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Trading Mechanisms and Stock Returns: An Empirical Investigation

YAKOV AMIHUD and HAIM MENDELSON*

ABSTRACT

This paper examines the effects of the mechanism by which securities are traded on their price behavior. We compare the behavior of open-to-open and close-to-close returns on NYSE stocks, given the differences in execution methods applied in the opening and closing transactions. Opening returns are found to exhibit greater dispersion, greater deviations from normality and a more negative and significant autocorrelation pattern than closing returns. We study the effects of the bid-ask spread and the price-adjustment process on the estimated return variances and covariances and discuss the associated biases. We conclude that the trading mechanism has a significant effect on stock price behavior.

I. Introduction

WHILE SECURITIES exchanges in the United States typically operate as continuous trading markets where specialists and dealers act as market-makers, the operation of many exchanges around the world resembles a periodic call market, where buy and sell orders accumulate during some time interval and are then executed simultaneously at a price which equates the quantity supplied to the quantity demanded.[1]

Recent developments in securities markets induce policy makers to critically evaluate existing trading procedures. The plans to establish a national market system, the increase in trading volumes, the fierce competition between exchanges and over-the-counter markets and the expansion of electronic trading, all made the securities industry ready for a change. All major U.S. exchanges are continuously evaluating new (mostly automated) trading procedures, and European capital markets are already allowing forms of continuous trading together with their ordinary call market procedures.[2] Thus, it is of interest to examine the effects that these alternative trading methods may have on stock price behavior.

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[1] For a recent survey of trading methods in the main world exchange markets, see Whitcomb (1985), Cohen, Maier, Schwartz and Whitcomb (1986, Ch. 2) and Ho, Schwartz and Whitcomb (1981).

[2] For example, the *Borsa di Milano*, where orders are batched and executed periodically applying the call method, is moving to continuous trading in some active stocks. On the other hand, Ho, Schwartz and Whitcomb (1981) proposed to adopt a batched trading system for some NYSE stocks. Amihud and Mendelson (1985) proposed an integrated computerized trading system which will allow the two trading mechanisms to operate simultaneously. A system that applies some of their principles is to be implemented, on an experimental basis, in the Tel Aviv Stock Exchange.

The dealership market regime has been studied quite extensively, both theoretically and empirically (see a review by Stoll (1985)). The periodic call trading procedure received less attention, and was recently studied by Mendelson (1982, 1985, 1986, 1987a) and by Ho, Schwartz and Whitcomb (1985). Theoretical comparisons of the two market mechanisms are scarce (Garbade and Silber (1979), Mendelson (1985, 1987a)), and empirical comparisons of price behavior under these mechanisms are virtually non-existent. The difficulty with the empirical comparison is that different markets trade different assets and these assets are traded in different environments, hence it would be hard to discern differences resulting from the trading mechanism itself from differences due to dissimilarities of securities and environments.[3]

This paper offers to resolve this difficulty by comparing the price behavior of New York Stock Exchange stocks in the opening transactions with the price behavior of the same stocks traded at the same exchange during the same period in the closing transactions. The opening transactions represent the outcome of a call trading procedure, whereas trading at the close is carried out at prices which are set or affected by the exchange's market-makers.

Our analysis of the opening and closing transaction prices distinguishes between the intrinsic *value* of a security and its observed *price*; the difference between the two may be attributed to *noise* (Black (1986)). We propose that this noise is due in part to the process by which prices are set in the market, i.e., to the trading mechanism. Studying the effect of the trading mechanism on observed prices will enable us to account for this part of the noise, and will improve our understanding of the price discovery process.[4]

This study examines the characteristics of stock returns, as reflected by their time-series behavior, under different trading mechanisms. We compare the dispersion of the observed return distributions, the nature of convergence of prices to values, the return serial correlation patterns and their implications for market efficiency, and the effects of the bid-ask spread.

In what follows, Section II discusses the differences between the two trading mechanisms and Section III presents a simple model of price adjustment. Section IV outlines the nature of the opening and closing transactions on the NYSE, which constitute the data analyzed in this study. Our empirical analysis starts in Section V by comparing the dispersion of stock returns. In Section VI we examine the deviations of the return distribution from normality, Section VII tests the random-walk form of market efficiency under the two trading mechanisms, and Section VIII studies the effect of the bid-ask spread. Our concluding remarks are offered in Section IX. Our findings show that the trading mechanism has distinct implications on stock price behavior.

[3] For example, a comparison of price behavior in the *Bourse de Paris* (which operates as a periodic call market) with the price behavior on a U.S. exchange may reflect differences which are due to factors other than the trading mechanism, such as differences in the securities themselves, differences in the regulatory and economic environment, etc.

[4] Price discovery is the process by which transaction prices adjust to asset values (see Schreiber and Schwartz (1986)).

