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Abstract

We analyze the mechanism of return and volatility spillover effects from the Chinese to the Japanese stock market. We construct a stock price index comprised of those companies that have substantial operations in China. This China-related index responds to changes in the Shanghai Composite Index more strongly than does the TOPIX (the market index of the Tokyo Stock Exchange). This result suggests that China has a large impact on Japanese stocks via China-related firms in Japan. Furthermore, we find evidence that this response has become stronger as the Chinese economy has gained importance in recent years.

Keywords: return and volatility spillover; China related stock index; high-frequency data; intraday periodicity; long memory

JEL Classification Number: G10, G14, G15

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1. Introduction

In this paper we empirically investigate the intraday stock price spillover effects between Japanese and Chinese[1] stock markets, with a special focus on overlapping trading hours. We focus on both the return and volatility of stock prices in this paper. There exist studies that analyze interactions between the two markets using daily (Liu and Chen 2008; Nishimura and Men 2010) or high-frequency (Nishimura *et. al.* 2012; Tsutsui and Hirayama 2013) data. Almost all of those studies conclude that there is a one-way influence running from China to Japan. The main purpose of this paper is to investigate the mechanism producing this one-way causality.

Most past studies of return and/or volatility spillover effects utilize intraday (opening and closing price data; Hamao *et. al.* 1990, Bae and Karolyi 1994), daily (closing price data; Karolyi 1995, Christofi and Pericli 1999, Caporale *et. al.* 2006) or longer-frequency data (Theodossiou and Lee 1993, Longin and Solink 1995, Ng 2000). However, dramatic advances in communications and computer technology now make it possible to obtain information from other markets extremely rapidly. If the stock market is informationally efficient, this should result in speedy responses in overseas markets. Since Chinese and Japanese markets are simultaneously open for certain hours each day, it is extremely interesting to use these hours to analyze high-frequency spillover effects that cannot be accurately captured using daily or longer-frequency data. In addition, if daily closing prices are used to represent daily observations, the fact that the Chinese market closes just one hour after Tokyo implies that causality from Japan to China will be over-emphasized relative to the opposite causality. Tokyo's closing price on the following day will be influenced by all other intervening major stock markets, weakening or blurring the effects of Shanghai on Tokyo. Any positive finding of spillover effects from Shanghai to Tokyo thus gains credibility. For this reason, recent analyses of spillover

[1] "China" in this paper is defined to be mainland China, excluding Hong Kong, Macau, and Taiwan.

effects between the two neighboring markets with overlapping trading hours have begun to utilize high-frequency data (Jeong 1999; Baur and Jung 2006; Égert and Kočenda 2007; Harju and Hussain 2008; Nishimura *et. al.* 2012; and Tsutsui and Hirayama 2013).

These recent studies make use of market indices to estimate the extent of stock price spillover effects between different stock markets, but they have not focused on the factors that lead to international transmission of stock price changes. This paper, however, endeavors to analyze why and how such transmission arises across national borders. Such an analysis has heretofore not been undertaken by researchers in our field.

Tsutsui and Hirayama (2005) propose three possible causes of international stock price spillover effects. In the first place, common global shocks may be buffeting firms across borders. When this is the case, use of daily observations tends to reveal causation from Japan to Asia, to Europe, and to the Americas, because that is the order in which these markets open and close on a given day. If one utilizes high-frequency intra-day data during overlapping trading hours, the effects of common global shocks are likely to be observed almost simultaneously. In this case, the observed one-way influence from the Chinese to the Japanese stock market (Nishimura *et. al.* 2012; Tsutsui and Hirayama 2013) cannot be explained by the existence of common global shocks.

The second cause of inter-market correlation is that a large change in the stock price index of one country usually receives a great deal of attention from investors of other countries like a "sun-spot". This phenomenon seems to occur particularly at the time of market opening when the news about other markets is processed, but is probably not likely during normal trading hours.

The third cause is portfolio adjustment by international investors. Portfolios of institutional investors are significantly diversified across national boundaries, and international capital movements caused by portfolio adjustments of these investors thus affect stock prices worldwide. In the case of China, however, international capital flows are strictly regulated, and individual and institutional investors in China are not allowed to invest in overseas stock markets in principle (except for some institutional investors).[2] Likewise, acquisition of Chinese stocks by foreign investors is also subject to strict regulations.[3] Therefore, portfolio adjustments cannot explain the stock price spillover effects between China and Japan.

These three hypotheses of international stock price spillovers as proposed by Tsutsui and Hirayama (2005) presume stock markets that are highly open to international investment. Thus, none of the hypothesis is applicable to a regulated stock market such as China's. To explain the one-way stock price spillover effects from China to Japan, we propose an alternative route through transactions by international investors who focus on Japanese companies that have substantial operations in China. Since individuals and financial institutions in China cannot buy or sell Japanese shares, it is these international investors who affect prices of those Japanese companies. We hypothesize in this paper that their behavior is the primary mechanism of the one-way spillover from China to Japan.

Let us explain this point in greater detail. Suppose Chinese stock prices decline for some reason. Since stock prices reflect information/expectations about the future developments, such a decline is interpreted as a signal foretelling subsequent worsening economic conditions. Japanese companies that operate in China will be affected adversely if the Chinese economy worsens situation. Therefore, international investors will sell their shares in those Japanese companies, resulting in drops in the share prices. Negative news about Chinese economy is, of course, bad news to the Japanese economy

[2] Since 2006, China has partially opened the door to international investment to those institutions that have acquired the status of QDII (Qualified Domestic Institutional Investor). As of March 31, 2013, the permitted amount of overseas investment balance at these QDIIs is 84.127 billion US dollars (data source: The State Administration of Foreign Exchange of the People's Republic of China); this amounts to only about 2.2% of the total market capitalization of the Tokyo Stock Exchange, which stands at 3825.268 billion US dollars (data source: The Tokyo Stock Exchange for market capitalization and the Bank of Japan for the US$/JPY exchange rate). Thus the degree of cross-border investments by the Chinese is quite limited. Furthermore, not all permitted amount can be invested in risky assets. Hence, the share of foreign stocks in QDII's portfolios is only a tiny fraction of the total balance.

[3] Foreign financial institutions are required to obtain the status of QFII (Qualified Foreign Institutional Investor) in order to purchase Chinese stocks. The permitted amount of investment by QFII is 268.545 billion RMB (using the exchange rate of 6.1787 RMB per US dollar) which is equal to just 1.26% of the market capitalization of the Chinese stock markets (Shanghai and Shenzhen combined). Consequently, the presence of foreign investors in China is quite limited. The data on market capitalization was obtained from the websites of Shanghai and Shenzhen Stock Exchanges. The amount of QFII permitted and the exchange rate data were obtained from the State Administration of Foreign Exchange of the People's Republic of China.

overall. Thus, the broad market index will also tend to register a fall, but its extent should be smaller than that of the shares of China-related companies. The difference in the extent of the return and volatility spillover effects between the market index and the China-related index will be investigated in this paper.

In recent years the importance of China is rising for many Japanese companies, which are constrained by the shrinking domestic economy and ageing population. This may lead to a higher sensitivity of Japanese stock prices to Chinese movements. We will analyze whether evidence of such an evolution can be found in the data.

The structure of this paper is as follows. In Section 2, we delineate our hypotheses and the empirical procedures we use to test them. Section 3 describes our dataset. Section 4 presents the results of statistical tests of our hypotheses on the return and volatility spillover effects between Chinese and Japanese stock markets. Section 5 concludes the paper.

2. Methodology

We present our hypotheses regarding return and volatility spillovers from China to Japan in Section 2.1, and explain our testing procedures in Section 2.2.

2.1 Hypotheses about Return/Volatility Spillover Effects from China to Japan

We first hypothesize that Tokyo's overall market index (henceforth MI) and the China-related Index (CRX) respond differently to changes in Chinese stock prices (represented by the Shanghai Composite Index.) If international investors' transactions in companies included in the CRX are the main cause of the one-way transmission from China to Japan, the CRX must respond to China more strongly than does the MI. Let θ_l and λ_l $(l = MI, CRX)$ denote the response of Japanese stock price returns and volatility, respectively, to Chinese stock price returns and volatility. Spillover effects may in principle be present in both of these measures or in either or in neither; the empirical answer to this question will be reported later in this paper.

We propose two separate hypotheses about the spillover effects.

Hypotheses 1: *The response of return/volatility of the CRX (θ_{CRX} / λ_{CRX}) to Chinese stock return/volatility is greater than that of the MI (θ_{MI} / λ_{MI}).*

If this hypothesis is accepted, then it implies that the main factor behind the one-way spillover from China to Japan is the behavior of international investors who buy/sell companies included in the CRX.

As the Chinese economy grows rapidly, the business ties between Chinese and Japanese companies also become closer, which is expected to raise the sensitivity of the CRX against Chinese stock price movements. Hence our next hypothesis:

Hypothesis 2: *The responses of return and volatility of Japanese stock prices to those of Chinese stock prices have become larger more recently.*

2.2 Empirical Procedure

Tests of volatility spillover effects require some estimate of volatility, since this is not observed directly in the market. As has been done in many studies in the field, we use as a measure of volatility the conditional variance estimated in an ARCH-type model.

