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Volatility, Efficiency, and Trading: Evidence from the Japanese Stock Market

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ABSTRACT

We study the joint effect of the trading mechanism and the time at which transactions take place on the behavior of stock returns using data from Japan. The Tokyo Stock Exchange employs a periodic clearing procedure twice a day, at the opening of both the morning and the afternoon sessions. This enables us to discern the effect of the clearing mechanism from the effect of the overnight trading halt. While the periodic clearing at the beginning of the trading day is noisy and inefficient, the midday clearing transaction appears to be no worse than the two closing transactions.

IN A RECENT ARTICLE in this Journal (Amihud and Mendelson (1987a)) we examined the effects of two major trading mechanisms on the behavior of stock returns. One mechanism is the continuous dealership market, where investors trade with market makers at their quoted bid-ask prices, and the other is the periodic clearing procedure, where buy and sell orders accumulate during some time interval and are then executed *simultaneously* at a single price which equates the quantity demanded to the quantity supplied.

Our study of the two trading mechanisms compared the time-series behavior of stock returns over the open-to-open and close-to-close time intervals for the same stocks over the same period on the New York Stock Exchange (NYSE). By this methodology, any information about the value of the stock equally affects both return series. Yet, there is a difference between the trading mechanisms by which opening and closing prices are set: The opening transaction in major NYSE stock issues is executed by a periodic clearing procedure, whereas trading continues afterward in a dealership market controlled by the Exchange specialist. If the different trading mechanisms had no effect on stock prices, the variances and autocorrelations would be the same for the two return series.

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We found, however, significant differences between the return series of the opening and closing transactions. First, the variance of the open-to-open returns was higher than the close-to-close return variance for 29 out of the 30 stocks that comprised the Dow Jones Industrial list, and the average ratio of the two return variances was 1.20. Second, the autocorrelations of the open-to-open returns were predominantly more negative than those of the corresponding close-to-close returns, consistent with more noise and with a mean-reversion pattern at the opening. This methodology was recently applied by Stoll and Whaley (1990) to all NYSE stocks, and by Amihud and Mendelson (1989b) and Amihud, Mendelson, and Murgia (1990) to study the behavior of stock returns on the stock exchanges of Tokyo and Milan. These studies reached similar conclusions.

The question is whether the higher variance and the more negative autocorrelation at the opening are due to differences in the trading mechanisms or to the long period of no trading which precedes the opening transaction (this was pointed out to us by Fischer Black). The answer bears on recent proposals (including our own) to institute periodic clearing procedures *during* the trading day.

This question is addressed in this study. In the Tokyo Stock Exchange (TSE), there are *two* daily clearing transactions: one opens the morning trading session, and the other opens the afternoon session. Studying the price behavior in the clearing transaction that opens the *afternoon* trading session enables us to discern the effect of the periodic clearing mechanism from the effect of the extended nontrading period that precedes the morning opening transaction. We compare the volatility and autocorrelations of daily returns measured at four time points, the opening and the closing of both the morning and the afternoon trading sessions. We also analyze the behavior of returns and of the market-model *residuals* for our four data series. This enables us to focus on the idiosyncratic market microstructure effects on stock returns and to perform statistical significance tests on the results.

We find that the midday clearing has a different effect on price behavior than the morning clearing, and that it may well exhibit the least volatile and most efficient value discovery process of the four. We also examine the effect of trading activity on volatility (Black (1986), French and Roll (1986)) by studying the return variances over trading and nontrading periods during the day and overnight. Our results show that trading contributes greatly to volatility. Finally, we find that investors *reverse* price trends of one period during the period that follows, particularly in the morning trading session.

An understanding of the effect of the clearing transaction on the value discovery process and on the associated price behavior is important for the design of securities markets. A number of exchanges around the world are in the process of planning to implement either continuous trading or periodic clearing procedures. On the one hand, some European markets are transforming their trading systems from periodic call markets to continuous trading markets (for example, the Paris *Bourse* has completed this transformation and the Milan Stock Exchange is debating the issue). On the other hand, the New York Stock Exchange is planning to implement additional periodic clearing procedures as part of its 24-hour trading project; the Chicago Mercantile Exchange has a periodic clearing procedure as a component of its GLOBEX trading system; and new proprietary systems based on periodic clearing are under development.[1] This procedure would be less desirable if it were the cause of the larger volatility and negative serial autocorrelation of the opening transaction returns found by Amihud and Mendelson (1987a). On the other hand, if the higher volatility and negative autocorrelations are caused by the preceding long period of no trading, a clearing transaction at the middle of the trading day would generate the benefits discussed in Amihud and Mendelson (1985, 1988, 1990) without hampering value discovery.

In what follows, we review the methods of trading in the TSE in Section I and our methodology and data in Section II. We study the return variances and autocorrelations in Section III, and we examine the behavior of returns over trading and nontrading periods in Section IV. The pattern of price reversals is studied in Section V, and our concluding discussion and interpretation of the results are in Section VI.

I. Trading on the Tokyo Stock Exchange

The Tokyo Stock Exchange employs two trading methods which are considered so distinct that they have different names: the *Itayose*, the clearing transaction, is applied at the opening of each of the *two* daily trading sessions; and the *Zaraba* is applied in the subsequent continuous trading. Both trading methods are managed by the *Saitori*, who use an order sheet that lists for each stock the orders to buy and sell at each price. This procedure is employed mainly for the most heavily traded stocks of the TSE.

Orders submitted prior to the opening of the two sessions accumulate and are executed together by the Itayose method. The Saitori use the orders' limit prices to determine, in the ordinary manner (cf. Mendelson (1982)), the market clearing price which equilibrates the buy and sell orders: the cumulative quantity offered and bid at each feasible price effectively defines the supply and demand schedules, respectively, and their intersection determines the market-clearing price.[2]

After the opening transaction, trading continues by the Zaraba method. The marginal unexecuted orders remaining on the Saitori's book determine the bid and ask prices and quantities. Over time, additional orders are continuously added to the book or executed against the orders on the book, up to the closing transaction which is also part of the continuous Zaraba market.

[1] See *Investment Dealer's Digest*, March 5, 1990, p. 4.

[2] The Itayose method resembles the mode of operation of the "clearing transaction" (or "clearing house") studied by Mendelson (1982, 1985, 1987) and proposed by Amihud and Mendelson (1985, 1988, 1990) as a component of an Integrated Computerized Trading System. Under this concept, the clearing transaction will take place a number of times during the day, while the continuous trading process is going on.

Unlike the NYSE, the TSE has *two* daily trading sessions: a morning session from 9:00 A.M. to 11:00 A.M., and an afternoon session from 1:00 P.M. to 3:00 P.M. While the morning Itayose transaction follows 18 nontrading hours, the afternoon Itayose transaction follows a short two-hour trading break. This enables us to discern between patterns of return behavior that are due to the Itayose mechanism per se and those that are due to the long preceding period of no trading. Ideally, we would like to be able to examine the clearing transaction in a setting where continuous trading is taking place up to the clearing; but using the Japanese data is as close as we can get to such an experimental setting.