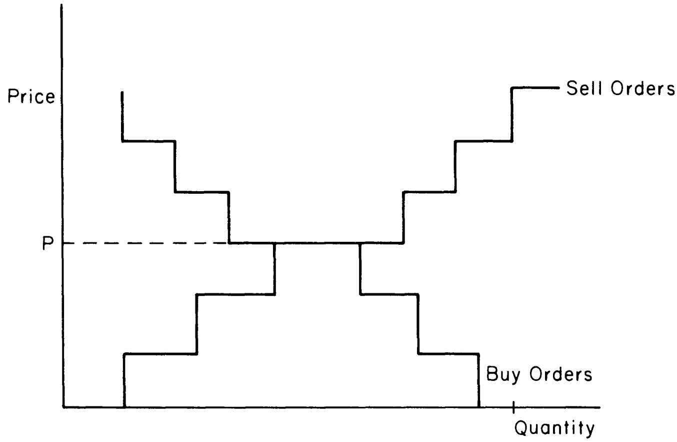

Figure 1. Price setting in a clearing house. The schedules depict the orders submitted to the market at limit prices in steps of $1/8.

II. The Dealership Market and the Clearing House

Two trading mechanisms which model many of the securities exchanges around the world are the dealership market and the clearing house. In the dealership market, trading is carried out continuously through market-makers who quote bid and ask prices at which they are willing to buy or sell (respectively). In the New York Stock Exchange, a designated specialist makes the market in a security and has an affirmative obligation to provide continuous quotes. In other markets, such as the OTC market or the New York Futures Exchange, the trading process is carried out by multiple traders making a market in the security.

An alternative trading mechanism is the clearing house (cf. Mendelson (1982))—a periodic market clearing procedure under which traders submit two types of orders to buy or sell specified quantities of the traded security: limit orders, which state the order quantity and the minimum sale price or the maximum purchase price at which the order is to be executed; and market orders, which specify only the quantity to be sold or bought with no price limits.[5] Orders accumulate and remain sealed until clearing time. Then, all sell orders are sorted according to the type of order (market or limit; market orders are sorted first) and limit orders are further sorted by increasing price sequence. Buy orders are sorted by type of order (market orders first) and by decreasing price sequence. This gives rise to supply and demand schedules constructed from the orders submitted to the market (see Figure 1). These schedules are then intersected at a single price which clears the market and applies to all executed orders. The clearing house procedure is employed extensively by European stock exchanges, where the market is cleared periodically (see references in footnote 1), and is also applied in some commodities exchanges (Jarecki (1976)). This form of exchange is closely related to the classical concept of competitive market clearing; it was

[5] A market order may be construed as a limit order whose limit buy or sell price is arbitrarily high or low, respectively.

the subject of a number of empirical laboratory experiments (e.g., Smith (1976)), and was studied theoretically by Mendelson (1982, 1986, 1987a) and by Ho, Schwartz and Whitcomb (1985).

The interest in comparing the two trading mechanisms is related to the re-evaluation of prevailing trading procedures under the plans to establish a national market system in the U.S., to forthcoming changes in European securities markets, and to the expected expansion in the role of electronic trading (Amihud and Mendelson (1985)). These factors may lead to the establishment of one of the competing forms of exchange or both, and it is important to study the effects that each trading mechanism is expected to have on securities price behavior and on the liquidity of the market.[6]

III. A Simple Model of Price Adjustment

In this section we outline a simple model of price behavior which will guide our empirical tests. The model distinguishes between the intrinsic *value* of a security at time t, V_t, and its observed *price*, P_t. The difference between value and price is attributable to noise (Black (1986)). These two effects are formally captured by a partial-adjustment model with noise,[7]

$$P_t - P_{t-1} = g \cdot [V_t - P_{t-1}] + u_t, \tag{3.1}$$

where V_t and P_t are in logarithms and the adjustment coefficient g satisfies $0 < g < 2$. As usual, $\{u_t\}$ is a "white noise" sequence of i.i.d. random variables with zero mean and finite variance σ^2. This noise, which pushes the observed price of the security away from its value, comes from two main sources: First, it is the result of noise trading (Black (1986)) induced, e.g., by transitory liquidity needs of traders and investors and by errors in the analysis and interpretation of information. Second, it reflects the impact of the trading mechanism by which prices are set in the market. The latter includes, for example, the random arrival of buy and sell orders to the market (Mendelson (1982, 1985, 1986, 1987a)), the transitory state of dealers' inventory positions (cf. Amihud and Mendelson (1980)), the discreteness of stock prices (Gottlieb and Kalay (1985)), delayed price discovery (Cohen, Maier, Schwartz and Whitcomb (1986)) and price fluctuations between the bid and the ask. The bid-ask effect is obviously pronounced in the dealership market.