The volatility of high-frequency returns of stocks is also known to follow a long-memory process, as documented by many authors (Andersen and Bollerslev; 1997, 1998, among others). In this paper, we adopt the FIGARCH (Fractionally Integrated GARCH) model, which is an extension of the GARCH (Generalized ARCH) model (Bollerslev, 1986) to capture the long-memory property of stock price returns.[4]

The final model to estimate return and volatility spillover effects from the Chinese stock price (denoted by CHN) to either of the Japanese indices (denoted by $l = MI, CRX$) is an AR(k)-FIGARCH(p,d,q) model as follows:

$$r_{l,t(i)} = c_l + \phi_l(L) r_{l,t(i)} + \theta_l(L) r_{CHN,t(i)} + \varepsilon_{l,t(i)}, \quad \varepsilon_{l,t(i)} = \sigma_{l,t(i)} z_{l,t(i)}, \quad z_{l,t(i)} \sim WN(0,1) \tag{1}$$

$$\sigma^2_{l,t(i)} = \omega_l + \left\{1 - \left[1 - \beta_l(L)\right]^{-1} \alpha_l(L)(1-L)^d\right\} \varepsilon^2_{l,t(i)} + \lambda_l(L) \hat{\sigma}^2_{CHN,t(i)} \tag{2}$$

Equation (1) is the mean equation. Since the 5-minute returns exhibit a high serial correlation, they are modeled as an autoregressive process. In the above, L denotes the lag operator: $L^p r_{t(i)} = r_{t(i-p)} (p = 0,1,\cdots)$ where the subscripts $t(i)$ refer to day t and intra-day sequential number i . $\phi_l(L)$ and $\theta_l(L)$ are polynomials in L: $\phi_l(L) \equiv \phi_{1,l} L + \phi_{2,l} L^2 + \cdots + \phi_{k,l} L^k$ and $\theta_l(L) \equiv \theta_{1,l} L + \theta_{2,l} L^2 + \cdots + \theta_{j,l} L^j$. $\varepsilon_{t(i)}$ is the error term and $z_{t(i)}$ is a white noise with a zero mean and a variance equal to 1.

The parameters $\theta_{1,l}, \theta_{2,l}, \cdots, \theta_{j,l}$ in the polynomial $\theta_l(L)$ represent the coefficients on the seasonally adjusted Chinese stock returns $r_{CHN,t(i-1)}, r_{CHN,t(i-2)}, \cdots, r_{CHN,t(i-j)}$. Thus, the parameters $\theta_{j,l}$ measure the degree of responsiveness of the Japanese stock return (either r_{CRX} or r_{MI}) to lagged Chinese returns up to previous j periods. If buying and selling of shares in the CRX are the cause of the spillover effects from China to Japan, Hypothesis 1 implies that $\theta_{1,CRX} + \cdots + \theta_{j,CRX} > \theta_{1,MI} + \cdots + \theta_{j,MI}$ and Hypothesis 2 implies that $\theta^{now}_{1,CRX} + \cdots + \theta^{now}_{j,CRX} > \theta^{past}_{1,CRX} + \cdots + \theta^{past}_{j,CRX}$ ($\theta^{now}_{1,MI} + \cdots + \theta^{now}_{j,MI} > \theta^{past}_{1,MI} + \cdots + \theta^{past}_{j,MI}$) where the superscript *now* refers to a more recent sub-period and

[4] Baillie *et al.* (1996) first proposed the FIGARCH model. Chung (1999) pointed out a structural problem with this model and proposed an improved version, which we adopt in this paper. See for more details Laurent and Perets (2002) and Xekalaki and Degiannakis (2010).

past to an older sub-period.

Equation (2) is the variance equation of a FIGARCH model. $\beta_l(L)$, $\alpha_l(L)$, and $\lambda_l(L)$ are polynomials in L : $\beta_l(L) \equiv \beta_{1,l}L + \beta_{2,l}L^2 + \cdots + \beta_{p,l}L^p$, $\alpha_l(L) \equiv \alpha_{1,l}L + \alpha_{2,l}L^2 + \cdots + \alpha_{q,l}L^q$, and $\lambda_l(L) \equiv \lambda_{1,l}L + \lambda_{2,l}L^2 + \cdots + \lambda_{j,l}L^j$. The parameter, *d*, is the key to the FIGARCH model. It captures the dynamic properties of volatility. Namely, if $d = 0$, the volatility follows a short-memory process, and if $0 < d < 1$, it follows a long-memory process. The parameters $\lambda_{1,l}, \lambda_{2,l}, \cdots, \lambda_{j,l}$ in the polynomial $\lambda_l(L)$ measure the effect of lags of estimated Chinese volatilities, $\hat{\sigma}^2_{CHN,t(i-1)}, \hat{\sigma}^2_{CHN,t(i-2)}, \cdots, \hat{\sigma}^2_{CHN,t(i-j)}$, on the Japanese volatility. Under Hypothesis 1 we will observe that $\lambda_{1,CRX} + \cdots + \lambda_{j,CRX}$ > $\lambda_{1,MI} + \cdots + \lambda_{j,MI}$ and under Hypothesis 2 the following inequality should hold: $\lambda^{now}_{1,CRX} + \cdots + \lambda^{now}_{j,CRX} > \lambda^{past}_{1,CRX} + \cdots + \lambda^{past}_{j,CRX}$ ($\lambda^{now}_{1,MI} + \cdots + \lambda^{now}_{j,MI} > \lambda^{past}_{1,MI} + \cdots + \lambda^{past}_{j,MI}$).

In order to examine the spillover effects between the two countries, it is natural to augment equations (1) and (2) with the following companion equations:

$$r_{CHN,t(i)} = c_{CHN} + \phi_{CHN}(L) r_{CHN,t(i)} + \theta_{CHN}(L) r_{l,t(i)} + \varepsilon_{CHN,t(i)} \tag{3}$$

$$\sigma^2_{CHN,t(i)} = \omega_{CHN} + \left\{1 - \left[1 - \beta_{CHN}(L)\right]^{-1} \alpha_{CHN}(L)(1-L)^d\right\} \varepsilon^2_{CHN,t(i)} + \lambda_{CHN}(L)\hat{\sigma}^2_{l,t(i)} \tag{4}$$

Since this model does not address the issue of the long-memory property, the resultant residuals and their squares exhibited serial correlation.[5] Thus we decided to use a FIGARCH model to tackle the problem of the long-memory property of stock returns.

However, a bivariate AR model can be reduced to a univariate AR model (Yamamoto 1988; Zellner and Palm, 1974; Enders, 2003). This is accomplished by substituting out one variable by utilizing the information on the other variable from the second equation. The resultant equation contains one AR term and two MA processes. The sum of two independent moving average processes

[5] Equations (1) to (4) constitute a VAR-Multivariate FIGARCH, but unfortunately a feasible estimation method of this system is not yet known. Thus, we instead estimated a multivariate BEKK-GARCH model proposed by Engle and Kroner (1995). Since this model does not address the issue of the long-memory property, the resultant residuals and their squares exhibited serial correlation.

can be expressed as one moving average process (Box and Jenkins, 1976, p. 121) and if this MA process is invertible, the equation can be written as an AR(∞). Assuming this is the case with our system of (1) and (3), we derive a univariate AR model for $R_{CHN,t(i)}$ as in the following (3'). Since it is not possible as well as not practical to estimate an infinite number of AR coefficients, we cut off at lag *k*. Thus, we utilize a univariate AR(*k*)-FIGARCH(*p, d, q*) model to estimate the volatility of the Chinese stock market.

$$r_{CHN,t(i)} = c_{CHN} + \phi_{CHN}(L) r_{CHN,t(i)} + \varepsilon_{CHN,t(i)} \tag{3'}$$

$$\sigma^2_{CHN,t(i)} = \omega_l + \left\{1 - \left[1 - \beta_{CHN}(L)\right]^{-1} \alpha_{CHN}(L)(1-L)^d \right\} \varepsilon^2_{CHN,t(i)} \tag{4'}$$

where $\varepsilon_{CHN,t(i)} = \sigma_{CHN,t(i)} z_{CHN,t(i)}$ and $z_{CHN,t(i)}$ is a mean zero white noise with a unit variance. Estimations (3') and (4') give us a conditional variance which can be substituted into the right-hand side of equation (2) to test for volatility spillover from China to Japan.[6] Compared with simultaneous estimations of (1) through (4), this is a two-stage estimation procedure. This has been adopted by many researchers in the field such as Hamao *et. al.* (1991), Bae and Karolyi (1994), Lin *et al.* (1994), Ng (2000), Kim (2005), Baur and Jung (2006), etc.

There is an alternative justification for estimating (3') and (4'). As was stated in Section 1, many studies find there is a one-way return/volatility spillover from China to Japan. Therefore, even if (3) and (4) are estimated, the coefficients on $r_{l,t(i)}$ and on $\hat{\sigma}^2_{l,t(i)}$, θ_{CHN} and λ_{CHN}, will turn out to be insignificant. Excluding these variables from the beginning, namely estimating (3') and (4'), would produce little bias in estimation. Consequently, instead of using a multivariate model, we apply a two-stage estimation to univariate models.

To determine the lag orders of *k, p, q* we follow a conventional method applied by many

[6] Considering the possibility that the standardized residuals do not follow normal distribution, we used quasi-maximum likelihood estimation. For details of this estimation method, see Sec. 2.2 of Xekalaki and Degiannakis (2010).

researchers. To determine the lag order k of the AR part, we increase it sequentially from 1 to 5 and choose the value k^* which minimizes the AIC (Akaike Information Criterion). We then compute four combinations of p and q, each of which varies between 1 and 2. Out of these four estimation results, we choose p^* and q^* that minimize the AIC. With k^*, p^*, and q^* thus determined, we estimate the AR(k^*)-FIGARCH(p^*, d, q^*) model to compute standardized residuals and their squares. These two series are subjected to Ljung-Box tests (Ljung and Box, 1978) and LM ARCH tests (Engle, 1982) to check for serial correlation and ARCH effects. If these tests are satisfactory, the model is regarded as valid, but if not, the lag order of k^* is increased and the next AR(k^*+1)- FIGARCH(p^*, d, q^*) model is estimated, and so forth.

