

Are Chinese Stock Investors Watching Tokyo? International Linkage of Stock Prices Using Intraday High-Frequency Data

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ABSTRACT

Intraday minute-by-minute data of Tokyo and Shanghai 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 each day during which the two 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.

Keywords: International linkage of stock prices, High frequency data, Inefficiency, Overreaction, China

JEL Classification: G14; G15; F36

1. Introduction

The growth of Chinese stock market has been phenomenal. In about two decades since its establishment in 1990, the market capitalization of the Shanghai Stock Exchange at the end of 2011 was roughly 3.34 trillion dollars, which trails Tokyo's 3.54 trillion dollars by a narrow margin, and Tokyo is second only to New York (15.64 trillion dollars).¹ China's stock market, as well as her economy, now exerts 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 market. This inefficiency, if any, 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 the Chinese stock market has not yet been examined in detail. In this paper, we attempt to shed light on this issue.

Our approach to this task is to focus on intraday interactions between the two countries' stock prices during overlapping trading hours. There is a substantial body of 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)).² This finding suggests that the Chinese stock market is isolated from others and that its efficiency may still be in a fledgling stage. We find the lack of response of Chinese stock prices to other markets interesting and worth exploring.

However, the existing studies that analyze stock price linkages between Japan and China utilize daily data, which has a following disadvantage. The stock markets of Tokyo and Shanghai both close at 3 pm local time, but due to a one-hour time difference, Shanghai actually closes one hour later than Tokyo. If one uses daily closing prices to investigate the stock price linkage between the two markets, one is faced with an asymmetry in detecting mutual influence. Since Shanghai closes just one hour after Tokyo, the effect of Tokyo on Shanghai is easily examined by comparing the two closing prices. But, the effect of Shanghai on Tokyo is observed with a 23-hour lag. In the meantime, we obtain new daily closing prices of other major markets in Europe and North America, which will affect the subsequent closing price in Tokyo. Namely, closing price in Tokyo is contaminated by new information from European and American

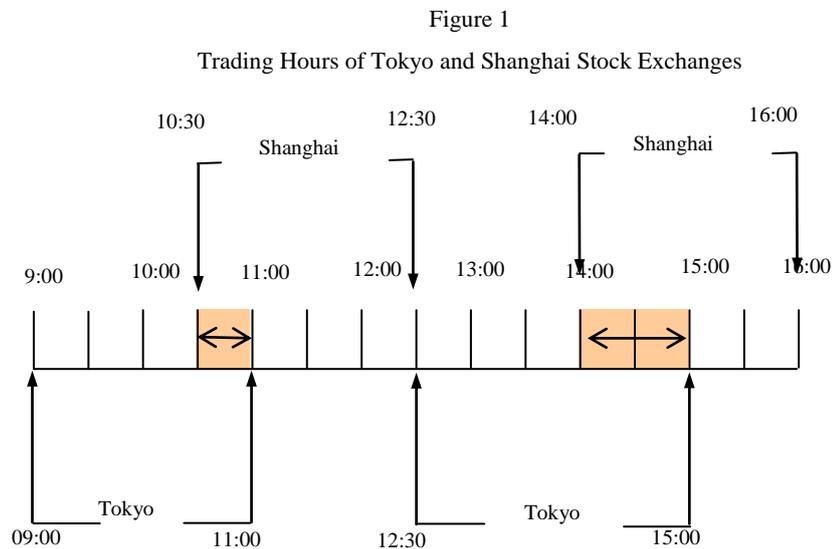
markets. It is not simple to extract the effect of China on Japan using daily data. Thus, the use of daily data is characterized by a strong asymmetry in detecting influence from Japan to China more clearly than the other way around.

Therefore, since the Japanese and Chinese stock exchanges are open at the same time, albeit for limited time periods each day, it is appropriate to use such real-time high-frequency data to explore stock price linkages between the two markets. As we will see in more detail later, the two markets are open simultaneously between 10:30 and 11:00 and between 14:00 and 15:00 JST each day. Since Japan is eight hours ahead of Europe and 14 hours ahead of the U.S., no markets in Europe and North America are open during these time periods. Thus, there is no influence from these markets on mutual interactions between Japan and China. Analyzing simultaneous high-frequency data of these two markets is ideal in exclusively focusing on their mutual interactions.