The timing of the periodic clearing transaction could affect its performance for the following reason. In a continuous market, the value-discovery process is facilitated by traders' ability to observe a sequence of recent transactions that provide information about the changing value of the security. In contrast, the most recent transaction information available on the "single-shot" opening following the overnight trading halt is 18 hours old. Because traders cannot observe a sequence of recent transaction prices to infer the current value of the security (as well as the value of the market), we should expect more noisy and less efficient value discovery following a nontrading period. Note that since information about value changes is ultimately incorporated in the stock price, any differences between the returns measured at different transaction epochs reflect differences in the value-discovery processes rather than differences in the underlying information sets.

The importance of the Itayose transactions is reflected in the large trading volumes that they attract. Data for the most actively traded group of 150 stocks on the TSE (which are traded on the Exchange floor) show the following. In three recent randomly selected days, 7/2/90, 7/16/90, and 8/6/90, the trading volumes in the morning and afternoon opening Itayose transactions constituted, on average, 11.6% and 9.2%, respectively, of the total daily trading volume in these stocks.[3] These trading proportions are much higher than the corresponding proportions in the NYSE, where the opening clearing transaction in the 30 Dow Jones Industrial stocks constituted 5.6% of their daily trading volume (Amihud and Mendelson (1987a)). The fact that both openings in Tokyo attract a high and comparable proportion of trading volume indicates their importance and facilitates our comparisons.

Another advantage of the Tokyo data is that the closing transaction of the day may not be the best representative of the continuous market. For example, Harris (1989) found a day-end transaction anomaly on the NYSE, where a large mean price change is observed in the last daily transaction. This effect is small for firms such as the ones in our sample. Yet, the ability to compare the last transaction of the morning session with the last transaction of the day using our Tokyo data is valuable.

[3] These data were kindly collected by the Tokyo Stock Exchange. Historical volume data were unfortunately unavailable from the TSE.

II. The Empirical Investigation

In our earlier paper (Amihud and Mendelson (1987a)) we analyzed NYSE data applying a model of partial price adjustment with noise. The model distinguished between the intrinsic value of the stock and its observed price. Changes in value and their ensuing volatility reflect information, whereas differences between price and value are due to imperfect price adjustment and noise (Black (1986)). The price may either adjust gradually to new information or it may overreact to changes in value. In addition, there are transitory price disturbances resulting from trading friction, the bid-ask spread, and price impact due to incidental liquidity pressures and from traders' reactions to each other's information.

Our hypothesis is that the trading mechanism under which stock prices are set and its timing affect the adjustment process of prices to value changes as well as the noise disturbances. Correspondingly, differences in trading mechanisms or in the timing of transactions bring about differences in value discovery. We focus on two summary statistics for the time-series behavior of stock returns: the return variance, which measures volatility, and the return autocorrelation, which reflects market inefficiency (Fama (1970)) and illiquidity (Roll (1984)).

The data consist of four daily prices: P_{o1}, P_{c1}, P_{o2}, and P_{c2}, where P_o and P_c are the opening and closing prices, and 1 and 2 signify the first (morning) and second (afternoon) trading sessions. The opening prices P_o are determined by the Itayose method, and the closing prices P_c are set in a continuous trading market by the Zaraba method. The data were collected from daily stock reports available from the TSE, and cover the period July 1, 1987 through June 30, 1988. We excluded the unusual week of the stock market crash, October 19–25, 1987. The sample includes the 50 stocks with the largest trading volume on the TSE during 1987.[4]

From the four price series, we calculated four daily return series, defined by

$$R_{ijt} = \log(P_{ijt}/P_{ij,t-1}),$$

where t indexes the trading day; $i = o, c$; and $j = 1, 2$ for the first and second trading session, respectively. These timing conventions are shown in Figure 1. Days with half-day trading, such as Saturdays on which trading occurs, were excluded and the reported Monday return was measured relative to Friday.[5] This is done to ensure that both prices used to estimate the returns are from the same trading session and method, and all four returns are measured over the same time period. The return series thus cover, for each

[4] The stock list is available upon request from the authors.

[5] These days were included, however, in the calculation of returns over intraday intervals (see Sections IV and V).

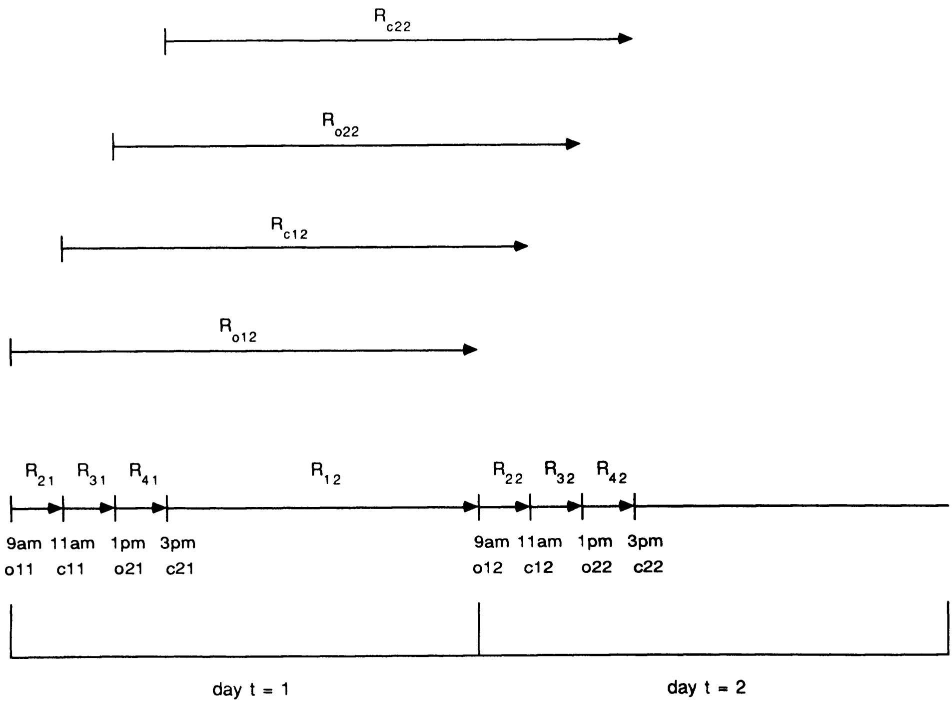

Figure 1. Timing of transactions in the Tokyo Stock Exchange. There are four daily transactions:

$o1$ = the opening of the morning session, at 9 A.M.

$c1$ = the closing of the morning session, at 11 A.M.

$o2$ = the opening of the afternoon session, at 1 P.M.

$c2$ = the closing of the afternoon session, at 3 P.M.

$R_{ijt} = \log(P_{ijt}/P_{ij,t-1})$ is the return on transaction ij ($i = o$ for opening, c for closing; $j = 1$ for the morning session, 2 for the afternoon session) from day $(t - 1)$ to day t. For example, R_{o22} is the return measured from the afternoon opening of day 1 to the afternoon opening of day 2. R_{kt} is the return on the kth interval of day t, where

$k = 2$ for the morning session (9 A.M.–11 A.M.),

$k = 3$ for the midday break (11 A.M.–1 P.M.),

$k = 4$ for the afternoon session (1 P.M.–3 P.M.), and

$k = 1$ for the overnight interval (from 3 P.M. on day $(t - 1)$ to 9 A.M. on day t).

stock, the very same time period, and differ only in the time of day at which we observe the prices. Permanent changes in the underlying stock values due to the arrival of new information should be *equally* incorporated in *all* four return series. Thus, any observed differences in the variances and autocorrelations of the four series reflect differences in value discovery and in the transitory price disturbances among them.