3. Data

For the empirical analysis we use a representative Chinese stock price index and two Japanese stock price indices (Market Index and China-related Index) at 5-minute intervals.[7] Log differences are multiplied by 100 to compute returns. We utilize Shanghai Composite Index (SHCOMP) as the representative Chinese stock price index. The 5-minute data were retrieved from *FoxTrader*. The Tokyo Stock Price Index (TOPIX) is used as the Market Index (MI) for Japan. It is a capitalization-weighted index of all the companies listed in Section 1 of the Tokyo Stock Exchange. We also compiled our own China-related Stock Index (CRX) based on 50 companies whose

[7] The reason for adopting a 5-minute frequency is two-fold. First, we need to strike a balance between the greater degree of freedom provided by higher frequency (e.g., minute-by-minute or even shorter observation intervals) and increasing market microstructure noise (e.g., bid-ask bounces) arising at such a frequency. The 5-minute frequency is recommended as optimal by Andersen *et al.* (2001), Koopman *et al.* (2005) and many others. These and other authors have used 5-minute returns in analyzing international return/volatility spillover effects (Jeong, 1999; Égert and Kočenda, 2007; Harju and Hussain 2008; Nishimura *et. al.* 2012). The second reason for using a 5-minute frequency is to deal with the high serial correlation at 5-minute intervals apparently caused by a peculiar system called 'Special Quotes' in the Tokyo Stock Exchange (Tsutsui *et al*. 2007). A special quote is announced whenever the next transaction price is likely to exceed a certain preset range. At the same time, buy/sell matching is halted in order to lure potential buyers/sellers into this stock. If this signaling fails to induce an actual transaction, the special quote is revised upward or downward by one notch after 5 minutes. Tsutsui *et al*. (2007) report that a sizable number stocks are subject to these special quotes, resulting in spikes in autocorrelations in the minute-by-minute Nikkei 225 Index returns at 5-minute intervals. We have to be wary, however, of the spurious nature of this phenomenon, because transactions are halted when a special quote is announced. One cannot execute buy/sell orders at these special quotes. Thus, use of the 5-minute frequency is desirable to circumvent this microstructure noise.

businesses are closely linked to the Chinese economy. We retrieved stock prices at 5-minute intervals for these 50 companies and computed a capitalization-weighted index of these shares (see Appendix A for details of this procedure). The source of these data is tick data released by NIKKEI Digital Media, Inc.

Our sample runs from November 4, 2003 to November 18, 2011.[8] The Tokyo Stock Exchange (TSE) is open for trading for four and a half hours and the Shanghai Stock Exchange (SSE) for four hours every day. See Figure 1 for the specific trading hours of the TSE and SSE. Note that Japan Standard Time (JST) is one hour ahead of China Standard Time (CST). Excluding overnight and lunch-time returns, there are 54 5-minute returns for MI and CRX and 48 returns for SHCOMP. During our sample period, there were 1973 trading days for Tokyo and 1955 days for Shanghai, resulting in 106542 observations in total for Tokyo and 93840 observations for Shanghai.

The volatility of intraday high-frequency stock returns is known to have intraday periodicity.[9] As is pointed out by many researchers such as Andersen and Bollerslev (1997, 1998) and Andersen *et al.* (2000), this intraday periodicity may produce a serious bias in estimation. We adjust 5-minute returns data for this periodicity by Flexible Fourier Form (FFF) as proposed by Gallant (1981) and used extensively by Andersen and Bollerslev (1997, 1998). Appendix B provides a detailed description of this method. The adjusted 5-minute returns, however, still exhibited a long-memory property and this is the reason we adopt a FIGARCH model in this paper.

To analyze mutual return/volatility spillover effects, we extract data points during the overlapping trading hours each day between the Tokyo and Shanghai Stock Exchanges. The TSE is open for trading between 9:00-11:00 (Japan Standard Time, JST) for the morning session and between

[8] Beginning on November 21, 2011, the morning session of the TSE was extended to 11:30 instead of 11:00. Since the morning session starts at 9 am, it thus became two and a half hours long. This constitutes a rather grave change in the trading environment, thus we decided to end the sample period at this time, namely November 18, 2011.

[9] Andersen and Bollerslev (1997) find a U-shaped intraday periodicity in the S&P 500 futures return volatility and Andersen *et. al.* (2000) report a doubly U-shaped intraday periodicity in the return volatility of the Nikkei 225 Index. Nishimura *et. al.* (2012) also point out a strong intraday periodicity in the return volatility of SHCOMP.

12:30-15:00 (JST) for the afternoon session. The SSE is open between 10:30-12:30 (JST) for the morning session and between 14:00-16:00 (JST) for the afternoon session. Therefore, there is a 30-minute interval in the morning (10:30-11:00 JST) and a one-hour interval in the afternoon (14:00-15:00 JST) when the two stock exchanges are open at the same time (Figure 1).

[Insert Figure 1 about here]

Table 1 displays basic descriptive statistics for returns data during the overlapping trading hours. The data are adjusted for intraday periodicity. There are 33,444 5-minute returns data during the overlapping trading hours. The means of the intraday returns are not significantly different from zero. The excess kurtosis and skewness are both significantly different from the values of a Normal distribution at the 1% significance level (0 and 3 respectively), indicating that these returns have fatter tails than a normal distribution.

LB_{10} and LB_{10}^2 are the Ljung-Box statistics to test the null hypothesis that autocorrelation coefficients in the returns and their squares up to 10 lags are all zero. The results indicate that both returns and their squares exhibit a high degree of serial correlation.

[Insert Table 1 about here]

4. Are Transactions of China-related Shares the Cause of Return/Volatility Spillover Effects?

Here we report the results of hypothesis tests on the transmission mechanism from the Chinese stock market to Japanese market. Section 4.1 first presents the estimated volatility in SHCOMP. Section 4.2 displays the test results for Hypothesis 1 discussed in Section 2.1. Section 4.3 applies a path analysis to further investigate return spillover effects. Section 4.4 gives the results for Hypothesis 2 presented in Section 2.1.

4.1 Estimated Volatility of SHCOMP

We first determined the lag order k of AR(k)-FIGARCH(p, d, q) model as delineated in Section 2.2. We chose lag 4 as the optimal k*. We then tested for p and q to minimize the AIC and obtained p=1 and q=1 as the optimal values. We thus estimate an AR(4)-FIGARCH(1, d, 1) model for our hypothesis test. Table 2 displays estimation results for SHCOMP. All of our inferences are based on robust standard errors from the quasi-maximum likelihood estimation, because the distribution of standardized residuals may not follow a normal distribution.

[Insert Table 2 about here]

The parameter d, which determines the long-memory property, is estimated to be 0.3950 at the 1% significance level. This result indicates that the intraday volatility of SHCOMP follows a long-memory process.

We test for autocorrelation and ARCH effects in the standardized residuals. LB_{10} and LB_{10}^2 are the Ljung-Box statistic, which tests the null hypothesis that the autocorrelation coefficients from lag 1 to lag 10 of the standardized residuals and their squares are all zero. According to this table, the null hypothesis of no autocorrelation cannot be rejected in any of these variables. The ARCH LM test statistic, LM_{10}^{ARCH}, can be used to test the null hypothesis that there is no ARCH effect up to lag order 10. The LM_{10}^{ARCH} test statistic indicates that this hypothesis cannot be rejected at the 5% significance level, suggesting that there is no ARCH effect remaining in the standardized residuals. These results provide support for the specification of the selected AR-FIGARCH model.

We now regard the conditional variance estimated by the variance equation as a measure of the volatility of SHCOMP, and proceed to analyze the return/volatility spillovers between China and Japan.

4.2 Is the Spillover Effect of Chinese Stock Market Different between the China-related Index and the Market Index?

We repeat the same procedure described above to determine the lag order of the AR(*k*)-FIGARCH(*p, d, q*) model, as explained in Section 2.2. The model applied to the CRX turned out to be AR(4)-FIGARCH(1, *d*, 1) and that of the MI was AR(30)-FIGARCH(1, *d*, 1). Given this model, we then determin the lag order of the exogenous variable ($r_{CHN,t(i)}$ and $\hat{\sigma}^2_{CHN,t(i)}$) on the right-hand side of equations (1) and (2) by minimizing the AIC. The optimal lag order turned out to be 1 for the CRX model and 3 for the MI model. The results of our test of Hypothesis 1 are presented in Table 3.[10] The Ljung-Box statistics indicate non-rejection of the null hypothesis of no serial correlation in the residuals and their squares. The ARCH LM test also indicates that there is no ARCH effect. Hence, our model can be regarded as suitably specified.

We first consider return spillover effects. The sum of the parameters indicating spillover from SHCOMP to MI, $\theta_{1,MI} + \theta_{2,MI} + \theta_{3,MI}$, is 0.0147.[11] The parameter of spillover effect from SHCOMP to CRX, $\theta_{1,CRX}$, is 0.0315, which is significant at the 1% level. This parameter is more than twice the sum of the parameters on MI, vindicating Hypothesis 1. This result suggests that the impact of China on China-related firms is stronger than its impact on the other firms.

