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Abstract

This paper uses one-minute returns on the TOPIX and S&P500 to examine the efficiency of the Tokyo and New York Stock Exchanges. Our major finding is that Tokyo completes reactions to New York within six minutes, but New York reacts within fourteen minutes. Dividing the sample period into three subperiods, we found that the response time has shortened and the magnitude of reaction has become larger over the period in both markets. The magnitude of response in New York to a fall in Tokyo is roughly double that of a rise.

JEL Classification Numbers: G14, G15, F36
Keywords: international linkage, stock prices, market efficiency, high frequency data

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1. Introduction

Stock prices of major economies are well known to be interdependent, and there is an extensive literature on international stock price linkage (Eun and Shim 1989, Jeon and von Furstenberg 1990, Mathur and Subrahmanyam,1990, Jeon and Chiang 1991, Chan *et al*. 1992, Kasa 1992, Corhay *et al*. 1993, Blackman *et al*. 1994, Chung and Liu 1994, Choudhry 1994, 1997, and Hirayama and Tsutsui, 1998a, 1998b), including a few research papers which investigate the possible causes of the linkage (Tsutsui 2002, Tsutsui and Hirayama 2004b, 2005). One of the findings in this literature is that a country's stock prices tend to advance when a neighboring market, closing just before that of the country's market, has advanced (Tsutsui and Hirayama 2004a).

Therefore, one can predict the course of the stock price index of the Tokyo stock market, such as the TOPIX or the Nikkei 225, by observing whether the stock price indices of the New York stock market, such as the S&P500 and the New York Dow Jones Industrial Average (henceforth known as NYDJ), have advanced or declined. This predictability might seem to contradict the market efficiency hypothesis, but such is not the case. When the New York Stock Exchange (NYSE) is open for trading, the Tokyo Stock Exchange (TSE) is closed due to time differences. Consequently, one must wait for the opening of the TSE to execute transactions based on the new information from New York. If the Tokyo stock market is efficient, the TOPIX reacts fully to the information of the S&P500 on the previous day at the opening but is not influenced thereafter.

Using daily opening and closing values, Tsutsui (2002) found that the Nikkei 225 reacts to a large change (over 1.5%) of NYDJ by the closing time of the next day, and the Nikkei 225 does not show a significant change beyond the following day. Thus, the Tokyo stock market is efficient over the daily time span.

Although the studies above use daily observations at best, there is a body of literature that utilizes observations of high frequency.[1] The markets for foreign exchange and interest rate futures seem to react extremely rapidly to macroeconomic news announcements, e.g., within forty seconds according to Ederington and Lee (1995) and Almeida *et al*. (1998). However, equity markets respond more slowly to earnings and dividend announcements, requiring ten to fifteen minutes (Patell and Wolfson 1984). The response of the S&P500 index to unexpected changes in the money supply and Consumer Price Index (CPI) is completed within one hour (Jain 1988). In this paper, we will employ one-minute returns on the TOPIX and the S&P500 to analyze the speed of reactions of each stock exchange to the other.

The only work thus far, to our knowledge, using intraday data in a study of the price linkage between the U.S. and Japanese stock markets is that of Becker *et al*. (1992). They used hourly data for the S&P500 and Nikkei 225 Indices from October 5, 1985 to December 31, 1989. They calculated the correlations between hourly returns of one country with the other country's daily return of the previous day.[2] They found that the effect of the previous day's Nikkei return on the subsequent S&P500 returns is absorbed within the first half hour after opening in New York, while the effect of the previous day's S&P500 return on the subsequent Nikkei returns is absorbed within the first hour of trading in Tokyo, and that the effect of the lagged S&P500 returns on the subsequent Nikkei returns is larger than the reverse effect. Thus, the stock markets in Tokyo and New York seem to absorb the effects from the other stock exchange rather rapidly. However, due to the hourly observations that they used we cannot infer how speedily the effects are absorbed.

This paper uses high-frequency data to examine how fast the Tokyo and New York stock markets respond to each other. We obtained the tick data for the S&P500 from Tickdata.com and the TOPIX data at one-minute intervals from the Tokyo Stock Exchange.[3] Our data started earlier, but to avoid the

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[1]For an overall introduction to high-frequency finance, see Dacorogna *et al*. (2001). Goodhart and O'Hara (1997) is also a good review and companion papers in the same *Journal of Empirical Finance*, vol. 4, no. 2-3 are research results with high-frequency data.
[2] Since the New York Stock Exchange opens at 09:30 EST, the first US return of the day is a half-hour return from 09:30 to 10:00.
[3] The TOPIX is a capitalization-weighted index of all the stocks listed on the Tokyo Stock Exchange.

extreme effects of Black Monday, we discarded data before December 1987. The last day for our sample was November 27, 2003. Since our sample period is considerably longer than that used in Becker *et al*. (1992), we can also examine whether there was a change in this reaction time during the sample period.

In this paper we measure how quickly the reaction to the other market at the opening dissipates. However, the short reaction time does not necessarily imply the market efficiency when one uses high-frequency data. For example, the market microstructure may explain the difference in reaction time. Specifically, the TSE accepts buy and sell orders for one hour prior to the market opening and the opening price is determined by the batch process known as *itayose*.[4] The NYSE, on the other hand, does not accept orders before the market opening and the prices are formed by continuous auction. This difference in trading rules apparently leads to different reaction time. Another microstructure effect arises due to nonsynchronous trading.[5] It is known that nonsynchronous trading results in serially correlated stock returns (Lo and MacKinlay 1990).[6] The length of reaction time is, thus, affected by such microstructure effects.

If the preceding US (Japan) closing price affects the opening price in Japan (the US) systematically and significantly, the return volatility at the beginning of daily trading tends to be larger. Indeed, it is well-known that the intraday return volatility is W-shaped in Japan (Andersen, Bollerslev, and Cai 2000) and U-shaped in the US (Andersen and Bollerslev 1997), both of which imply high volatility at the opening. Thus, this study also constitutes an analysis of microstructure of the stylized fact of high

[4] Opening and closing prices of the morning and afternoon session of the Tokyo Stock Exchange are formed by a batch process, called *itayose*, while other trades during the day are carried out by continuous trading, called *zaraba*. Amihud and Mendelson (1991) analyze *itayose* system and argue that this difference in the two price formation processes, *itayose* and *zaraba*, may produce differences in prices and trading volumes.

[5] The bid-ask bounces are also known to affect autocorrelation in stock returns (Roll 1984). However, they result in negative autocorrelation while we are concerned with positive autocorrelation in stock price index returns such as S&P500 or TOPIX.

[6] They proved that the degree of autocorrelation becomes stronger, the higher the probability of nontrading for a given time interval. Tsutsui, *et al*. (2007) report that this probability of nontrading is greater in the NYSE than in the TSE.

volatility at the beginning of NYSE and TSE.

The rest of the paper is organized as follows. In Section 2 we discuss intraday patterns of one-minute stock returns in Tokyo and New York. Section 3 analyzes the speed of reaction to the other market changes and Section 4 presents analyses with subperiods. In Section 5 we focus on positive and negative market changes and analyze whether there is an asymmetry in reaction. Section 6 concludes the paper.

2. Intraday patterns of one-minute stock returns

2.1 Intraday patterns of TOPIX returns

We obtained the TOPIX data at one-minute intervals from 09:01 to 15:00 JST (Japan Standard Time) from May 23, 1987 to November 27, 2003 from the Tokyo Stock Exchange. There was a two-hour lunch break between 11:00 and 13:00 until April 26, 1991 and a 90 minute lunch break between 11:00 and 12:30 after April 30, 1991. Although the actual starting date of our dataset is May 23, 1987, we deleted observations up to the end of 1987 in order to avoid overwhelming influence of the Black Monday. One-minute returns of the TOPIX are computed as:

$$RJhhmm_t = \frac{TOPIX\ at\ hhmm - TOPIX\ at\ hhmm-1}{TOPIX\ at\ hhmm-1} \times 100, \qquad (1)$$

where *hhmm* is a four-digit number denoting the hours and minutes in Japan Standard Time and *hhmm*–1 refers to the time one minute before *hhmm*. It takes on values from 0901 to 1100 for the morning session and from 1231 to 1500 for the afternoon session.[7] The notation, 1000–1, means 0959, but 0901–1 refers to 1500 of the previous day. Therefore, note that *RJ0901* is actually an overnight return from the previous day's close at 15:00. Likewise, 1231–1 is actually 1100, because there is a lunch break. Hence, *RJ1231* is a 90-minute return from 11:00 to 12:31.

[7] Due to a longer lunch break, *hhmm* starts at 1301 and ends at 1500 for the afternoon session until April 26, 1991.

These TOPIX returns, *RJ0901*, …, *RJ1500*, are averaged across days during the sixteen-year period (January 1988 to November 2003), and these means are plotted in Figure 1 along with 95% confidence bands based on the null of a zero mean. We observe the following five characteristics of intraday one-minute stock returns in Tokyo. 1) The first four minutes immediately following a day's opening exhibit significantly positive returns. 2) There are significantly positive returns for about six minutes before a day's closing. 3) There are significantly negative returns for about ten minutes after the opening (12:31) of the afternoon session. 4) One-minute returns tend to be negative after the first eight minutes of the day's opening. Out of 52 one-minute returns from *RJ0909* to *RJ1000*, there are 25 significantly negative values at a 95% level. 5) Most returns other than the above are statistically not different from zero during the day. There are only six cases of significant non-zero means for 60 one-minute returns during 10:01 and 11:00. For the interval between 12:41 and 14:54, there are 11 such means out of 134 one-minute returns.

Using *five-minute* returns of the Nikkei 225 Index, Andersen *et al*. (2000) examined their volatility during the period from 1994 to 1997. The mean returns averaged across days are plotted in their Figure 1A and these conform to points 2, 3, and 5 above. Although the first observation of the morning session in their paper exhibits a negative return, this is due to their deletion of the daily initial observation (from 9:00 to 9:05).

Table 1 lists summary statistics of selected daily TOPIX returns.[8] To test for serial correlation up to the fifth order, we use Diebold's heteroscedasticity-adjusted Ljung-Box statistic (Diebold 1986, Silverpulle and Evans 1998), because stock returns are widely known to have ARCH effects. The serial correlation thus measured is significant at or immediately following the opening of either morning or afternoon session and returns for a longer time period such as *RJCC* or *RJOC*. But most of other

[8] Normality tests are not shown here, because the Jarque–Bera measure indicates overwhelming rejection of normality in every variable.

one-minute returns are not serially correlated.

In Table 1 *RJ0901* is actually the daily close-to-open overnight return, the mean of which is positive, whereas the daily open-to-close return (*RJOC*) is negative. There is a tendency for the TOPIX to rise during the night but to decline during the trading hours (Tsutsui 2003). The morning return between 09:01 and 12:31 (*RJMN*) tends to be negative, but the afternoon return between 12:31 and 15:00 (*RJAN*) positive. The volatility as measured by the standard deviation is higher at the opening of either the morning or the afternoon session and at the closing of the day. However, the very high standard deviation of *RJ0901* can be regarded as a natural result of a long time period for this overnight return. *RJ0901* is observed on a 1,080-minute interval (18 hours from 3 pm to 9 am the following morning). One may have to adjust for this long interval depending on their purpose of the study. If one wants to assess the magnitude of information flow, he or she will compare the standard deviation per minute, which is 0.0091 during night.[9]

We next turn to the issue of intraday pattern of volatility. To measure volatility in stock prices, we computed and graphed the mean of absolute TOPIX one-minute returns (Fig. 2). Volatility is high at the opening and closing of the morning and afternoon sessions (see also standard deviations in Table 1). The intraday volatility has three peaks, giving rise to a W-shaped pattern, which is also reported for five-minute TOPIX absolute returns by Andersen, Bollerslev, and Cai (2000). At the time of market opening, there is an accumulated stock of new information which may result in higher volatility. This is what we focus on in this paper, but it does not explain the W-shaped pattern entirely. The TSE

[9] The logged stock price is known to follow a random walk model fairly well (or a Wiener process in continuous time) which has a property that the variance is proportional to the number of periods (or the duration of the elapsed time). Then, the standard deviation is proportional to the square root of the observation duration. The time length for *RJ0901* is 1,080 times the other one-minute returns. Thus, its standard deviation may be divided by the square root of 1,080 to give 0.0091 ($= 0.30/\sqrt{1080}$). The magnitude of this looks small compared with standard deviations of other one-minute returns which typically have values around 0.03, signifying that the information flow during non-trading hours is smaller that that during trading hours. However, in order to analyze the impact of the whole information accumulated during non-trading hours, this per-minute standardization does not seem appropriate. Indeed, the subsequent one-minute returns, *RJ0902* and *RJ0903*, have a standard deviation of 0.123 and 0.067 respectively, which is much larger than the per-minute value for *RJ0901*.

determines opening and closing prices of two daily sessions by *itayose* method (TSE 2004, pp. 70-73) which coincides with the three peaks in volatility, suggesting that *itayose* is one of the causes for high volatility (Amihud and Mendelson 1991). Since *itayose* treats all the outstanding orders as arriving at the same time, the likelihood of successful transactions is higher than during the normal *zaraba* auctioning. As a result, more orders are accumulated for the *itayose* auction because of the reduced risk of non-execution. This contributes to higher volume and volatility at the opening and the closing of the two sessions, giving a partial explanation for three peaks during a day.

2.2 Why does the TOPIX decline at the opening of the afternoon session?

What about the apparent tendency of stock prices to decline at the opening of the afternoon session (point 3 above)? Our conjecture is that investors give a second thought to rising prices at the opening. This may also be behind the tendency of declining prices during 09:15 and 10:00 (point 4 above). Correlation coefficients between the overnight return (*RJ0901*), the return during the lunch break (*RJ1231*), and the 45-min. return from 09:15 to 10:00 (denoted by *RJ45M1000*) are presented in Table 2. *RJ0901* is negatively correlated with both *RJ1231* and *RJ45M1000*, which seems to support our view that advances at the opening are corrected afterwards.[10]

Since correlation coefficients measure pair-wise relationships only, we also ran some regressions to explain the negative return at the opening of the afternoon session. We regressed the over-lunch return (*RJ1231*) on a constant, the overnight return (*RJ0901*), five one-minute returns immediately preceding the lunch break, and the dependent variable lagged by one day.[11] The result is shown under equation (i) in Table 3. The coefficient on *RJ0901* is negative at a 15% significance level and the *RJ1100* variable has also a highly significantly negative effect on the dependent variable.[12] *RJ1231* lagged one day has a

[10] There is, however, sensitivity to the choice of duration. The 50-min. return from 09:10 to 10:00 (*RJ50M1000*) is positively correlated with *RJ0901*.
[11] See the next section for the details of this regression specification.
[12] In this paper White's robust standard error is used to evaluate the significance in regressions. This

significantly positive effect. Overall this regression gives an adequate explanation of *RJ1231*.

