as appropriate to examine real-time interactions between China and Japan during these overlapping trading hours. Considering the fact that investors are now obtaining information very rapidly thanks to recent advances in information and communication technology, this use of high-frequency data is expected to shed more light on the informational efficiency of international stock markets.

Hirayama and Tsutsui (2009) is one of the few studies on interactions between Chinese and Japanese stock markets using high-frequency data, but they focus only on return spillovers. They do not adjust for the intraday periodicity of the data, but we have adjusted the data for this periodicity. While they compute conventional linear regressions, we have applied cross-correlation functions to test for causality in both mean and variance.

We compiled stock price data sets at a 5-min. frequency for Shanghai and Tokyo markets for the period from Jan. 2, 2008 through Nov. 30, 2010. The empirical analyses revealed both return and volatility one-way spillover effects running from Shanghai to Tokyo. The return spillover effect is observed with a 1- to 2-period (5- to 10-min.) lag, but the volatility spillover occurs with a three-period (15-min.) lag. Volatility spillover is found to occur more slowly relative to return spillovers.

The first result (China not being affected by Japan) is consistent with past studies which also report China's independence of other markets. The cause for this would be found in the fact that the scope of foreign investors' activity is strictly regulated in China and that Chinese individual investors' portfolios are not diversified internationally. In principle, foreign investors can buy only B shares of Shanghai Stock Exchange. The market capitalization of B shares represents only 0.96% of the entire market capitalization (A+B) at the end of 2010. Thus, foreign influence on Shanghai is quite limited.[17]

China's stock market participation abroad started in 2006 when it was legalized with a small group of institutional investors who were approved as Qualified Domestic Institutional Investors (QDII). [18] Excluding this group of investors, most other Chinese institutional investors' portfolio does not contain foreign stocks. Thus, they have no incentive to collect and analyze information on foreign markets.

Why, then, do we have a lagged response in volatility spillovers? We interpret this phenomenon as follows: A rise or fall in returns is easy to interpret, but changes in volatility are difficult to disentangle. When a stock return rises, it contains a good news about the prospect of a firm or an economy, and vice versa. When volatility rises, it cannot be immediately interpreted as a good news or a bad news. It would take investors some effort and time to infer what lies behind the volatility rise or fall. Ross (1989) hypothesizes a close relationship between information flows and volatility. An increase in information flow leads to a rise in volatility, but it would be difficult to determine the implications of such an increase.

Some may argue that a rise in volatility implies a rise in uncertainty and that its effects on other markets are clear-cut. However, one needs to have a sufficient number of observations to conclude a rise in volatility. The volatility measure estimated in this paper is an *ex post* proxy for the underlying uncertainty. In reality some time is required to recognize a rise in uncertainty. This is another interpretation for the delayed volatility spillover reported in this paper.

[17] To be precise, foreign investors can also buy A shares if they become eligible as Qualified Foreign Institutional Investors (QFII). The QFII status is accorded to only 97 institutions with up to 19.7 billion US dollars in investible assets as of end 2010. And their share of stock holdings in China is a mere 0.57%. Thus, it would be fair to conclude that their influence on Chinese stock market is almost negligible.

[18] Foreign assets that QDII can hold are also subject to many regulations. Risky investments particularly in stocks are restricted such that the share of stocks in their foreign portfolio is still very small.

Appendix: Flexible Fourier Form (FFF)

In this appendix we explain the Flexible Fourier Form (FFF) which removes intraday periodicity from the raw data. The intraday return observed at time *i* on day *t*, $r_{t(i)}$ ($t = 1, 2, \cdots, T$; $i = 1, 2, \cdots, n$), is expressed as:

$$r_{t(i)} = E[r_{t(i)}] + \sigma_{t(i)} s_{t(i)} z_{t(i)} \quad , \tag{A1}$$

Where $E[r_{t(i)}]$ is the expected return, $\sigma_{t(i)}$ is an intraday volatility factor, $s_{t(i)}$ is an intraday periodic factor, and $z_{t(i)}$ is an *i.i.d* mean 0 and variance 1, error term. These are all independent of each other with $\sigma_{t(i)}, s_{t(i)} > 0$ assumed. Equation (A1) is squared and logged. After rearranging the terms, we get:

$$x_{t(i)} \equiv 2\ln(|\, r_{t(i)} - E[r_{t(i)}]\,|) - \ln(\sigma_{t(i)}^2) = c + 2\ln(s_{t(i)}) + u_{t(i)} \tag{A2}$$

where $c = E[\ln(z_{t(i)}^2)]$ and $u_{t(i)} = \ln(z_{t(i)}^2) - E[\ln(z_{t(i)}^2)]$.