Despite this advantage of high-frequency data, there have been few studies utilizing such data to analyze simultaneous stock price linkages. To the best of our knowledge, there are only two papers that analyze intraday stock price indexes for several stock exchanges observed simultaneously (Černý and Koblas (2008) and Égert and Kočenda (2007)). Both analyze European markets, but neither pays sufficient attention to the following problems inherent in using high-frequency data. In the first place, we have to carefully select lagged values in estimating a vector autoregression (VAR) system. We usually select a time window each day in which all markets are open simultaneously. Observations on a certain stock price (or index) are chosen from these time windows and are joined consecutively to form one long time series. When a VAR is estimated with such a data series, each regression equation has many lagged values on the right-hand side. But, this estimation has a couple of problems as follows.

The trading hours of Tokyo and Shanghai are shown in Fig. 1. As is apparent from this figure, the overlapping trading hours between the two exchanges are from 10:30 to 11:00 and from 14:00 to 15:00 each day. Since we work with minute-by-minute returns, the actual time window is between 10:31 and 11:00 (30 observations) and between 14:01 and 15:00 (60 observations). A researcher would typically pick values from these time windows and join them to form one long time series data. When a VAR model is estimated, lagged values are extensively used on the right-hand side. Since each variable is observations during two time windows, i.e. between 10:31 and 11:00 and between 14:01 and 15:00, lagged values are falsely chosen from these windows in conventional VAR models. Then, the equation to explain a return at 10:31 in Tokyo has lagged values which are from the previous day. However, in the case of Tokyo returns, the true lags at 10:30, 10:29, 10:28, etc. are available. The first problem with our dataset generation

is that wrong values are specified as lagged variables if the conventional VAR method is used. Thus, we will propose in this paper a new approach to using true lagged values in VAR estimation.



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

The second problem with VAR estimation is related to volatility at market opening. Since the Shanghai market opens later than Tokyo, each of our daily time windows inevitably starts with the opening of the morning (and afternoon) session in Shanghai. Opening prices are, however, known to be especially volatile because they have to respond to information flows accumulated over long non-trading hours. When Shanghai opens in the morning, its stock market has to digest news accumulated during overnight non-trading hours since previous day's close. While these opening prices of Shanghai are included in the dataset, those of Tokyo are not included because they are not part of the common time window. The asymmetry that the dataset includes opening prices of Shanghai but not those of Tokyo is likely to produce biased estimation results. To remove this asymmetry, it is desirable to exclude opening prices of Shanghai as well.

Exclusion of several observations at the beginning of each time window leads us to devise a novel method to use those excluded observations as lagged values in regressions. Suppose, as we will do later, we delete the first 10 observations from each window. The dependent variables are from two truncated time windows: 10:41-11:00 and 14:11-15:00. Suppose further that the lag order of the VAR model is 10. Then, in the equation to explain the return at 10:41, 10 lagged values are recovered from those deleted observations between 10:31 and 10:40. Though

the first 10 observations of each time window is excluded from the dependent variable, they are used as lagged, explanatory variables on the right-hand side of regressions. In the next equation to explain the return at 10:42, observations from 10:32 to 10:41 are used as lagged variables on the right-hand side, etc., etc.

In summary, we note there are two problems with using observations from common trading hours (time windows). Firstly, the lagged variables for Tokyo in a VAR equation do not use true lags, because they have been discarded in the process of creating the dataset. Secondly, the volatile opening prices of Shanghai are not suitable to analyze effects of Tokyo on Shanghai due to influence of information flows accumulated during the non-trading hours. To cope with these two problems, we propose to delete the first ten observations from each time window. But, the deleted observations are used as lagged variables on the right-hand side of regressions, because they are actually the true lagged values. This method solves the above two problems at the same time. It catches two birds with one stone.

Another feature of this paper is the fact that our sample period includes the incidence of the collapse of the Lehman Brothers in September 2008. It is well known that the global stock price linkage intensified after the Black Monday of 1987 (Tsutsui and Hirayama (2009), pp. 170-171). Similarly, the Chinese stock market may have undergone 'globalization' after the meltdown of 2008 and consequently their stock prices are routinely and significantly swayed by global stock market movements. Investigation of this possibility is one of the purposes of this study.

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 the Chinese market 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 Tokyo and Shanghai stock exchanges, we check for cointegration between the two indexes. Since we employ a bivariate system, the number of cointegrating relationships is one, at most, and thus there is no need for system estimation by Johansen tests. We apply Engle-Granger two-step estimation to check for cointegration.³ If cointegration exists, the VAR model should be modified to a vector error correction (VEC) model. As shown later, our results

indicate no evidence of cointegration between the two indexes. Consequently, we can make our estimations by conventional VAR models only, without an error correction term.