Next, we find that the parameters to capture the volatility spillovers are almost all insignificant statistically. The volatility of SHCOMP does not affect the volatility of either CRX or MI, leading us to conclude that there is no observable volatility spillover from China to Japan.

4.3 Return Spillover Mechanism: Further Investigation

While SHCOMP affects CRX with only one lag, its statistically significant effect on MI is observed

[10] To make the table readable, estimated coefficients on the autoregressive terms are omitted from the table.
[11] If we add statistically significant parameters – i.e., only ($\theta_{1,MI} + \theta_{3,MI}$) – the value is 0.0154.

with lag 1 and lag 3. What does this difference imply? We should note that changes in MI may include those in CRX. Thus, when SHCOMP affects MI, this may arise through stocks included in CRX and/or through stocks not included in CRX.

To compare these two possible channels of spillover effects, we added the current value and a first lag of CRX (r_{CRX}) to the right-hand side of the MI return equation, and run an OLS regression. The reason for adding the current value of CRX is that the China-related stocks included in CRX are also part of the MI. In other words, changes in CRX also represent simultaneous changes in MI. If SHCOMP affects MI through changes in CRX, then CRX must be significant and the significance of SHCOMP would be lost in the return equation. The estimation results are displayed in Table 4. The first column presents OLS estimates of equation (1). (Note, however, coefficients on the own lags of MI are omitted to save space.) The first lag of SHCOMP is considerably significant and the second lag is also significant at the 5% level. The second column (labeled "Model A") presents results when the current value and the first lag of CRX are added to the right-hand side. The estimated coefficients on these additional variables are not only highly significant but also quite large numerically. The coefficient on the first lag of SHCOMP decreases dramatically (about 1/8 of its value in the Base Model) and it becomes insignificant statistically. However, the coefficient on the third lag of SHCOMP remains significant at the 5% level. We also tried adding two more lags of CRX to the equation, and the estimation results are shown in the columns (labeled "Model B"). Parameter estimates remain essentially the same as in Model A. This result implies that the effect of the first lag of SHCOMP on MI as revealed by Table 3 actually works entirely through the influence of CRX stocks. The effect of SHCOMP on MI arises with a three-period lag possibly through effects on companies not included in CRX.

To repeat, the first lag of SHCOMP affects MI mainly through effects on CRX, and has little direct effect on stocks other than those in CRX. This result can be verified by a path analysis (Asher, 1983). For simplicity's sake, we suppose that MI is affected by its own first lag, the current value of CRX, and a first lag of SHCOMP, and that CRX is affected by its own first lag and the first lag of SHCOMP. The results of the path analysis are graphed in a path diagram (Figure 2). Numerical values of this diagram do not change substantially even if we increase the lag orders of MI and CRX. The diagram shows that the direct effect of SHCOMP on MI is about 1/10 of the indirect effect through CRX. Thus, the spillover effect from SHCOMP to MI arises largely through effects on CRX.

Test results in this subsection give evidence that spillover effects from China to Japan are mainly caused by transactions by international investors in China-related Japanese stocks, and these spillovers are observed in returns but not in volatility.

[Insert Table 4 and Figure 2 about here]

4.4 Are Spillover Effects Getting Stronger in Recent Years?

This subsection presents test results of the hypothesis that, as the Chinese economy grew in its importance in the world, its spillover effects became stronger. To be specific, we estimate our model for each one-year interval sequentially and compare the parameter estimates across subsamples. Since there are many studies such as Rozeff and Kinney (1976) and Ariel (1987) that report existence of seasonal patterns in spillover effects, we chose a one-year subsample to average out seasonal patterns.[12]

Table 5 displays the estimation results of the model we use to examine return and volatility spillovers from SHCOMP to CRX, and Table 6 shows those from SHCOMP to MI. In all the subsamples, the lag orders of the AR(k)-FIGARCH(p,d,q) model were determined by the same method as in the previous subsections. In the second row of the tables are shown optimal lag orders

[12] Many such anomalies have been found in stock markets, e.g. day of the week effects, monthly effects, and the half-year effects, etc.

for each subsample.[13]

[Insert Table 5 about here]

[Insert Table 6 about here]

The parameter θ , which captures return spillover effects, is statistically significant at lag 1 (i.e. θ_1) both in the CRX and MI equations. The influence of SHCOMP gradually increases over time in both CRX and MI returns. For example, in 2004, the parameter θ_1 is -0.0004 in the CRX equation (0.0009 in the MI equation) and it is not significantly different from 0. It starts to take on positive, significant values in 2006, gradually grows in magnitude, and eventually reaches 0.0661 (0.0389 in the MI equation), which is significant at the 1% level in 2011.

The path of θ as time elapses is plotted in Figure 3, in order to intuitively understand the phenomenon. The estimate of θ in the CRX equation is plotted as a solid line and that of the MI equation a dotted line. Both grew larger over time. This is consistent with Hypothesis 2. The response of CRX is also larger than that of MI. The difference between the two parameters is also plotted in the figure, and it also grows wider in more recent years.

We find no clear evidence of increasing magnitude of the parameter λ (which measures volatility spillovers) in Tables 4 and 5. The result with the entire sample in Section 4.2 that spillover effects are observed only in returns but not in volatility thus holds true in the case of annual subsamples as well.

[Insert Figure 3 about here]

[13] Only in one case did we fail to eliminate serial correlation and ARCH effects, even though we increased the autoregressive lags up to 50; this was the subsample of year 2010 for the MI model. For this subsample, the lags were determined by the minimum AIC principle.

5. Conclusion

In this paper we measured international stock price spillovers by focusing on the relationship between the Chinese and Japanese stock markets. The Chinese stock market is special, because it affects other markets while not being greatly affected by them. This is probably due to the fact that Chinese ownership of foreign stocks is forbidden and foreign ownership of Chinese stocks is strictly. In other words, the Chinese stock market is a striking natural experiment in one-way international spillovers. A second special feature of this paper is the use of high-frequency data during overlapping trading hours between the two countries; this enables us to examine real-time spillover effects. Beyond merely identifying spillover effect, we investigated the mechanism by which spillover effects arise. We advanced the hypothesis that the international investors who trade China-related stocks in Japan in response to Chinese stock prices are the agents of the return/volatility spillovers from China to Japan. To test this hypothesis we constructed our own high-frequency China-related stock price index (CRX) from 50 Japanese companies with substantial operations in China. We estimated the return/volatility spillovers between the Shanghai Composite Index (SHCOMP) and CRX, and compared these to spillovers between SHCOMP and the Japanese market as a whole. We hypothesized that changes in Chinese stock prices should lead to larger changes in CRX than in the Japanese Market Index (MI).

Our results indicate that CRX responds to SHCOMP more strongly than does MI. This vindicates our hypothesis that the return spillover effects are more pronounced in China-related stocks. In particular, the immediate effect of SHCOMP arises only in China-related stocks with a one-period lag, and the effect of SHCOMP on other companies occurs with a three-period lag. Volatility spillover effects were, however, not observed. Information transmission from China to Japan is detected mainly in returns, but not in volatility.

We also tested a hypothesis that the Chinese influence on Japan has been getting stronger more recently. Our estimation again revealed no significant volatility spillovers, but the return spillover effects from SHCOMP to either CRX or MI indeed became larger in recent years. Also, the response of CRX has became stronger relative to MI over the years. As the Chinese economy surpassed Japan in the size of real GDP to become the second largest economy in the world, the exposure of China-related Japanese companies to China increased proportionately, giving rise to stronger spillovers from China to Japan.

One problem with our approach in this paper is its use of MI. MI is a stock price index based on all the companies listed in Section 1 of the TSE (1749 companies as of October 2013); thus it includes the 50 companies included in the China-related index we constructed. Responses of MI to China include those of non-CRX stocks. While the estimations of Section 4.3 have shown that CRX responds to SHCOMP immediately and that stocks not included in CRX respond with a three-period lag, the examination of this mechanism would be easier and more direct if we had a non-CRX index to capture the delayed responses. However, compilation of such an index is too demanding and daunting for us to achieve in this paper. [14] This is left as a future research item.

[14] One might think that non-CRX index can be easily calculated as a difference between the TOPIX and the CRX, but this is not the case because the TOPIX is not a simple weighted average but is adjusted for the so-called Free Float Weight (the proportion of shares held for short-term investment horizon), which requires close examination of shareholder distribution of each stock.

Appendix A. Compilation of China-related Stock Index

The list of companies included in our China-related stock index is entirely based on the companies adopted in the Nikkei China Related Stock Index 50, compiled and released by the Nikkei, Inc. See Appendix Table A below for the details.

Our intraday tick data database contains around 30 or 40 billion records for over 1700 companies listed in the TSE for the period from November 4, 2003 to November 18, 2011 (1973 trading days). We extracted at 5-minute intervals prices of the 50 companies included in the CRX and computed a capitalization-weighted average of those 50 prices. Specifically, we computed the index as follows:

$$CRX_{t(i)} = \sum_{l=1}^{50} \delta^{l}_{t(i)} p^{l}_{t(i)} \quad \text{, where} \quad \delta^{l} = \frac{V^{l}_{t} p^{l}_{t(i)}}{\sum_{l=1}^{50} V^{l}_{t} p^{l}_{t(i)}} \quad .$$

$p^{l}_{t(i)}$ is the stock price of company *l* on day *t* and time sequence *i*, and V^{l}_{t} is the number of shares on day *t* for company *l*. Price data were taken from the "Tick Stocks Multiple Quotes" database released by Nikkei Shimbun Digital Media. The data on the number of shares was extracted from Nikkei NEEDS Financial-QUEST.