Andersen and Bollerslev (1997, 1998b) have applied the FFF to deseasonalize the periodic factor and the FFF was originally proposed by Gallant (1981). The FFF is applied to our periodic factor $s_{t(i)}$ as follows:

$$2\ln(s_{t(i)}) = f\left(\theta; t(i)\right) = \sum_{j=0}^{J} \sigma_t^j \left[\mu_{0,j} + \mu_{1,j}\frac{i}{N_1} + \mu_{2,j}\frac{i^2}{N_2} + \sum_{l=1}^{P}\left(\gamma_{l,j}\cos\frac{2l\pi i}{n} + \delta_{l,j}\sin\frac{2l\pi i}{n} \right) + \sum_{k=1}^{D} \lambda_k I_k\left(t(i)\right) \right] \tag{A3}$$

where *t* is the observation date, *i* the time on the observation date, *n* the number of intraday observations, $N_1 = (n+1)/2$, $N_2 = (n+1)(n+2)/6$, and $\mu_{0,j}, \mu_{1,j}, \mu_{2,j}, \gamma_{l,j}, \delta_{l,j}, \lambda_k$ parameters to be estimated. The second and third terms in the square brackets on the right-hand side of (A3) represent linear and quadratic time trends during one day and the fourth term with trigonometric functions capture the intraday periodic patterns. $I_k(t(i))$ in the last term is an event dummy with value 1 if a certain event occurs on day *t*, at time *i*, and 0 otherwise. We consider the day-of-the-week effects in this paper, thus the day of the week is the event we adopt for $I_k(t(i))$.[19]

[19] If we set *J*=0 and *P*=0 in (A3), it is equivalent to the standard FFF of Gallant (1981). However, Andersen and Bollerslev (1997) assert that it is important to consider the interactions between periodic

There are two steps in the actual estimation of (A3). The first step is to determine $E[r_{t(i)}]$ and $\sigma^2_{t(i)}$ which will then define $x_{t(i)}$ of (A2). Andersen and Bollerslev (1997, 1998b) propose that $E[r_{t(i)}]$ be replaced by $\overline{r}_{t(i)}$ which is a sample mean and that $\sigma^2_{t(i)}$ be replaced by $\hat{\sigma}^2_{t(i)} = \hat{\sigma}^2_t / n$ where $\hat{\sigma}^2_t$ is the one estimated by a GARCH model. In this paper, however, $\hat{\sigma}^2_t$ is replaced by $\hat{\sigma}^2_{t(i)} = RV_t / n$, where RV_t is a Realized Volatility which is a more accurate estimator of volatility as proposed by Andersen and Bollerslev (1998a). The Realized Volatility for day *t* is simply a sum over squared intraday returns:

$$RV_t = \sum_{i=1}^{n} r^2_{t(i)} \quad . \qquad \text{(A4)}$$

If the number of daily observations, *n*, is sufficiently large, RV_t is a consistent estimator of the true volatility under certain conditions. Its proof is provided by Andersen *et al* (2001), Barndorff-Nielsen and Shephard (2002), Andersen *et al.* (2003), and others.[20]

The second step is to estimate (A3) by OLS using $\overline{r}_{t(i)}$ and $\hat{\sigma}^2_t$. The intraday return purged of periodicity is computed as $\tilde{r}_{t(i)} = r_{t(i)} / \hat{s}_{t(i)}$.

patterns and σ^j_t with $J \geq 1$. Thus we set $J \geq 1$ and varied *P* from 1 to 30 and chose appropriate *P* that minimizes the AIC.