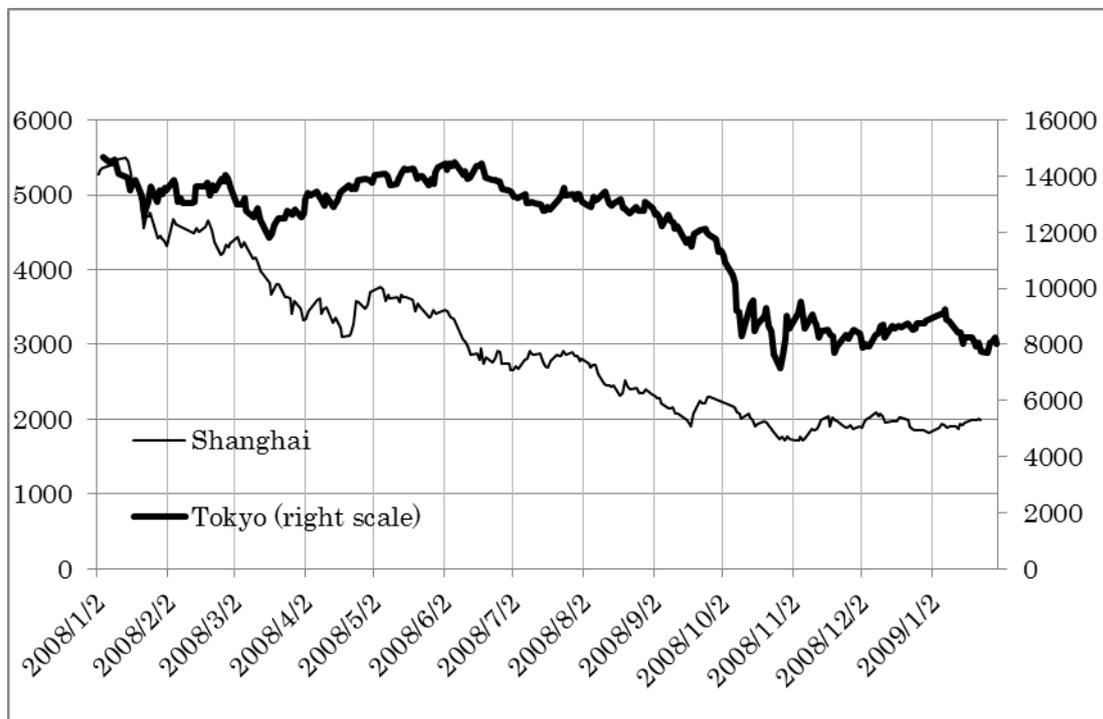
While long-run relationships are examined by cointegration tests, short-run dynamic interactions are analyzed by Granger causality tests, variance decompositions computations, and impulse response functions (IRF), which are standard tools for short-run dynamic analysis.

2.2. Data

We analyze return spillover effects between the Japanese and Chinese markets by focusing on pair-wise relations between Tokyo and Shanghai, using the Nikkei 225 Index and Shanghai Composite Index. Minute-by-minute observations of these two 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 Section I of the Tokyo Stock Exchange. Although the Shanghai Stock Exchange trade A shares for domestic investors (traded in local currency) and B shares for foreign investors (traded in US dollars), only the composite index of all shares was available to us.

Fig. 2

Daily Closing Stock Prices of Tokyo and Shanghai Markets



Note: The stock price index of Tokyo is the Nikkei 225 and that of Shanghai is the Shanghai Composite Index.

Daily closing prices for our sample period are plotted in Figure 2, showing downward trends in the Chinese market 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.

Trading hours for the two stock exchanges are given in Figure 1. 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 the Chinese market, pre-market call auctions between 09:15 and 09:25 (Chinese Standard Time, CST) determine the opening prices for the day at 9:25 CST. Continuous auction takes place between 09:30 and 11:30 for the morning session and between 13:00 and 15:00 for the afternoon session. Since there is a one-hour time difference between Japan and China, the only time windows during which the two 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