Before introducing the 45-min. return, *RJ45M1000*, to the regression for *RJ1231*, let us consider what effects it may have on *RJ1231*. There are two views. First, suppose that the size of correction to an over-reaction at 09:01 is determined first and that it is divided into *RJ45M1000* and *RJ1231*. Then, if sufficient second thought is given during the 45-min. interval up to 10:00, the extent of corrective reaction at 12:31 must be small, making the coefficient on *RJ45M1000* negative. Second, suppose that the size of correction is not immediately known but is gradually revealed during the actual trading session. Then, if a relatively large adjustment occurred in *RJ45M1000*, it would lead to a further adjustment after lunch. In this instance, the coefficient on *RJ45M1000* in a regression for *RJ1231* tends to be significantly positive, indicating a further, strengthened correction after lunch. In any case, the lunch break gives investors further time to reconsider the excessive rise at the opening of the day.

Equation (ii) of Table 3 is the result of regressing *RJ1231* on a constant, the overnight return at the opening (*RJ0901*), and the 45-min. return to 10:00 (*RJ45M1000*). The coefficient on *RJ0901* is negative at a 15% significance level and that on *RJ45M1000* is positive at a 0.3% level. This result implies the second view above is appropriate.

We added five lagged one-minute returns and one-day lag of the dependent variable to the right-hand side and the basic result is the same in this equation (iii) of Table 3. These results imply that the mean negative return at the opening of the afternoon session is a reaction to the mean positive return at the opening of the morning session. Having lunch gives investors reflective time to digest the excessive rise at the day's opening.

2.3 Intraday patterns of S&P500 returns

For the U.S. stock prices we obtained tick data on S&P500 from January 2, 1987 to November 27,

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procedure adjusts for serial correlation and heteroscedasticity.

2003. As noted above, we discard observations up to the end of 1987. We compute one-minute returns of S&P500 as:

$$RUhhmm_t = \frac{S\,\&\,P500\ at\ hhmm - S\,\&\,P500\ at\ hhmm-1}{S\,\&\,P500\ at\ hhmm-1} \times 100\,. \qquad (2)$$

Since the New York Stock Exchange opens at 09:30 and closes at 16:00, *hhmm* takes on values from 0931 to 1600. Unlike Tokyo, the NYSE has no lunch break and trades shares continuously for six and a half hours every day. The time difference between Tokyo and New York is fourteen hours (thirteen hours during the Daylight Saving Time period). Expressed in Greenwich Mean Time, the trading hours are from 0:00 to 6:00 GMT in Tokyo and from 14:30 to 21:00 GMT in New York. Thus, the two markets are never synchronously open.

Mean one-minute returns of S&P500 are plotted in Figure 3 along with 95% confidence bands based on the null of a zero mean. We observe the following features from this Figure similar to those of TOPIX one-minute returns: 1) The first seven minutes after the day's opening tend to exhibit significantly positive returns. However, their absolute magnitude is smaller than that of Tokyo. 2) The last four minutes before the day's closing are also significantly positive, but their absolute magnitude is smaller than in Tokyo or the first few minutes after opening. 3) Some of the returns tend to be *negative* between 9:51 and 10:13. Out of 23 one-minute returns during this interval, nine are significantly negative. 4) Except for these intervals noted above, most of the mean returns are statistically not different from zero. Out of 343 one-minute returns during 10:13 and 15:56, only 28 are significant at a 5% level.

The correlation coefficient between the overnight return at the opening (*RU0931*) and the 45-min. return from 09:45 to 10:30 is –0.0401 with a *t*-statistic of 2.54, the *p*-value of which is 1.1%, indicating a significantly negative correlation. As in Tokyo, this may also imply that the investors in the NYSE give a second thought to the rise at and immediately after the day's opening.

Table 4 gives summary statistics for these and other daily returns.[13] Again the normality is overwhelmingly rejected, thus not shown therein. Unlike the TOPIX, the S&P500 tends to rise during the trading hours (significantly positive open-to-close return, *RUOC*). Most of this rise during the daytime occurs in the afternoon (significantly positive afternoon return from 13:01 to 16:00, *RUAN*). The volatility is high when the market opens, as indicated by a high standard deviation of *RU0931*, but it declines gradually over time.[14] Unlike Tokyo, there is no increase in volatility toward the end of the day. Serial correlation is also present at and immediately following the opening or for daily returns such as *RUCC*.

Mean absolute one-minute returns are plotted in Figure 4 to check for volatility. It is very high at the market opening, but it dissipates very rapidly and then gradually decline toward the middle and then again very slowly increases toward the closing of the market. The graph does not show a typical U-shaped pattern, but it is more like reverse J-shaped which is also pointed out by Goodhart and O'Hara (1997, p. 86).

3. How quickly does one market react to the other?

3.1 Correlation coefficients

Since it is well known that the two stock markets affect each other, our primary focus here is on determining how rapidly this influence is absorbed after the opening of a market. As a preliminary

[13] There is a slight discrepancy in the data for S&P500. The S&P500 price level at 16:00 is not precisely equal to the closing value as reported by the TickWrite, software provided by the data vendor (TickData) to retrieve data points at desired frequency. It turns out that the original tick data contain values at a few minutes after 16:00. The last value for the day is reported as the closing price. A similar discrepancy occurs with the opening price. If two or more data points exist between 09:30 and 09:31, the last value is reported as the price at 09:31, but the very first value is reported as the opening price on a daily frequency. In empirical analyses below, the daily close-to-close or open-to-close returns (*RUCC* and *RUOC*) and the like are based on true opening and closing values. However, the difference is extremely small and the results are almost identical even if the values at 09:31 and 16:00 are treated as the opening and closing prices.

[14] If the length of the overnight nontrading is taken into account, the standard deviation of *RU0901* becomes 0.005775 ($=0.18713/\sqrt{1050}$) and this appears to be too small compared with the following one-minute returns.

investigation, we compute correlation coefficients between the previous day's daily return in New York and *each* one-minute return in Tokyo. We denote by *RUCC* the daily close-to-close return in New York on the previous day.[15]

These correlation coefficients are displayed with 95% confidence bands derived from the null of zero correlation in Figure 5. They are positive and of no small magnitude until 09:21. Namely, correlations with preceding $RUCC_{t-1}$ persist for about twenty minutes after the opening of the TSE. There are spikes at 09:01, 09:06, 09:11, 09:16 and 09:21, but they disappear when the sample period is restricted to before March 1997. Thus, these spikes are most likely related to five-minute periodicity in autocorrelation coefficients which Tsutsui *et al*. (2007) ascribe to the automatic updating of special quotes.[16] After 09:21 correlation coefficients are roughly close to zero, except at and for several minutes after 12:31 (opening of the afternoon session) when they are significantly negative. Thus far, the pattern is similar to that of mean returns of Figure 1. A notable difference exists toward the end of the day. While mean returns indicate that stock prices rise toward the end of the day, they are totally uncorrelated with previous day's movements in New York.

Next we reverse the direction and compute correlation coefficients between *each* one-minute S&P500 return and the preceding daily close-to-close return observed in Tokyo (*RJCC*). In this instance, the daily return in Tokyo is the one observed on the same calendar date as New York because the close of Tokyo at 15:00 JST is 01:00 EST (Eastern Standard Time) in New York and the NYSE opens its trading eight and a half hours later on the same day. These coefficients are plotted in Figure 6. There are significantly positive correlations in the first fifteen minutes (until 09:45), but their magnitude is far less

[15] Although this daily close-to-close return in New York is recorded on the previous calendar date, it is observed only three hours before the opening of the Tokyo market since 16:00 in New York is 06:00 the next day in Tokyo.

[16] 'Special quotes' are arranged by the TSE and issued whenever the next equilibrium price is likely to exceed a certain prescribed limit in order to bring market participants' attention to a likely jump in stock price. If an announcement of a special quote fails to cause a successful trade, the next special quote at a one-notch higher or lower price is announced automatically at a five-minute interval, which seems to cause a serial correlation in stock price index at these intervals.

than that of Tokyo. After the initial responses, coefficients seem to be random around zero.

In both Tokyo and New York, the responses to the other's daily movements dissipate within the first fifteen to twenty minutes of daily trades. Thus, information from the other market seems to be rather quickly absorbed.

3.2 Regression analysis: effect of New York on Tokyo

The main purpose of this paper is to determine how the other market affects one-minute returns of the day and especially how rapidly the effects are dissipated at the opening of daily trades. In order to investigate this effect, regression analysis taking into account other effects on the stock returns may be more appropriate than computing simple correlation coefficients.

One-minute returns averaged across days as plotted in Figures 1 and 3 exhibit non–random behavior immediately after the opening and toward the closing of the day. In Tokyo, the returns are significantly negative at and after the opening of the afternoon session. This pattern may be evidence of serial correlation that persists for a few minutes. In addition, as discussed above, returns are correlated with the same values of the previous day, indicating a daily periodicity. A model of this influence should take into account both short-run serial correlation and daily periodicity.

Thus, our model of one-minute TOPIX returns is specified as follows:

$$RJhhmm_t = \alpha_{hhmm} + \sum_{i=1}^{5} \beta^i_{hhmm} RJ(hhmm - i)_t + \gamma_{hhmm} RJhhmm_{t-1} + \delta_{hhmm} RUCC_{t-1} + u_t , \tag{3}$$

where *hhmm* refers to a time of the day in hours and minutes and *hhmm–i* indicates the time *i* minutes prior to *hhmm*. In the case of TOPIX returns, *hhmm* takes the values from 0901 and 1100 for the morning session and from 1231 to 1500 for the afternoon session (from 1301 to 1500 before April 26, 1991 due to a longer lunch break). Therefore, (1000–3) refers to 09:57. However, (0901–1) and (0901–2) indicate 15:00 and 14:59 of the previous day respectively. Likewise, (1231–1) denotes 11:00

due to the lunch break. The subscript t denotes a date during our sample. The second term on the right-hand side of equation (3), $RJ(hhmm-i)_t$, captures serial correlation that lasts a few minutes. Due to the five-minute periodicity reported in Tsutsui, et al. (2007), the lag order is set at five for this term. The third term $RJhhmm_{t-1}$, is inserted to account for daily periodicity. $RUCC_{t-1}$ is the explanatory variable that is the focus of this exercise and is a daily close-to-close S&P500 return observed just prior to the opening of daily trades in Tokyo. δ_{hhmm} captures the effect of the previous day's close-to-close return in New York on each one-minute return in Tokyo.

Since the Tokyo Stock Exchange is open for four and a half hours each day, there are 270 one-minute returns every day, and we ran 270 regressions for each return and obtained as many coefficient estimates for δ_{hhmm}. The sample period is from January 5, 1988 to November 27, 2003, and the number of observations is 2,374 for returns from 12:31 to 13:00 and 3,001 to 3,034 for others.[17]

Estimation results of equation (3) at 9:01, 12:31, and 14:00 are presented in Table 5. The result for 14:00 (*RJ1400*) is given as a typical example of all other regressions. Figure 7 plots 270 regression estimates of δ_{hhmm} together with their 95% confidence bands. It shows that δ_{0901} is about 0.18 and that the coefficients decline rapidly. Most of the coefficients after 09:06 are trifling in magnitude and are not significantly different from zero. In other words, the Tokyo Stock Exchange reacts to the previous day's movements in New York within the first six minutes after opening. This reaction speed is much faster than that indicated by the correlation coefficients of Figure 5 which exhibit positive correlation with $RUCC_{t-1}$ up to around 09:21. These correlation coefficients only capture the pairwise relation between each one-minute return and $RUCC_{t-1}$, hence they do not account for the lagged effects of immediate past returns. However, the regression equation takes serial correlation into account by adding lagged one-minute returns (the second term on the right-hand side of equation (3)). In fact, these lagged series

[17] The slight difference in the number of observations is due to: 1. a few missing values, 2. a peculiar convention in the TSE whereby only morning sessions are held on the last and first day of the year, 3. during the earlier part of the sample period (before February 1989), two or three Saturdays per month were open for trading, but were only for the morning session.

are significantly positive in most regression equations.

Another interesting finding from the regressions is that, while returns in the past few minutes usually have a positive effect on the subsequent returns (see right columns of Table 5), the last return of the day (*RJ1500*) has a significantly *negative* effect on *RJ0901* (see left columns of Table 5). Its coefficient is –0.202 with a *p*-value of 0.000005%.

Another remarkable fact shown in the middle columns of Table 5 is that the coefficient for $RUCC_{t-1}$ is significantly negative in a regression for *RJ1231*, which means that the opening price of the afternoon session reverses the reaction at the opening of the morning session. Furthermore, just as *RJ0901* reacts negatively to the previous day's closing ($RJ1500_{-1}$), *RJ1231* reacts negatively to the closing of the morning session (*RJ1100*). The coefficient on *RJ1100* in a regression for *RJ1231* is –0.207 with a *p*-value of 0.000004%.

Just one example of all other mundane results is given by the regression for *RJ1400,* in which $RUCC_{t-1}$ is not significant. Three out of five lagged one-minute returns are significant, but the independent variable lagged one day is not.

One may wonder whether our results are valid, when intraday seasonality is removed. Indeed, seasonal adjustment on the first moment does not change the results at all except for the constant term as far as the seasonal factors are constant during the season, because our regression equation (3) essentially has daily frequency, which is estimated for every minute.[18] We did run regressions with seasonally-

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[18] Suppose we use a regression approach to achieve this. We first run a regression of a long one-minute stock return series on 270 dummy variables each of which represents a specific time during the day. A dummy variable for 09:01 is equal to unity at this time of day, but is zero for all other minutes. A 09:02 dummy takes the value of unity at 09:02, but is zero otherwise, etc. One can easily ascertain that the estimated coefficient on each *hhmm* dummy is equal to the average of associated one-minute return across days. Hence, denoting such a mean by μ_{hhmm}, the deseasonalized series is simply $RJhhmm_t - \mu_{hhmm}$, which implies the adjusted series has a zero mean. Therefore, the above equation (3) now becomes,

$$RJhhmm_t - \mu_{hhmm} = \alpha'_{hhmm} + \sum_{i=1}^{5} \beta'^{i}_{hhmm} \left[RJ(hhmm-i)_t - \mu_{hhmm-i}\right] + \gamma'_{hhmm}(RJhhmm_{t-1} - \mu_{hhmm}) + \delta'_{hhmm} RUCC_{t-1} + u_t,$$

but, this simplifies to

$$RJhhmm_t - \mu_{hhmm} = \alpha'_{hhmm} + \sum_{i=1}^{5} \beta'^{i}_{hhmm} \left[RJ(hhmm-i)_t - \mu_{hhmm-i}\right] + \gamma'_{hhmm}(RJhhmm_{t-1} - \mu_{hhmm}) + \delta'_{hhmm} RUCC_{t-1} + u_t$$

.This

adjusted data, and we confirmed the above proposition.

