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Are Chinese Stock Investors Watching Tokyo?
An Analysis of Intraday High-Frequency Data from Two Chinese Stock Markets and the Tokyo Stock Market

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ABSTRACT

Intraday minute-by-minute data from the Tokyo, Shanghai, and Shenzhen stock exchanges from January 7, 2008, to January 23, 2009, are analyzed to investigate the interaction between the Japanese and Chinese stock markets. We focus on two windows of time during which all three stock exchanges trade shares simultaneously, and specify appropriate lags in vector autoregression (VAR) estimations. Granger causality tests, variance decompositions, and impulse response functions show that, while Tokyo is impacted by Chinese stock price movements, China is relatively isolated. This implies that investors in Japan are more internationally oriented and alert to foreign markets than those in China.

JEL Classification Numbers: G14, G15, F36
Keywords: international linkage of stock prices, high frequency data, inefficiency, overreaction, China

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1. Introduction

The growth of Chinese stock markets has been phenomenal. Less than 20 years since their establishment (in 1990 and 1991, respectively), the combined market capitalization of the Shanghai and Shenzhen stock exchanges at the end of 2007 was roughly 4.4 trillion dollars, which trails Tokyo's 4.8 trillion dollars by a narrow margin, and Tokyo is second only to New York. China's stock markets, as well as her economy, now exert significant influence on other countries. When the Shanghai Composite Index dropped by 8.84% on February 27, 2007, it precipitated drops in stock prices in all the major stock markets of the world. However, this huge drop may have been a sign of weakness or inefficiency in the Chinese stock markets. This inefficiency, if it exists, should affect not only Chinese investors, but also investors in other countries because of international linkage of stock prices as well as international portfolio holdings. To the best of our knowledge, the efficiency and performance of Chinese stock markets has not yet been examined in detail. In this paper, we attempt to shed light on this issue.

There is much literature on the international linkage of stock prices (e.g., Jeon and von Furstenberg (1990), Hirayama and Tsutsui (1998), Masih and Masih (1999), Heimonen (2002), Bessler and Yang (2003), Worthington, Katsura, and Higgs (2003), and Darrat and Zhong (2005)). Almost all studies report on a bidirectional causality between pairs of stock prices. However, while Chinese stock prices are little affected by other markets, some major stock markets do respond to changes in Chinese stock prices (Huang, Yang, and Hu (2000), Groenewold, Tang, and Wu (2004), and Zhang 2008)).[1] This finding suggests that Chinese stock markets are isolated from others and that their efficiency may still be in a fledgling stage. We find the lack of response

[1] Chen and Liu (2008) analyze volatility spillover effects between China and other markets. They found causality from China to other markets, but not vice versa.

of Chinese stock prices to other markets interesting and worth exploring.

The primary purpose of this paper is to clarify whether Chinese stock markets are really isolated from markets in other countries. If such isolation exists, the next question is whether and when it will disappear. In this sense, a recent event comes to mind: the global stock market meltdown of September/October 2008. Although it started in the U.S.A., other stock markets responded, magnifying the negative effects. Chinese stock prices also plunged during this tumultuous period. Considering the wide-spread international spillover effects after Black Monday of 1987 (Tsutsui and Hirayama (2009), pp. 170-171), it may be that Chinese stock markets underwent 'globalization' after the meltdown of 2008 and that their stock prices will henceforth be routinely and significantly swayed by global stock market movements. Investigation of this possibility is one of the purposes of this study.

The second purpose of this paper is to establish a methodology for investigating international stock price spillover effects using tick or high-frequency data. Most studies on this subject utilize daily, weekly, or monthly closing prices. However, vector autoregression (VAR) estimation using such data is an indirect method of measuring inter-market responses. For example, when studying New York and Tokyo, it should be noted that the two stock exchanges are not open simultaneously. When the New York stock market closes, Tokyo cannot respond because it is not yet open. It is only at market opening at 09:00 Japan Standard Time (JST) that Tokyo stock prices can respond to New York. As daily data typically consist of closing prices, all other sorts of information that drive stock prices during the day contaminate the effect of New York on the Tokyo market. By using high-frequency data, we can investigate the effect of the New York market at the opening of the Tokyo market, unequivocally capturing the linkage.

While using daily data produces a murky picture, when the stock markets under investigation are open for trading at the same time, analysis of bidirectional simultaneous causality becomes feasible and can yield interesting results. We can thus conduct direct tests of spillover effects with real-time, simultaneous data from the Tokyo, Shanghai, and Shenzhen markets and propose an appropriate method for such an analysis.

There is a line of research that utilizes intraday data from simultaneously open stock exchanges. Most such studies, however, focus on stocks that are cross-listed on two stock exchanges.[2] To the best of our knowledge, there are only two papers that analyze intraday stock price indexes for several stock exchanges observed simultaneously. One is Èerny and Koblas (2008) who utilized high-frequency data on stock price indexes from New York and six European cities. Using data of different frequencies, the authors found that mutual information is transmitted very rapidly, so that an empirical analysis of stock price linkages using daily data may not accurately capture the true reactions. The other is Égert and Kočenda (2007) who studied stock price spillover effects among six European cities using five-minute data. Although they found no cointegration, they reported evidence of short-term Granger causality. However, as will be explained in Section 2.3, neither of these papers seems to adopt appropriate lags in VAR estimation.

Tokyo, Shanghai, and Shenzhen are ideal for studying stock price spillover effects because the markets are open simultaneously for two periods each day. There is a 30-min window (10:30-11:00 JST) in the morning and a 60-min window

[2] For example, Grammig, Melvin, and Schlag (2005) analyze three German stocks cross-listed in New York and Frankfurt. Hupperets and Menkveld (2002) examine seven blue-chip Dutch companies that are also listed in New York. Lok and Kalev (2006) investigate stocks of Australian and New Zealand companies that are cross-listed in the Australian and New Zealand markets. These papers focus on individual stocks to determine where price discovery occurs along the line developed by Hasbrouck (1995).

(14:00-15:00 JST) in the afternoon when the Tokyo and Chinese stock exchanges are open at the same time. In this paper we analyze the markets in Japan and China, focusing on the time windows when both exchanges are open. We utilize minute-by-minute stock returns in Granger causality tests, variance decompositions, and impulse response functions (IRF) to explore mutual interactions between the two countries. Special attention is paid to lagged values in VAR estimation (Section 2.3), one of the features of this paper.

The rest of this paper is organized as follows. Section 2 explains the data and methodology. Section 3 presents estimation results. Section 4 examines whether Chinese markets became more efficient after the global financial crisis of 2008. Section 5 checks whether our lag methodology produces more plausible results and discusses possible causes of our results. The final section concludes the paper.

2. Data and Methodology

2.1. Methodology: Cointegration Tests and VAR Model Estimation

After preliminarily testing for unit roots that confirm commonly found nonstationarity in the indexes of the three stock exchanges, we check for cointegration between each pair of stock prices. We focus on two bivariate systems: the Tokyo-Shanghai and Tokyo-Shenzhen bivariate models, because we are interested in the bidirectional dependence between Japanese and Chinese markets. Shanghai-Shenzhen is analyzed merely as a reference. Since we employ bivariate systems, the number of cointegrating ranks is one, at most, and there is no need for system estimation by Johansen tests. We employ Engle-Granger two-step estimation to check for cointegration.[3] If cointegration exists, the VAR model should be

[3] A practical reason for adopting this test is that econometric packages cannot handle our particular

modified to a vector error correction (VEC) model. As shown later, our results indicate no evidence of cointegration between pairs. Consequently, we can make our estimations by conventional VAR models only, without VEC terms.

While long-run relationships are examined by cointegration tests, short-run dynamic interactions are analyzed by Granger causality tests, variance decompositions computations, and IRF, which are standard tools for short-run dynamic analysis.

2.2. Data

We analyze return spillover effects between the Japanese and Chinese markets by focusing on pair-wise relations between Tokyo and Shanghai (or Shenzhen), using the Nikkei 225 Index and Shanghai (or Shenzhen) Composite Index. Minute-by-minute observations of these three indexes were obtained from Tickdata.com for the period from January 7, 2008, to January 23, 2009. Similar to the Dow Jones 30 Industrials Index, Nikkei 225 is an arithmetic average of 225 representative stocks traded on the Tokyo Stock Exchange. Although the Shanghai and Shenzhen Stock Exchanges trade A shares for domestic investors (traded in local currency) and B shares for foreign investors (traded in US dollars in Shanghai and HK dollars in Shenzhen), only composite indexes of all shares were available to us. Daily closing prices for our sample period are plotted in Figure 1, showing downward trends in both Chinese markets and reflecting adjustments following the bursting of a stock market bubble in China that started in November 2007. The Nikkei average hovered between 12,000 and 14,000 until September/October 2008 after which it plunged to around 8000.