We carefully selected data to be used in our VAR model which utilizes many lags. In summary, the rules we use are characterized by the following four points: (a) we use minute-by-minute stock price returns when the stock exchanges are simultaneously open, i.e., 10:31 to 11:00 and 14:01 to 15:00 (JST); (b) we drop the first ten observations in each window. This deletes the opening prices in the Chinese market (both morning and afternoon sessions), resulting in slightly truncated windows, 10:41 to 11:00 and 14:11 to 15:00, each day. This rule has a merit that the prices at the opening (determined by a pre-market call auction by 9:25 CST) and immediately after the opening are excluded from the analysis. Otherwise, our calculations would include opening prices in China but not in Japan. Since stock prices at the opening of a stock market reflect information accumulated during night-time non-trading hours and are more volatile than prices during normal trading hours, it is appropriate to exclude opening prices of both markets to make a fair comparison.; (c) time series data is constructed by sequentially combining data from these windows over the estimation period; and (d) the basic dataset constructed under rules (a) through (c) above is further modified. In the traditional VAR estimation, the equation to explain a stock return at 10:41 has a one-period lag which is the last observation of the previous day at 15:00 and has a two-period lag observed at 14:59 on the previous day. However, true lags at 10:40, 10:39, 10:38, etc. are available in the deleted set of observations. Therefore, we re-use these values as lagged values in the regressions. Although

we delete first 10 observations from each time window, these values are used as true lagged values on the right-hand side of VAR equations.

Basic statistics on the levels and rates of change for the two indexes are provided in Table 1.

Table 1
Stock Price Indexes of Tokyo and Shanghai

	Variable	Mean	St. Dev.	Maximum	Minimum	Skewness	Excess Kurtosis	JB	<i>p</i> -value
Logged Level	Tokyo	9.36388	0.21067	9.59177	8.8591	-0.84368	-1.0067	2721.75	0.0000
	Shanghai	7.9303	0.32603	8.61251	7.42791	0.3168	-1.08355	1110.74	0.0000
Minute-by-Minute Rate of Change	Tokyo	0.00074	0.08298	1.07348	-1.54325	-0.55788	22.52593	358607.17	0.0000
	Shanghai	0.00111	0.08803	0.49049	-0.47809	0.0726	1.53379	1673.37	0.0000

Note: The stock price indexes used for Tokyo and Shanghai are the Nikkei 225 and Shanghai Composite Index, which are observed at a minute-by-minute frequency. The sample period is from 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.

The data are obtained for 20 minutes in the morning and 50 minutes in the afternoon window. For minute-by-minute rates of change, Tokyo's mean is smaller than that of Shanghai, but the standard deviations are about the same in the two markets. However, the maximum and minimum in Tokyo are two to three times larger (in absolute value) than those of Shanghai. The excess kurtosis of Tokyo returns is over 22.5 whereas it is only 1.5 in Shanghai, 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 not shown to save space).⁴ 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 the two stock price levels are $I(1)$, we next test for cointegration of logged stock prices in a bivariate system (results are not displayed to save space). 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 Tokyo-Shanghai bivariate system. Thus, we can safely proceed to estimating a conventional VAR model without error correction terms.

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 two stock indexes. The bivariate VAR system is 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.⁵

After estimating VAR(10) for the Tokyo-Shanghai bivariate system, 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 2. 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.

Table 2
Granger Causality Tests for Tokyo-Shanghai System

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	52.16	0	49.39	0	22.42	0.0131
Shanghai	→	Tokyo	41.56	0	67.63	0	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	13,198.37	0	4106.34	0	2714.2	0

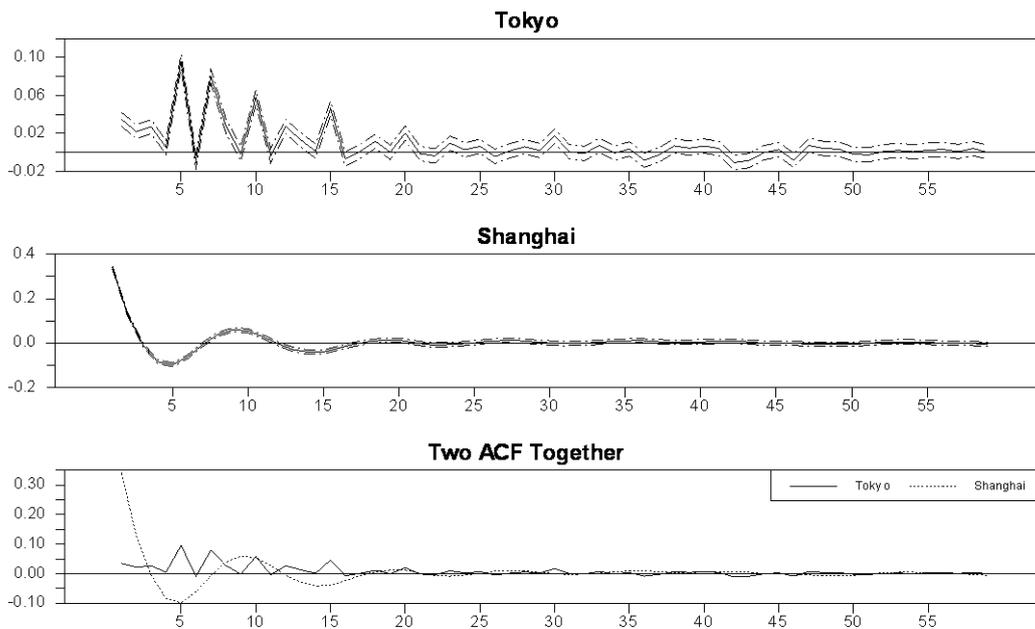
Note: Granger causality tests are conducted by testing the hypothesis that all ten coefficients of the lagged variables are zero. The test statistic is distributed as Chi-squared. The full period is from January 7, 2008, to January 23, 2009, and contains 16,920 observations. The first (pre-financial 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).