How about seasonal adjustment for the second moment? The price volatility in the beginning of a market is well known to be high, as was confirmed in Figure 2. One of the causes for this is the revelations of new information during the nontrading hours and the closing price at the NYSE is probably the single most important factor.[19] If we make seasonal adjustment for the variance, e.g. applying the method of Andersen and Bollerslev (1997), to get rid of the high volatility, it will dampen the effect of New York's closing price on the NIKKEI at the beginning.[20] We are trying to determine the cause of high volatility at the market opening, and therefore, adjusting the seasonality in intraday volatility is incompatible with what we are trying to estimate in the sense that the magnitude of the response of Tokyo to New York is altered. However, since the t-value of the estimated coefficient does not change, how fast Tokyo absorbs the effect of New York's closing price is not altered.

The importance of New York to Tokyo's market opening can be shown by simple arithmetic. The standard deviation of *RJ0901* is 0.30 (Table 1). The regression of *RJ0901* on *RUCC* gives an estimated coefficient of 0.178 (Table 5). When we multiply the standard deviation of *RUCC* (=1.04 according to Table 4) by this coefficient, the product becomes 0.18 approximately. More than half of the standard

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equation differs from (3) only in the constant term. Other explanatory variables are exactly the same as in (3).

[19] The importance of New York to Tokyo's market opening can be shown by simple arithmetic. The standard deviation of *RJ0901* is 0.30 (Table 1). The regression of *RJ0901* on *RUCC* gives an estimated coefficient of 0.178 (Table 5). When we multiply the standard deviation of *RUCC* (=1.04 according to Table 4) by this coefficient, the product becomes 0.18 approximately. More than half of the standard deviation of *RJ0901* is explained by the effect of *RUCC*.

[20] Andersen and Bollerslev (1997) analyze intraday seasonality in volatility as follows. The high-frequency return on day *t*, period *n* is denoted by $R_{t,n}$ and they assume a decomposition, $R_{t,n} = N^{-1/2}\sigma_t s_n Z_{t,n}$, where *N* is the number of periods per day, σ_t is the volatility level for a specific day, s_n is the seasonal intraday volatility component, and $Z_{t,n}$ is an i.i.d. mean zero, unit variance error term. Intraday seasonal volatility is estimated by applying the flexible Fourier form and the original return series is divided by estimated $\hat{s}_n$ to give a seasonal-volatility adjusted series. If we applied this adjustment to our one-minute returns, the estimated coefficient in equation (3) would be divided by this factor, $\hat{s}_n$. However, because the standard error is also divided by this factor, the t-value is unaffected.

deviation of *RJ0901* is explained by the effect of *RUCC*. All this shows the importance of New York's closing price in explaining a high volatility at the market open in Tokyo. Intraday seasonality in stock price volatility is partly a result of influences from New York.

3.3 Regression analysis: effect of Tokyo on New York

Next, we examine the effects of the Tokyo stock market on New York. We regress each of $RUhhmm_t$ (one-minute returns of S&P500 at each minute of the day *t*) on a constant, lagged one-minute returns of the preceding three minutes, the return at the same time the day before, and a daily close-to-close return observed in Tokyo prior to the opening of the NYSE:

$$RUhhmm_t = \alpha_{hhmm} + \sum_{i=1}^{3} \beta_{hhmm}^{i} RU(hhmm - i)_t + \gamma_{hhmm} RUhhmm_{t-1} + \delta_{hhmm} RJCC_t + u_t \, , \qquad (4)$$

where $RJCC_t$ is the daily close-to-close return of the TOPIX observed eight and a half hours before the opening of the New York stock market. As in equation (3), we include lagged one-minute returns (the second term on the right-hand side of (4)), but the lag order is three, which seems to be enough to capture the very short-run serial correlation in *RUhhmm*.

Estimation results at 09:31 and 15:00 are presented in left and middle columns of Table 6. When the NYSE opens in the morning, $RJCC_t$ has a significantly positive and the lagged dependent variable ($RU0931_{t-1}$) a significantly negative effect on *RU0931*. But the previous day's final one-minute return at the closing has no effect.

The result for *RU1500* is displayed as a typical example of all other regressions, where $RJCC_t$ has no effect. Of the three lagged one-minute returns, only that of one minute previously is significant. The dependent variable lagged one day is not significant either.

The estimated coefficients on δ_{hhmm} are presented in Figure 8. Comparing Figure 8 with Figure 7, we initially notice that the first several coefficients in Figure 6 are significant but that they are much smaller in magnitude than those in Figure 7. Thus, the effect of the Tokyo stock market on the New York market is far weaker than the reverse effect. There are possibly two reasons for the small effect of Tokyo on New York. First, the U.S. economy is apparently more important to the Japanese economy than the other way round. In fact, the dominant effect of the U.S. stock prices on other countries' stock prices is well documented in many studies (e.g., Eun and Shim 1989). Second, although New York is the nearest predecessor to Tokyo, closing right before Tokyo opens, the NYSE opens eight and a half hours after the TSE closes. In the meantime Frankfurt and London start their daily trading before New York. Tsutsui and Hirayama (2004a) analyze these four countries using daily closing prices and report a finding that the market which closes immediately before one market has the largest effect. In light of this finding, it would be natural to have a small effect of Tokyo on New York due to the intervening effects of Frankfurt and London.

To account for these effects, we include the daily close-to-close return in FAZ Index of Frankfurt Stock Exchange ($RGCC_t$) in the regression equation:

$$
\begin{aligned}
RUhhmm_t = \alpha_{hhmm} + \sum_{i=1}^{3} \beta_{hhmm}^{i} RU(hhmm - i)_t \\
+ \gamma_{hhmm} RUhhmm_{t-1} + \delta_{hhmm} RJCC_t + \varepsilon_{hhmm} RGCC_t + u_t \,,
\end{aligned}
\tag{5}
$$

where ε_{hhmm} captures the effect of Frankfurt on New York. The effect of London's daily closing cannot be incorporated, because London's closing time is later than the opening of the NYSE. London closes its daily trading at 16:30 GMT, which is 11:30 EST in New York. Namely, when New York opens at 09:30 local time, London's closing value is not yet known. Thus, we had to drop London's daily close-to-close return variable.[21] The Frankfurt Stock Exchange, on the other hand, is open for trading between 10:30 and 13:30 local time. This closing time is two hours before opening of New York. Frankfurt's daily close-to-close return is known to New York, the effect of which is captured by ε_{hhmm}

[21] If we had intra-day data of London, we could compute a return up to the time of New York's opening to capture the effect of London on New York. Unfortunately we could obtain only daily closing prices for London and Frankfurt, which compelled us to disregard this effect of London.

in equation (5) above.

We ran a regression for this equation and the estimated ε_{0931} is about 0.042 (see the right columns of Table 6) which is greater than $\delta_{0931} = 0.028$ in equation (4) (see the left columns of Table 6). [22] However, it is only one-quarter of the effect of New York on Tokyo (see the left columns of Table 5 and $0.178 \div 4 \approx 0.045$). The result seems to vindicate our two conjectures above offered as an explanation for the small effect of Tokyo on New York. Though this smallness is partly caused by the intervening market in Frankfurt, Frankfurt's effect on New York is also very small compared with the effect of New York on Tokyo, which implies a dominant influence of New York on other markets.

We report, in passing, the estimated δ_{0931}, the coefficient on the first one-minute return after opening, in equation (5). It is now 0.015, which is roughly half that in equation (4). δ_{0932} is also significantly positive, but not after these first two minutes. This reduction implies that about half of Tokyo's effect on New York as measured by equation (4) is absorbed by Frankfurt.

Next, in Figure 8, coefficients up to *RU0944* tend to be significant, which means it takes the NYSE about fourteen minutes to absorb new information from Tokyo. Closer inspection reveals that eight out of fourteen coefficients on $RJCC_t$ are statistically significant. When we examine the effect of Frankfurt on New York in equation (5), it is significant for most of the first fifteen minutes after 09:31.[23] Since the reaction time is six minutes in Tokyo, the reaction time of New York is longer than that of Tokyo.

This difference in reaction time does not necessarily reflect differences in efficiency. It may be explained by the fact that the opening price of the Tokyo Stock Exchange is formed by a batch process (*itayose*, see Footnote 4), in which trading orders are accepted during sixty minutes prior to the market opening at 09:00. However, in the New York Stock Exchange, the usual continuous trading process determines the opening price. Another reason for this difference may be due to different degree of nonsynchronous trading.

[22] This coefficient of 0.042 does not change much even if $RJCC_t$ is excluded from equation (5).
[23] This result is basically unaltered even if $RJCC_t$ is dropped from equation (5).

3.4 What returns do the markets react to?

In the previous section, we assume that the markets react to daily close-to-close returns. Since the media, such as TV and newspapers, regularly announce this return, this assumption is reasonable. In this subsection, we will investigate whether the markets react to the information from more specific periods than the close-to-close return.

The close-to-close return of the TOPIX (*RJCC*) can be divided into a close-to-open return (*RJ0901*; nontrading-hours return) and an open-to-close return (*RJOC*; trading-hours return). *RJOC* can further be divided into a morning return (*RJMN*; 9:01 to 12:31) and an afternoon return (*RJAN*; 12:31 to 15:00).

Likewise, the close-to-close return of S&P500, *RUCC*, is divided into a close-to-open return, *RUCO*, an open-to-close return, *RUOC*, a morning return, *RUMN*, and an afternoon return, *RUAN*, where morning means 9:31 to 13:00 and afternoon is 13:01 to 16:00.[24]

Let us first look at correlations between these returns. While *RUOC* highly correlates with *RUCC* (coefficient is 0.995), the correlation coefficient between *RUCO* and *RUCC* is only 0.28. Actually, *RUOC* is almost identical to *RUCC*, which can also be ascertained by their means and standard deviations in Table 4. This fact leads us to expect that the Tokyo market reacts to *RUOC* just the same way as to *RUCC* in equation (3). Indeed, replacing *RUCC* with *RUOC* in regression equation (3) yields nearly the same result. The same applies to *RJOC* and *RJCC* in equation (4).

In order to find out which return the markets react to, we compare the explanatory power of the returns in equation (3) or in equation (4). For the ease of exposition, let us refer to equation (3) as Model A and the equation in which *RUCC* is replaced with *RUOC*, *RUCO*, *RUMN* or *RUAN* as Model B. Construction of these models requires a non-nested test, because neither is a subset of the other model.

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[24] *RUCO* is the close-to-open overnight return, which is slightly different from *RU0931* that is defined as the return between 16:00 in the previous day and 09:31. See Footnote 13.

In this paper we apply Deaton's *F* test (Deaton 1982). In this test, we compare Model A and B, and focus on the variables that are not included in the other model. In the test of Model A (equation 3) vs. Model B (*RUxx* replaces *RUCC* in equation 3), equation (3) is run first; then we add the alternative return variable and test the explanatory power of this variable by a standard *F* test (equivalent to a *t* test, since there is only one additional variable). If the additional variable is statistically significant, Model B is selected over Model A. In the test of Model B vs. Model A, Model B is run first; then we add *RUCC* and test the explanatory power of *RUCC*. If *RUCC* is significant, Model A is selected over Model B. Naturally, a pair of these tests may not produce an unequivocal result.

P-values of the test for the first seven minutes of TOPIX returns are presented in Table 7, since the first six minutes are the time the Tokyo market significantly reacts to New York. In the left columns, we compare additional explanatory power of *RUOC* and *RUCC*. When *RUOC* is added to equation (3) (Model A), *RUOC* is significant at a 10% level for three cases out of seven (see the second column).[25] The third column shows the results when *RUCC* is added to Model B. Three cases out of seven cases are significant, implying *RUOC* and *RUCC* have almost the same explanatory power. The result is reasonable because *RUOC* and *RUCC* are almost identical series.

Comparing *RUCO* and *RUCC*, while *RUCC* is significant in six cases, *RUCO* is significant only in two cases. This implies that the close-to-close return is more important and is the one focused on by Japanese investors. Similar results are obtained for the morning return (*RUMN*) and the afternoon return (*RUAN*). In summary, Table 7 suggests that the Tokyo market watches the close-to-close return (*RUCC*) more than other returns, probably because this is what the media usually reports. *RUOC* has strong explanatory power simply because it is almost identical to *RUCC*.

The same procedure is applied to equation (4) to compare the explanatory power of *RJCC* with other returns such as *RJOC* and the results for the first fifteen minutes are shown in Table 8. In the first

[25] We also provide the number of significant cases at a 5% level in the Table, which leads to the same conclusions.

pair, *RJOC* is significant in four cases at a 10% level, while *RJCC* is significant in six cases. *RJ0901* is significant in four cases, and *RJCC* in eleven cases. *RJMN* is insignificant in all cases and *RJAN* is significant only in one case. *RJCC* is significant in eight and seven cases in the last two pairs of tests in Table 8. These results suggest the same conclusion as the Tokyo market: the close-to-close return of TOPIX is what the U.S. investors focus on.

4. Changes in the linkage over sub-periods

In order to examine whether the response pattern has changed during our sample period, we divide the whole sample into three subperiods and conduct the same analysis of the previous section. We examined the daily closing prices of S&P500 and TOPIX for our sample period and divided the whole period into the following three subperiods[26]: Period I: January 5, 1988 to December 31, 1989 when stock prices exhibited an upward trend in both the U.S. and Japan. Period II: January 4, 1990 to October 15, 1998, when stock prices in the U.S. exhibited an upward trend, while those in Japan fell significantly at first and were stagnant thereafter. Period III: October 16, 1998 to November 27, 2003, when stock prices in both countries moved in a similar fashion, exhibiting an inverted U-shaped pattern.