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method of selecting lags.

Trading hours for the three stock exchanges are given in Figure 2. In Tokyo, opening prices are determined by batch trading (*itayose*). After opening at 09:00 JST, a continuous auction takes place until 11:00. After a 90-min lunch break, the afternoon session starts at 12:30 and ends at 15:00. In both Chinese markets, pre-market call auctions between 09:15 and 09:25 (Chinese Standard Time, CST) determine the opening prices for the day. Continuous auction takes place between 09:30 and 11:30 for the morning session and between 13:00 and 15:00 (14:57 in the case of Shenzhen) for the afternoon session. Since there is a one-hour time difference between Japan and China, the only times during which all three stock exchanges are simultaneously open for trading are 10:30 to 11:00 and 14:00 to 15:00 (JST). We focus on these two windows of 30 minutes and 60 minutes in this study.

2.3. Data Selection

In defining the dataset we use the VAR model, which utilizes many lags. In summary, the rules we use are characterized by the following four points: (a) minute-by-minute stock prices when the stock exchanges are simultaneously open, i.e., 10:31 to 11:00 and 14:01 to 15:00; (b) to avoid biases due to asymmetric treatment of opening prices, we drop the first ten observations in each window. This deletes the opening prices on the Chinese markets, resulting in slightly different windows, 10:41 to 11:00 and 14:11 to 15:00, each day. Otherwise, our calculations would include opening prices in China but not in Japan. Since stock prices at and immediately following the openings of stock markets reflect information accumulated during night-time non-trading hours and are more volatile than prices during normal trading hours, it is necessary to exclude opening prices of both markets to make a fair comparison; (c) time series data is constructed by sequentially combining data from the windows; and (d) the basic dataset constructed under rules (a) through (c), above, includes appropriate regression lags. To explain stock returns observed at 10:41 in Tokyo, there are lagged returns on the right-hand side of the VAR equation. Since the dataset is a combined series of data from two windows each day, a one-period lag for the Tokyo index at 10:41 is that of 15:00 of the previous day; a two-period lag is that of 14:59; etc. However, true lags are the index at 10:40, 10:39, etc. Only these truly relevant lags should be used as explanatory variables for VAR equations. The same applies to the Chinese regression equations. Due to deletion of the first ten observations from each window, true lagged values are available from these deleted data points.

Levels and rates of change for the three indexes are provided in Table 1. The data are obtained for 20 min in the morning and 50 min in the afternoon. For minute-by-minute rates of change, Tokyo's mean is smaller than those of Shanghai and Shenzhen, but the standard deviations are about the same in all three markets. However, the maximum and minimum in Tokyo are two to three times larger (in absolute value) than those of China. The kurtosis of Tokyo returns is over 22.5 whereas it is only 1.5 in Shanghai and 2.2 in Shenzhen, indicating much fatter tails in the distribution of returns in Tokyo. As with other stock price returns, the Jarque-Bera test of normality strongly rejects the null of normality, but the extent of this rejection is extreme in Tokyo, apparently due to its large kurtosis.

3. Results

3.1. Unit Root Tests

The logged levels and rates of change of the three stock price indexes are tested for nonstationarity by the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Results are shown in Table 2 . A constant term is included in the regression, but a linear time trend is not. The result is typical of stock prices, namely, levels can be regarded as I(1) but rates of change are stationary, i.e., I(0).

3.2. Engle-Granger Tests of Cointegration

Since all three stock price levels are I(1), we next test for cointegration of logged stock prices in each bivariate system. Results are displayed in Table 3 . According to critical values as given by MacKinnon (1991), the null of nonstationarity in the residuals cannot be rejected, indicating absence of cointegration for the two bivariate systems: Tokyo-Shanghai and Tokyo-Shenzhen. Thus, we can safely proceed to estimating a conventional VAR model without error correction terms.

For reference purposes, we also compute the Engle-Granger tests for the Shanghai-Shenzhen system. When Shanghai is the dependent variable, the null of a unit root in the regression residual cannot be rejected at a 5% confidence level. However, when Shenzhen is the dependent variable, the null is rejected at a 10% level. There is mild evidence of cointegration between Shanghai and Shenzhen, which is plausible given their highly correlated movements (see Figure 1).

3.3. VAR Estimation and Granger Causality Tests

Since variables in VAR models must be stationary, we use minute-by-minute rates of change in the three stock indexes. The two bivariate VAR systems (Tokyo-Shanghai and Tokyo-Shenzhen) are estimated by ordinary least squares (OLS) with White's heteroscedasticity-consistent variance-covariance matrix. To determine the optimal lag order of the VAR model, we examine Ljung-Box Q statistics for the regression residuals. They indicate that ten lags are sufficient to eliminate serial correlation in the residuals. We thus adopt this lag order for all the following VAR models.[4]

After estimating VAR(10) for the two bivariate systems, we conduct Granger causality tests for each set of lagged variables. The null hypothesis is that all ten coefficients on lagged values are zero, whose test statistic is distributed as Chi-squared. Results are presented in Table 4 . Own lags are all highly significant. We, however, are interested in cross terms. Shanghai Granger causes Tokyo very significantly, but Tokyo Granger causes Shanghai with only 3.85% significance. Shenzhen also Granger causes Tokyo very significantly, but Tokyo's effect on Shenzhen is not significant. Its *p*-value is 41%, indicating an absence of Granger causality from Tokyo to Shenzhen. We also compute the Granger causality tests for the Shanghai-Shenzhen system. Cross causality is extremely significant between the two exchanges, indicating a very substantial mutual influence between Shanghai and Shenzhen.

While Tokyo responds to Shanghai and Shenzhen in the sense of Granger causality, Shanghai's response to Tokyo is somewhat weak and Shenzhen does not respond to Tokyo at all. These results are consistent with those of the studies on daily return spillovers between China and other countries (Huang, Yang, and Hu (2000), Groenewold, Tang, and Wu (2004), and Zhang (2008)).

3.4. Autocorrelation Functions

Another feature that characterizes Chinese markets is the extremely large test

[4] The lag order was altered from 1 to 20 and both Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC) were computed. The regressions to explain Tokyo exhibit minimal AIC and SBIC at nine lags. But, the regressions to explain Shanghai or Shenzhen do not exhibit local minima between 1 and 20 lags. Stock prices in these exchanges seem to have a strong and persistent serial correlation, which might imply lack of efficiency in information processing. In any case, taking 20 lags is a bit excessive given that the morning window is only 30 min long.

statistic for its own lags. Table 4 shows that while Tokyo's lags in the equation to explain Tokyo produce a Chi-squared test statistic of 66, those of Shanghai and Shenzhen are 15,845 and 32,905, respectively. This apparently results from very strong serial correlation in Chinese stock returns, and may be a sign of relative inefficiency in the Chinese stock markets. Although autocorrelation arises from various reasons such as bid-ask bounces and non-synchronized trading, which may not reflect efficiency, serial correlation reflects market inefficiency and is worth examining. An easy way to check this is to compute autocorrelation functions (ACF). Figure 3 shows that the magnitude of autocorrelation at one-minute lags is almost 10 times greater in Shanghai or Shenzhen than in Tokyo, suggesting informational inefficiency in the Chinese markets.

The ACF of Tokyo exhibit spikes at five-minute intervals. However, as Tsutsui et al. (2007) made clear, this merely reflects automatic updating of special quotes, and is not evidence of high autocorrelation of actual prices. On the other hand, ACF of Shanghai and Shenzhen are cyclical, having significantly and numerically large peaks and troughs that may indicate overreaction in stock prices and subsequent adjustments. According to the overreaction hypothesis proposed by De Bondt and Thaler (1985), abnormal negative (positive) returns follow positive (negative) events. Although they analyzed the predicted profitability of long-term winners and losers, the hypothesis also applies to the short-term reversal of stock prices, e.g., Ketcher and Jordan (1994). Thus, not only the magnitude of the ACF, but also their cycles may be evidence of informational inefficiency on the Chinese markets.