III. Variances and Autocorrelations

A. Returns

Table I presents the averages of the variances and first-order autocorrelations of the four return series. Regarding the variances, we obtain that $\text{Var}(R_{o1})$ is the largest variance of the day, whereas the other three variances, $\text{Var}(R_{c1})$, $\text{Var}(R_{o2})$, and $\text{Var}(R_{c2})$, are not different from each other. Focusing on the open-to-open returns, in the morning session $\text{Var}(R_{o1}) > \text{Var}(R_{c2})$ for 47 stocks with an average variance ratio of 1.18, whereas in the afternoon session $\text{Var}(R_{o2}) > \text{Var}(R_{c2})$ holds for only 28 stocks and the average variance ratio is 1.01.

The relatively large volatility in the opening transaction of the day may be due to two factors: (i) the effect of the Itayose trading mechanism employed in this transaction; or (ii) the effect of the preceding long nontrading period. Our results enable to discern between the two effects. When the Itayose is employed in the middle of the day, it has essentially the same volatility as that of the closing transactions of the morning and afternoon sessions, which are executed in the continuous Zaraba market. This is unlike the opening transaction of the day, which is substantially more volatile. Further, since both Itayose transactions attract a large and comparable proportion of the total trading volume, the lower volatility of the midday Itayose cannot be explained by a lower volume at this transaction. Thus, the results suggest that the higher volatility in the clearing transaction at the daily opening is caused by the preceding nontrading period rather than by the trading mechanism. These results are consistent with the notion that a sequence of recent transaction prices facilitates value discovery due to traders' ability to make a better inference about value changes for the security itself or for the market as a whole.

We next examined the dependence of these results on the "thinness" of trading in the stock by dividing the sample into two 25-stock subsamples, based on their 1987 trading volumes, and averaging the variance ratios for each subsample (see Table I, Panel A (2) and (3)). The results for the two subsamples are essentially the same as for the whole sample: $\text{Var}(R_{o1})$ is the largest variance of the day, with the other three variances being about equal to each other. This shows the robustness of our results.

Another measure of return behavior is the first-order autocorrelation presented in Table I, Panel B. For the 50 stocks in our sample, the daily open-to-open returns had uniformly negative autocorrelations, similar to what we found in the U.S. The correlation coefficients for the daily open-to-open returns averaged about −12%. The negative autocorrelations may result from price overreaction to value changes, from transitory price disturbances (such as the bid-ask spread, liquidity impacts, and pricing errors), or from both (Amihud and Mendelson (1987a)). The negative autocorrelation at the opening in both the NYSE and the TSE is noteworthy given that, in the NYSE, the opening is managed by a monopolistic specialist (who can affect prices), whereas in the TSE the opening is determined by competitive orders.

Table I

Variances and Autocorrelations of Returns

R_{o1} and R_{c1} are the open-to-open and close-to-close daily returns in the morning trading session, and R_{o2} and R_{c2} are the respective returns for the afternoon trading session. The table presents the means of the variances and of the first-order autocorrelations for each of the four return series, calculated for each stock over the period 7/1/87 to 6/30/88 and then averaged over the 50 sampled stocks. The sample consists of the 50 stocks with the highest trading volume in 1987 on the Tokyo Stock Exchange. The subsamples consist of the 25 lowest-volume and the 25 highest-volume stocks in the sample (based on reported 1987 trading volumes).

Panel A: Variances ($\times 10^6$)

	Morning Opening		Morning Close		Afternoon Opening		Afternoon Close
Samples	$\mathrm{Var}(R_{o1})$	$\frac{\mathrm{Var}(R_{o1})}{\mathrm{Var}(R_{c2})}$	$\mathrm{Var}(R_{c1})$	$\frac{\mathrm{Var}(R_{c1})}{\mathrm{Var}(R_{c2})}$	$\mathrm{Var}(R_{o2})$	$\frac{\mathrm{Var}(R_{o2})}{\mathrm{Var}(R_{c2})}$	$\mathrm{Var}(R_{c2})$
1. Whole Sample							
Mean	629	1.18	542	1.02	539	1.01	537
Standard deviation	151	0.13	128	0.11	131	0.11	137
Number of ratios >1		47		28		28	
2. Low-volume subsample of 25 stocks							
Mean	588	1.19	515	1.04	508	1.02	497
Standard deviation	144	0.11	131	0.12	134	0.12	118
Number of ratios >1		25		16		16	
3. High-volume subsample of 25 stocks							
Mean	669	1.18	569	1.00	571	1.00	577
Standard deviation	149	0.16	121	0.10	122	0.10	144
Number of ratios >1		22		12		12	

Table I—*Continued*

Panel B: First-Order Autocorrelations

	$\rho(R_{o1})$	$\rho(R_{c1})$	$\rho(R_{o2})$	$\rho(R_{c2})$
1. Whole sample				
Mean	−0.1201	−0.0126	0.0070	−0.0038
Standard deviation	0.0588	0.0692	0.0588	0.0585
Number of $\rho > 0$	0	20	28	25
2. Low-volume subsamples of 25 stocks				
Mean	−0.1151	−0.0189	0.0053	−0.0085
Standard deviation	0.0700	0.0745	0.0632	0.0725
Number of $\rho > 0$	0	10	13	12
3. High-volume subsample of 25 stocks				
Mean	−0.1252	−0.0063	0.0086	0.0009
Standard deviation	0.0460	0.0644	0.0553	0.0410
Number of $\rho > 0$	0	10	15	13

The autocorrelation of the close-to-close returns for the morning session averaged −1.26%; it was positive for 20 stocks and negative for 30. In the afternoon session, the average autocorrelation was 0.7% for the opening returns and −0.38% for the closing returns. The number of positive/negative coefficients was 28/22 at the opening and 25/25 at the close, and the autocorrelation of R_{o2} was higher than that of R_{c2} for 29 stocks. Again, the opening transaction of the day is distinct from the other three transactions, whereas there is practically no difference between the behavior of the opening and closing return series in the afternoon session.

The two volume-based subsamples of 25 stocks similarly exhibit mixed behavior for the afternoon openings and for the two closing sessions, in contrast to the uniformly negative return autocorrelations of the morning opening. The high-volume subsample has a slightly more negative average autocorrelation, although the difference between the two subsamples was minor. More negative autocorrelations for the subsample of "thinner" stocks are consistent with Roll's (1984) result (for AMEX and NYSE stocks) that the implicit bid-ask spread is higher for such stocks. Since the autocorrelation is decreasing in the relative spread, lower-volume stocks are expected to exhibit more negative autocorrelations. Overall, the behavior of the autocorrelations across the trading sessions for both subsamples reconfirms the robustness of our results: The afternoon opening transaction, although executed by the Itayose method just as the morning opening transaction, follows a similar pattern to that of the two closing transactions.