While Tokyo responds to Shanghai in the sense of Granger causality, Shanghai's response to Tokyo is weak. This result is 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 the Chinese market is an extremely large test statistic for its own lags. Table 2 shows that while Tokyo's lags in the equation to explain Tokyo produce a Chi-squared test statistic of 66, those of Shanghai are 15,845. This apparently results from very strong serial correlation in Chinese stock returns, and may be a sign of relative inefficiency in the Chinese stock market.⁶ 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 than in Tokyo, suggesting informational inefficiency in the Chinese market.

Figure 3
Autocorrelation functions of Tokyo and Shanghai



Note: Minute-by-minute returns and 95% confidence levels shown. Horizontal axis measures time in minutes.

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 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 of the Chinese market.

We tested whether one can make unusually large profits by exploiting this inefficiency. We estimated an AR(10) model for the minute-by-minute returns on the Shanghai Composite Index and then generated dynamic forecasts for the next 10 minutes.⁷ We utilized rolling-sample regressions, namely the initial regression used the first half of the sample (sample size was 30618) for estimation and dynamically forecast (i.e., out of sample) subsequent 10 minutes. We then added the next observation to increase the sample size by one and repeated the process of estimation and out-of-sample forecasting. Since this was repeated 30608 times, we obtained 30608 series of 10 forecast returns. Over each 10-min forecast horizon, we computed cumulative returns and tabulated the distribution of these returns. We then chose 1 percentile and 99 percentile values. Positive and negative returns exhibited maximum absolute values over the three-min horizon: 0.177% in the case of increasing stock prices and -0.181% in the case of declining prices.

To evaluate whether this represents a profitable trading strategy we need information on the transactions cost. In the case of Nikkei 225, Kohsaka (2010) carefully examines the buy/sell transactions cost in the Tokyo Stock Exchange and reports that it is around 0.002%. Therefore this cost is negligibly small. But, this constitutes only a part of the total transactions cost. We must also take into account a bid-ask spread and a possible market impact (effect on prices when a sizable order is placed). According to Kohsaka, the market impact is also negligible, unless the buy/sell order is substantially large. Kohsaka estimates the bid-ask spread to be between 0.1% and 0.2%. We conjecture that the costs in Shanghai are comparatively close to those in Tokyo, such that the estimated returns of around 0.18% would be barely sufficient to cover the transactions cost and thus we will not be able to make any excess profit. After all, the observed inefficiency in the Shanghai Stock Exchange does not seem to provide an exploitable profit opportunity.

3.5. Variance Decompositions

A VAR model can be converted into a vector moving average representation (VMA) and the forecast error variance decomposed into factors explained by each disturbance. In Table 3, 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. 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 market is even smaller. 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 between Japan and China in this paper.

Table 3
Variance Decomposition for Tokyo-Shanghai System

Forecast Error		After			
Variance of:	Accounted for by:	Full Period	First Period	Second Period	November 3, 2008
Tokyo	Shanghai	0.361%	0.780%	0.366%	0.513%
Shanghai	Tokyo	0.231%	0.153%	0.507%	0.640%