We regress equation (3) by OLS and the sum of coefficients on $RUCC_{t-1}$ in regressions for *RJhhmm* cumulated over each one-minute interval is depicted in Figure 9 for the Tokyo stock market. Thus, the graph shows cumulative effects of the S&P500 on the TOPIX during the course of a day's trading. Individual coefficients are statistically significant only at the beginning of the day. Others are seldom significant, thus rendering the cumulative sums statistically not very meaningful. However, even though they are not different from zero statistically, whenever they tend to be positive over

[26]We should ideally search for break points by conducting structural break tests. However, equation (3) consists of 270 regression equations and each one of them has to be subjected to such a test. We will then have 270 sets of break points. There is no established method to aggregate those into a single set. Namely it seems quite difficult to specify break points uniquely with these tests. Hence we give these points exogenously.

successive minutes the cumulative sum tends to rise, which does imply that the effect from the other market is cumulatively positive. Thus, aside from strict statistical significance, we can infer a general direction of the other market's influence during the day from this graph. Figure 9, which plots these cumulative sums for three subperiods, reveals the following: 1)The length of reaction time has decreased over the sixteen-year period. In Period I, positive responses continue until around 09:30 and thereafter negative responses follow during the morning session. In Period II, positive responses dissipate by around 09:15 and the decline afterwards is much smaller. Period III exhibits a rapid increase after the opening and the peak is observed at 09:06. 2) The magnitude of the cumulative reaction has become greater, from around 0.1 for Period I to 0.3 for Period III. Two reasons can be offered. One is that the increase reflects intensified economic integration between the U.S. and Japan. The other is that the relative size of the Tokyo stock market to the New York stock market, as measured by annual turnover, has declined over the period. Tokyo's turnover exceeded that of New York in 1988 and 1989. However, the Japanese stock prices have declined and stagnated since then, whereas the New York market has seen a spectacular rise in the 1990s. Thus, the U.S. turnover has grown tremendously, dwarfing that of Tokyo. 3) A *negative* response at the opening of the afternoon session is visible in all three subperiods.[27]

Cumulative sums of coefficients on *RJCC* in regression equation (4) for the New York stock market are displayed in Figure 10. The speed of reaction has become greater from Period I to Period II. Specifically, positive responses, small in magnitude, continue for about two hours after the opening in Period I, but in Periods II and III initial positive responses abate in about fifteen minutes after opening.

The overall magnitude of cumulative responses is much higher in Period III than in Period I or II. However, it is much smaller than that of Tokyo. This is probably due to the relative importance of the economy.

[27] In Period I when the afternoon session started at 13:00 this negative response is observed at 13:01.

5. Is there asymmetry in the reaction as the other market rises or falls?

In order to see if there is asymmetry in responses to the other market's rise or fall, we regress Japanese returns on positive $RUCC_{t-1}$ and on negative $RUCC_{t-1}$ separately. Although the regression equation is equation (3), we divide the observations into one group where $RUCC_{t-1}$ is positive and another where $RUCC_{t-1}$ is negative. Thus, we ran two sets of regressions. The resultant estimates are displayed in Figure 11, in which cumulative sums of coefficients are shown. The cumulative responses to the positive and negative $RUCC_{t-1}$ are remarkably similar.

Likewise, estimating equation (4) with positive and negative $RJCC_t$ separately, we compute the cumulative sums of coefficients for the New York stock market reacting to positive and negative $RJCC_t$ values which are depicted in Figure 12. Unlike Tokyo, New York exhibits clear asymmetry in reaction. Bad news from Japan has a considerably stronger effect on New York than good news. The magnitude of the response in New York to a fall in Tokyo is roughly double that of a rise. The response pattern is also different: when Tokyo has advanced, responses in New York are spread over a longer period, about one and a half hours, but when Tokyo has fallen, positive responses swiftly reach a peak within about fourteen minutes. This asymmetry in reaction to a rise or fall in Tokyo is in contrast to the finding of Tokyo's symmetric responses to New York.[28]

This asymmetry in New York might be strongly influenced by the rapid declines in the TOPIX during the period from January 1990 to July 1992. To check on this possibility, we divided the sample into three subperiods as above and ran the same regressions. We again obtained asymmetric responses in New York to a rise or fall in Japan in all three subperiods, indicating asymmetry throughout the sixteen-year period. Why investors in New York are more sensitive about the fall in Tokyo is another agenda for future research.

[28] Analyzing the daily stock price index data from 1975 to 1995 for the U.S., the U.K., Germany, and Japan, Hirayama and Tsutsui (1998b) found that negative large changes have a clearer effect than positive ones.

6. Conclusions

This paper explores how rapidly the Tokyo and New York stock markets respond to the movements of the stock price index of the other market using high-frequency data over the period from January 5, 1988 to November 27, 2003. Estimating the reactions of one-minute returns of one country to the preceding daily return of the other country, we find that:

1) A positive response of the Tokyo stock market dissipates within six minutes, while that of New York dissipates within fourteen minutes. The TSE is more efficient in absorbing the impact at the opening than NYSE, possibly because TSE employs a batch process called *itayose* for forming the opening price, in which trading orders are accepted during one hour prior to opening.
2) The magnitude of the response is around 0.054 (cumulative sum for the first fourteen minutes) for the New York stock market and 0.22 (cumulative sum for the first six minutes) for Tokyo. Thus, the effect of New York on Tokyo is over four times greater than the reverse effect.
3) The response time has shortened over the period. The magnitude of the response has grown for the Tokyo stock market over the three periods, while that of the New York stock market has grown between the first and the second period. Its reason is probably increased market integration and changes in the relative size of the two markets
4) The response of the Tokyo stock market is symmetric in terms of a fall or rise in New York, while the response of the New York stock market to a fall in Tokyo is twice as great as that to a rise.
5) The opening price of the afternoon session of the Tokyo stock market negatively responds to the previous movement in New York.
6) The fact that daily stock price movements of New York and Tokyo exert positive influences on each other at the market opening tends to increase price volatility and more than half of the standard deviation of *RJ0901* is explained by the daily close-to-close return in New York. This

can be interpreted as one of the causes of intraday seasonality in volatility.

Determining the causes of interesting findings 4) and 5) remains an agenda for future research. We suggested, however, that 5) is the result of giving a second thought over lunch to the excessive response at the opening of the day.

The reaction time is on the average six minutes for Japan and fourteen minutes for the U.S. This is consistent with the findings on stock price reactions to earnings and dividend announcements which are typically ten to fifteen minutes (Patell and Wolfson, 1984). The difference in the response time may not imply difference in market efficiency. It may be explained by the market microstructure. One relevant feature was the *itayose* process at the market opening in Tokyo. Another candidate is nonsynchronous trading. Different behavioral patterns may also be a part of the picture, but we await research in behavioral finance comparing the two markets' participants. [29]

[29] According to a questionnaire survey of stock investors in both Japan and the U.S. reported in Shiller *et al*. (1996), wishful thinking distinctly characterizes Japanese investors.

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Table 1. Summary Statistics of Selected TOPIX Returns

	Mean	Max.	Min.	S.D.	LB Q(5)	N. Obs.
RJCC	–0.005414	9.544252	–7.099952	1.241356	0.000000	3946
RJOC	–0.028921	9.535624	–7.077842	1.120321	0.000000	3946
RJMN	–0.061056	4.928397	–7.383014	0.848256	0.000000	3878
RJAN	0.027906	4.986915	–4.181279	0.651292	0.000000	3882
RJ0901	0.022538	1.290985	–1.384551	0.300236	0.000002	3946
RJ0902	0.009977	0.531608	–0.467999	0.122559	0.000664	3946
RJ0903	0.002953	0.313808	–0.370573	0.066933	0.137623	3946
RJ0904	0.002050	0.335886	–0.307720	0.053931	0.284805	3946
RJ0905	–0.000182	0.304305	–0.259738	0.049527	0.015789	3946
RJ0906	0.005068	0.874180	–0.837865	0.129583	0.000777	3946
RJ0907	–0.000177	0.372772	–0.415340	0.054780	0.021402	3946
RJ0908	–0.000180	0.293806	–0.294364	0.048681	0.200642	3946
RJ0909	–0.002076	0.287059	–0.336252	0.046205	0.040822	3946
RJ0910	–0.001682	0.257447	–0.231399	0.042652	0.040816	3946
RJ0911	–0.000919	0.628561	–0.678866	0.070972	0.000000	3946
RJ0912	–0.001643	0.338236	–0.303619	0.043420	0.150820	3946
RJ0913	–0.002397	0.225850	–0.258847	0.041816	0.393895	3946
RJ0914	–0.001593	0.265057	–0.300950	0.041100	0.539881	3946
RJ0915	–0.000664	0.331735	–0.263754	0.040282	0.189326	3946
RJ1058	0.000893	0.253167	-0.203527	0.003117	0.460764	3946
RJ1059	0.000958	0.270980	-0.231672	0.003779	0.544917	3946
RJ1100	0.000383	0.624921	-0.343656	0.013196	0.000000	3946
RJ1231	–0.020839	0.495607	–0.512869	0.110544	0.000000	3080
RJ1232	–0.006396	0.374045	–0.272433	0.053161	0.000549	3080
RJ1233	–0.004164	0.233465	–0.237738	0.036479	0.192422	3080
RJ1456	0.002471	0.336507	–0.223676	0.042856	0.811288	3891
RJ1457	0.002008	0.295976	–0.361518	0.044994	0.758851	3891
RJ1458	0.006019	0.310071	–0.434954	0.050495	0.506295	3891
RJ1459	0.007532	0.429410	–0.331767	0.053642	0.152021	3891
RJ1500	0.031975	0.881639	–0.613469	0.142120	0.000000	3891

Notes: Variables are TOPIX returns (in percent). *RJOC* is daily open-to-close return, *RJMN* morning return from 09:01 to 12:31 (opening of the afternoon session), *RJAN* afternoon return from 12:31 to 15:00. *RJhhmm* where *hhmm* is 0902, …, 1500 is a one-minute return except *RJ0901* which is daily close-to-open (overnight) return and *RJ1231* which is a 91-min. return over the lunch break. S.D. is the standard deviation. LB Q(5) is the Diebold's heteroscedasticity-adjusted Ljung–Box Q statistic which tests the null hypothesis that every autocorrelation coefficient up to the fifth order is zero. *p*-values are shown in this column. The sample period is from January 5, 1988 to November 27, 2003. See Footnote 15 for the reasons for different numbers of observations.

Table 2. Correlation Coefficients between Selected TOPIX Returns

	RJ0901	*RJ45M1000*	*RJ1231*
RJ0901	1.0000		
RJ45M1000	–0.0288	1.0000	
RJ1231	–0.0348	0.0554	1.0000

Notes: *RJ0901* is the overnight return from the previous day's close to the opening, *RJ45M1000* is the 45-min. return from 09:15 to 10:00, and *RJ1231* is the one-and-a-half hour return during the lunch break. The sample period is from April 30, 1991 to November 27, 2003.

Table 3. OLS Regressions to Explain *RJ1231*

	Eq. (i)		Eq. (ii)		Eq. (iii)	
Variable	Coeff.	*p*-val.	Coeff.	*p*-val.	Coeff.	*p*-val.
Constant	–0.018	0.000	–0.020	0.000	–0.017	0.000
RJ0901	–0.013	0.149	–0.011	0.145	–0.011	0.216
RJ45M1000			0.016	0.028	0.019	0.024
RJ1100	–0.205	0.000			–0.208	0.000
RJ1059	0.103	0.121			0.096	0.142
RJ1058	0.066	0.411			0.064	0.425
RJ1057	–0.011	0.898			–0.012	0.888
RJ1056	0.101	0.197			0.099	0.204
$RJ1231_{-1}$	0.082	0.002			0.083	0.002
$\bar{R}^2$	0.023		0.004		0.026	
p-value of *F* test	0.000		0.025		0.000	
Num. of Obs.	2371		3077		2371	

Notes: The dependent variable is *RJ1231*, over-lunch return from 11:00 to 12:31. *RJ0901* is the overnight return from the previous day's close to the opening price at 09:01. *RJ45M1000* is the 45-min. return from 09:15 to 10:00. *RJhhmm*, where *hhmm* is 1056, …,1100, is the one-minute return up to *hhmm*. The subscript, $_{-1}$, denotes a one-day lag. The sample period is from April 30, 1991 to November 27, 2003. The sample size is reduced in equations (i) and (iii) relative to equation (ii) due to the lagged dependent variable on the right-hand side. *p*-values are calculated based on the White's robust standard errors.

Table 4. Summary Statistics of Selected S&P500 Returns

	Mean	Max.	Min.	S.D.	LB Q(5)	N. Obs.
RUCC	0.041675	5.451431	–6.865681	1.042395	0.023050	4014
RUOC	0.036210	6.205689	–6.865681	1.017440	0.000000	4014
RUMN	–0.003487	4.023462	–4.341921	0.758387	0.000023	4014
RUAN	0.039431	5.018159	–5.240286	0.637614	0.000000	4014
RU0931	0.008265	1.401524	–1.649356	0.187130	0.000000	4014
RU0932	0.001432	0.886300	–0.591704	0.079346	0.000046	4014
RU0933	0.003773	0.677632	–0.487086	0.071638	0.000000	4014
RU0934	0.002902	0.602593	–1.214823	0.070406	0.000023	4014
RU0935	0.001415	0.434428	–0.502196	0.061016	0.489507	4014
RU0936	0.001634	0.566342	–0.269207	0.056813	0.008811	4014
RU0937	0.001818	0.371824	–0.587030	0.053691	0.010972	4014
RU0938	0.000900	0.367519	–0.950650	0.054016	0.036028	4014
RU0939	0.000352	0.369199	–0.588413	0.050169	0.089316	4014
RU0940	–0.000672	0.975905	–1.347478	0.056239	0.012362	4014
RU0941	0.000453	1.419375	–0.320305	0.048864	0.228744	4014
RU0942	–0.000378	0.273372	–0.920964	0.048071	0.118769	4014
RU0943	–0.000724	0.333264	–0.375926	0.043056	0.016551	4014
RU0944	–0.000625	0.845680	–0.402200	0.044064	0.189585	4014
RU0945	–0.001040	0.622440	–0.374209	0.042680	0.145902	4014
RU0946	–0.000456	1.035158	–0.320899	0.042752	0.075415	4014
RU0947	–0.000024	0.295632	–0.401757	0.042440	0.281982	4014
RU0948	–0.000946	0.498991	–0.415385	0.042172	0.015185	4014
RU0949	–0.000868	0.312094	–0.381088	0.041142	0.786378	4014
RU0950	–0.001124	0.318218	–0.412264	0.041282	0.007237	4014
RU1556	0.000446	0.225533	–0.161202	0.026527	0.519119	4014
RU1557	0.000957	0.223683	–0.170993	0.026275	0.484659	4014
RU1558	0.001198	0.132838	–0.212960	0.025592	0.063213	4014
RU1559	0.002425	0.224797	–0.189719	0.026541	0.184533	4014
RU1600	0.001906	0.189216	–0.231702	0.026650	0.122381	4014

Notes: Variables are several S&P500 returns. *RUCC* is daily close-to-close return, *RUOC* daily open-to-close return, *RUMN* morning return from 09:31 to 13:00, and *RUAN* afternoon return from 13:01 to 16:00. *RUhhmm* where *hhmm* is 0932, …, 1600 is a one-minute return except *RU0931* which is close-to-open (overnight) return. S.D. is the standard deviation. LB Q(5) is Diebold's heteroscedasticity-adjusted Ljung-Box Q statistic which tests the null hypothesis that every autocorrelation coefficient up to the fifth order is zero. *p*-values are shown in this column. The sample period is from January 5, 1988 to November 27, 2003.