3.5. Variance Decompositions

A VAR model can be converted into a vector moving average (VMA) and the forecast error variance decomposed into factors explained by each disturbance. In Table 5 , we compute such decomposition at 30-min horizons. In the Tokyo-Shanghai system, Shanghai accounts for only 0.361% of the forecast error variance of Tokyo's minute-by-minute returns, while the remaining portion (99.639%) is explained by Tokyo's own shocks (the latter figure not shown in the table because it is trivial). In the decomposition of Shanghai, Tokyo explains an even smaller percent (0.231%) of Shanghai's variance and the rest is explained by Shanghai's own shocks. In the Tokyo-Shenzhen system, Shenzhen explains 0.314% of Tokyo's variance, while Tokyo explains only 0.192% of Shenzhen's. Although Granger causality tests indicate some causality from China to Japan, the proportion of forecast error variance explained by China is numerically quite small. And Tokyo's influence on Chinese markets is even smaller. Using the same dataset, we compute variance decompositions for the Shanghai-Shenzhen bivariate system. Within China, the proportion explained by the other stock exchange is very large.[5] These results suggest that the linkage between Chinese and Japanese markets is quite weak. The same tendency can be found using daily data. Zhang (2008) reports that only 0.05% of China's 20-day ahead forecast error variance is accounted for by shocks to Japan and that 0.15% of Japan's forecast error variance is explained by events in China. Using a four-country VAR (U.S., U.K., Germany, and Japan) and daily data, Hirayama and Tsutsui (1998) found that 6.5% of a 20-day ahead forecast error variance of Japan is explained by the U.S. and that 2.0% of the U.S. variance is accounted for by Japan. These magnitudes are much larger than the ones we find

[5] While 13.5% of the forecast error variance of Shanghai is accounted for by Shenzhen, 69.2% of Shenzhen is explained by Shanghai. Thus, the influence of Shanghai over Shenzhen is substantially greater than the other way around.

between Japan and China.

3.6. Impulse Response Functions

Our next tool to analyze short-run interactions is IRF, which are actually coefficients of the VMA model. They capture how a shock to one variable arising at a certain period affects endogenous variables in subsequent periods.

The IRF for the Tokyo-Shanghai system are plotted in Figure 4. Responses to own shocks are far greater in magnitude than responses to shocks on the other stock market. The maximum on the 'own' charts is 20 times greater than on the 'cross' charts, consistent with the results of variance decomposition. However, although the responses of Tokyo to its own shocks dissipate very quickly (within some 10 min), Shanghai's responses to its own shocks oscillate and are statistically quite significant for about 30 min. This cyclical pattern may be a result of overreaction in one direction and subsequent adjustments in the reverse direction, which also caused strong serial correlation in Shanghai's stock returns.

In the 'cross' charts, more of Tokyo's responses are statistically significant than those of Shanghai up to 10 lags, in agreement with results of the Granger causality tests that indicate more significant response of Tokyo to Shanghai than of Shanghai to Tokyo. Shanghai's responses exhibit an oscillating pattern which may be a sign of overreaction of the Shanghai stock market to Tokyo, although negative responses at 8 and 9-min lags are not statistically significant.

Figure 5 shows that the IRF of the Tokyo-Shenzhen system are generally similar to those of the Tokyo-Shanghai system. The cross IRF are qualitatively similar to those of Tokyo-Shanghai. Tokyo's responses to Shenzhen are slightly more significant than the reverse. Tokyo's IRF dissipate monotonically, but Shenzhen's oscillate, although most are not statistically significant.

4. Were the Chinese Stock Markets Transformed by the Global Financial Crisis of 2008?

4.1. The Global Financial Crisis and International Linkage of Stock Prices

In the previous section we determined that Chinese stock markets are not much affected by Tokyo, i.e., international return spillover effects are unidirectional from China to Japan. However, during our sample period, the New York stock market experienced a precipitous plunge that had far-reaching effects on other markets. Just as international stock price comovements were reinforced after Black Monday of 1987, the 2008 global financial crisis may have strengthened international return spillover effects so that, during our sample period, China may have undergone changes in its responsiveness to Tokyo. In this section we examine whether China became more responsive to Tokyo after the stock market crash of September/October 2008. To do so, we split the sample into two subperiods and recompute some of our tests. The first subperiod is January 7, 2008, to August 29, 2008; the second is September 1, 2008, to January 23, 2009.

4.2. Granger Causality Tests: Causality from Tokyo to China Became Stronger

The Granger causality results are presented in Table 4 . Focusing on cross effects, we immediately notice that Chinese markets seem to have paid more attention to developments in Tokyo in the second, turbulent, post crisis period of 2008.[6] Namely, the *p*-value of the Chi-squared statistic testing the explanatory

[6] While Shanghai and Shenzhen significantly Granger cause Tokyo in the first period, their significance declined substantially and they are barely statistically significant at a 10% confidence level in the second period. During the second period, variability was wider in Tokyo (see Figure 1), which probably underweighted the influence from China.

power of Tokyo over Shanghai is 0.1987 in the first period, but 0.0656 in the second, indicating increased significance of Tokyo (see shaded cells). The influence of Tokyo over Shenzhen changed similarly. According to the causality results in the second period, the relative independence of Chinese stock prices seems to have disappeared.

4.3. Variance Decompositions: Sensitivity of Chinese Markets Became Stronger

Next, we re-estimate the forecast error variance decompositions for the two subperiods. Results are shown in Table 5 . In agreement with the above, the explanatory power of Tokyo over Shanghai and Shenzhen increased three and four times in the second period.[7] Tokyo's share is even greater than those of Shanghai or Shenzhen in accounting for Tokyo's error variance in the second period. Again, this is evidence of increasing sensitivity of the Chinese markets to Japan.

4.4. Impulse Response Functions: Response of Chinese Markets Became Stronger

The IRF for the Tokyo-Shanghai system are estimated for the two subperiods and shown in Figure 6. Tokyo's responses to its own shocks are greater in the second period than in the first, probably because of much higher market volatility. Likewise, Tokyo's responses to shocks in Shanghai are generally greater and more prolonged in the second period. Even starker are Shanghai's responses to Tokyo in the second period. In the first period, the IRF oscillated greatly with positive and negative values but, in the second period, the IRF tended to remain positive with a larger magnitude. The IRF of the Tokyo-Shenzhen model has almost identical results as in Figure 7. Consistent with the findings of the Granger causality and variance decompositions tests, the IRF also indicates a more significant response of the Chinese markets to

[7] The explanatory powers of Shanghai and Shenzhen over Tokyo weakened in the second period.

Tokyo in the second period.

4.5. Nonetheless, Chinese Markets Have Not Been Transformed

The question remains, did the Chinese stock markets undergo a permanent change after the global financial crisis, or were they temporarily linked to Tokyo during this turbulent period?

To check whether the change in sensitivity of Chinese markets is permanent or temporary, we re-compute the above tests using data from November 3, 2008, onwards, i.e., after the rapid fall ceased. Results appear in Tables IV and V. The Granger causality tests reveal that Shanghai and Shenzhen are not significantly explained by Tokyo in this period, suggesting that the increased influence of Tokyo was temporary and limited to September and October 2008. However, variance decomposition for the period after November 3, 2008, indicates otherwise; the proportions of forecast error variance explained by Tokyo remain rather high (Table 5). However, the variance decomposition results were not tested for statistical significance. We tend to trust the Granger causality tests which test statistical significance and lead to the conclusion that the Chinese markets remain isolated.

Since serial correlation at least partially reflects market efficiency, we compare the magnitude and pattern of ACF before and after the financial crisis. Results are shown in Figure 8. The qualitative pattern remains the same in the second period, even though the amplitude is slightly smaller. The same is true for ACF after November 3, 2008. Thus, efficiency in the Chinese markets seems to be unchanged in the second period.

5. Discussion

After analyzing stock price spillover effects between Tokyo and two Chinese stock markets (Shanghai and Shenzhen) using a novel VAR estimation with correct lagged values, we check in this section whether our methodology produces more plausible results than those obtained from conventional VAR estimation. Next, we interpret the results, considering possible causes of the international interdependence of the stock prices.

5.1. Evaluation of Our Methodology

We use tick data from three stock exchanges and methods (a) through (d) in section 2.3 to select data for analysis. First, let us see what happens if we do not follow (d), above. Using the same dataset for the dependent variable, we change the lag variable from the true lag to one that shifts the dependent variable just one period, as in normal VAR estimations. Using these incorrect lag values, we may underestimate the true effects of the lags. Results of Granger causality tests carried out by conventional VAR estimation are shown in Table 6 . The Chi-squared statistics are generally smaller than in Table 4 . Thus, using incorrect lag variables generally reduces statistical significance, as we conjectured.