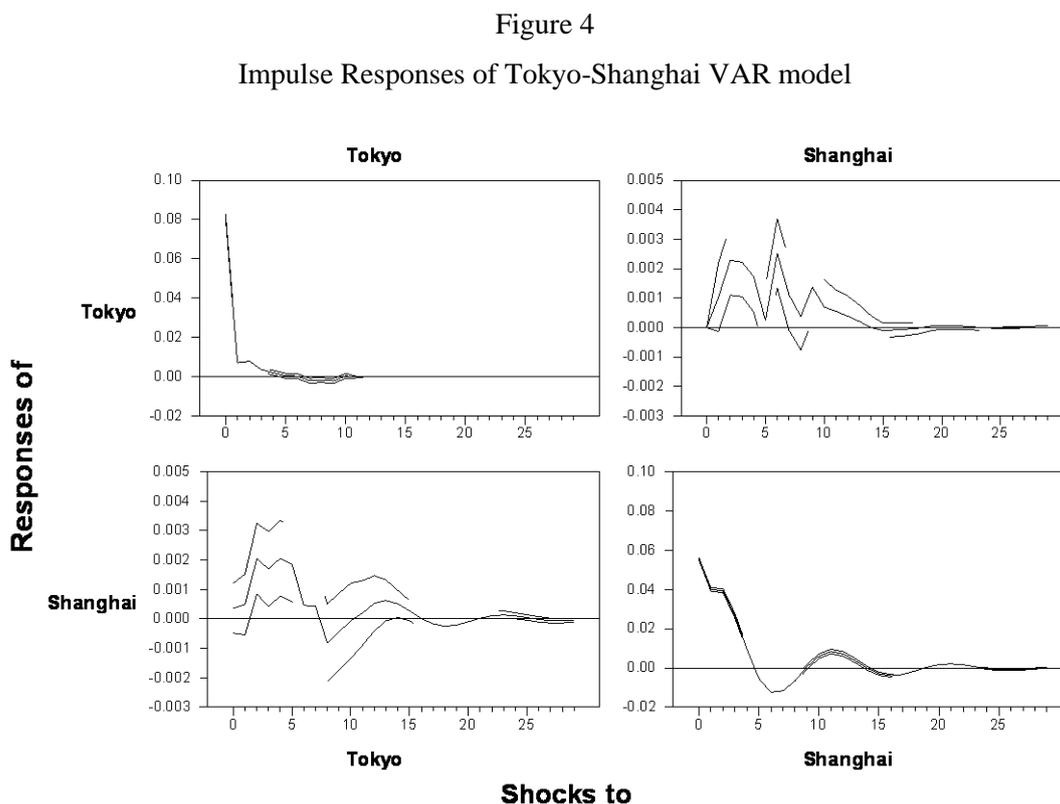
Note: Forecast error variance decomposition is computed for the Tokyo-Shanghai bivariate VAR system. Since the system is bivariate, only cross results are displayed. The remainder is accounted for by the other variable. The forecast horizon is 30 periods (minutes). When the causal ordering is reversed, the result is almost unchanged, because the correlation between the two residuals is very small. For definitions of the periods, see Table 2.

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.



Note: 95% Confidence bands are based on 10,000 random draws. Horizontal axis measures time in minutes.

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.

4. Was the Chinese Stock Market 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 the Chinese stock market is 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 2. Focusing on cross effects, we immediately notice that the Chinese market seems to have paid more attention to developments in Tokyo in the second, turbulent, post crisis period of 2008.⁸ Namely, the p -value of the Chi-squared statistic testing the explanatory 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). According to the causality results in the second period, the relative independence of the Chinese stock price seems to have weakened.