Table 5. Selected Estimation Results of Eq. (3)

RJ0901			*RJ1231*			*RJ1400*		
Variable	Coeff.	*p*-val.	Variable	Coeff.	*p*-val.	Variable	Coeff.	*p*-val.
Constant	0.017	0.000	Constant	–0.017	0.000	Constant	0.000	0.468
$RUCC_{-1}$	0.178	0.000	$RUCC_{-1}$	–0.010	0.000	$RUCC_{-1}$	–0.001	0.231
$RJ1500_{-1}$	–0.202	0.000	*RJ1100*	–0.207	0.000	*RJ1359*	0.098	0.001
$RJ1459_{-1}$	–0.049	0.587	*RJ1059*	0.088	0.174	*RJ1358*	0.054	0.039
$RJ1458_{-1}$	0.039	0.667	*RJ1058*	0.060	0.449	*RJ1357*	0.050	0.040
$RJ1457_{-1}$	–0.012	0.906	*RJ1057*	–0.004	0.960	*RJ1356*	0.020	0.402
$RJ1456_{-1}$	0.145	0.201	*RJ1056*	0.097	0.211	*RJ1355*	0.022	0.346
$RJ0901_{-1}$	0.025	0.292	$RJ1231_{-1}$	0.085	0.001	$RJ1400_{-1}$	–0.004	0.845
$\overline{R}^2$	0.369		$\overline{R}^2$	0.031		$\overline{R}^2$	0.017	
p-val. of *F*	0.000		*p*-val. of *F*	0.000		*p*-val. of *F*	0.000	
Num. Obs.	3034		Num. Obs.	2374		Num. Obs.	3001	

Notes: OLS estimation results of eq. (3) for *RJ0901*, *RJ1231*, and *RJ1400* only are displayed above. The subscript $_{-1}$ indicates a one-day lag. The sample period is from January 5, 1988 to November 27, 2003. '*p*-val.' is the *p*-value of a *t*-statistic on each explanatory variable, which is calculated based on the White's robust standard errors. '*p*-val. of *F*' is the *p*-value of the *F* test for the entire regression. For different numbers of observations see Footnote 12. The number of observations for *RJ1231* is particularly small because 12:31 was in the middle of a lunch break before April 26, 1991.

Table 6. Selected Estimation Results of Equations (4) and (5)

eq. (4) *RU0931*			eq. (4) *RU1500*			eq. (5) *RU0931*		
Variable	Coeff.	p-val.	Variable	Coeff.	p-val.	Variable	Coeff.	p-val.
Constant	0.010	0.003	Constant	0.001	0.143	Constant	0.010	0.002
RJCC	0.028	0.000	*RJCC*	–0.0002	0.631	*RJCC*	0.015	0.000
						RGCC	0.042	0.000
$RU1600_{-1}$	0.003	0.986	*RU1459*	0.327	0.000	$RU1600_{-1}$	–0.106	0.544
$RU1559_{-1}$	0.125	0.524	*RU1458*	0.002	0.960	$RU1559_{-1}$	0.072	0.702
$RU1558_{-1}$	0.250	0.193	*RU1457*	–0.019	0.544	$RU1558_{-1}$	0.094	0.612
$RU0931_{-1}$	–0.170	0.000	$RU1500_{-1}$	0.014	0.584	$RU0931_{-1}$	–0.192	0.000
$\overline{R}^2$	0.049		$\overline{R}^2$	0.112		$\overline{R}^2$	0.135	
p-val. of *F*	0.000		*p*-val. of *F*	0.000		*p*-val. of *F*	0.000	
Num. Obs.	3148		Num. Obs.	3148		Num. Obs.	3085	

Notes: OLS estimation results of eq. (4) for *RU0931*, *RU1500* and of eq. (5) for *RU0931* are displayed above. The subscript , $_{-1}$, indicates a one-day lag. Sample period is from January 5, 1988 to November 27, 2003. ‘*p*-val.’ is the *p*-value of a *t*-statistic on each explanatory variable, which is calculated based on the White’s robust standard errors. ‘*p*-val. of *F*’ is the *p*-value of the *F* test for the entire regression.

Table 7. Explanatory Power of *RUCC* and Other Returns: Deaton's *F*-tests

	A vs. B *RUOC*	B vs. A *RUCC*	A vs. B *RUCO*	B vs. A *RUCC*	A vs. B *RUMN*	B vs. A *RUCC*	A vs. B *RUAN*	B vs. A *RUCC*
RJ0901	0.00000	0.00000	0.00000	0.00000	0.00003	0.00000	0.00000	0.00000
RJ0902	0.00000	0.00000	0.00000	0.00000	0.76067	0.00000	0.35082	0.00001
RJ0903	0.37860	0.79958	0.37640	0.00000	0.01134	0.00000	0.00809	0.01945
RJ0904	0.60801	0.85829	0.61052	0.00102	0.82851	0.01907	0.93536	0.00818
RJ0905	0.37833	0.60912	0.38701	0.00151	0.40475	0.00536	0.32623	0.06289
RJ0906	0.09728	0.04036	0.10364	0.00008	0.15377	0.00521	0.07180	0.00004
RJ0907	0.53043	0.48952	0.53388	0.63545	0.35052	0.82338	0.30665	0.29799
10% signif.	3	3	2	6	2	6	3	6
5% signif.	2	3	2	6	2	6	2	5

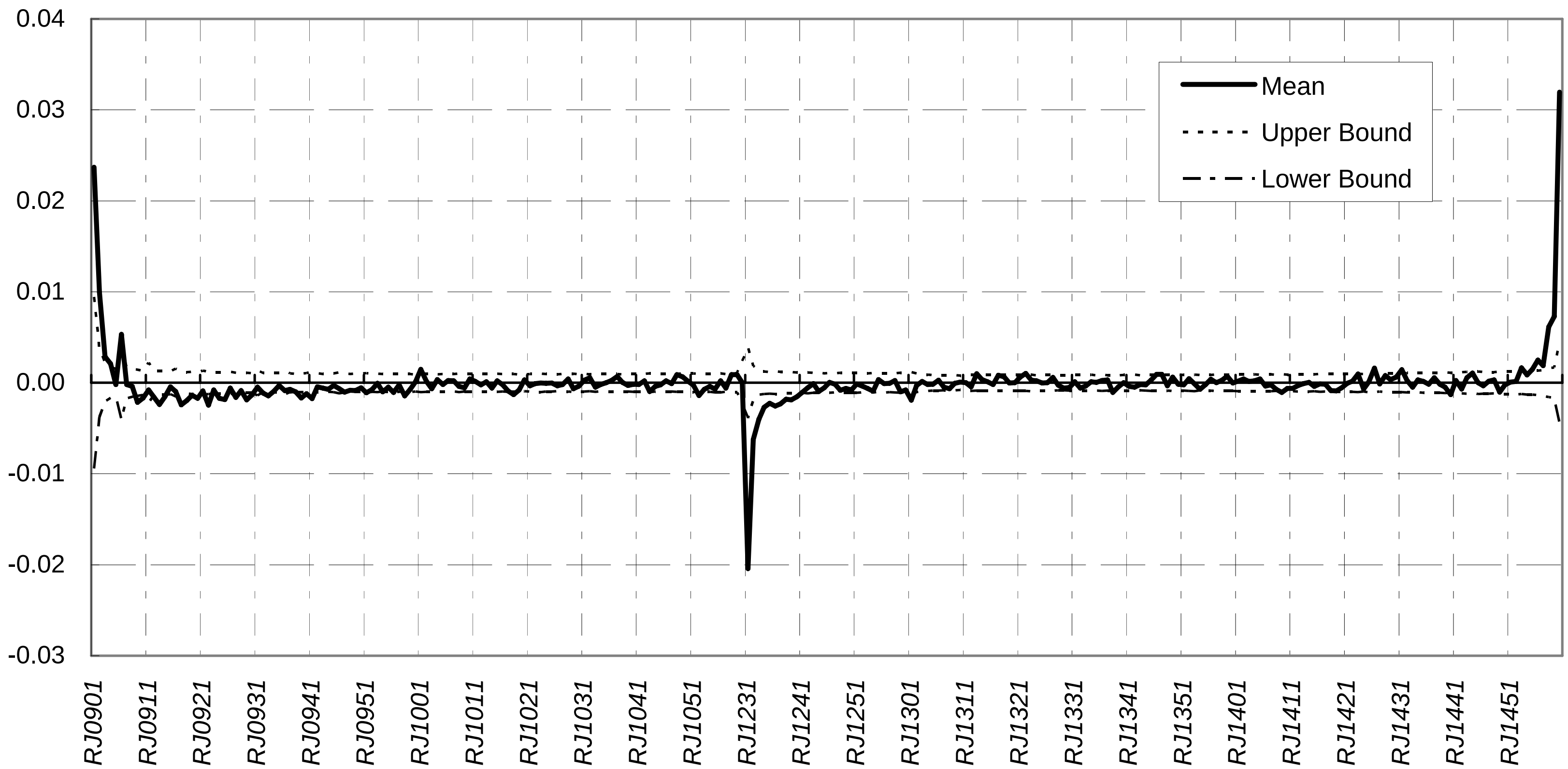
Notes: See notes to Table 4 for definition of the variables. *P*-values of the *F* tests, which are calculated based on the White's robust standard errors, are shown in the Table. 'A vs. B' in Deaton's *F* test takes Model A as given and inserts additional variables that appear in Model B. If the *F* test of these variables is not significant, these variables from Model B do not have additional explanatory power, which implies a rejection of Model B. In our tests, only a single variable is added at a time, thus the *F* test is equivalent to a *t* test. 'B vs. A' reverses the procedure. '10% signif.' stands for the number of cases, out of seven trials, that the alternative variable is significant at a 10% level. '5% signif.' is the same proportion at a 5% level. There are four pairs of Model A and B above: *RUOC* vs. *RUCC*, *RUCO* vs. *RUCC*, *RUMN* vs. *RUCC*, and *RUAN* vs. *RUCC*. Each row represents a regression equation explaining the variable indicated by the first column.

Table 8. Explanatory Power of *RJCC* and Other Returns: Deaton's *F*-tests

	A vs. B *RJOC*	B vs. A *RJCC*	A vs. B *RJ0901*	B vs. A *RJCC*	A vs. B *RJMN*	B vs. A *RJCC*	A vs. B *RJAN*	B vs. A *RJCC*
RU0931	0.08701	0.00307	0.08069	0.00000	0.52610	0.00000	0.58840	0.00000
RU0932	0.00003	0.00254	0.00003	0.00000	0.78705	0.03987	0.07646	0.08030
RU0933	0.03131	0.05086	0.03193	0.08660	0.79128	0.48696	0.17065	0.81794
RU0934	0.05012	0.01986	0.05255	0.04582	0.12225	0.00170	0.90445	0.03189
RU0935	0.71204	0.94945	0.71099	0.14229	0.50460	0.14189	0.43724	0.59558
RU0936	0.41659	0.61539	0.41858	0.08971	0.86585	0.46992	0.64979	0.41188
RU0937	0.18016	0.28604	0.19447	0.07882	0.79563	0.67209	0.62483	0.65790
RU0938	0.82304	0.36704	0.80526	0.01586	0.48304	0.02145	0.57207	0.03806
RU0939	0.18934	0.04452	0.19218	0.00375	0.98592	0.00925	0.38471	0.00027
RU0940	0.76914	0.89212	0.75645	0.03741	0.22794	0.02722	0.21665	0.34106
RU0941	0.83856	0.83646	0.84964	0.05430	0.46159	0.55585	0.53224	0.05512
RU0942	0.34485	0.54201	0.36746	0.11516	0.95438	0.48926	0.59744	0.54844
RU0943	0.68944	0.40623	0.69214	0.10050	0.42951	0.04708	0.62417	0.18059
RU0944	0.76082	0.21478	0.76204	0.00090	0.71530	0.00596	0.92634	0.00126
RU0945	0.49733	0.36807	0.48124	0.45776	0.67721	0.25476	0.98180	0.35034
10% signif.	4	5	4	11	0	8	1	7
5% signif.	3	4	3	7	0	8	0	5