B. Residual Returns

The behavior of returns in the four transaction series is affected both by the market microstructure and by the movements of the common market index. By analyzing the behavior of the *residual* returns obtained after controlling for the market index, we can estimate more efficiently the effects of differences in market microstructure on individual stocks. Also, the use of residual returns enables us to perform statistical significance tests on the results.

We thus estimated the market model for each stock under each trading mechanism i in session j,

$$R_{ijt} = \alpha_{ij} + \beta_{ij} R_{ijt}^{m} + \varepsilon_{ijt}, \tag{1}$$

where R_{ijt}^{m} is the return on an equally weighted portfolio of all 50 stocks under trading mechanism i in session j on day t. We then calculated the *conditional* variances and autocorrelations of returns under each trading mechanism, namely, the variances and autocorrelations of the residuals from model (1). By conditioning the returns on the common index, we account for the corresponding cross-section dependence in returns, and under the assumptions of the single-index model the resulting estimates are cross-sectionally independent.

Summary statistics for the residual variances and first-order autocorrelations are presented in Table II. The lowest average residual variance and the lowest (in absolute value) average residual autocorrelation are both obtained for the opening transaction of the afternoon trading session. At the other extreme, the residual-return series of the morning opening have greater variances and more negative autocorrelations than any of the other residual-return series. These results are consistent with those obtained for the unconditional-return series.

Examining the significance of the relations between the four residual-return series, we observe that the variance for the morning opening exceeds the variance of the afternoon closing for 37 out of the 50 stocks. Under the null hypothesis of equal variances for the two series, the binomial probability of this occurring is less than 0.0005. On the other hand, the residual variances of the afternoon opening exceed those of the afternoon closing for 9 stocks only. The probability of this resulting from chance is $2.8 \cdot 10^{-6}$. We thus conclude that the residual variance in the morning opening is significantly *higher* than that of the daily closing, whereas the residual variance of the afternoon opening is *lower* than that of the daily closing. The residual variance of the afternoon opening transaction is usually slightly lower than that of the morning closing, and exceeds it for only 14 out of 50 stocks.

The autocorrelation coefficients are significantly negative for the daily open-to-open and close-to-close residual return series ($t = -6.22$ and -2.43, respectively). The mean autocorrelations of the two midday residual return series are not significantly different from zero. Testing the significance of the proportion of cases with negative autocorrelations gives similar results. Again, the negative autocorrelation pattern is most significant at the daily opening, where it is positive for only eight stocks.

We again segregated the data based on trading volume into two 25-stock subsamples as we did in Table I. The variance ratios exhibited the same pattern as the whole sample, confirming the robustness of our results.[6] The volatility of the afternoon open-to-open returns was the lowest for both samples, and their autocorrelation was the highest, indicating the least noise. The first-order autocorrelations were significantly more negative in our low-volume subsample compared to the high-volume subsample (Table II, Panel B (2) and (3)). As already discussed, this is consistent with Roll's (1984) findings on the higher (implicit) bid-ask spread of "thinner" stocks. As discussed by Amihud and Mendelson (1987a), this effect may be offset by the partial price-adjustment process which tends to increase the return autocorrelation. We find that the morning open-to-open return autocorrelations are significantly negative for both subsamples, again reaffirming our general results. For the other return series, the average return autocorrelations of the low-volume subsample tend to be negative, whereas those of the high-

[6] The mean ratio of the open-to-open to close-to-close variances is slightly higher for our low-volume subsample, but the difference between the means is statistically insignificant.

Table II

Variances and Autocorrelations of Residual Returns

The residuals are ε_{ijt} from the model

$$R_{ijt} = \alpha_{ij} + \beta_{ijt} + R^m_{ijt} + \varepsilon_{ijt}$$

where R are daily returns on the stock, $i = o$, c signifies open-to-open or close-to-close, $j = 1$, 2 is the morning and afternoon trading session, respectively, and R^m is the return on the equally weighted portfolio of all 50 stocks. The model is estimated for each stock to obtain the residual series for which the variances and autocorrelations are calculated. The table presents summary statistics for the respective variances and autocorrelations calculated for each of the 50 sampled stocks over the period 7/1/87 to 6/30/88. The subsamples consist of the 25 lowest-volume and the 25 highest-volume stocks in our sample (based on reported 1987 trading volumes).

Panel A: Variances ($\times 10^6$)

	$\text{Var}(\varepsilon_{o1})$	$\frac{\text{Var}(\varepsilon_{o1})}{\text{Var}(\varepsilon_{c2})}$	$\text{Var}(\varepsilon_{c1})$	$\frac{\text{Var}(\varepsilon_{c1})}{\text{Var}(\varepsilon_{c2})}$	$\text{Var}(\varepsilon_{o2})$	$\frac{\text{Var}(\varepsilon_{o2})}{\text{Var}(\varepsilon_{c2})}$	$\text{Var}(\varepsilon_{c2})$
1. Whole sample							
Mean	346	1.08	308	0.95	296	0.91	326
Standard deviation	106	0.14	97	0.11	103	0.11	112
Number of ratios >1		37		17		9	
2. Low-volume subsample of 25 stocks							
Mean	337	1.10	296	0.97	274	0.90	306
Standard deviation	102	0.14	83	0.13	81	0.12	85
Number of ratios >1		21		11		5	
3. High-volume subsamples of 25 stocks							
Mean	354	1.05	320	0.93	318	0.92	347
Standard deviation	111	0.14	110	0.08	118	0.09	132
Number of ratios >1		16		6		4	

Table II—*Continued*

Panel B: First-Order Autocorrelations

	$\rho(\varepsilon_{o1})$	$\rho(\varepsilon_{c1})$	$\rho(\varepsilon_{o2})$	$\rho(\varepsilon_{c2})$
1. Whole sample				
Mean	−0.0789	−0.0180	0.0096	−0.0340
Standard deviation	0.0897	0.1027	0.0800	0.0988
Number of $\rho > 0$	8	22	28	20
2. Low-volume subsample of 25 stocks				
Mean	−0.1184	−0.0542	−.0180	−0.0776
Standard deviation	0.0899	0.094	0.0705	0.0982
Number of $\rho > 0$	1	9	10	5
3. High-volume subsample of 25 stocks				
Mean	−0.0395	0.0181	0.0372	0.0096
Standard deviation	0.0714	0.0999	0.0806	0.0794
Number of $\rho > 0$	7	13	18	15

volume subsamples are on average positive, reflecting the higher (implicit) bid-ask spread of the thinner stocks.

Summarizing the behavior of the residual-return series, we observe that the opening transaction of the day has the highest volatility and the most negative autocorrelation of the four transactions studied. In contrast, the midday opening transaction has the lowest volatility and practically zero autocorrelation.[7] This suggests that the periodic-clearing transaction per se does not hamper value discovery, and that the high volatilities and negative autocorrelations at the morning opening reflect the long preceding period of no trading.