The coefficient g reflects the adjustment of transaction prices towards the security's value. In particular, $g = 0$ represents the extreme case of no price reaction to changes in value, and $0 < g < 1$ represents partial price adjustment. A unit adjustment coefficient ($g = 1$) represents full (though noisy) price adjustment, since then (3.1) reads

$$P_t = V_t + u_t,$$

i.e., (log) price is given by (log) value plus noise. When $g > 1$, we have *overshooting* or *over-reaction* of traders to new information.

[6] The trading mechanism has a paramount effect on the liquidity of the market, which in turn affects securities returns. Amihud and Mendelson (1986a, 1986b) have shown that increased liquidity has a significant positive effect on stock prices.

[7] Cf. Goldman and Beja (1979), Garbade and Silber (1979).

We follow the convention that the logarithms of security values $\{V_t\}$ follow a random walk process with drift, i.e.,

$$V_t = V_{t-1} + e_t + m, \tag{3.2}$$

where m represents the expected daily value return and $\{e_t\}$ are i.i.d. random variables, independent of u_t, with zero mean and finite variance ν^2. We shall call the differences $(V_t - V_{t-1})$ the *value returns* of the security.

It is easy to demonstrate that (3.1) and (3.2) imply (by induction)

$$P_t = g \cdot \sum_{i=0}^{\infty} (1-g)^i V_{t-i} + \sum_{i=0}^{\infty} (1-g)^i u_{t-i}. \tag{3.3}$$

The *observed* returns, defined by $R_t = P_t - P_{t-1}$, are then

$$R_t = m + g \sum_{i=0}^{\infty} (1-g)^i (e_{t-i} - u_{t-i-1}) + u_t. \tag{3.4}$$

Using (3.4), we can now study the properties of the returns resulting from the price-adjustment equations. First, the observed return variance is given by

$$\text{Var}(R_t) = g^2 \sum_{i=0}^{\infty} (1-g)^{2i} (\nu^2 + \sigma^2) + \sigma^2$$

which, after rearrangement, yields

$$\text{Var}(R_t) = \frac{g}{2-g}\,\nu^2 + \frac{2}{2-g}\,\sigma^2. \tag{3.5}$$

The first term on the right-hand-side of (3.5) represents the contribution of the value return variance, ν^2, to the observed return variance, and the second—the contribution of the noise. When $0 < g < 1$, only a fraction of the value return variance ν^2 is transmitted over to the observed returns due to the "smoothing" effect of the partial adjustment process. When $g = 1$, the full extent of the value return fluctuations is passed on to the observed returns. When $g > 1$ (the over-reaction case), the first term of (3.5) (and hence certainly the overall observed return variances) becomes greater than the value return variance, since then value fluctuations are amplified by traders' over-reaction.[8]

The second term in (3.5) represents the contribution of the noise to the observed return variance. This term is an increasing function of the noise variance σ^2 and of the adjustment coefficient g. Intuitively, since the price disturbance in one period is transmitted by the partial adjustment process to the following period's price, the larger the adjustment coefficient—the larger the transmission of the noise to the observed return variance (see (3.1)). In sum, both a high adjustment coefficient g and a high noise variance σ^2 contribute to increase the observed return variance for any given level of the value return variance ν^2.

Equation (3.5) suggests that the measured return variance $\text{Var}(R_t)$ is a biased estimator of the value return variance, ν^2. In the case $g = 1$, where there is full (though noisy) price adjustment, $\text{Var}(R_t) = \nu^2 + 2\sigma^2$, i.e., the observed return

[8] French and Roll (1986) show that the assumption of price over-reaction is consistent with their findings on the relationship between stock return variances over trading and non-trading periods. Our formulation of the variance, (3.5), is also consistent with their findings that the variance of two-day holiday returns is less than twice the variance of a normal trading day. While the value return variance ν^2 should increase linearly with time, the noise variance, σ^2, remains unchanged, hence the observed return variance increases less than proportionately in time.

variance is the sum of the value return variance and the contribution of the noise variance. This corresponds to Black's (1986) suggestion that the volatility of price is greater than the volatility of value.

More generally, by (3.5), $\mathrm{Var}(R_t) \geq (\leq)\ \nu^2$ when $\sigma^2 \geq (\leq)\ \nu^2(1-g)$, respectively. Partial adjustment, i.e., $0 < g < 1$, induces a *downward* bias in the measurement of ν^2 whereas the noise variance biases it upwards. Thus, in general, the observed return variance may either over-estimate or under-estimate the value return variance, and the relationship between the two is an empirical question.