In constructing CRX, we encountered a few problems. We list below those problems and how we dealt with them.

- At the beginning of our sample period (November 4, 2003), not all of the 50 companies were listed. Seven & I Holdings (Code: 3382) went public in September 2005, Mitsubishi Chemical Holdings (Code: 4188) in October 2005, and JX Holdings (Code: 5020) in April, 2010. Before these IPOs, therefore, the CRX does not include these companies.
- There are some stocks at certain time points during a given day for which there is no price data due to no successful matching of orders. We filled this missing observation with the most recent value. We may justify this treatment on the grounds that, since no new information is produced, the old price information can be regarded as valid. Jeon and von Furstenberg (1990) adopt this

method for filling bank holidays, albeit at the daily frequency.

- Between January 19, 2006 and April 21, 2006 the afternoon session started at 13:00 instead of 12:30 in order to process heavy trading volume in the morning session. This was caused by a corporate scandal involving the then-popular IT startup company called "Livedoor." Since no data were available for this half hour between 12:30 and 13:00, we copied the closing price of the morning session to this period.
- Until January 4, 2008, there was only a morning session for the first trading day (January 4) and the last trading day (December 30) of the year. For these days, all the values for the afternoon session were filled by the closing price of the morning session.

Appendix Table A. List of Companies Included in the China-related Index

Security Code	Company Name	Security Code	Company Name
2502	Asahi Group Holdings, Ltd.	6503	Mitsubishi Electric Corporation
2503	Kirin Holdings Company, Limited	6701	NEC Corporation
2802	Ajinomoto Co., Inc.	6752	Panasonic Corporation
3382	Seven & I Holdings Co., Ltd.	6753	Sharp Corporation
3402	Toray Industries, Inc.	6762	TDK Corporation
4005	Sumitomo Chemical Company, Limited	6902	Denso Corporation
4063	Shin-Etsu Chemical Co., Ltd.	6954	FANUC Corporation
4183	Mitsui Chemicals, Inc.	6971	Kyocera Corporation
4188	Mitsubishi Chemical Holdings Corporation	6981	Murata Manufacturing Company, Ltd.
4452	Kao Corporation	7011	Mitsubishi Heavy Industries, Ltd.
4911	Shiseido Company, Limited	7201	Nissan Motor Co., Ltd.
5020	JX Holdings, Inc.	7203	Toyota Motor Corporation
5108	Bridgestone Corporation	7267	Honda Motor Co., Ltd.
5201	Asahi Glass Company, Limited	7731	NIKON Corporation
5401	Nippon Steel & Sumitomo Metal Corporation	7751	CANON Inc.
5405	Sumitomo Metal Industries, Ltd	8001	ITOCHU Corporation
5411	JFE Holdings, Inc.	8002	Marubeni Corporation
5713	Sumitomo Metal Mining Co., Ltd.	8031	Mitsui & Co., Ltd.
5802	Sumitomo Electric Industries, Ltd.	8035	Tokyo Electron Limited
6301	Komatsu, Ltd.	8053	Sumitomo Corporation (Sumitomo Shoji Kaisha, Ltd.)
6305	Hitachi Construction Machinery Co., Ltd.	8058	Mitsubishi Corporation
6326	Kubota Corporation	8113	Unicharm Corporation
6367	Daikin Industries, Ltd.	8267	AEON Co., Ltd.
6501	Hitachi, Ltd.	9104	Mitsui O.S.K.Lines, Ltd.
6502	Toshiba Corporation	9983	Fast Retailing Co., Ltd.

Source: Nikkei, Inc., http://indices.nikkei.co.jp/en/nkave/index/component?idx=nkcrs50

Appendix B Removal of Intraday Periodicity by FFF

We removed the intraday periodicity in the 5-minute return volatility by applying Flexible Fourier Form (FFF).[15] Figure A below plots the mean volatility at 5-minute intervals (absolute values of 5-minute returns during one day were averaged over the sample period) before and after the seasonal adjustment for the three indices, MI, CRX, and SHCOMP.[16] Figure B plots the autocorrelation functions of absolute 5-minute returns up to 540 lags for MI and CRX and up to 480 lags for SHCOMP. The solid line in these Figures plots the original series, which exhibits a pronounced pattern of intraday periodicity. The dotted line exhibits the adjusted series, which does not show any intraday periodicity. The removal of intraday periodicity has therefore been achieved quite successfully by applying FFF.

One notable feature is that the volatility of all three indices is highly serially correlated. The dotted lines of Figure B all lie far above the 5% critical value and decline very slowly over the 10-day period. This suggests that these series follow a long-memory process.

[15] For details of the FFF, see Andersen and Bollerslev (1997) Appendix B, pp.152-155 or Andersen and Bollerslev (1998) pp.235-239.
[16] Following Andersen and Bollerslev (1997, 1998), Andersen *et al.* (2000) and many others, we proxied the volatility by the absolute values of returns.

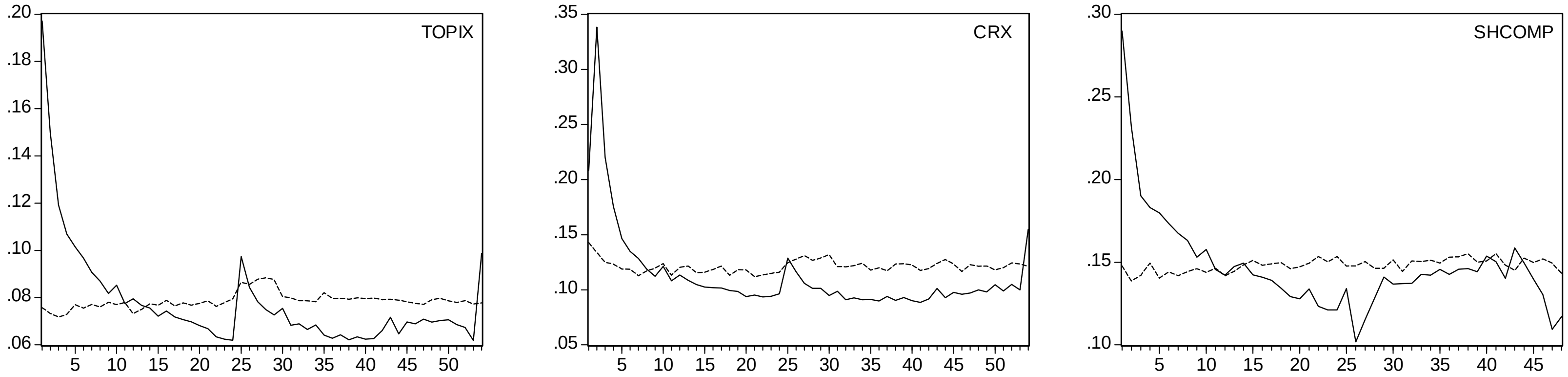

Figure A. Mean Intraday Volatilities at 5-minute Intervals

Notes: The absolute values of original 5-minute returns, $|r_{t(i)}|$, are plotted in the solid line and their periodicity-adjusted series are plotted in the dotted line. They are averaged across days over the entire sample period. There are 54 such values per day for MI and CRX and 48 for SHCOMP.

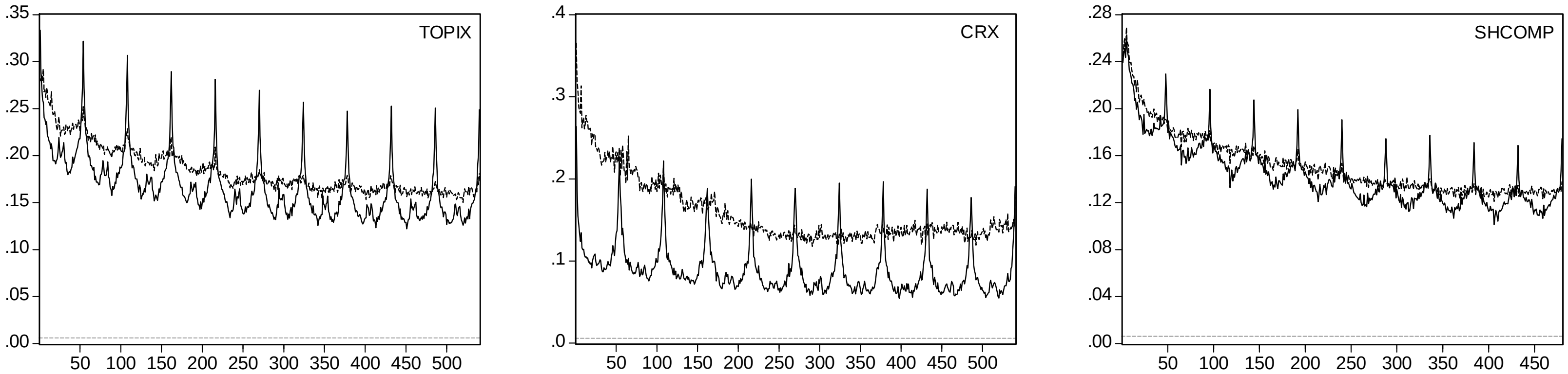

Figure B. Autocorrelation Coefficients of Intraday Volatility

Notes: Autocorrelation coefficients of the absolute values of original 5-minute returns are displayed by the solid line and those of the adjusted values by the dotted line. The horizontal axis measures lags up to 540 for MI and CRX (10 days times 54 per day) and up to 480 for SHCOMP (10 days times 48 per day). The straight dotted line depicts the 5% significance level of the null hypothesis that each autocorrelation coefficient is zero.