Our sample of 50 stocks includes five that are also traded in the U.S. Two stocks are listed on the New York Stock Exchange, and three are traded on the NASDAQ National Market System.[8] Because trading in the U.S. takes place during Japan's overnight period, the effective nontrading period for the five U.S.-traded Japanese stocks is considerably shorter than it is for the other 45 stocks in our sample, and value discovery for these stocks at the morning opening in Tokyo may be facilitated by the availability of U.S. trading prices during the overnight period in Japan. If the high volatility and the negative autocorrelation in the morning Itayose transaction are due to the long nontrading period that precedes it, we should expect for the five U.S.-traded stocks lower volatility at the morning opening (relative to the closing) and less negative first-order autocorrelations. We thus compared the respective statistics for these five stocks with those of the other 45 stocks.

The average ratio of the variances of open-to-open to close-to-close residuals is 1.003 for the five U.S.-traded stocks, compared to 1.085 for the 45 remaining stocks. The average autocorrelation of the open-to-open residual returns is 0.002 for the five U.S.-traded stocks, compared to −0.088 for the remaining 45 stocks. These findings are consistent with our hypothesis: U.S. trading prior to the daily opening in Tokyo seems to lead to a lower variance ratio and to a less negative autocorrelation.

To test the significance of these results, we estimated the following models for the variance ratios $\frac{\mathrm{Var}(\varepsilon_{o1,s})}{\mathrm{Var}(\varepsilon_{c2,s})}$ and the daily open-to-open autocorrelations $\rho(\varepsilon_{o1,s})$ of our fifty stocks:

$$\frac{\mathrm{Var}(\varepsilon_{o1,s})}{\mathrm{Var}(\varepsilon_{c2,s})} = a_0 + a_1 \cdot USDUM_s + u_s, \tag{2}$$

and

$$\rho(\varepsilon_{o1,s}) = b_0 + b_1 \cdot USDUM_s + b_2 \cdot \log(\mathrm{VOLUME}_s) + v_s. \tag{3}$$

[7] Recall that this is despite the fact that the midday opening transaction attracts a high trading volume.

[8] These stocks are, respectively, Hitachi, Matsushita Electric Industries, Mitsui, NEC and Tokio Marine & Fire Insurance. They appear in the Fall 1987 list of "SEC Filing Companies, Foreign Registrants."

In equations (2) and (3), ε is the residual return from the market model (1), $USDUM = 1$ if the stock is traded in the U.S. or zero otherwise, s is the stock index ($s = 1, 2, \ldots, 50$), a_0, a_1, b_0, b_1, and b_2 are the regression coefficients, and u, v are the error terms. Because the results may also depend on stock "thinness"—stocks with greater trading volume should have lower noise, which causes negative autocorrelation—we controlled for trading volumes by the variable VOLUME, the 1987 trading volume of the stock. Our hypotheses are $a_1 < 0$, $b_1 > 0$, and $b_2 > 0$.

The estimation results were as follows: $a_1 = -0.0829$ ($t = 1.25$), and $b_1 = 0.0919$ ($t = 2.30$), $b_2 = 0.0268$ ($t = 1.69$). In the variance ratio equation, the coefficient a_1 is negative, as expected, but insignificant. In the autocorrelation equation, both b_1 and b_2 have the expected signs and both coefficients are significantly different from zero at the 5% level. Thus, U.S. trading tends to increase the efficiency of the daily opening in Tokyo ($b_1 > 0$), consistent with our hypothesis. These results provide additional evidence that the high volatility at the daily opening may be attributed to the lengthy nontrading period that precedes it rather than to the trading mechanism employed at the opening transaction.

IV. Volatility in Trading and Nontrading Periods

Stock return volatility can result from the arrival of new information or from the trading process itself. Black (1986) and French and Roll (1986) suggested that some volatility might be generated by individual investors who interact with each other, reveal their private information and overreact to each other's trades. French and Roll (1986) examined this hypothesis by comparing the volatility on regular trading days to that of holidays and weekends, and Barclay, Litzenberger, and Warner (1990) studied the volatility of Japanese and U.S. stocks, some of which are listed in both countries. Both studies found that the ratio of the n-day return variances, when the n days include holidays, to the return variance of a single trading day, was much smaller than n. Barclay, Litzenberger, and Warner (1990) found that the two-day holiday return variance was only 30% higher than the average weekday return variance, and that the return variance on Saturdays when trading takes place only in the morning session was 63% of the average weekday return variance. French and Roll (1986) found that "the per-hour return variance was about 70 times larger during a trading hour than during a weekend nontrading hour" (p. 23), but it was unclear whether this reflects trading-induced volatility, or the fact that "the arrival of public information may be more frequent during the business day" (p. 23). Their results on the lower volatility of returns over two-business-day intervals including exchange holidays show that volatility is associated with trading and the private information it reveals.

We provide strong evidence on this issue by comparing the return volatility over trading and nontrading periods *during* the business day. In the TSE, we have two daily two-hour trading periods with a two-hour nontrading period between them. If information arrives uniformly during the six hours of the business day (between 9 A.M. and 3 P.M.) and is immediately incorporated in the price, and if volatility is generated only by the arrival of new information, the return variances should be the same for all three 2-hour periods. If trading contributes to volatility either through the revelation of private information or due to pricing errors, the return variance over the two-hour nontrading period should be lower. Clearly, a lower volatility during the 11 A.M. to 1 P.M. period could also reflect a lower intensity of new information arriving over these two hours.

We divided each day into four intervals and defined the four return series R_{kt} for our four time intervals, $k = 1, 2, 3, 4$, by

$$\begin{aligned} R_{1t} &= \log(P_{o1,t}/P_{c2,t-1}) \\ R_{2t} &= \log(P_{c1,t}/P_{o1,t}) \\ R_{3t} &= \log(P_{o2,t}/P_{c1,t}) \\ R_{4t} &= \log(P_{c2,t}/P_{o2,t}), \end{aligned}$$

(see Figure 1). Next, we calculated $R^m_{k,t}$, $k = 1, 2, 3, 4$, the return on the equally weighted index for each of the four time series. Finally, we calculated for each series k the residuals from the market model for each stock l,

$$R^l_{kt} = \alpha^l_k + \beta^l_k R^m_{kt} + \varepsilon^l_{kt}. \tag{4}$$

Table III presents the averages of the return variances during the four time intervals, the three daytime 2-hour periods and the overnight period.[9] The results support the hypothesis that trading and the associated process of information dissemination contribute to volatility. The average return variance of the morning (afternoon, respectively) trading period is 5.4 (4.5) times greater than the average return variance of the midday break (Panel A), and the average residual variance of the morning (afternoon) trading session is 3.8 (3.6) times greater than the average residual variance of the intraday break (Panel B), although all three periods are two hours long. Further, the per-hour return variance of the midday break is about twice as high as the per-hour return variance during the overnight period. This difference could result from the greater intensity of information arrival during the day compared to the overnight period. Given that the overnight period includes hours when businesses are open (trading closes at 3:00 P.M. and opens at 9:00 A.M.), the ratio of the return variances during business and non-business hours is actually greater than 2.

These results are consistent with some U.S. evidence on the behavior of volatility over the trading day. In the NYSE, where trading is continuous during the day, it was observed that the return variance during the middle of the day is lower than the return variance at the beginning and at the end of the day (Wood, McInish, and Ord (1985), Harris (1986), Lockwood and Linn

[9] These data include days with only morning trading.