[20] However, Aït-Sahalia, Mykland and Zhang (2005) show that, as the intraday observation frequency rises, the market microstructure noise contaminates estimation of Realized Volatlity. Consequently, one has to strike a delicate balance between the observation frequency and the effect of microstructure noise. An answer to this problem has been proposed by Andersen *et al.* (2001), Koopman, Jungbacker and Hol (2005), and Watanabe (2007). which is to use a 5-min. frequency. We have also used this frequency in this paper.

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Table 1. Descriptive Statistics of Intraday Returns $\tilde{r}_{t(i)}$ after Seasonal Adjustment

Sample period: Jan. 2, 2008 to Nov. 30, 2010

	Mean	Standard Deviation	Kurtosis	Skewness	$LB(10)$ r	$LB(10)$ $\lvert r \rvert$	N. Obs.
NKY	-0.0002 (0.0009)	0.1721	1.5116 (0.0125)	87.997 (0.0250)	78.006	30453	38358
SHCOMP	-0.0005 (0.0014)	0.2548	0.1655 (0.0133)	6.7246 (0.0266)	476.78	16231	33936

Notes: Numbers in parentheses are standard errors. $LB(10)$ is a Ljung-Box statistics with a null that autocorrelation coefficients on the first to tenth lags are all zero.

Table 2 Estimated Results of FIAPARCH Model

Sample period: Jan. 2, 2008 to Nov. 30, 2010

		NKY		SHCOMP	
ω		0.0399*	(0.0211)	0.0358**	(0.0174)
d		0.3624***	(0.0182)	0.4267***	(0.0157)
α		0.3044***	(0.0389)	0.1085***	(0.0155)
β		0.6205***	(0.0438)	0.5366***	(0.0216)
γ		0.1204***	(0.0316)	0.1952***	(0.0195)
δ		1.8458***	(0.0674)	1.9245***	(0.0361)
$L.L.$		22814.49		3735.84	
$LB(10)$	$\hat{z}_t$	8.7464		9.2704	
	$\hat{z}_t^2$	8.2750		6.5865	
$LB(30)$	$\hat{z}_t$	19.368		19.568	
	$\hat{z}_t^2$	18.493		34.340	
Obs		38448		33936	

（注）***, **, * denotes significance at a 1%，5%，10% level respectively. Estimation method is Quasi-Maximum Likelihood. Numbers in parentheses are standard errors derived from the QML estimation. σ^2 is an unconditional variance of $\varepsilon_{t(i)}$. $L.L.$ is log likelihood. $LB(k)$ is a Ljung-Box test statistic which has a null that autocorrelations from first to the k-th order lags are all zero. $\hat{z}_t$ and $\hat{z}_t^2$ are standardized residuals and their squares.

Table 3. Results of Causality-in-Mean and Causality-in-Variance Tests

	Causality in Mean		Causality in Variance	
Lag	NKY ⇒ SHCOMP	SHCOMP ⇒ NKY	NKY ⇒ SHCOMP	SHCOMP ⇒ NKY
1	-0.9825	7.4413***	-0.3244	-0.0634
2	0.8292	1.7504*	-0.2626	-0.1669
3	0.8250	0.1155	-0.8421	2.5111**
4	-1.2269	-0.7628	0.6492	-1.4340
5	0.6781	0.7243	-0.5602	0.7064
6	-0.8369	-0.9834	-0.3192	0.0750

（注）***, **, * denotes significance at a 1%, 5%, 10% level. The numbers in the table are CCF(k) statistics.

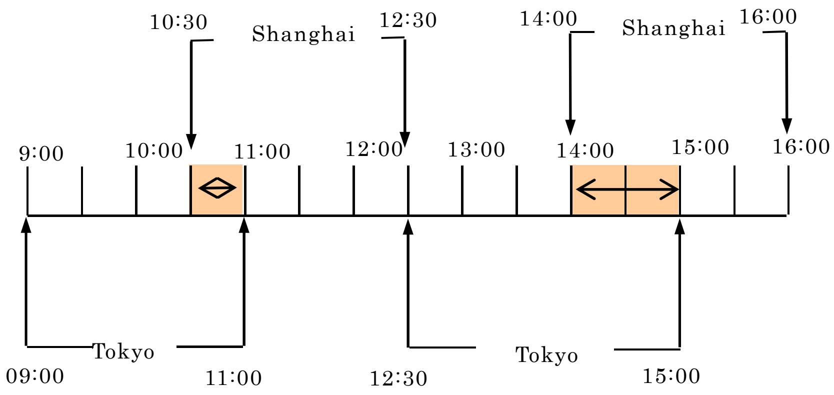

Figure 1. Trading hours of the Tokyo and Shanghai Stock Exchanges.