References

Andersen, T. G. and T. Bollerslev (1997), "Intraday Periodicity and Volatility Persistence in Financial Markets," *Journal of Empirical Finance*, 4(2-3), pp. 115-158.

Andersen, T. G. and T. Bollerslev (1998), "Deutsche Mark–Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies," *The Journal of Finance*, 23(1), pp.219-265.

Andersen, T. G., T. Bollerslev and J. Cai (2000), "Intraday and Interday Volatility in the Japanese Stock Market," *Journal of International Financial Markets*, *Institutions and Money*, 10(2), pp.107-130.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2001), "The Distribution of Exchange Rate Volatility," *Journal of the American Statistical Association*, 96, pp.42-55.

Ariel, R. A. (1987), "A Monthly Effect in Stock Returns," *Journal of Financial Economics*, 18(1), pp.161-174

Asher, H. B. (1983), *Causal Modeling*, Newbury Park CA: Sage Publications Inc.

Bae, K-H. and G. A. Karolyi (1994), "Good News, Bad News and International Spillovers of Stock Return Volatility between Japan and the U.S.," *Pacific-Basin Finance Journal*, 2(4), pp. 405-438.

Baillie, R. T., T. Bollerslev and H. O. Mikkelsen (1996), "Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 74(1), pp.3-30.

Baur, D. and R. C. Jung (2006), "Return and Volatility Linkages between the US and the German Stock Market," *Journal of International Money and Finance*, 25(4), pp.598-613

Bollerslev, T. (1986), "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 31(3), pp.307-327.

Box, G. E. P. and G. M. Jenkins (1976) *Time Series Analysis: Forecasting and Control*, San Francisco:

Holden-Day.

Caporale, G. M, N. Pittis and N. Spagnolo (2006), "Volatility Transmission and Financial Crises," *Journal of Economics and Finance*. 30(3), 376-390.

Christofi, A. and A. Pericli (1999), "Correlation in Price Changes and Volatility of Major Latin American Stock Markets", *Journal of Multinational Financial Management*, 9(1), pp.79-93.

Chung, C-F (1999), "Estimating the Fractionally Integrated GARCH Model," Working Paper, Institute of Economics, Academia Sinica, 1999.

Égert, B. and E. Kočenda (2007), "Interdependence between Eastern and Western European Stock Markets: Evidence from Intraday Data," *Economic Systems*, 31(2), pp.184-203.

Enders, W. (2003), *Applied Econometric Time Series*, 2nd ed., Hoboken, NJ: Wiley.

Engle, R. F. (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, 50(4), pp.987-1007.

Engle, R. and F. K. Kroner (1995), "Multivariate Simultaneous Generalized ARCH," *Econometric Theory*, 11(1), pp.122-150.

Gallant, A. R. (1981), "On the Bias in Flexible Functional Forms and an Essentially Unbiased Form: The Fourier Flexible Form," *Journal of Econometrics*, 15(2), pp.211-245.

Hamao, Y., R. W. Masulis and V. Ng, (1990), "Correlations in Price Changes and Volatility across International Stock Markets," *Review of Financial Studies*, 3(2), pp.281-307.

Harju, K., and S. M. Hussain (2008), "Intraday Return and Volatility Spillovers Across International Equity Markets," *International Research Journal of Finance and Economics*, 22, pp.205-220.

Jeon, B. N. and G. M. Von Furstenberg (1990), "Growing International Co-Movement in Stock Price Indexes ," *Quarterly Review of Economics and Business*, 30(3), pp.15-30.

Jeong, J.-G. (1999), "Cross-border Transmission of Stock Price Volatility: Evidence from the Overlapping Trading Hours," *Global Finance Journal*, 10(1), pp.53-70.

Karolyi, G. A. (1995), "A Multivariate GARCH Model of International Transmissions of Stock Returns and Volatility: The Case of the United States and Canada," *Journal of Business and Economic Statistics*, 13(1), pp.11-25.

Kim, S-J. (2005), "Information Leadership in the Advanced Asia–Pacific Stock Markets: Return, Volatility and Volume Information Spillovers from the US and Japan," *Journal of the Japanese and International Economies*, 19(3), pp.338-365.

Koopman, S. J., B. Jungbacker, and E. Hol. (2005), "Forecasting Daily Variability of the S&P 100 Stock Index Using Historical, Realised and Implied Volatility Measurements." *Journal of Empirical Finance*, 12(3), pp.445-475.

Laurent, S. and Perets J. P. (2002) "G@RCH 2.2: An Ox Package for Estimating and Forecasting Various ARCH Models," in M. McAleer and L. Oxley (eds.), *Contributions to Financial Econometrics: Theoretical and Practical issues*, pp.211-250, Oxford: Blackwell Publishing Ltd.

Lin, W. L., R. F. Engle and T. Ito (1994), "Do Bulls and Bears Move Across Borders? International Transmission of Stock Returns and Volatility as the World Turns," *Review of Financial Studies*, 7(3), pp. 507-538.

Liu, C. and S. Chen (2008), "The Volatility Spillover between Chinese and Major International Stock Markets: New Evidence from a Causality-in-Variance Approach," *World Economic Papers*, 5, pp.30-44. (in Chinese)

Ljung, G. M. and G. E. P. Box (1978), "On a Measure of Lack of Fit in Time Series Models," *Biometrika*, 65(2), pp.297-303.

Longin, F. and B. Solink (1995), "Is the Correlation in International Equity Returns Constant: 1960–1990?" *Journal of International Money and Finance*, 14(1), pp. 3–26.

Ng, A. (2000), "Volatility Spillover Effects from Japan and the US to the Pacific–Basin," *Journal of International Money and Finance*, 19(2), pp. 207–233.

Nishimura, Y. and M. Men (2010), “The Paradox of China’s International Stock Market Co-movement: Evidence from Volatility Spillover Effects between China and G5 Stock Markets,” *Journal of Chinese Economic and Foreign Trade Studies*, 3(3), pp.235-253.

Nishimura, Y., Y. Tsutsui and K. Hirayama, (2012), “Return and Volatility Spillovers between Japanese and Chinese Stock Markets: An Analysis of Overlapping Trading Hours with High-frequency Data,” *Discussion Papers in Economics and Business*, No.12-01, Osaka University.

Rozeff, M. S. and W. R. Kinney, Jr. (1976), “Capital Market Seasonality: The Case of Stock Returns,” *Journal of Financial Economics*, 3(4), pp.379-402.

Theodossiou, P. and U. Lee (1993), “Mean and Volatility Spillovers across Major National Stock Markets: Further Empirical Evidence,” *Journal of Financial Research*, 16(4), pp.337-350.

Tsutsui, Y. and K. Hirayama (2005), “Estimation of the Common and Country-Specific Shock to Stock Prices,” *Journal of the Japanese and International Economies*, 19(7), pp.322-337.

Tsutsui, Y. and K. Hirayama (2013), “Are Chinese Stock Investors Watching Tokyo? International Linkage of Stock Prices Using Intraday High-Frequency Data,” *Japanese Journal of Monetary and Financial Economics*, 1(1), pp. 37-57.

Tustsui, Y., K. Hirayama, T. Tanaka, and N. Uesugi (2007), “Special Quotes Invoke Autocorrelation in Japanese Stock Prices,” *Asian Economic Journal*, 21(4), pp.369-389.

Xekalaki, E. and S. Degiannakis (2010), *ARCH Models for Financial Applications*, John Wiley & Sons, New York.

Yamamoto, T. (1988) *Keizaino Jikeiretu Bunseki* (Time Series Analysis in Economics), Tokyo : Sobunsha Publishing Company. (in Japanese)

Zellner, A. and F. Palm (1974), “Time Series Analysis and Simultaneous Equation Econometric Models,” *Journal of Econometrics*, 2(1), pp.17-54.

Figures and Tables

Table 1. Basic Statistics of 5-Minute Returns of the Two Markets
Sample period: Nov. 4, 2003, to Nov. 18, 2011 (T=33444)

	Mean	Std.Dev	Kurtosis	Skewness	LB_{10}	LB_{10}^2
CRX	-0.0002	0.2101	87.3786	0.2750	98.052	17156
MI	0.0002	0.1176	19.5414	-0.3379	326.51	12406
SHCOMP	0.0012	0.2121	8.2224	0.0463	36.880	9340.9

Notes: Let T denote the number of observations and $\hat{\sigma}$ the standard deviation. Then the standard error of the mean, kurtosis, and skewness is $\hat{\sigma}/\sqrt{T}$, $\sqrt{6/T}$, and $\sqrt{24/T}$ respectively. The standard deviations of the mean of CRX, MI, and SHCOMP are 0.0011, 0.0006, and 0.0012 respectively. The standard errors of the kurtosis and skewness are 0.0134 and 0.0268 respectively. LB_{10} and LB_{10}^2 are the Ljung-Box statistics to check for absence of serial correlation up to 10 lags in the standardized residuals and their squares.