Table III

Volatility of Returns and Market-Model Residuals for Intraday Intervals

The table presents the average estimated variances of the daily series R_k and of the market model residuals ε_k over the 50 stocks. There are four intraday returns R_k: R_1 = overnight return; R_2 = return over the morning trading session; R_3 = return over the lunch break; and R_4 = return over the afternoon trading session. The residuals (Panel B) are ε_{kt} from the model

$$R_{kt} = \alpha_k + \beta_k R_{kt}^m + \varepsilon_{kt},$$

where R_{kt} is the return on the stock in day t over interval k (k = 1, 2, 3, 4), α_k and β_k are constants, and R_{kt}^m is the return on the equally weighted portfolio of all 50 stocks for day t and interval k. The variances are calculated for each stock over the period 7/1/87 to 6/30/88 and then averaged over the 50 sampled stocks.

Panel A: Average Return Variances ($\times 10^6$)*				
	Overnight R_1	Morning session R_2	Lunch break R_3	Afternoon session R_4
Variance	188	207	38	172
	(42)	(59)	(14)	(43)
Panel B: Average Residual Variances ($\times 10^6$)*				
	ε_1	ε_2	ε_3	ε_4
Variance	105	127	33	119
	(30)	(34)	(13)	(31)

* Numbers in parentheses are standard deviations.

(1990)). It could be that the rate of arrival of news during lunchtime is lower, or that traders retire to lunch and trading intensity declines, and then informed traders are less inclined to trade on their information. These reasons can explain our evidence from the TSE on the low volatility during the midday break. Thus, our results provide new evidence that the trading process, the pricing errors it generates and the private information it reveals contribute to volatility.

The results in Table III suggest that the time-series behavior of returns over the four time intervals is not a random walk. Specifically, the sum of the average variances of the four interval returns is greater than the average daily return variance.[10] This difference indicates that the returns over the four time intervals include a great deal of noise which dissipates through the trading day. This dissipative noise is expected to be smaller for the five stocks which are also traded in the U.S., because the longer trading period for these stocks can mitigate pricing errors. While foreign listing of domestic stocks does not change their total daily return variance (Barclay, Litzenberger, and Warner (1990)), the longer trading hours due to foreign

[10] This is seen by comparing the sum of the four interval variances with the respective close-to-close daily variances in Panel A of Tables I and II.

listing can affect value discovery and, hence, the noise during the trading day.

We tested the mitigating effect of U.S. trading on the noise as follows. We first calculated for each stock s the ratio of the sum of the four intraday residual variances to the daily residual variance,

$$VRATIO_s = \left[\mathrm{Var}(\varepsilon_{1,s}) + \mathrm{Var}(\varepsilon_{2,s}) + \mathrm{Var}(\varepsilon_{3,s}) + \mathrm{Var}(\varepsilon_{4,s})\right]/\mathrm{Var}(\varepsilon_{c2,s}).$$

The mean of $VRATIO_s$ was 1.217 with a standard error of 0.025, significantly different from unity. We then regressed $VRATIO_s$ on the dummy variable *USDUM* which takes a value of 1 for stocks traded in the U.S., and obtained the following results:

$$\underset{}{VRATIO_s} = \underset{(50.76)}{1.242} - \underset{(3.25)}{0.252} \cdot USDUM_s,$$

(t-values are in parentheses). This implies that the variance ratio for the five U.S.-traded stocks is practically unity, while that for the remaining 45 stocks it is significantly greater than 1.

Trading volume, which proxied for liquidity, is also expected to affect trading noise. Stocks with greater trading volume should exhibit less noise during the trading day, whereas "thinner" stocks should have more noise. Thus, we added the volume variable to the above regression, obtaining

$$VRATIO_s = \underset{(5.08)}{2.170} - \underset{(3.44)}{0.256} \cdot USDUM_s - \underset{(2.17)}{0.064} \cdot \log(\mathrm{VOLUME}_s).$$

These results establish that the prices set in the market during the day are noisy, and that the noise is smaller for heavily traded stocks and for stocks which traded in the U.S. This may imply that the globalization of trading can reduce noise in asset pricing and improve value discovery.

Noise and pricing errors also result in price reversals over the trading day. These are explored in the next section.

V. Intraday Price Reversals

If some of the observed volatility is noise, it ought to be subsequently "corrected." In this section we present evidence on the existence of price reversals in the TSE during the trading day. When the price of a stock changes, particularly when the change is perceived to deviate from the market, investors reverse this deviation and make the stock price conform more closely to the general market trend. That is, the deviations of stock prices from their expected levels conditional on the market are partly *transitory* rather than permanent. These deviations may reflect pricing errors due to the market impact of orders, the bid-ask spread (explicit or implicit)[11] and

[11] On the TSE, there is no market-designated specialist who sets bid-ask prices, and the spread is determined by traders' limit orders.

other market-microstructure factors. As we show below, the pattern of price reversals differs across trading sessions.

A simple interpretation of the relation between price reversals and transitory pricing errors is due to Roll (1984). Consider three transaction epochs 1, 2, and 3, and assume that the value of the security at the ith transaction epoch is V_i, where the value-returns over nonoverlapping intervals, $(V_2 - V_1)$ and $(V_3 - V_2)$, are independent. Also assume that the *price* measured in transaction i is $p_i = V_i + u_i$, where u_i reflect pricing errors or noise (interpreted by Roll (1984) as the implicit bid-ask spread) and are mutually independent and independent of V_i. The measured returns over the intervals from 1 to 2 and from 2 to 3 are then given by $R_{12} = p_2 - p_1 = (V_2 - V_1) + (u_2 - u_1)$ and $R_{23} = p_3 - p_2 = (V_3 - V_2) + (u_3 - u_2)$. A positive "noise" error in transaction 2, u_2, will be added to R_{12} and subtracted from R_{23}, leading to an observed transitory price reversal. The magnitude of the price reversal is quantified by the return covariance,

$$\mathrm{Cov}(R_{12}, R_{23}) = -\mathrm{Var}(u_2). \tag{5}$$

Thus, the (negative) return covariance reflects the pricing noise u_2 at the trading epoch joining the two intervals, and its size is equal to minus the noise variance.[12] Similarly, negative return autocorrelations reflect the preponderance of prices to correct (or reverse) themselves over subsequent intervals.

We estimated the correlation coefficients between the returns in each of the four intervals and the returns in the immediately preceding four intervals, encompassing the chain of possible reversions over the 24-hour period. Thus, for example, R_{2t} was correlated with R_{1t}, $R_{4,t-1}$, $R_{3,t-1}$, and $R_{2,t-1}$, where t indexes the trading days.[13] We also estimated the residual correlations in a similar way. The resulting correlation coefficients enable us to examine the way in which the market "corrects" for price deviations (or, equivalently, the noise in each of the four transactions).

We denote by $\rho(R_{k,-n})$ the correlation between the return in interval k and the return in the nth interval which precedes it (k, $n = 1, 2, 3, 4$); and $(\rho\varepsilon_{k,-n})$ denotes the corresponding correlation for the market-model residuals. A negative correlation coefficient implies price reversal. For $\rho(R_{k,-n})$, the reversal is toward a constant mean, and for $\rho(\varepsilon_{k,-n})$ the reversal is toward a mean conditional on the market.