Next, we disregard rule (b) of subsection 2.3 and include the first ten observations following the opening of each trade session in China. We line up the data for the 30-min and 60-min windows contiguously. The windows include the opening prices of the Chinese markets, but not of the Tokyo market. Since opening prices respond to information accumulated during non-trading hours, their responsiveness is stronger than during normal trading hours. Since the data for Tokyo do not include opening prices, comparing the magnitude of responses is unfair. Results are given in Table 6 . Compared to Table 4 , the significance of Tokyo on Shanghai and Shenzhen increases, confirming our prediction that the inclusion of opening prices distorts causality results. The difference is starker in the case of Shenzhen. There, the *p*-value of the causality of Tokyo on Shenzhen is 0.4088 in Table 4 but only 0.0341 in Table 6 , leading to the wrong conclusion that Shenzhen does respond to Tokyo. On the other hand, the *p*-value of the causality of Tokyo on Shanghai declines by a small amount.[8] In sum, both rules of data selection, (b) and (d), are necessary to obtain undistorted results. In particular, symmetric treatment regarding exclusion of opening prices is critical to reach the conclusion that responses of the Chinese and Japanese markets to each other are asymmetric.

5.2. Possible Causes of Why Chinese Markets Do Not Respond to the Tokyo Market

A main result of our analysis is that while Chinese markets seem to affect the Tokyo market, the effect of Japan's market on China seems to be almost zero. In fact, according to the Granger causality test, there is no statistically significant effect of Tokyo on Shenzhen. What causes this result?

Our sample period includes the bursting of a stock price bubble in China that can be interpreted as causing an asymmetric response in China.[9] It can be argued that during the burst, stock price volatility in China became so great that it affected Japan more than the other way round. However, Table I reveals that this is not the case. Indeed, the maximum and minimum Tokyo returns are roughly twice those of China, though the standard deviations are similar in all three markets. Therefore, if we extract

[8] Although fundamentally very significant, the Chi-squared test statistics for own lags in the two Chinese markets become much smaller. With this dataset, lagged values for the opening prices are inevitably those from the previous day or window, which would normally have less explanatory power than immediate lags.

[9] Another factor accounting for the asymmetry between the countries is that China lists stocks of state enterprises, especially A shares whose liquidity is especially low. We hypothesize that these shares make the sensitivity of Chinese stock prices generally low.

Tokyo's minute-by-minute returns that fall within China's maximum/minimum range, they should have less significant impact on China. This would reinforce our results in Section 3 that Chinese markets are not influenced by Tokyo.

To verify this statement, we divide Tokyo returns into those that fall within the maximum/minimum range of Chinese returns and those beyond this range. We then test the Granger causality of the two categories, large and small changes in Tokyo. We found: (a) both large and small changes in Tokyo impact Shanghai at 5% but not 1% significance, and (b) Tokyo's large changes have no impact on Shenzhen at 5% significance and Tokyo's small changes have no impact even at 20% significance. These results are basically the same as in Table 4 . This is because there are very few data points, only 47 (0.28%) of 16,920 observations, that belong to the 'large' category of changes and the 'small' changes are almost identical to the whole sample, making their explanatory power almost equal to that of the whole.

Asymmetric causality between Tokyo and China can be attributed to different investor behaviors. We claim that Japanese investors pay attention to Chinese stock prices in determining their portfolios, but that Chinese investors do not study Japanese prices. This implies that Chinese investors collect less information than their Japanese counterparts and is consistent with the long and persistent serial correlations amply shown by IRF and ACF (Figures 3, 4, and 5).

6. Conclusion

In this paper we analyze intraday minute-by-minute data from the Tokyo, Shanghai, and Shenzhen stock exchanges to investigate mutual interaction between Japanese and Chinese stock markets. Specifically, we focused on a 20-min window (10:41-11:00 JST) in the morning and a 50-min window (14:11-15:00 JST) in the afternoon during which all three stock exchanges are simultaneously trading shares. Our basic tool of empirical analysis was estimation of two bivariate VAR models (Tokyo-Shanghai and Tokyo-Shenzhen). Our methodology, we believe, correctly specifies the appropriate lagged variables in VAR equations. It also avoids using the volatile values that characterize the Chinese market after opening, thus treating the two markets symmetrically.

We then conduct Granger causality tests, variance decompositions, and computed IRF. Empirical analyses with the entire sample (from January 7, 2008, to January 23, 2009) confirmed findings from earlier studies using daily data that China is relatively isolated from other countries. The Shenzhen market, which is much smaller than the Shanghai market, seems to be more autonomous than Shanghai. However, Tokyo seems to be statistically significantly impacted by Chinese stock price movements, implying that Japanese investors are more internationally oriented and alert to foreign markets than Chinese investors.

Another feature of the Chinese stock markets is the fact that their minute-by-minute stock returns exhibit strong and persistent serial correlation. The IRF to their own shocks exhibit very significant and numerically large effects, with oscillating patterns of influence. This may reflect overreaction. Namely, stock prices overreact to new information, which is later reversed, indicating relative informational inefficiency.

Many studies show that after Black Monday, the world's stock markets became more cointegrated. Likewise, the global financial crisis of 2008 might have ushered in the internationalization of Chinese stock investors. To check, we split our sample into two subperiods at the end of August. We found that while China did not respond to Tokyo in the first period, it did so in the second. However, it would be hasty to conclude that China became permanently attentive to Tokyo from September onwards. Indeed, if we exclude the September and October data points from the second period, the Granger causality tests qualitatively returned to the results of the first period. This implies that Chinese markets were subject to influences from Japan only during September/October 2008, and that Chinese markets are still basically isolated from foreign countries.

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Table 1

Stock Price Indexes of Tokyo, Shanghai, and Shenzhen

The stock price indexes used for Tokyo, Shanghai, and Shenzhen are the Nikkei 225, Shanghai Composite, and Shenzhen Composite Indexes, which are determined at a minute-by-minute frequency. The sample period is January 7, 2008, to January 23, 2009. Intraday data are for the 20-min period from 10:41 to 11:00 and the 50-min period from 14:11 to 15:00 (Japan Standard Time). The number of observations is 16,920. The rates of change are not log differences, but arithmetic rates of change from the previous minute. JB is the Jarque-Bera test of normality. The *p*-value is its significance.

	Variable	Mean	St. Dev.	Maximum	Minimum	Skewness	Kurtosis	JB	*p*-value
Logged Level	Tokyo	9.36388	0.21067	9.59177	8.85910	-0.84368	-1.00670	2721.75	0.0000
	Shanghai	7.93030	0.32603	8.61251	7.42791	0.31680	-1.08355	1110.74	0.0000
	Shenzhen	6.70379	0.35473	7.36228	6.11737	0.22869	-1.22856	1211.58	0.0000
Minute-by-Minute	Tokyo	0.00074	0.08298	1.07348	-1.54325	-0.55788	22.52593	358607.17	0.0000
Rate of Change	Shanghai	0.00111	0.08803	0.49049	-0.47809	0.07260	1.53379	1673.37	0.0000
	Shenzhen	0.00105	0.09085	0.52035	-0.66380	-0.05071	2.21745	3473.80	0.0000

Table 2

Unit Root Tests for Nonstationarity of Three Stock Price Indexes

The logged levels and rates of change of the stock price indexes of the Tokyo, Shanghai, and Shenzhen Stock Exchanges are tested for nonstationarity by the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests. *AR* gives the order of lagged dependent variables in the ADF regression. The order increases if a serial correlation remains in the residual series at a 10% significance level. In this table, all the series need only one lagged dependent variable to eliminate serial correlation. The sample period and intraday data are defined in Table I.

Stock Price Index	Augmented Dickey-Fuller			Phillips-Perron	
	$T(\hat{\rho}-1)$	τ	*AR*	$Z_{\hat{\rho}}$	$Z_{\hat{\tau}}$
Logged Level					
Nikkei 225	-0.87	-0.4159	1	-0.89	-0.4245
Shanghai Composite	-2.46	-1.7724	1	-2.47	-1.7702
Shenzhen Composite	-2.1	-1.5592	1	-2.1	-1.5573
Rate of Change in Index (%)					
Nikkei 225	-12824.09	-80.0594	1	-16366.08	-119.0206
Shanghai Composite	-6364.98	-56.4053	1	-5626.75	-56.9562
Shenzhen Composite	-9351.2	-68.367	1	-4819.31	-51.2613

Table 3

Engle-Granger Tests of Cointegration for Tokyo-Shanghai and Tokyo-Shenzhen Systems

Regressions include a constant and a linear trend. For each of the three bivariate systems (including Shanghai-Shenzhen for reference), the regressor and the dependent variable are reversed to check for consistency. The *t*-statistic tests for a unit root in the residuals from the bivariate regressions. Critical values for the *t*-statistic are: -4.33 (1%), -3.78 (5%), and -3.50 (10%), based on MacKinnon (1991). For data description, see Table I.