Table 2. Estimation of AR-FIGARCH Model of SHCOMP

Sample period: Nov. 4, 2003, to Nov. 18, 2011 (T=33444)

Parameter	*Coefficient*	*Std.Error*
c	0.0009	(0.0009)
ϕ_1	0.1001***	(0.0070)
ϕ_2	-0.0551***	(0.0062)
ϕ_3	-0.0109	(0.0061)
ϕ_4	0.0265***	(0.0060)
ω	0.0298***	(0.0066)
d	0.3950***	(0.0183)
α_1	0.3023***	(0.0207)
β_1	0.6116***	(0.0220)
L.L.	10444.31	
AIC	-0.6240	
LB_{10}	11.399	
LB_{10}^2	7.9460	
LM_{10}^{ARCH}	0.7875	

Notes: *** and ** denote significance at the 1% and 5% level respectively. Numbers in parentheses are robust standard errors based on the quasi-maximum likelihood approach. *L.L.* is log likelihood. LB_{10} and LB_{10}^2 are the Ljung-Box statistics with lag 10 for standardized residuals and their squares, respectively. LM_{10}^{ARCH} is the ARCH LM test statistic for the null hypothesis that there is no ARCH effect up to order ten.

Table 3. Return and Volatility Spillover Effects from SHCOMP to CRX and MI
Sample period: Nov. 4, 2003, to Nov. 18, 2011 (T=33444)

	CRX		MI	
θ_1	0.0315***	(0.0041)	0.0089***	(0.0024)
θ_2	-	-	-0.0007	(0.0026)
θ_3	-	-	0.0065**	(0.0026)
λ_1	-0.0021	(0.0110)	0.0251	(0.0197)
λ_2	-	-	0.0067	(0.0192)
λ_3	-	-	-0.0185	(0.0112)
ω	0.1045***	(0.0216)	0.0079***	(0.0021)
d	0.4783***	(0.0207)	0.3548***	(0.0200)
α_1	0.2516***	(0.0355)	0.3075***	(0.0334)
β_1	0.5852***	(0.0436)	0.5901***	(0.0389)
$L.L.$	17606.26		31253.67	
AIC	-1.0523		-1.8667	
LB_{10}	7.0407		2.7738	
LB_{10}^2	10.190		17.643	
LM_{10}^{ARCH}	1.0266		1.7842	

Notes: *** and ** denote significance at the 1% and 5% level respectively. Numbers in parentheses are robust standard errors based on the quasi-maximum likelihood approach. $L.L.$ is log likelihood. LB_{10} and LB_{10}^2 are the Ljung-Box statistics with lag 10 for standardized residuals and their squares, respectively. LM_{10}^{ARCH} is the ARCH LM test statistic for the null hypothesis that there is no ARCH effect up to order ten. The results on mean equations are omitted to save space.

Table 4. Investigation of the Mechanism of Return Spillover Effects from China to Japan
Sample period: Nov. 4, 2003, to Nov. 18, 2011 (*T*=33444)

	Base Model		Model A		Model B	
θ_1	0.0128***	(0.0030)	0.0017	(0.0021)	0.0017	(0.0021)
θ_2	0.0065**	(0.0030)	-0.0001	(0.0021)	-0.0001	(0.0021)
θ_3	0.0029	(0.0030)	0.0044**	(0.0021)	0.0045**	(0.0021)
β_0	-	-	0.4012***	(0.0022)	0.4011***	(0.0022)
β_1	-	-	0.0704***	(0.0031)	0.0697***	(0.0031)
β_2	-	-	-	-	-0.0044	(0.0031)
β_3	-	-	-	-	-0.0008	(0.0031)
$\bar{R}^2$	0.0118		0.5137		0.5137	

Notes: *** and ** denote significance at the 1% and 5% level respectively. Numbers in parentheses are standard errors. $\bar{R}^2$ is adjusted R-squared. The estimation results on the AR terms ($\phi_i, i=1,\cdots,30$) are omitted to save space.

Base Model:

$$r_{TOPIX,t(i)} = c_{TOPIX} + \phi_1 r_{TOPIX,t(i-1)} + \cdots + \phi_{30} r_{TOPIX,t(i-30)} + \theta_1 r_{CHN,t(i-1)} + \cdots + \theta_3 r_{CHN,t(i-3)} + \varepsilon_{TOPIX,t(i)}$$

Model A:

$$r_{TOPIX,t(i)} = c_{TOPIX} + \phi_1 r_{TOPIX,t(i-1)} + \cdots + \phi_{30} r_{TOPIX,t(i-30)} + \theta_1 r_{CHN,t(i-1)} + \cdots + \theta_3 r_{CHN,t(i-3)} + \beta_0 r_{CRX,t(i)} + \beta_1 r_{CRX,t(i-1)} + \varepsilon_{TOPIX,t(i)}$$

Model B:

$$r_{TOPIX,t(i)} = c_{TOPIX} + \phi_1 r_{TOPIX,t(i-1)} + \cdots + \phi_{30} r_{TOPIX,t(i-30)} + \theta_1 r_{CHN,t(i-1)} + \cdots + \theta_3 r_{CHN,t(i-3)} + \beta_0 r_{CRX,t(i)} + \cdots + \beta_3 r_{CRX,t(i-3)} + \varepsilon_{TOPIX,t(i)}$$

Estimation method is ordinary least squares.

Table 5 Return and Volatility Spillover Effects from SHCOMP to CRX in Different Periods

	2004	2005	2006	2007	2008	2009	2010	2011
Model	AR(4) FIGARCH(1,*d*,1) SHCOMP(1)	AR(3) FIGARCH(1,*d*,1) SHCOMP(1)	AR(4) FIGARCH(2,*d*,1) SHCOMP(1)	AR(3) FIGARCH(1,*d*,1) SHCOMP(3)	AR(4) FIGARCH(1,*d*,1) SHCOMP(2)	AR(5) FIGARCH(1,*d*,1) SHCOMP(1)	AR(5) FIGARCH(2,*d*,1) SHCOMP(3)	AR(5) FIGARCH(1,*d*,1) SHCOMP(1)
θ_1	-0.0004 (0.0137)	-0.0028 (0.0089)	0.0272 (0.0154)	0.0287*** (0.0077)	0.0361*** (0.0108)	0.0422*** (0.0114)	0.0637*** (0.0111)	0.0661*** (0.0164)
θ_2	-	-	-	-0.0112 (0.0073)	0.0169 (0.0102)	-	0.0117 (0.0125)	-
θ_3	-	-	-	0.0069 (0.0067)	-	-	0.0123 (0.0116)	-
λ_1	0.0584 (0.0692)	-0.0154*** (0.0043)	0.0934 (0.0764)	0.0010 (0.0301)	-0.0504 (0.0530)	0.0279 (0.0602)	-0.0811 (0.0704)	-0.0246 (0.0483)
λ_2	-	-	-	0.0278 (0.0348)	0.0593 (0.0653)	-	0.3046** (0.1261)	-
λ_3	-	-	-	-0.0380** (0.0186)	-	-	-0.1794** (0.0700)	-
ω	0.0187*** (0.0049)	0.0124*** (0.0020)	0.0230*** (0.0084)	0.0244*** (0.0085)	0.2333 (0.2245)	0.0347** (0.0169)	0.0262* (0.0155)	0.0406 (0.0222)
d	0.2733*** (0.0536)	0.2159*** (0.0425)	0.3570*** (0.0560)	0.2732*** (0.0480)	0.4961*** (0.0979)	0.3789*** (0.0528)	0.4050*** (0.0544)	0.7932*** (0.1138)
α_1	0.2007 (0.1835)	0.5046** (0.1978)	0.1232 (0.1183)	0.0000 (1.2807)	0.1681* (0.0881)	0.2821*** (0.0667)	0.0000 (0.5027)	0.1037** (0.0507)
β_1	0.3925 (0.2111)	0.5817*** (0.1983)	0.3548*** (0.1219)	0.0907 (1.1930)	0.4865*** (0.1243)	0.5742*** (0.0805)	0.2882 (0.5582)	0.8268*** (0.0756)
β_2	-	-	0.0740** (0.0342)	-	-	-	0.1058 (0.1971)	
L.L.	2457.04	3498.60	2171.29	2550.93	-40.030	1280.183	3105.92	2648.68
AIC	-1.1765	-1.6708	-1.0253	-1.2150	0.0255	-0.6180	-1.4987	-1.4507
LB_{10}	6.2545	4.5097	4.5486	7.6358	7.8297	3.6427	3.8492	7.7720
LB_{10}^2	4.1444	8.3292	11.216	3.7842	1.4729	6.5354	1.7564	8.7777
LM_{10}^{ARCH}	0.4003	0.8501	1.2008	0.3862	0.1524	0.6404	0.1744	0.8792
N. Obs.	4158	4176	4212	4176	4158	4104	4122	3635

Notes: . *** and ** denote significance at the 1% and 5% level respectively. Numbers in parentheses are robust standard errors based on the quasi-maximum likelihood approach. *L.L.* is log likelihood. LB_{10} and LB_{10}^2 are the Ljung-Box statistics with lag 10 for standardized residuals and their squares, respectively. LM_{10}^{ARCH} is the ARCH LM test statistic for the null hypothesis that there is no ARCH effect up to order ten. The results on mean equations are omitted to save space.