The results are presented in Table IV. Panel A presents $\rho(R_{k,-n})$ and Panel B presents $\rho(\varepsilon_{k,-n})$. Consider first the returns: the mean of $\rho(R_{2,-1})$ is -19.4%, and all the corresponding 50 coefficients for the individual stocks are negative. The correlation coefficient is far more negative than $\rho(R_{k,-1})$

[12] Note that neither u_1 nor u_3 affect the covariance (5).

[13] For days following a day with a single (morning) trading session, the correlations were calculated with the preceding morning session serving as the last trading session of the day, and correlations of lags -2 and -3 were omitted. In this way the autocorrelations never reached beyond one trading day back.

Table IV

Correlations of Returns and Residuals for Intraday Intervals

Correlations of returns R_k and residuals ε_k with the four preceding values. The subscript k signifies the four time intervals: $k = 1$ for the overnight returns (and residuals), $k = 2$ for the morning trading session, $k = 3$ for the lunch break, and $k = 4$ for the afternoon trading session. For example, $\rho(R_1, R_{-1})$ is the correlation between the overnight return and the return over the preceding afternoon session; $\rho(R_2, R_{-1})$ is the correlation between the return over the morning session and the preceding overnight return, etc. The correlations are calculated for each stock over the period 7/1/87 to 6/30/88. The numbers presented are the averages of the correlations for the 50 stocks. Numbers in parentheses are standard deviations. F_{-1} is the F-statistic from a test of equality of the first-order correlations.[a]

Panel A: Average Autocorrelations of Returns

	R_{-1}	R_{-2}	R_{-3}	R_{-4}
R_1	−0.007	0.026	0.083	0.093
	(0.086)	(0.075)	(0.072)	(0.062)
R_2	−0.194	−0.004	−0.020	−0.008
	(0.076)	(0.078)	(0.097)	(0.083)
R_3	−0.048	0.027	0.008	−0.012
	(0.115)	(0.075)	(0.080)	(0.094)
R_4	−0.042	−0.073	0.064	−0.029
	(0.082)	(0.071)	(0.067)	(0.076)

Panel B: Average Correlations of Market-Model Residuals

	ε_{-1}	ε_{-2}	ε_{-3}	ε_{-4}
ε_1	−0.159[b]	0.012	0.072[b]	0.067[b]
	(0.076)	(0.067)	(0.081)	(0.065)
ε_2	−0.190[b]	−0.003	−0.011	0.011
	(0.104)	(0.083)	(0.088)	(0.059)
ε_3	−0.193[b]	0.039[b]	−0.015	0.001
	(0.102)	(0.068)	(0.069)	(0.072)
ε_4	−0.099[b]	−0.013	0.004	0.007
	(0.071)	(0.063)	(0.069)	(0.090)

[a] $F_{-1} = 12.00$. The F value results from a test of the hypothesis that the means of the first-order correlations in the panel are equal.

[b] Significantly different from zero at the 1% level.

for $k = 1$, 3, and 4, suggesting that the prices set during the morning session reverse the returns set at the opening transaction. By (5), this is associated with pricing errors in the opening transaction of the day.

A test of equality of the four average first-order correlations produced a value of $F = 41.7$, highly significant. Pairwise tests of the differences between the mean of $\rho(R_{2,-1})$ and the means of the other three correlations $\rho(R_{k,-1})$ for $k = 1$, 3, and 4 produced t-values of 11.71, 7.74, and 9.29, respectively, all highly significant. The price reversal during the morning session is completed in that session: $\rho(R_{2,-n})$ for $n = 2$, 3, and 4 are practically zero. We also find a weak pattern of price reversals during the intraday nontrading period and during the second trading session, as indicated by the negative mean values of $\rho(R_{3,-1})$ and $\rho(R_{4,-1})$.

The results in Panel B on the correlations of the market-model residuals $\rho(\varepsilon_{k,-n})$ show considerable intraday price reversals *conditional* on the market. The conditional price reversals are usually stronger than the unconditional ones: the average autocorrelation coefficient for the residuals $\rho(\varepsilon_{k,-1})$ (Panel B) is more negative for $k = 1$, 3, and 4 than it is for the returns in Panel A, and it is about the same for $k = 2$. The first-order correlation $\rho(\varepsilon_{k,-1})$ is the least negative for $k = 4$, and significantly so. An F-test for the equality of the first-order correlations yields an F-value of 12.0, and the t-statistics for the differences between $\rho(\varepsilon_{4,-1})$ and $\rho(\varepsilon_{k,-1})$ for $k = 1, 2,$ and 3 are (respectively) 4.40, 5.14 and 5.55, highly significant. This implies fewer price reversals in the interval following the midday opening, pointing again at the relatively higher quality of prices set at this clearing transaction.

The *magnitude* of the price reversals was measured in two ways. First, we calculated the first-order *covariances* of the returns and residual returns.[14] By (5), a more negative covariance reflects greater pricing errors at the transaction joining the two intervals over which returns are measured. The sample applies to the residual return series ε_{kt}. The results, presented in Table V, mirror the behavior of the first-order correlations: The magnitude of price reversals is largest in the morning session, as evidenced by its most negative autocovariance. This applies both to the returns (Panel A) and to the market-model residuals (Panel B). While all the autocovariances of the residual returns are negative and significant, the price-reversal magnitude is the smallest over the afternoon session (R_4). By (5), this corresponds to a smallest noise variance in the opening of the afternoon trading session.

The second measure of the price-reversal magnitude is obtained by simulating a trading rule designed to exploit the reversal pattern by buying following a price decline in the previous interval and selling following a price increase. Specifically, assume that when the price in one time interval rises, a trader takes a short position for the next interval in anticipation of a price decline; and when the price declines, the trader takes a long position in the stock for the next interval in anticipation of a price increase. The returns to a trader following such a strategy for the kth interval on trading day t, denoted by TR_{kt}, are defined as follows. Let $R_{kt,-1}$ denote the return in the interval just preceding the kth interval of day t. That is, $R_{kt,-1} = R_{k-1,t}$ for $k = 2, 3,$ or 4, and $R_{1t,-1} = R_{4,t-1}$. If $R_{kt,-1} > 0$, we define $TR_{kt} = -R_{kt}$; and if $R_{kt,-1} < 0$, we set $TR_{kt} = R_{kt}$ (if $R_{kt,-1} = 0$, no transaction takes place and the return is omitted from the calculations).

We averaged the returns associated with this trading rule by the number of such transactions to obtain the gain per transaction. Clearly, the greater

[14] The return covariance for interval k is the average product of the return series $R_{kt}(k = 1, 2, 3, 4)$ with the preceding returns (adjusted for their means), and serves as a natural measure of the size of price reversals. By Roll (1984), the first order covariance measures the implicit bid-ask spread.

Table V

Magnitude of Price Reversals for Intraday Intervals

Measures of the magnitude of price reversals in each time interval k ($k = 1, 2, 3, 4$), signifying (respectively) the overnight period, the morning trading period, the midday break, and the afternoon trading period, for the returns R_k (Panel A) and for the market-model residuals ε_k (Panel B).

Measure 1: First-order autocovariance.