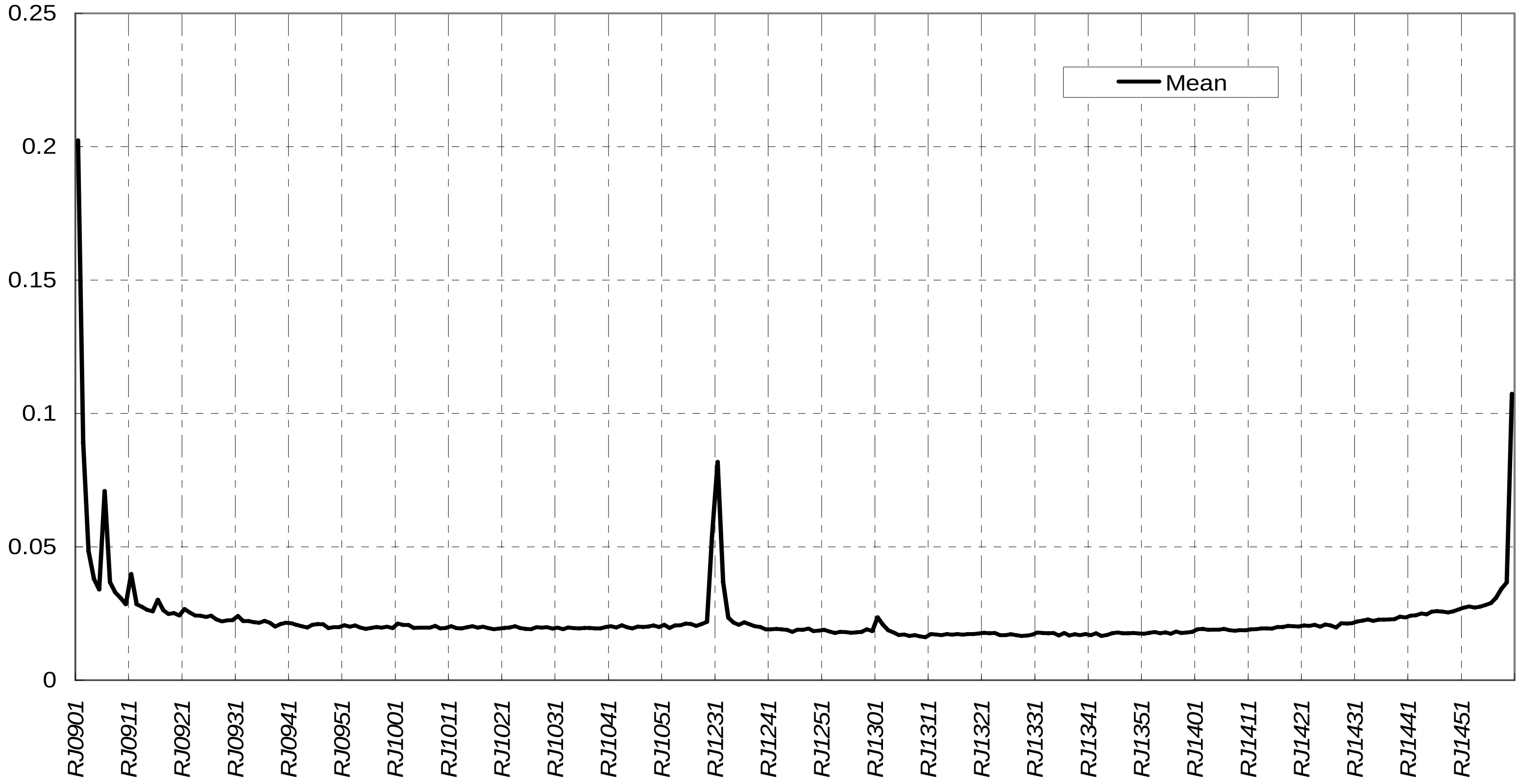
Notes: See notes to Table 1 for definition of the variables. *P*-values of the *F* tests, which are calculated based on the White's robust standard errors, are shown in the Table. For the test procedure, see notes to Table 7. '10% signif.' stands for the number of cases, out of fifteen trials, that the alternative variable is significant at a 10% level. '5% signif.' is the same based on a 5% level. There are four pairs of Model A and B above: *RJOC* vs. *RJCC*, *RJ0901* vs. *RJCC*, *RJMN* vs. *RJCC*, and *RJAN* vs. *RJCC*. Each row represents a regression equation explaining the variable indicated by the first column.

Figure 1 Daily Means of TOPIX One-Minute Returns



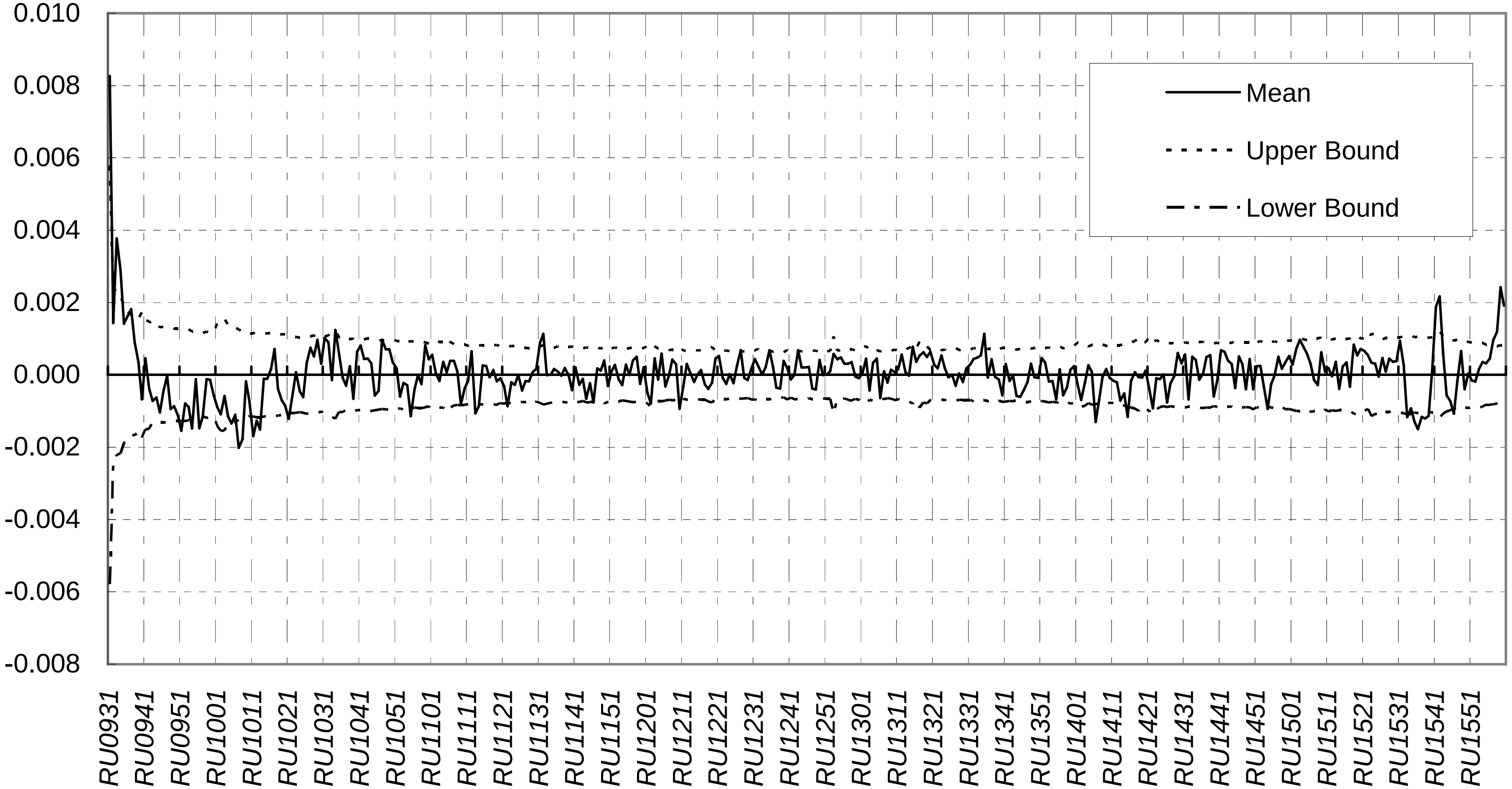
Notes: One-minute returns of TOPIX are averaged across days. The sample period is from January 5, 1988 to November 27, 2003. The sample size varies between 3,080 and 3,946. See Table 1 for the differing sample sizes. 95% confidence bands are shown for the null of a zero mean.

Figure 2.   Daily Means of Absolute TOPIX One-Minnute Returns



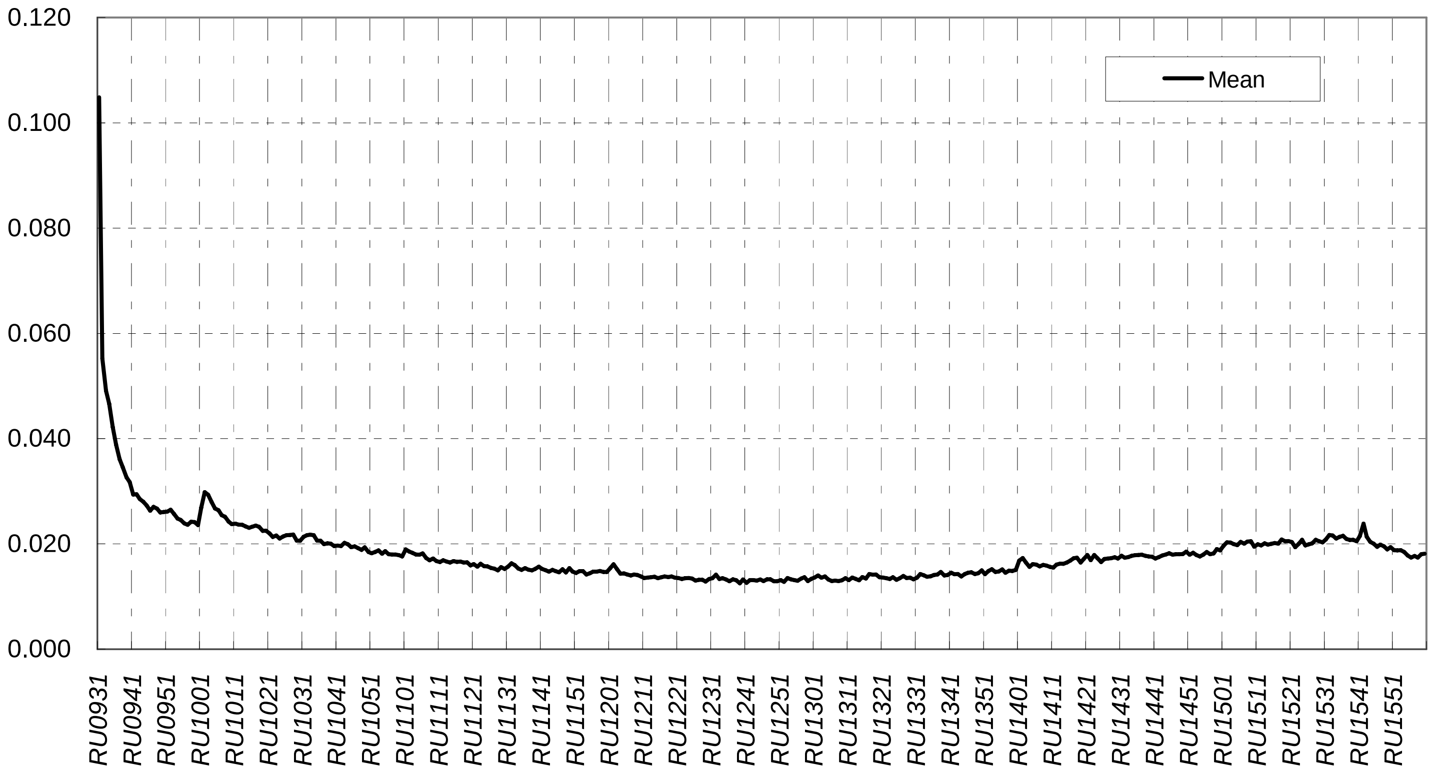
Notes: Absolute TOPIX one-minute returns are averaged across days. The sample period is from January 5, 1988 to November 27, 2003. The sample size varies between 3,080 and 3,946. See Table 1 for the differing sample sizes.

Figure 3 Daily Means of S&P500 One-Minute Returns



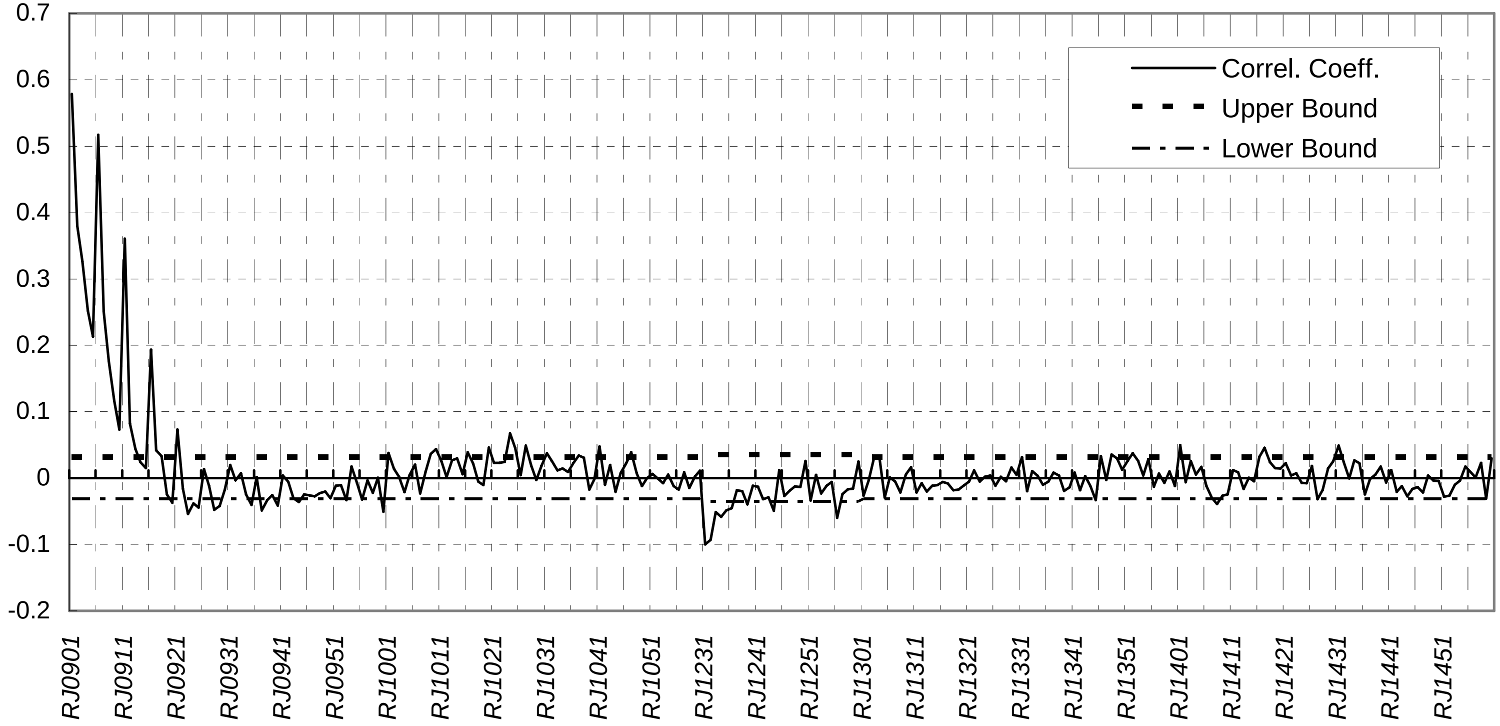
Notes: One-minute returns of S&P500 are averaged across days. The sample period is from January 5, 1988 to November 27, 2003. The sample size is 4014. 95% confidence bands are shown for the null of a zero mean.