Table 6 Return and Volatility Spillover Effects from SHCOMP to MI in Different Periods

	2004	2005	2006	2007	2008	2009	2010	2011
Model	AR(1) FIGARCH(1,*d*,1) SHCOMP(3)	AR(1) FIGARCH(1,*d*,1) SHCOMP(1)	AR(4) FIGARCH(1,*d*,1) SHCOMP(1)	AR(3) FIGARCH(1,*d*,1) SHCOMP(3)	AR(2) FIGARCH(1,d,1) SHCOMP(1)	AR(1) FIGARCH(1,d,1) SHCOMP(2)	AR(1) FIGARCH(1,d,1) SHCOMP(1)	AR(5) FIGARCH(1,d,1) SHCOMP(1)
θ_1	0.0009 (0.0084)	-0.0078 (0.0053)	0.0210** (0.0089)	0.0040 (0.0047)	0.0170** (0.0071)	0.0230*** (0.0014)	0.0292*** (0.0070)	0.0389*** (0.0120)
θ_2	0.0155* (0.0091)	-	-	-0.0096 (0.0052)	-	0.0071 (0.0046)	-	-
θ_3	0.0011 (0.0089)	-	-	0.0093 (0.0048)	-	-	-	-
λ_1	0.0488 (0.1178)	-0.0033 (0.0043)	0.0298 (0.0263)	0.0439 (0.0386)	0.0227 (0.0237)	-0.0601*** (0.0001)	0.0250 (0.0217)	-0.0173 (0.0370)
λ_2	-0.0705 (0.0744)	-	-	-0.0193 (0.0389)	-	0.0504*** (0.0006)	-	-
λ_3	0.0679 (0.0473)	-	-	-0.0114 (0.0154)	-	-	-	-
ω	0.0063*** (0.0014)	41.5161*** (9.9671)	81.2897*** (21.4430)	90.8033*** (22.2850)	0.0375*** (0.0123)	0.0191*** (0.0038)	0.0076*** (0.0037)	0.0057*** (0.0017)
d	0.2197*** (0.0443)	0.2911*** (0.0477)	0.3228*** (0.0484)	0.3346*** (0.0437)	0.3694*** (0.0539)	0.4693*** (0.0154)	0.3556*** (0.0924)	0.3571*** (0.0794)
α_1	0.0000 (0.5011)	0.4792*** (0.1230)	0.2052*** (0.0722)	0.2037** (0.0860)	0.1714 (0.0915)	0.3743*** (0.0076)	0.3416*** (0.0616)	0.3997*** (0.0552)
β_1	0.1559 (0.5251)	0.6786*** (0.1112)	0.4892*** (0.0991)	0.4910*** (0.0994)	0.4651*** (0.1124)	0.7809*** (0.0091)	0.6360*** (0.0636)	0.6661*** (0.0792)
L.L.	4579.50	5757.28	3727.25	3852.28	1598.59	3050.10	4538.78	3659.09
AIC	-2.1970	-2.7535	-1.7646	-1.8383	-0.7646	-1.4825	-2.1983	-2.0067
LB_{10}	11.016	3.8658	17.404	7.4800	2.5520	8.7993	7.1657	3.8658
LB^2_{10}	3.9437	4.4687	6.5391	5.1812	9.1249	7.8232	25.078***	4.4687
LM^{ARCH}_{10}	0.3952	0.2872	0.6603	0.5166	0.9157	0.6984	2.5176***	0.4665
N. Obs.	4158	4176	4212	4176	4158	4104	4122	3635

Notes: . *** and ** denote significance at the 1% and 5% level respectively. Numbers in parentheses are robust standard errors based on the quasi-maximum likelihood approach. *L.L.* is log likelihood. LB_{10} and LB^2_{10} are the Ljung-Box statistics with lag 10 for standardized residuals and their squares, respectively. LM^{ARCH}_{10} is the ARCH LM test statistic for the null hypothesis that there is no ARCH effect up to order ten. The results on mean equations are omitted to save space.

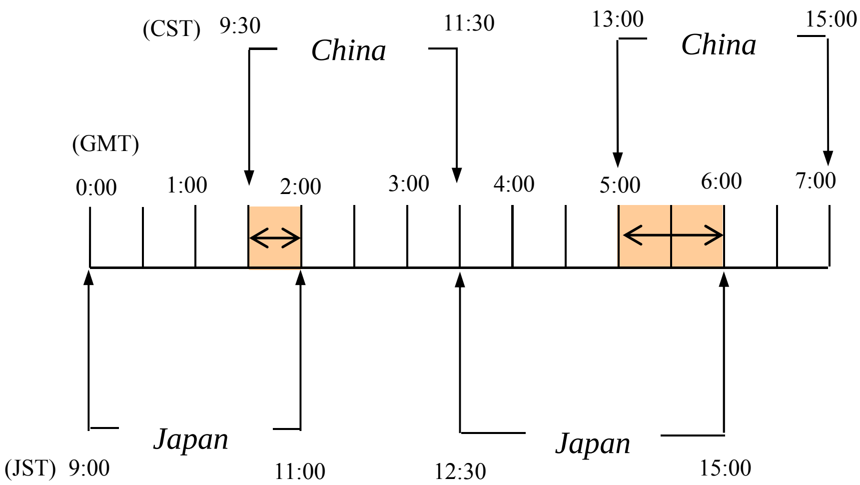

Figure 1. Trading Hours of the Japanese and Chinese Stock Exchanges.

Notes: The timeline in the middle represents Greenwich Mean Time (GMT). The opening and closing hours of the morning and afternoon sessions of Japan are in Japan Standard Time (JST) and those of China are in China Standard Time (CST). Overlapping trading hours (windows of simultaneous trading) are shaded.

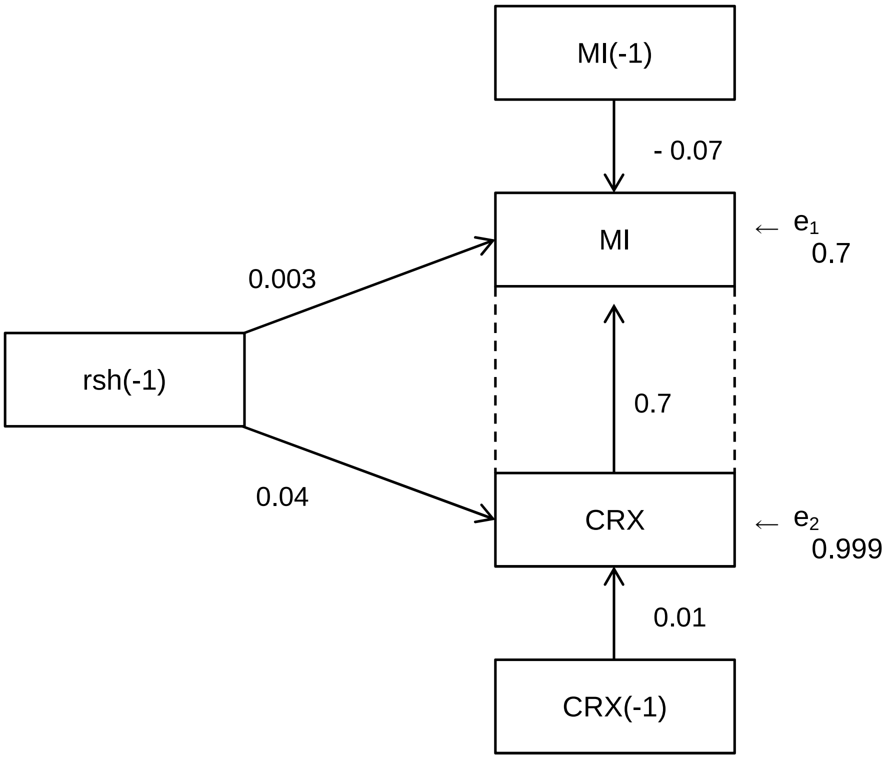

Figure 2. Path Diagram

Note: Values in the figure are standardized coefficients. e_1 and e_2 are random terms.

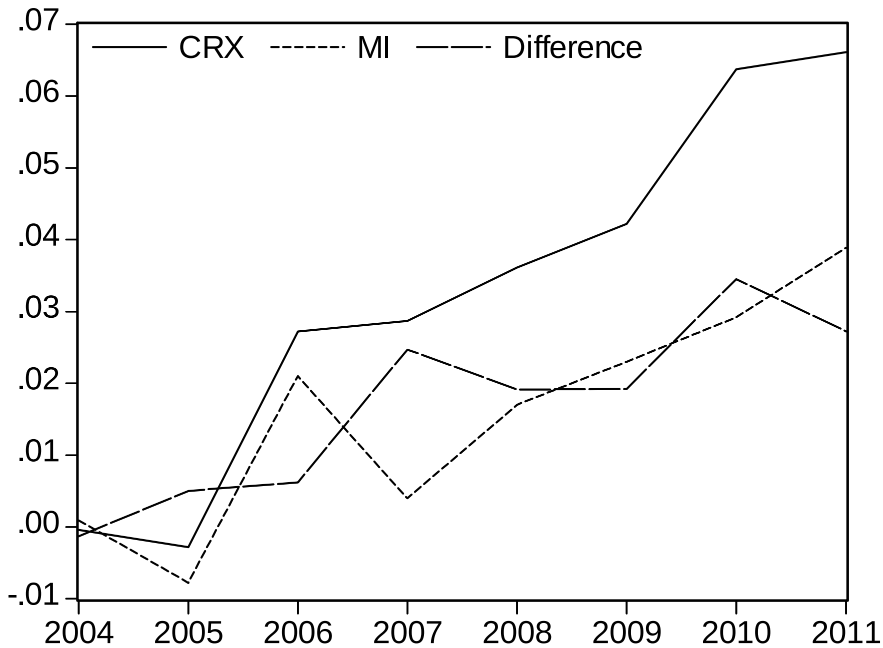

Figure 3. Responses of Japanese Stock Price against Chinese Stock Price Movements Estimated Annually

Notes: The graph plots the parameter θ of equation 1, which measures the response of Japanese stock returns against lagged Chinese stock returns. The solid line is for CRX (θ_{CRX}), the dotted line is for TOPIX (θ_{MI}), and the broken line is for the difference between the two ($\theta_{CRX} - \theta_{MI}$).