Hours are according to time in Tokyo (Japan Standard Time, JST). Overlapping hours (windows of simultaneous trading) are shaded.

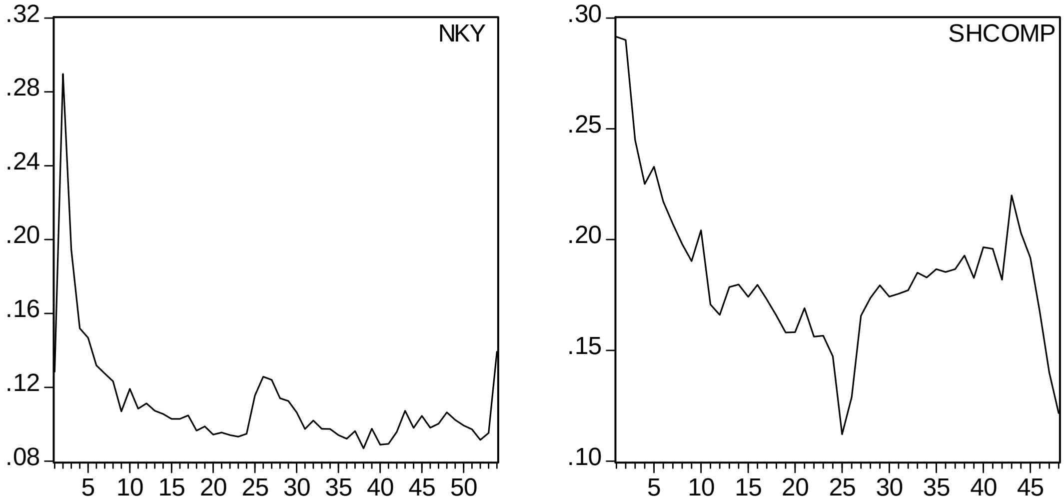

Figure 2. Mean Intraday Volatilities at 5-min. Intervals

Notes: The absolute 5-min. returns $|r_{t(i)}|$ is averaged across days in the sample. One period measured along the horizontal axis is a 5-min. interval. NKY has 54 periods and SHCOMP has 48 periods per day.

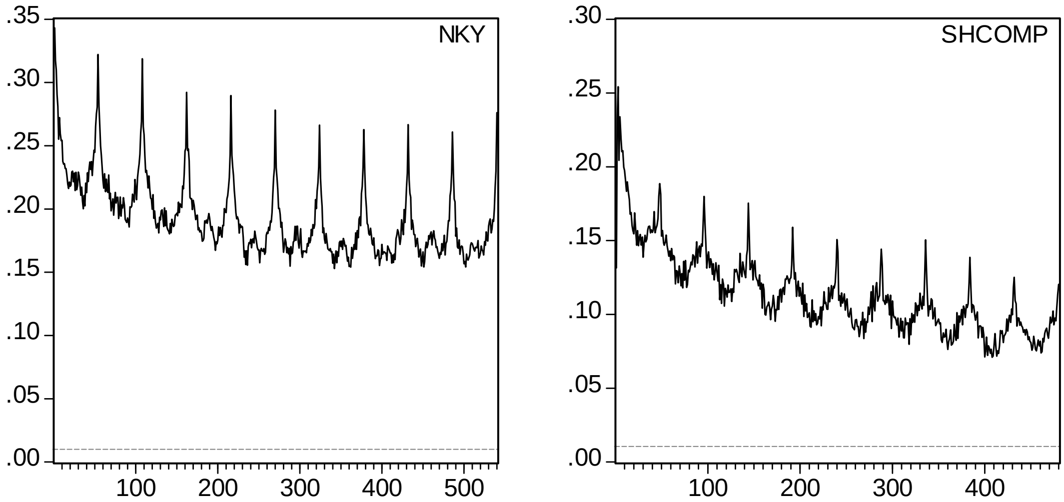

Figure 3. Autocorrelation Coefficients of Intraday Volatility

Notes: The vertical axis measure autocorrelation coefficients and the horizontal axis measures the number of lags (periods). Lags are taken from the first lag through 540th (10 days in total) for NKY and from the first through 480th (10 days) for SHCOMP.