Measure 2: Average of trading-rule returns TR_k, calculated for a trading rule that sells following a price increase and buys following a price decline:

$$\text{If} \quad R_{kt,-1} > 0, \qquad TR_{kt} = -R_{kt}$$
$$\text{If} \quad R_{kt,-1} < 0, \qquad TR_{kt} = R_{kt}.$$

$R_{kt,-1}$ is the return on the interval that just precedes interval k on day t. The same measures are applied to the residuals (Panel B). Numbers shown are averages of the respective measures over 50 stocks. Numbers in parentheses are standard deviations.

	Overnight R_1	Morning session R_2	Lunch break R_3	Afternoon session R_4
Panel A: Returns				
1. Autocovariance ($\times 10^4$)	−0.012	−0.378	0.041	0.033
	(0.153)	(0.168)	(0.096)	(0.063)
2. Trading-rule returns (in %)	0.026	0.270	0.033	−0.006
	(0.117)	(0.124)	(0.059)	(0.124)
Panel B: Residuals				
	ε_1	ε_2	ε_3	ε_4
1. Autocovariance ($\times 10^4$)	−0.180*	−0.210*	−0.121*	−0.061*
	(0.092)	(0.128)	(0.073)	(0.047)
2. Trading-rule returns (in %)	0.128*	0.176*	0.082*	0.048*
	(0.080)	(0.082)	(0.052)	(0.074)

* Significant at better than 1%.

the magnitude of the price reversals, the greater the measured gain from this trading rule. The results are presented in Table V. For the returns (Panel A), the only case showing a meaningful gain is the morning trading session, during which there is a strong reversal relative to the opening Itayose price. We applied a similar procedure to the residual returns, producing the series $T\varepsilon_k$ defined by $T\varepsilon_{kt} = -\varepsilon_{kt}$ when $\varepsilon_{kt,-1} > 0$, and $T\varepsilon_{kt} = \varepsilon_{kt}$ when $\varepsilon_{kt,-1} < 0$, (where $\varepsilon_{kt,-1}$ denotes the residual in the interval just preceding interval k on day t, and $T\varepsilon_{kt} = 0$ when $\varepsilon_{kt,-1} = 0$). The results for the residual-return series are shown in Table V, Panel B. Because all four intervals reverse the previous returns, the trading rule generates significant gains. As was the case using the other measures, these gains were largest for the morning trading session and smallest for the afternoon trading session which follows the midday Itayose transaction. Again, the price of the afternoon opening transaction seems to be reversed the least. It is worth pointing out that the trading-rule "profits" reported in Table V do not necessarily represent real profit opportunities but are merely measures of the price-reversal magnitude. This is because trading-rule profits are calculated under the assumption that transactions could actually be executed at the reported prices (see Amihud and Mendelson (1987b)).

VI. Conclusions and Implications

In this paper we presented evidence on the effects of the trading mechanism coupled with the timing of transactions on stock price behavior. The comparison uses data from the Tokyo Stock Exchange, where a periodic clearing mechanism (Itayose) is employed in the opening transaction of both the morning and the afternoon trading sessions, and then trading proceeds by the continuous method (Zaraba). Thus, we can analyze the impact of a clearing transaction which is straddled by continuous trading sessions, an analysis which could not be done in the U.S. stock markets, where a clearing transaction takes place only at the morning opening, after a long non-trading period. Our empirical methodology compares the behavior of returns measured over the same time periods but at different epochs. If only information were to cause price variations, then all the return series we measured would exhibit the same behavior. Our results show, however, that, in addition to information, market microstructure factors have an effect on price behavior.

We find that the periodic clearing mechanism has a different impact on prices when employed in the middle of the day. The daily open-to-open returns are more volatile and exhibit more negative autocorrelations than the close-to-close returns, consistent with our earlier findings on U.S. stocks (Amihud and Mendelson (1987a)). However, the afternoon open-to-open return series in Tokyo, which reflects the effect of the Iyatose without a long preceding nontrading period, has practically the same volatility and autocorrelation as the close-to-close returns of the morning and afternoon sessions. Thus, unlike the daily opening transaction, the midday clearing transaction does not produce greater pricing errors than the continuous market.

We extend our basic methodology—examining the variances and autocorrelations of returns over overlapping daily intervals—to study the market-model *residuals* of each return series. This enables us to focus on the idiosyncratic market microstructure effects on stock returns and to perform statistical significance tests on the results. Examining the market-model residuals of our four return series, we obtain that the afternoon open-to-open residual series has lower volatility and higher (less negative) autocorrelation than the other three residual return series. This, it seems that the culprit in the high volatility and negative autocorrelation of daily open-to-open returns is the preceding nontrading period rather than the clearing transaction mechanism itself. These results prevailed when we split our sample into two 25-stock subsamples based on trading volumes: both subsamples exhibit similar behavior across the trading sessions, although the low-volume subsample had more negative autocorrelations, as might be expected.

Our results show that (i) the midday clearing transaction is characterized by low price volatility and efficient value discovery, and (ii) a sequence of recent transaction prices facilitates value discovery and eases traders' inference on the current value of the security as well as on the market as a whole.

Five of the 50 stocks in our sample also trade in the U.S. For these stocks, value discovery may be facilitated by the available sequence of transaction prices from the U.S. trading day. We indeed find that the daily (open-to-open)/(close-to-close) variance ratio is lower than it is for the other 45 stocks, and the open-to-open return autocorrelation is significantly less negative. That is, the pricing errors in the opening are lower for the five stocks with U.S. trading. In addition, the ratio of the sum of the residual variances over the four daily intervals to the daily residual variance, which is a measure of the pricing noise, is lower for the five cross-listed stocks. These results suggest that the globalization of trading may have a beneficial effect on value discovery.

Another comparison of the morning and afternoon clearing transactions is obtained by comparing the price reversals that follow them. We find strong short-term price reversals in the morning session, where changes in the stocks' opening prices (relative to the previous day's closing prices) are partially reversed during the two-hour trading interval that follows. The average correlation between the morning session's return and the previous overnight return is nearly −20%. The midday opening, however, is not followed by a price reversal, consistent with smaller pricing errors in this transaction. We also find a pattern of conditional mean price reversals: The market-model residuals in each session are negatively correlated with the residuals in the previous session, but the price reversal following the morning opening transaction (measured by the first-order correlation) is about twice as high as it is following the afternoon opening. Similar conclusions are reached using two measures of the magnitude of price-reversals, the serial covariances of the returns and market-model residuals, and the profits from a simulated trading rule that exploits the price reversals. These results show again that pricing errors in the midday clearing transaction are lower than those on any of the other three daily transactions.

The results have practical implications for the design of trading mechanisms in securities markets.[15] Amihud and Mendelson (1985, 1988, 1990) proposed instituting a periodic clearing transaction in the middle of the continuous trading session, suggesting that it has significant advantages in terms of the depth and liquidity it provides and the ability to cross-condition orders for different securities (Mendelson (1982, 1985), Amihud and Mendelson (1985, 1988)). Our results suggest that the clearing transaction mecha-

[15] The design of securities markets is important since it affects liquidity, which is a determinant of asset returns (see Amihud and Mendelson (1986, 1988, 1989a, 1991).

nism is not inferior (and perhaps it is superior) in terms of its volatility and efficiency when instituted during the trading day concurrently with continuous trading.

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