Fig. 4 Daily Means of Absolute SP500 One-Minute Returns



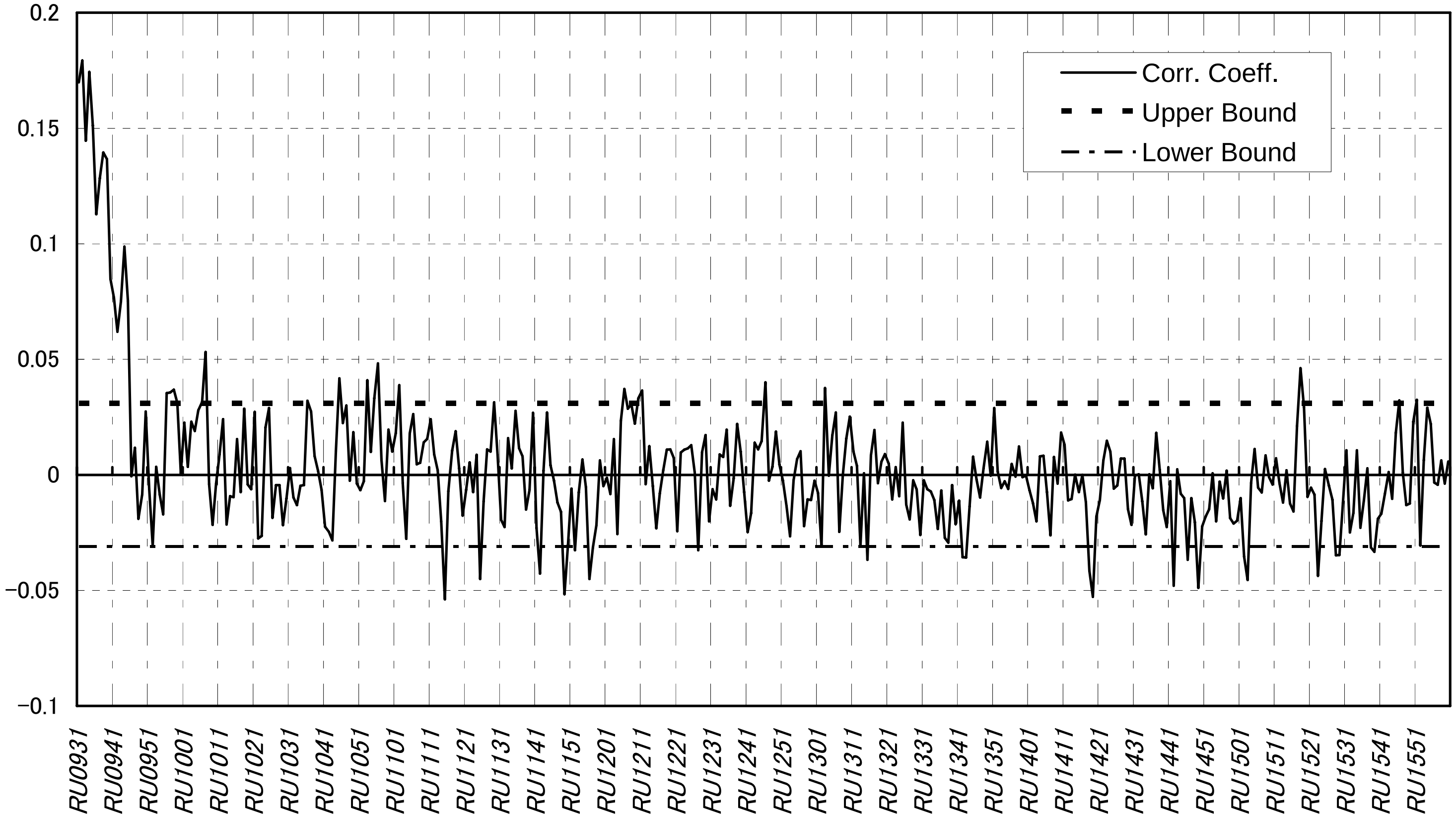
Notes: Absolute S&P500 one-minute returns are averaged across days. he sample period is from January 5, 1988 to November 27, 2003. The sample size is 4014.

Figure 5 Correlation Coefficient of TOPIX 1 Min-Returns
with Previous Day's Close-to-Close Daily Return of S&P500 (RUCC)



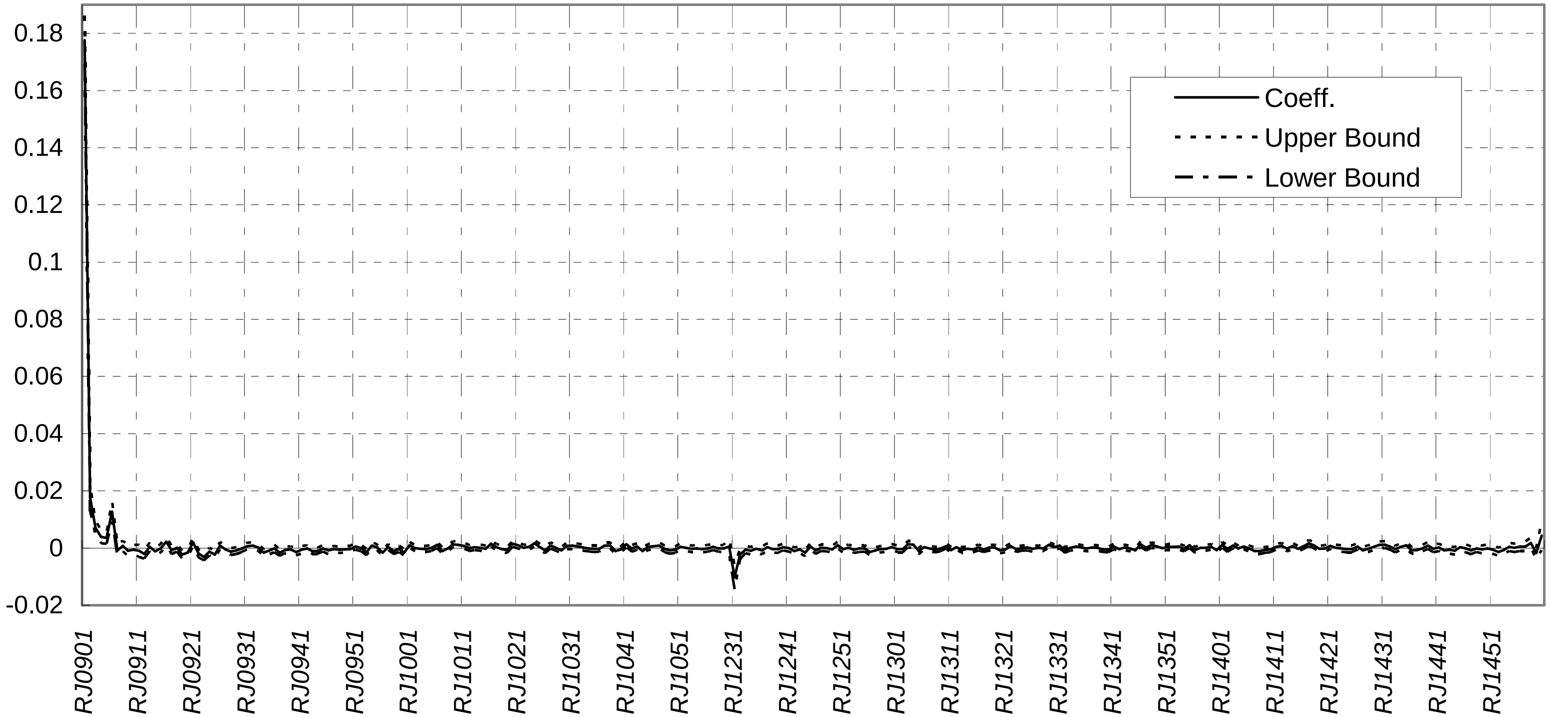
Notes: *RJhhmm*, where *hhmm* is the hours and minutes of the time of day, is the one-minute return of TOPIX. Notice there is a lunch break between 11:00 and 12:30. Correlation coefficients between each of *RJhhmm* and $RUCC_{t\text{-}1}$ (previous day's close-to-close daily return of S&P500) are plotted. The sample period is from January 5, 1988 to November 27, 2003. The sample size is 3080 for the half-hour duration from 12:31 to 13:00 due to a longer lunch break before April 26, 1991 and is between 3891 and 3946 for other times. See Footnote 15 for description of this difference in the sample size. Upper and lower bounds indicate 95% confidence bands for the null of a zero correlation coefficient.

Figure 6 Corrrelation Coefficient of S&P500 1-Min. Returns with
Previous Day's Close-to-Close Daily Return of TOPIX (RJCC)



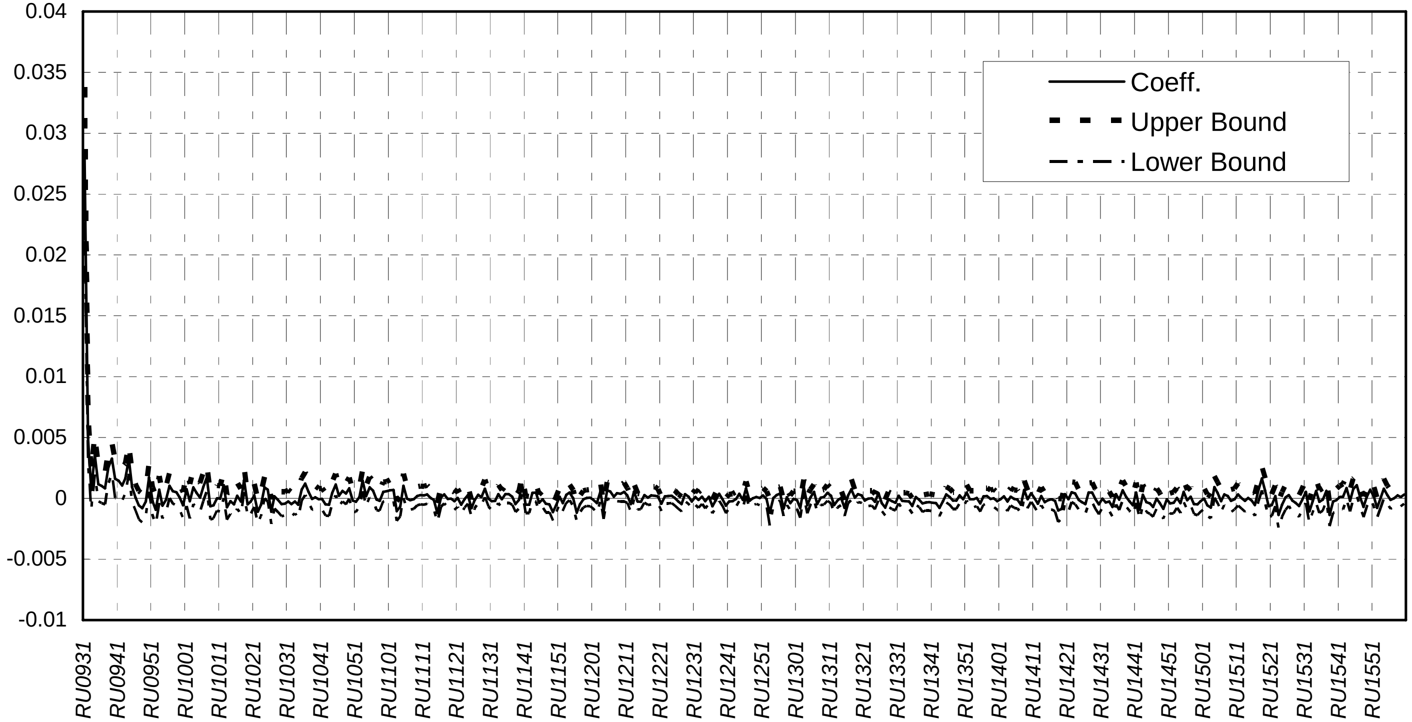
Note: *RUhhmm*, where *hhmm* is the hours and minutes of the time of day, is the one-minute return of S&P500. Correlation coefficients between each of *RUhhmm* and $RJCC_t$ (previously observed close-to-close daily return of TOPIX) are plotted. The sample period is from January 5, 1988 to November 27, 2003. The sample size is 4014. Upper and lower bounds indicate 95% confidence bands for the null of a zero correlation coefficient.

Figure 7 Regression Coefficients on *RUCC*



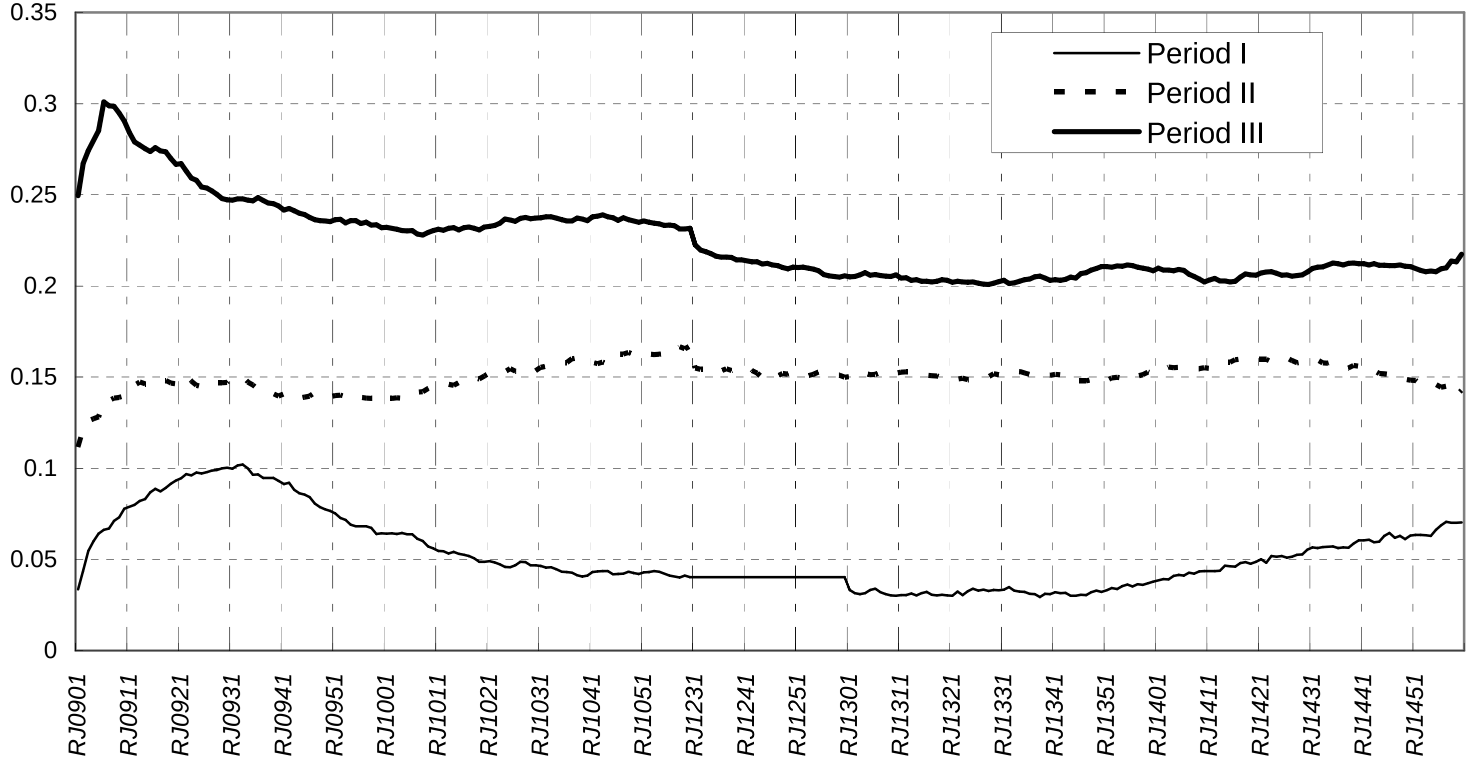
Note: This plots regression coefficients on $RUCC_{t\text{-}1}$ of equation (3), $RJhhmm_t = \alpha_{hhmm} + \sum_{i=1}^{5} \beta^i_{hhmm} RJ(hhmm-i)_t + \gamma_{hhmm} RJhhmm_{t-1} + \delta_{hhmm} RUCC_{t-1} + u_t$, and their 95% confidence bands. They capture the effect of previous day's close-to-close return of S&P500 on each of the TOPIX one-minute returns. See notes to Figure 5.