Dependent Variable	Explanatory Variable	*t*-statistic
Tokyo	Shanghai	-1.9645
Shanghai	Tokyo	-2.3776
Tokyo	Shenzhen	-1.9011
Shenzhen	Tokyo	-1.4356
Shanghai	Shenzhen	-3.9238
Shenzhen	Shanghai	-3.4194

Table 4

Granger Causality Tests for Tokyo-Shanghai and Tokyo-Shenzhen Systems

Granger causality tests are conducted by testing the hypothesis that all ten coefficients of the lagged variables are zero. The test statistic is distributed as Chi-squared. The full period is from January 7, 2008, to January 23, 2009, and contains 16,920 observations. The first (pre-financial crisis) period is from January 7 to August 29, 2008, with 10,584 observations. The second (post-financial crisis) period is from September 1, 2008, to January 23, 2009, with 6336 observations. The period after November 3, 2008 (after the rapid fall of prices ceased) has 3672 observations. The *p*-value of the Chi-squared statistic testing for the explanatory power of Tokyo over Shanghai is 0.1987 for the first period, but 0.0656 in the second, indicating an increased influence of Tokyo after the global financial crises of September/October 2008 (shown in shaded cells).

From		To	Full Period		First Period		Second Period		Period after November 3, 2008	
			Chi Square	*p*-value	Chi Square	*p*-value	Chi Square	*p*-value	Chi Square	*p*-value
Tokyo	→	Tokyo	65.63	0.0000	52.16	0.0000	49.39	0.0000	22.42	0.0131
Shanghai	→	Tokyo	41.56	0.0000	67.63	0.0000	17.39	0.0661	18.96	0.0407
Tokyo	→	Shanghai	19.15	0.0385	13.47	0.1987	17.42	0.0656	9.52	0.4837
Shanghai	→	Shanghai	15,845.29	0.0000	13,198.37	0.0000	4106.34	0.0000	2714.20	0.0000
Tokyo	→	Tokyo	65.54	0.0000	52.54	0.0000	49.28	0.0000	22.81	0.0115
Shenzhen	→	Tokyo	44.59	0.0000	65.2	0.0000	16.07	0.0977	16.85	0.0778
Tokyo	→	Shenzhen	10.37	0.4088	12.32	0.2644	17.44	0.0651	7.35	0.6922
Shenzhen	→	Shenzhen	32,905.13	0.0000	21,469.37	0.0000	4407.5	0.0000	3126.59	0.0000
Shanghai	→	Shanghai	1929.82	0.0000	1672.48	0.0000	525.23	0.0000	306.68	0.0000
Shenzhen	→	Shanghai	1629.86	0.0000	1073.46	0.0000	605.88	0.0000	542.98	0.0000
Shanghai	→	Shenzhen	3826.25	0.0000	2753.01	0.0000	1353.62	0.0000	860.32	0.0000
Shenzhen	→	Shenzhen	4168.65	0.0000	2720.92	0.0000	1460.07	0.0000	1094.27	0.0000

Table 5

Variance Decomposition for Tokyo-Shanghai and Tokyo-Shenzhen Systems

Forecast error variance decomposition is computed for each system. Since the systems are bivariate, only cross results are displayed. The remainder is accounted for by the other variable. The forecast horizon is 30 periods (minutes). When the causal ordering is reversed, the result is almost unchanged, because the correlation between the two residuals is small. For definitions of the periods, see Table 4.

Forecast Error Variance of:	Accounted for by:	Full Period	First Period	Second Period	After November 3, 2008
Tokyo	Shanghai	0.361%	0.780%	0.366%	0.513%
Shanghai	Tokyo	0.231%	0.153%	0.507%	0.640%
Tokyo	Shenzhen	0.314%	0.758%	0.315%	0.482%
Shenzhen	Tokyo	0.192%	0.111%	0.486%	0.675%
For reference only					
Shanghai	Shenzhen	13.538%	13.465%	13.007%	17.411%
Shenzhen	Shanghai	69.152%	71.130%	67.390%	67.768%

Table 6

Results of Granger Causality Tests, if our Data Construction Rules are Disregarded

This table indicates the results of the Granger causality tests if the dataset is formed disregarding our rules of construction. Column (1) shows the results if rule (d) of subsection 2.3 is violated, i.e., lags on the right-hand side of a regression are based on the usual method of referring to values from previous periods. Column (2) shows the results if, in addition to rule (d), we disregard rule (b), i.e., opening prices of the Chinese markets are included in the dataset, while those of the Tokyo market are not.

From		To	Conventional VAR Estimation (1)		Chinese Data Including Opening Prices (2)	
			Chi Square	*p*-value	Chi Square	*p*-value
Tokyo	→	Tokyo	62.59	0.0000	59.32	0.0000
Shanghai	→	Tokyo	29.55	0.0010	24.12	0.0073
Tokyo	→	Shanghai	24.93	0.0055	20.75	0.0229
Shanghai	→	Shanghai	11,978.13	0.0000	266.03	0.0000
Tokyo	→	Tokyo	62.29	0.0000	59.06	0.0000
Shenzhen	→	Tokyo	33.00	0.0003	24.04	0.0075
Tokyo	→	Shenzhen	10.75	0.3775	19.53	0.0341
Shenzhen	→	Shenzhen	16,316.52	0.0000	559.32	0.0000

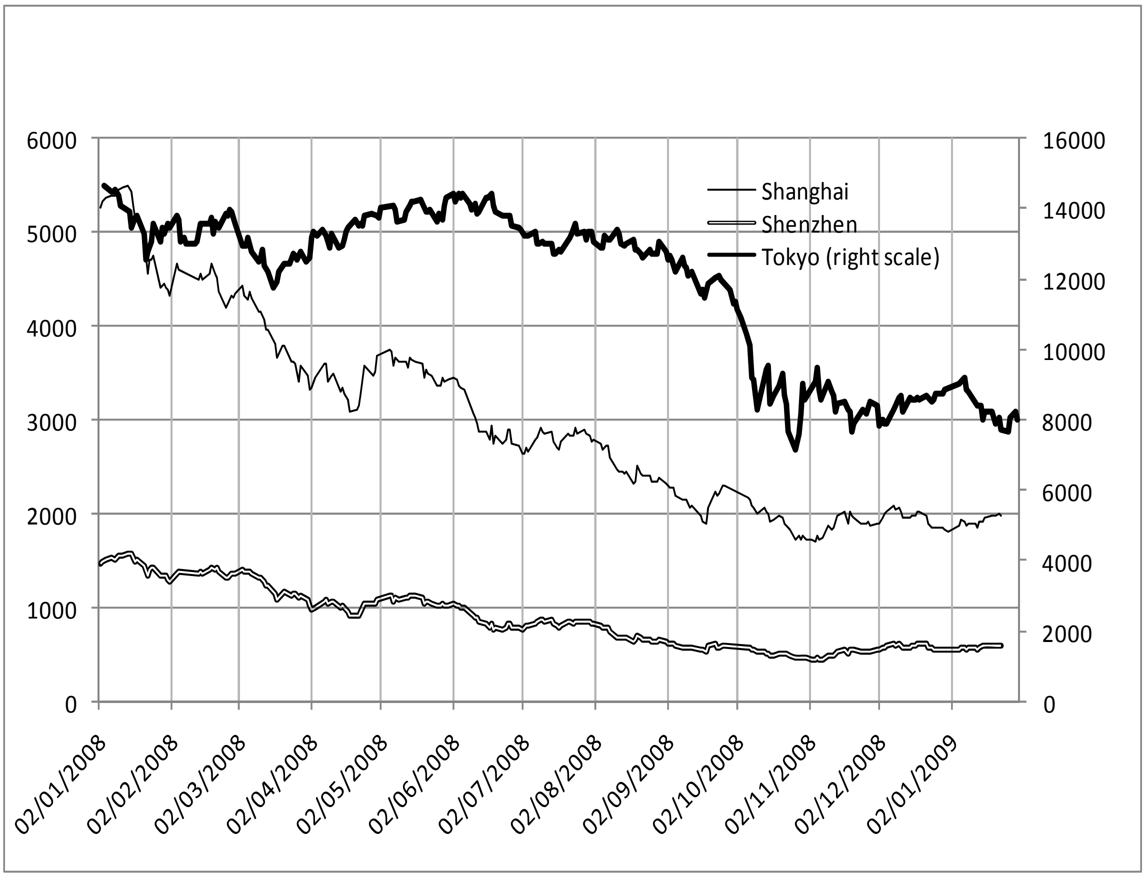

Figure 1. Daily closing stock prices on Tokyo, Shanghai, and Shenzhen markets. Shown by the Nikkei 225, Shanghai Composite, and Shenzhen Composite Indexes, respectively.