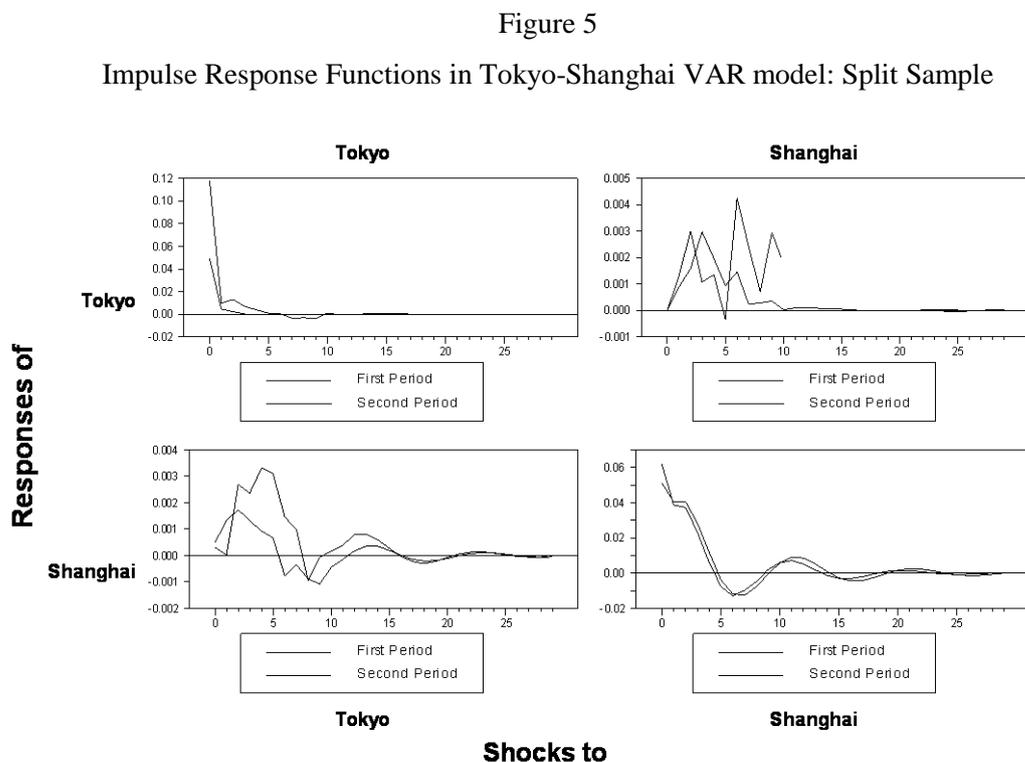
4.3. Variance Decompositions: Sensitivity of Chinese Market Became Stronger

Next, we re-estimate the forecast error variance decompositions for the two subperiods. Results are shown in Table 3. In agreement with the above, the explanatory power of Tokyo over Shanghai increased three to four times in the second period.⁹ Tokyo's share is even greater than that of Shanghai in accounting for Tokyo's error variance in the second period. Again, this is evidence of increasing sensitivity of the Chinese market to Japan.

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

The IRF for the Tokyo-Shanghai system are estimated for the two subperiods and shown in Figure 5. 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 response 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. Consistent with the findings of the Granger causality and

variance decompositions tests, the IRF also indicates a more significant response of the Chinese market to Tokyo in the second period.



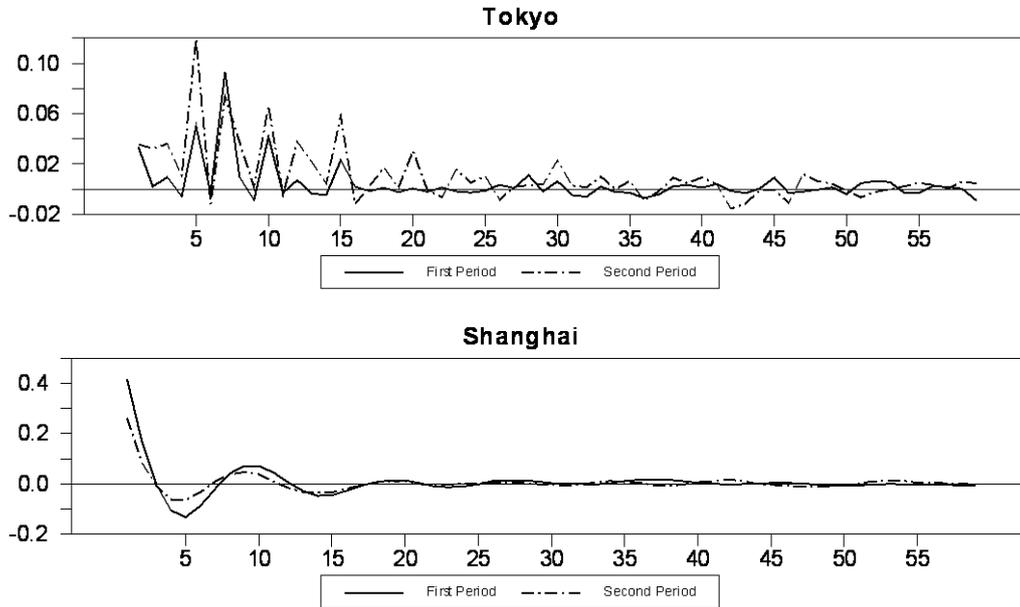
Note: Since the graphs are cluttered with so many lines, confidence bands are not depicted. Horizontal axis measures time in minutes. Note that the four graphs have different vertical scales.