Figure 8 Regression Coefficients on RJCC



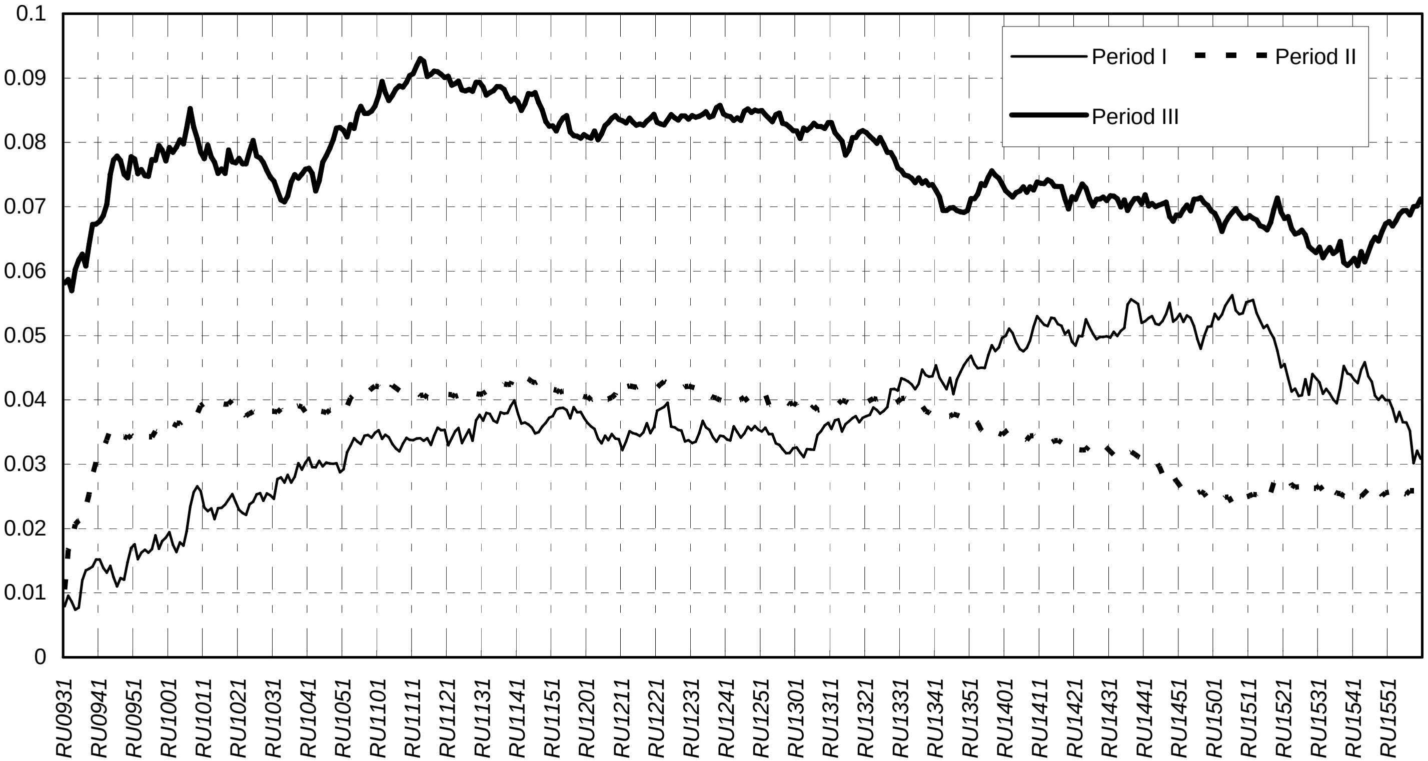
Note: This plots regression coefficients on $RJCC_t$ of equation (4) $RUhhmm_t = \alpha_{hhmm} + \sum_{i=1}^{3} \beta_{hhmm}^{i} RU(hhmm - i)_t + \gamma_{hhmm} RUhhmm_{t-1} + \delta_{hhmm} RJCC_t + u_t$, and their 95% confidence bands. They represent effects of the preceding close-to-close daily return of TOPIX on each one-minute return of S&P500. See notes to Figure 7.

Figure 9 Cumulative Sum of Regression Coefficients on *RUCC* : Three Subperiods



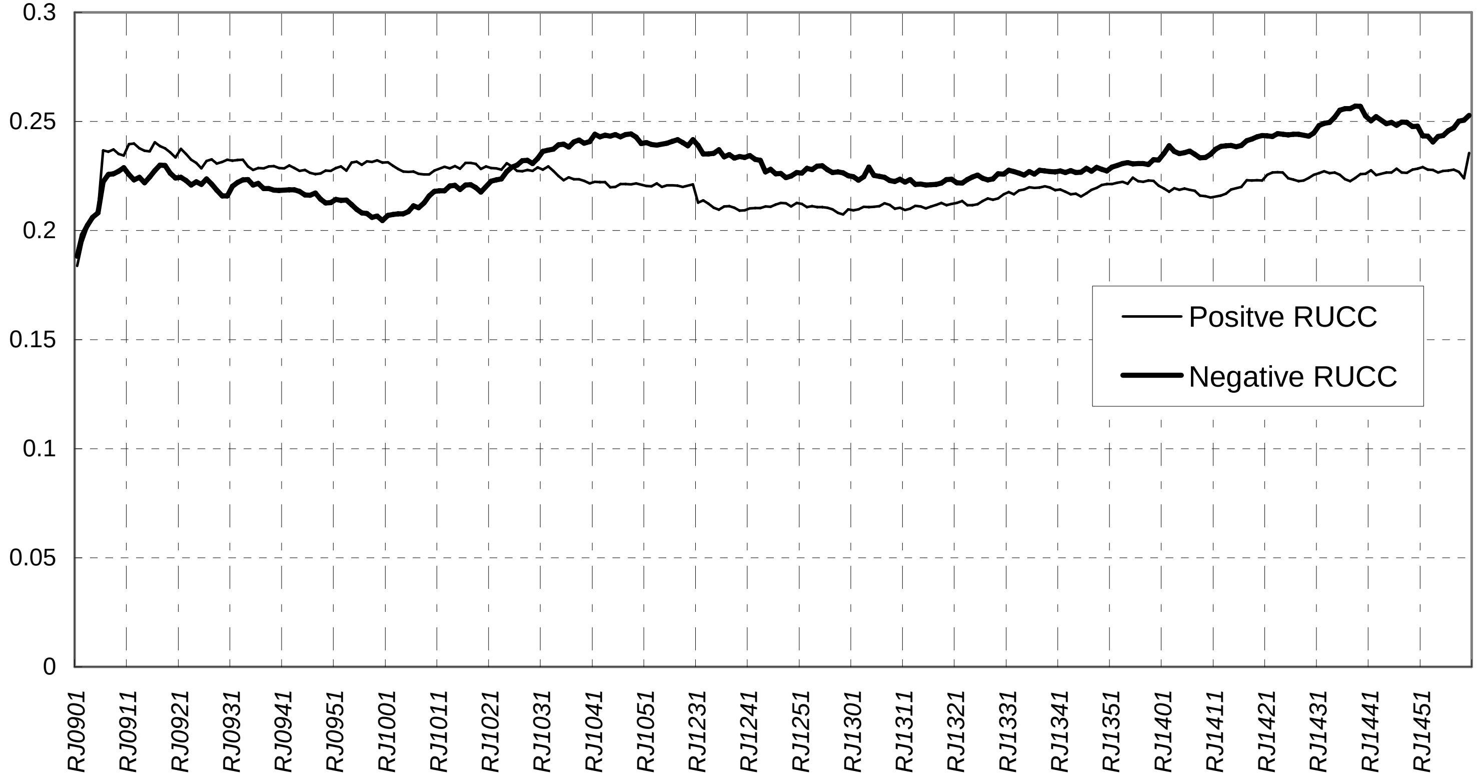
Note: Each line is a cumulative sum of regression coefficients on $RUCC_{t\text{-}1}$ for three subperiods. Period I is from January 5, 1988 to December 21, 1989, Period II from January 4, 1990 to October 15, 1998, Period III from Oct. 16, 1998 to November 27, 2003. Notice that there do not actually exist regressions for *RJ1231*, …, *RJ1300* for Period I because the lunch break was from 11:00 to 13:00 before April 26, 1991.

Figure 10 Cumulative Sum of Regression Coefficients on RJCC: Three Subperiods



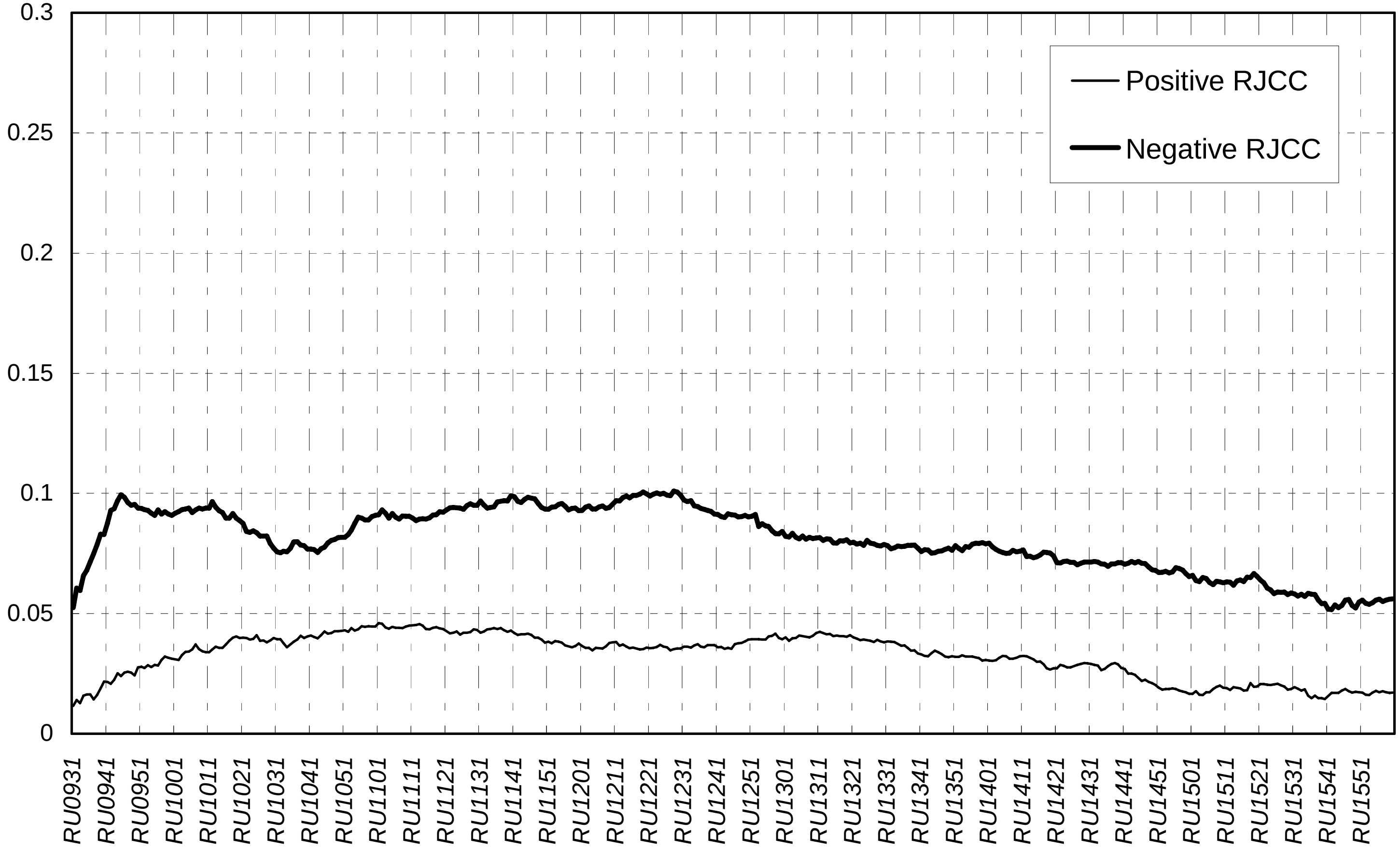
Note: Each line is a cumulative sum of regression coefficients on $RJCC_t$ in equation (4) for three subperiods. See also notes to Figure 9.

Figure 11 Cumulative Sum of Regression Coefficients on Positive and Negative RUCC



Note: Regression equation (3) is estimated separately for positive and negative $RUCC_{t\text{-}1}$.

Figure 12 Cumulative Sum of Regression Coefficients on Positive and Negative RJCC



Note: Regression equation (4) is estimated separately for positive and negative $RJCC_t$.