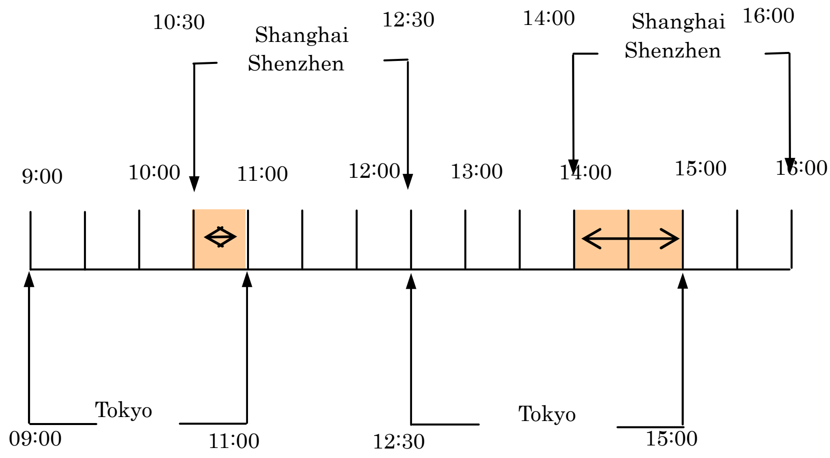

Figure 2. Trading hours of the Tokyo, Shanghai, and Shenzhen Stock Exchanges.

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

Fig. 3. ACFs of Tokyo, Shanghai, and Shenzhen

(minute-by-minute returns and 95% confidence bands)

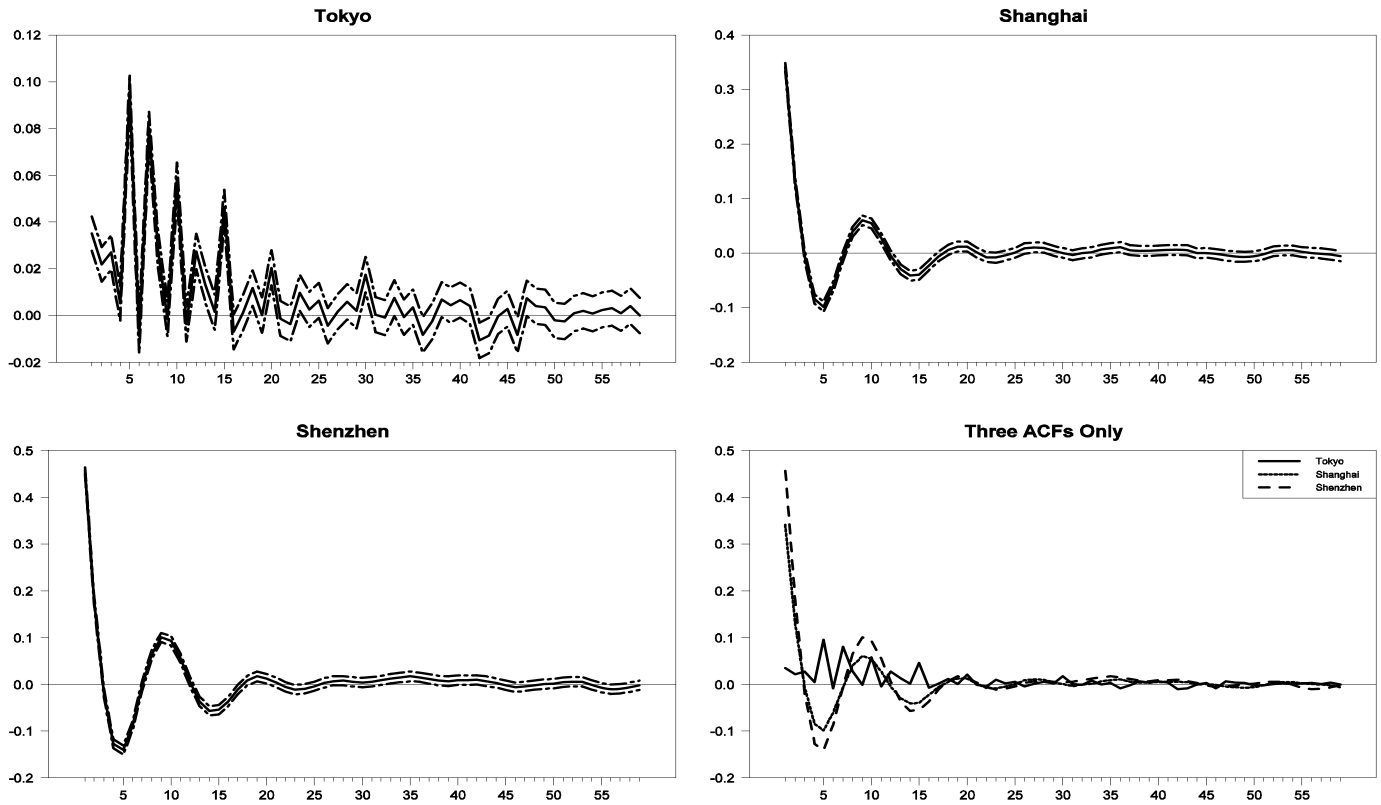

Figure 3. Autocorrelation functions of Tokyo, Shanghai, and Shenzhen. Minute by minute returns and 95% confidence levels shown. Horizontal axis measures time in minutes.

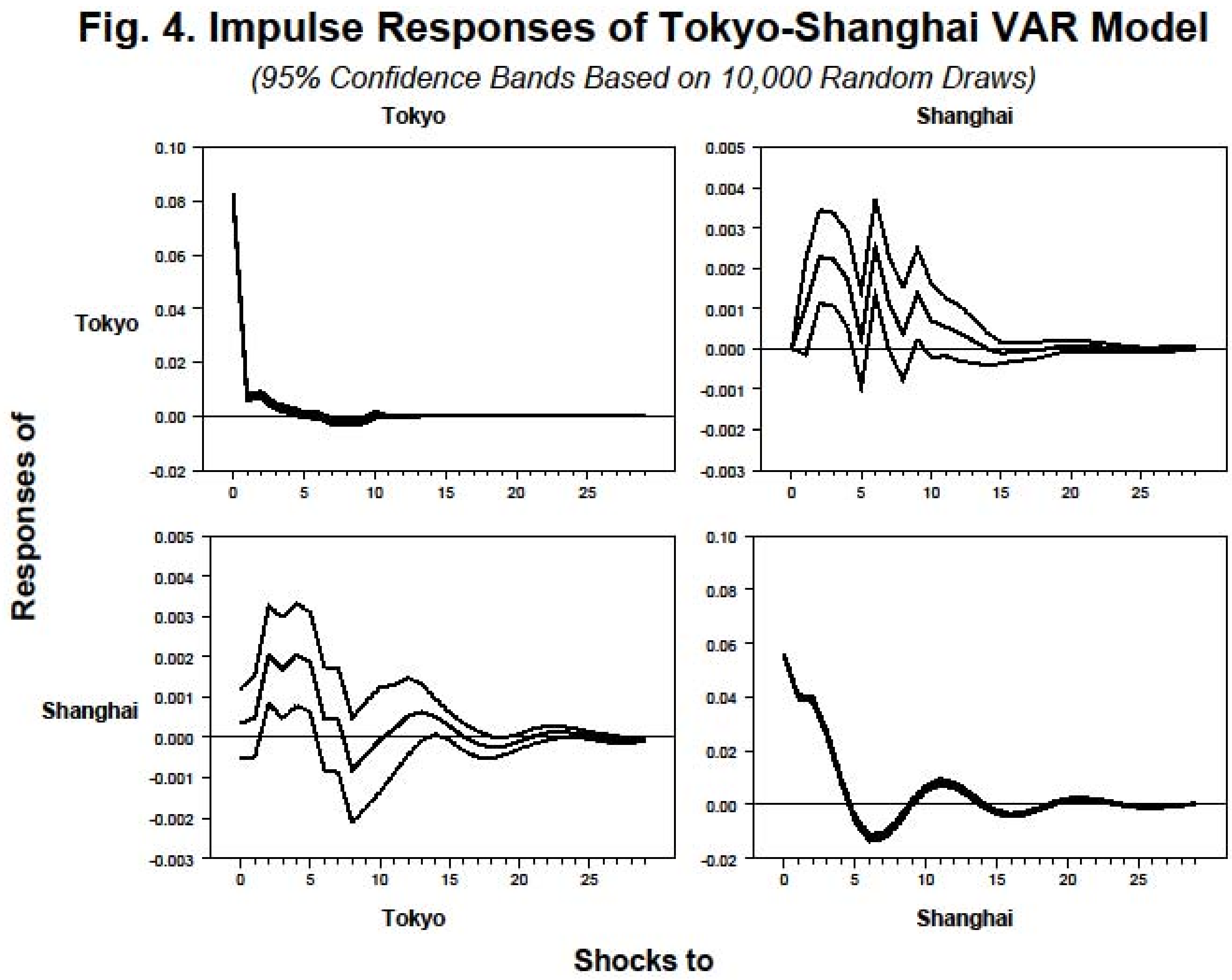

Figure 4. Impulse responses of Tokyo-Shanghai VAR model. 95% Confidence bands are based on 10,000 random draws. Horizontal axis measures time in minutes.