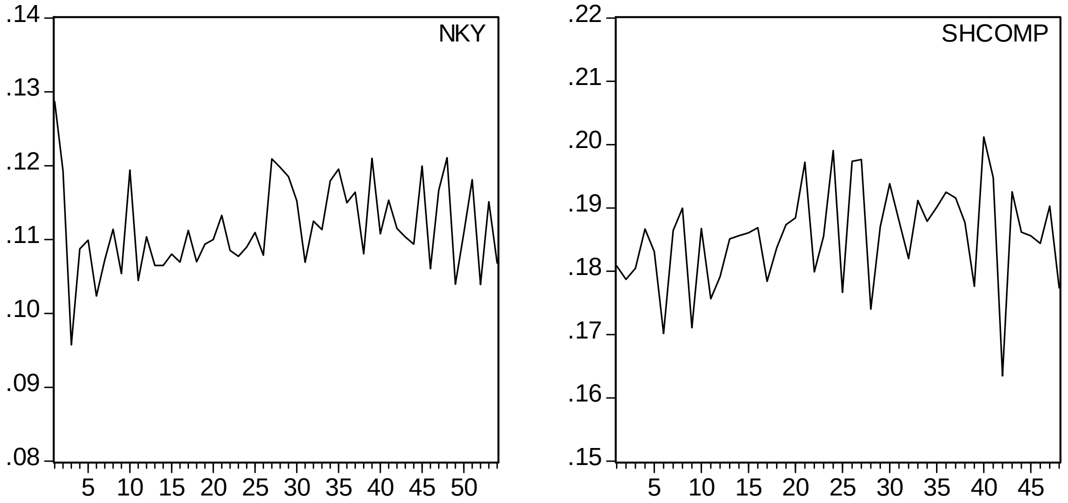

Figure 4. Mean Volatility at 5-min. Intervals after Seasonal Adjustments

Notes: The adjusted absolute 5-min. returns $|r_{t(i)}|$ are averaged across days in the sample. See notes to Figure 2.

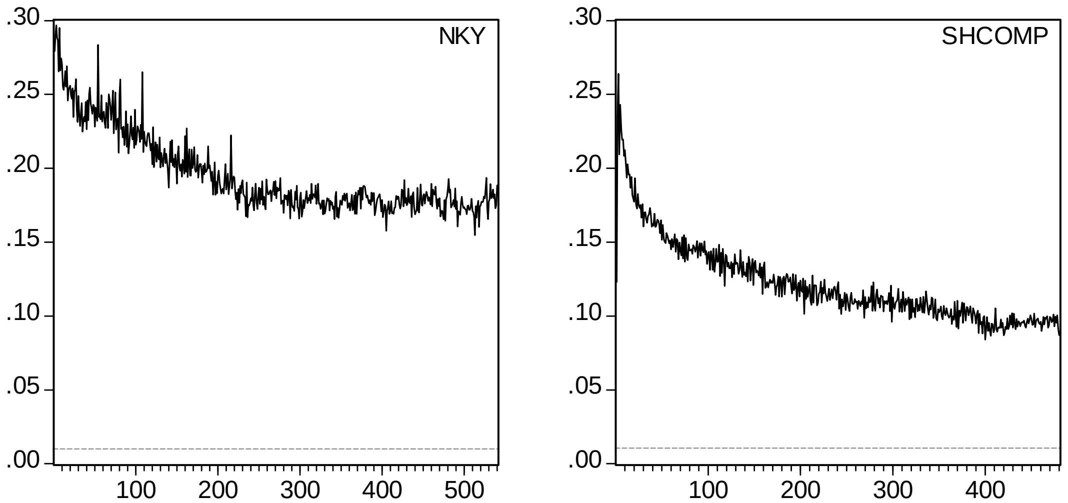

Figure 5. Autocorrelation Coefficients of Intraday Volatility after Seasonal Adjustments

Note: See notes to Figure 3 above.