4.5. Nonetheless, Chinese Market Has Not Been Transformed

The question remains, did the Chinese stock market 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 the Chinese market is permanent or temporary, we re-compute the above tests using data from November 3, 2008, onwards, i.e., after the rapid fall stopped. Results appear in Tables 2 and 3. The Granger causality tests reveal that Shanghai is 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 (Table 3) for the period after November 3, 2008, indicates otherwise; the proportions of forecast error variance explained by Tokyo remain rather high. 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 market remains isolated.

Figure 6
Autocorrelation Functions of Two Stock Returns: Split Sample



Note: 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

Since serial correlation at least partially reflects market inefficiency, we compare the magnitude and pattern of ACF before and after the financial crisis. Results are shown in Figure 6. 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 Shanghai markets 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 two stock exchanges and apply rules (a) through (d) in section 2.3 to select data for analysis. Let us see what happens if we do not follow these rules. 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 conventional 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 4 (column 1). The Chi-squared statistics are generally smaller than in Table 2. Thus, using incorrect lag variables generally reduces statistical significance, as we conjectured.

Table 4
Results of Granger Causality Tests, If Our Data Construction Rules are Disregarded

From	To	Conventional VAR Estimation		Chinese Data Including	
		(1)		Opening Prices	
		Chi Square	<i>p</i> -value	Chi Square	<i>p</i> -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

Note: 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.

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 4 (column 2). Compared with Table 2, the significance of Tokyo on Shanghai increases, confirming our prediction that the inclusion of opening prices distorts causality results.

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 Cause of Why the Shanghai Market Does Not Respond to the Tokyo Market

A main result of our analysis is that while the Shanghai market seems to affect the Tokyo market, the effect of Japan's market on China seems to be much weaker. 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.¹⁰ 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 1 reveals that this is not the case. Indeed, the maximum and minimum Tokyo returns (rates of change) are roughly twice those of Shanghai, though the standard deviations are similar in the two markets. Therefore, if we extract Tokyo's minute-by-minute returns that fall within Shanghai's maximum/minimum range, they should have less significant impact on China. This would reinforce our results in Section 3 that the Shanghai market 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 that both large and small changes in Tokyo impact Shanghai at 5% but not 1% significance. These results are basically the same as in Table 4.¹¹

Asymmetric causality between Tokyo and Shanghai can be attributed to different investor behavior. 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

Most studies of international stock price linkage has utilized daily data. However, as in the case of Japan and China which are located geographically close to each other and which share common trading hours, it is natural to use high-frequency data to examine mutual market interactions. In this paper we analyze intraday minute-by-minute data of the Tokyo and

Shanghai stock exchanges to investigate mutual interaction between Japanese and Chinese stock markets. Specifically, we focused on a 20-minute window (10:41-11:00 JST) in the morning and a 50-minute window (14:11-15:00 JST) in the afternoon during which the two stock exchanges are simultaneously trading shares. Our basic tool of empirical analysis was estimation of a Tokyo-Shanghai bivariate VAR model. 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.¹² 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 market 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 overreactions. 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 2008. 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 the Chinese market was subject to influences from Japan only during September/October 2008, and that it is still basically isolated from foreign countries.

NOTES

1. Data source is: <http://data.worldbank.org/indicator/CM.MKT.LCAP.CD>.
2. 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.
3. A practical reason for adopting this test is that econometric packages cannot handle our particular method of selecting lags.

4. A constant term is included in the regression, but a linear time trend is not.
5. 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 do not exhibit local minima between 1 and 20 lags. Stock prices of Shanghai 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 minutes long.
6. We should be careful, however, that autocorrelation arises from various reasons such as bid-ask bounces and non-synchronized trading, which may not reflect efficiency.
7. An ARIMA model typically performs better than simple models as shown by Brand and Bessler (1983), but estimating a nonlinear model over 30,000 times unfortunately turned out to be too time-consuming. Thus a simple linear model was chosen in our study.
8. While Shanghai significantly Granger causes Tokyo in the first period, its significance declined substantially and Shanghai is barely statistically significant at a 10% confidence level in the second period. During the second period, variability was wider in Tokyo (see Figure 2), which probably underweighted the influence from China.
9. The explanatory power of Shanghai over Tokyo weakened in the second period.
10. 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.
11. 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.
12. This result was obtained in a model that focuses only on Japan and China. If other important Asian markets such as Singapore and Korea are included in the analysis, the relative isolation of China may not hold. Bessler and Yang (2003) conduct an interesting analysis of causal relationships among multiple countries. Applying their novel methodology (Directed Acyclic Graphs) to a group of Asian countries may be an important next step.

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