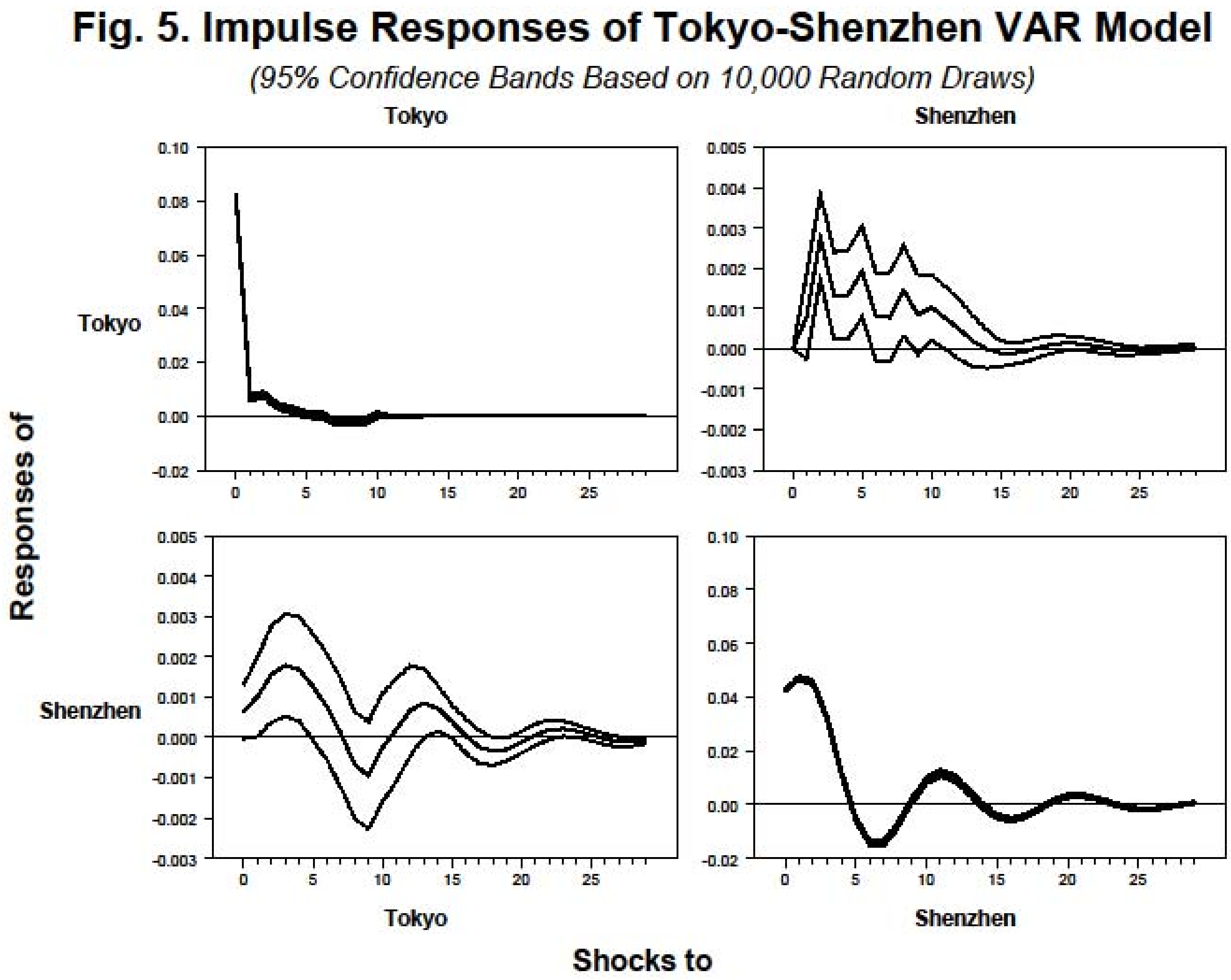

Figure 5. Impulse responses of Tokyo-Shenzhen VAR model. 95% Confidence bands are based on 10,000 random draws. Horizontal axis measures time in minutes.

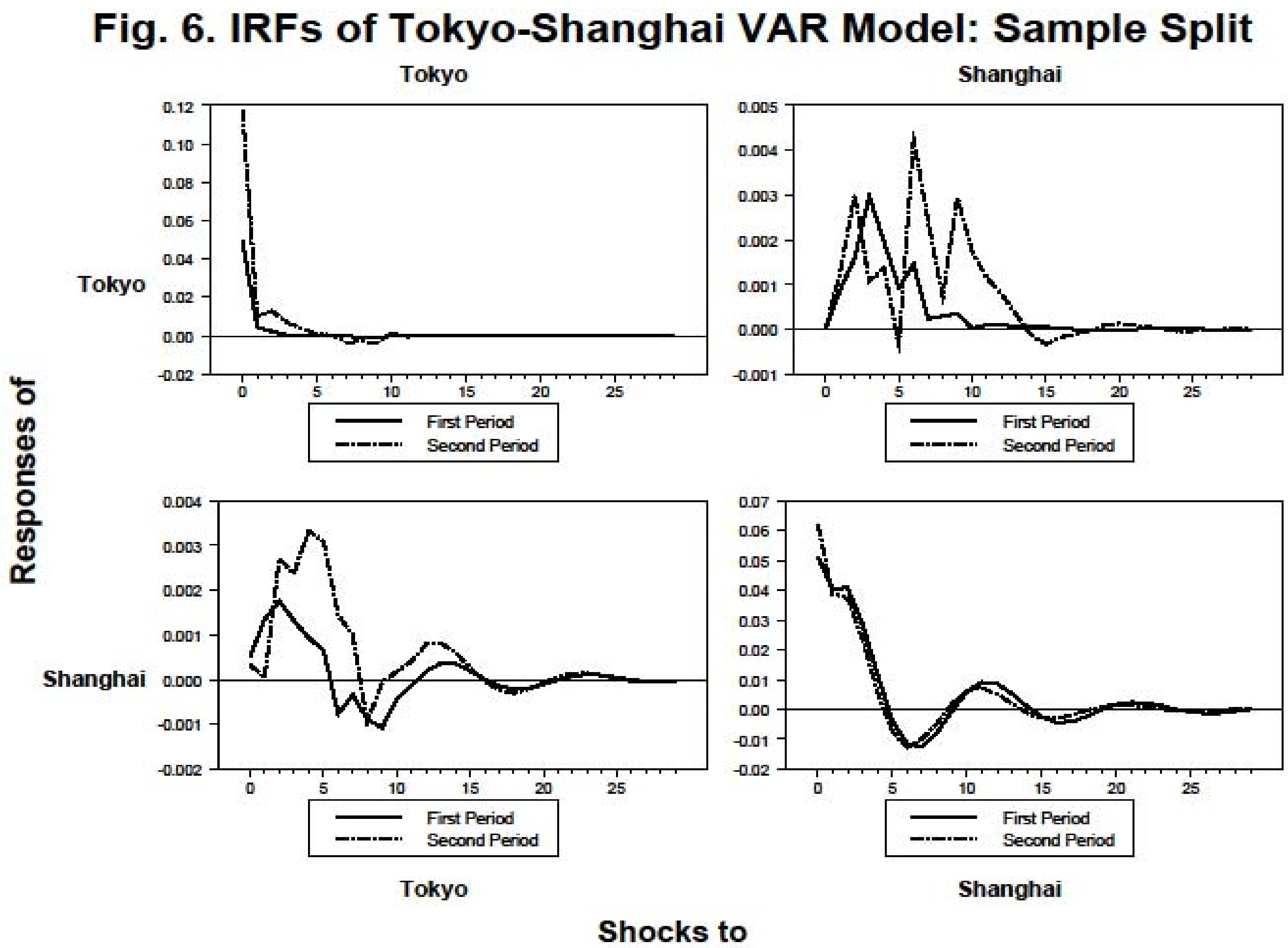

Figure 6. Impulse response functions in Tokyo-Shanghai VAR model: Split sample. Since the graphs are cluttered with so many lines, confidence bands are not depicted. Horizontal axis measures time in minutes. Note that the four graphs have different vertical scales.

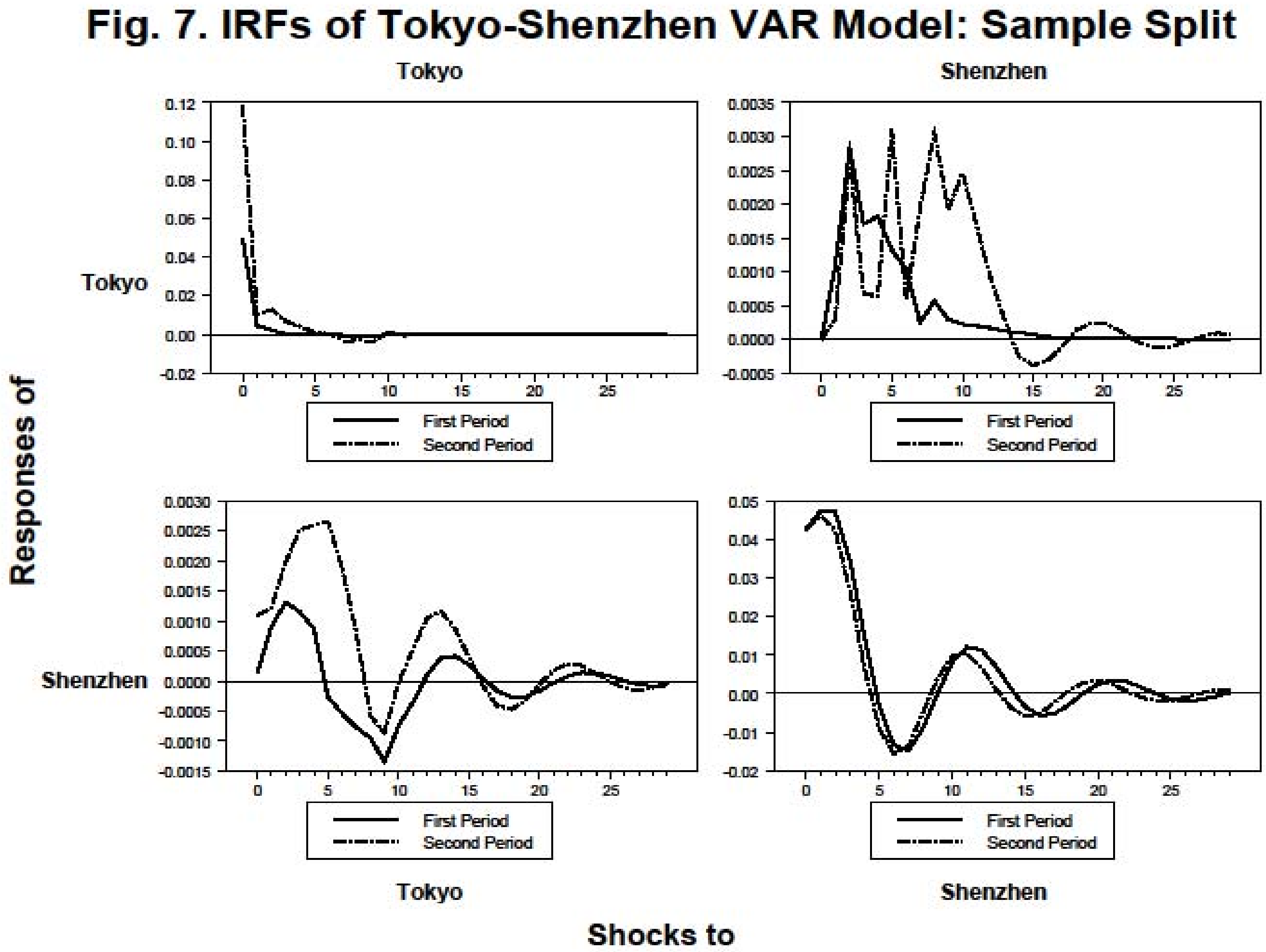

Figure 7. Impulse response functions in Tokyo-Shenzhen VAR model: Split sample. Since the graphs are cluttered with so many lines, confidence bands are not depicted. Horizontal axis measures time in minutes. Note that the four graphs have different vertical scales.

Fig. 8. ACFs of Three Stock Returns: Sample Split

First Period: 2008:01:07-2008:08:29, Second Period: 2008:09:01-2009:01:23

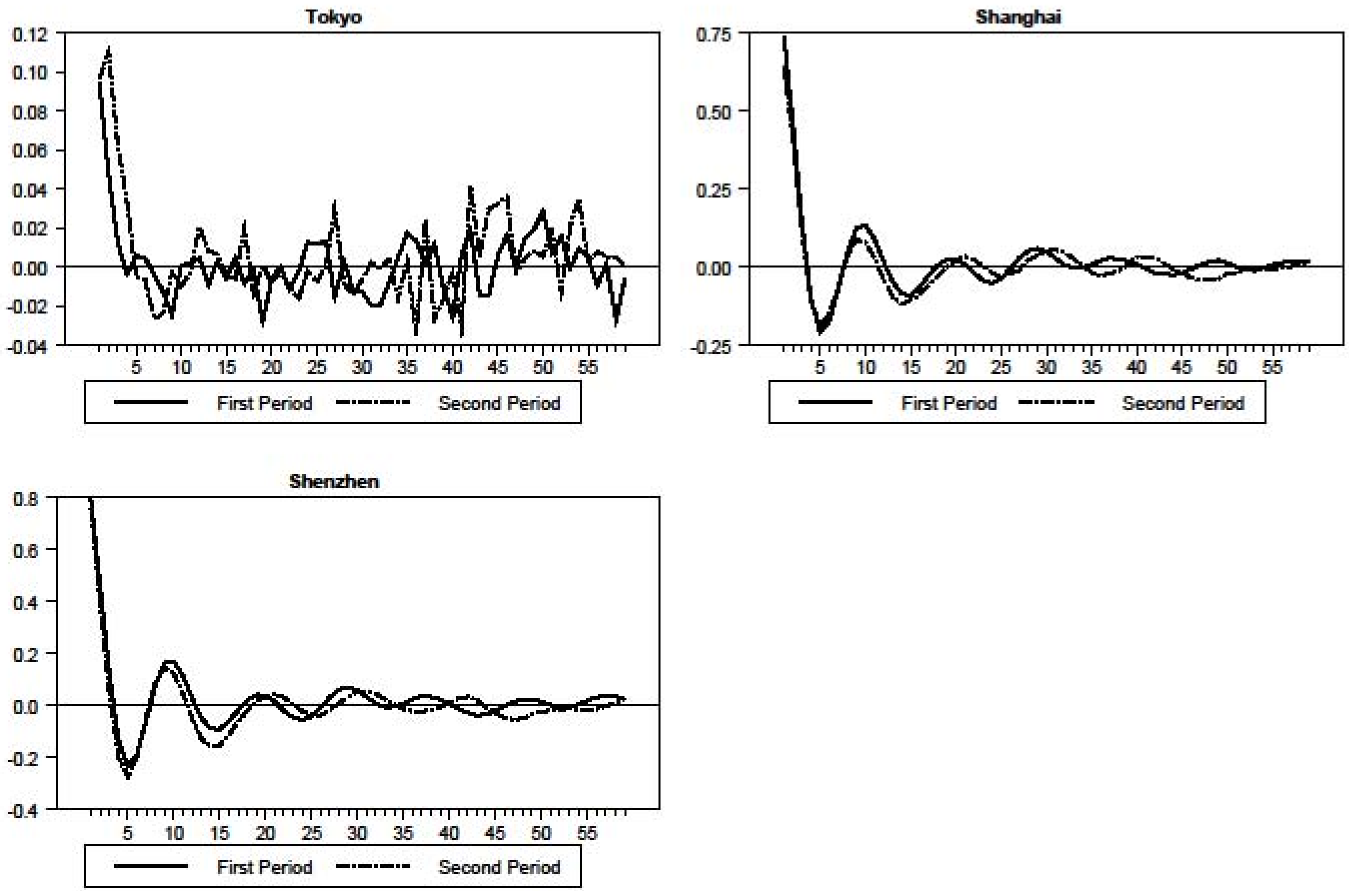

Figure 8. Autocorrelation functions of three stock returns: split sample. First period is from January 7 to August 29, 2008; the second period is from September 1, 2008, to January 23, 2009. Horizontal axis measures time in minutes.