Next, we consider the first order *autocovariance* of the observed returns,

$$\mathrm{Cov}(R_t, R_{t-1}) = \frac{g}{2-g}[(1-g)\nu^2 - \sigma^2], \tag{3.6}$$

and the first-order autocorrelation coefficient

$$\mathrm{Corr}(R_t, R_{t-1}) = \frac{g(1-g)\nu^2 - g\sigma^2}{g\nu^2 + 2\sigma^2}. \tag{3.7}$$

The sign of the first order autocorrelation coefficient is determined by two factors: The adjustment process and the noise. The contribution of the noise to the first-order autocorrelation is always negative, whereas the contribution of the adjustment process is positive when $0 < g < 1$ (the case of partial price adjustment) and negative when $g > 1$ (the over-reaction case). By (3.7), the sign of the first-order autocorrelation is determined by the magnitude of the adjustment coefficient g and by the relationship between the variances σ^2 and ν^2. In the special case $g = 1$, the correlation is negative and equals the relative weight of the noise variance in the total return variance.

IV. The Opening and Closing Transactions on the NYSE

Our empirical comparison of price behavior under the two trading mechanisms uses the daily opening and closing prices of the 30 New York Stock Exchange stocks which constituted the Dow Jones Industrial list during the period February 8, 1982–February 18, 1983.[9] The active opening in these stocks closely resembles the clearing house trading procedure, whereas the closing transaction represents the dealership market regime. This comparison enables us to focus on the effects of the trading mechanism *per se*, holding almost all "other things equal": We are comparing the same securities traded on the same exchange during the same time period.

The opening prices on the NYSE are determined in the following manner. Before the opening, there is a flow of orders to buy or to sell a specified quantity of the stock at a limit price or at the market price. Trading is performed at a *single* price which clears the market, and which applies to all orders executed at the opening. Clearly, there is no difference between the buying and selling price, i.e., prices do not fluctuate between the bid and the ask, as is the case during the day. This mechanism closely resembles the clearing house model of trade. The

[9] The composition of the list was slightly different until August 30, 1982, when John Manville was replaced by American Express.

closing prices on the NYSE (like other transaction prices over the trading day) are determined by trading with market-makers and thus pertain to the dealership market mechanism.

The importance of the opening transaction is demonstrated by its share of the daily trading volume (see Table 1). The volume on the opening transaction constituted on average 5.6% of the total NYSE daily volume in the sampled stocks, and was on average 8.4 times greater than the volume on the closing transaction.

Our empirical study considers the open-to-open returns,

$$R_{o,t} = \log(P_{o,t} + D_t) - \log(P_{o,t-1})$$

where $P_{o,t}$ is the day-t opening price, adjusted for splits and stock dividends, and D_t is the cash dividend (if t is an ex-dividend day). Similarly, the close-to-close

Table 1

Opening Trading Volume vs. the Trading Volume at the Close, and Total Daily Volume

	Stock Symbol	Mean Opening Volume/ Mean Closing Volume	Mean Opening Volume/ Mean Daily Volume
1	AA	5.9	.041
2	AC	2.9	.066
3	ALD	5.2	.025
4	AMB	3.0	.069
5	AXP	11.2	.070
6	BS	1.6	.051
7	DD	6.9	.077
8	EK	10.4	.054
9	GE	15.9	.073
10	GF	3.8	.040
11	GM	13.6	.053
12	GT	6.0	.049
13	HR	9.9	.076
14	IBM	19.4	.025
15	IP	4.6	.052
16	MMM	9.5	.083
17	MRK	6.5	.081
18	N	4.5	.073
19	OI	1.4	.056
20	PG	3.9	.064
21	S	13.2	.046
22	SD	6.1	.067
23	T	22.1	.025
24	TX	11.5	.018
25	UK	5.4	.068
26	UTX	7.2	.061
27	WX	10.7	.084
28	X	10.4	.036
29	XON	12.4	.021
30	Z	5.9	.083
Mean		8.4	.056

returns are defined by

$$R_{c,t} = \log(P_{c,t} + D_t) - \log(P_{c,t-1})$$

where $P_{c,t}$ is the day-t closing price (similarly adjusted). Thus, we obtain a sequence of open-to-open returns $\{R_{o,t}\}$ and a sequence of close-to-close returns $\{R_{c,t}\}$ which cover the very same period of time. Clearly, information which changes the values of the examined stocks is equally reflected in both $R_{o,t}$ and $R_{c,t}$.[10] Thus, observed differences in the distributions of $R_{o,t}$ and $R_{c,t}$ may be attributed to the different trading procedures. These differences may also reflect investors' different order-placement strategies under the two trading regimes.

V. The Dispersion of Stock Returns

The stochastic nature of stock returns is affected by two major factors: (1) the arrival of new information, which induces shifts in stock values, and (2) noise transactions and the trading process which perturb the value returns and generate the observed returns. In terms of the price adjustment model of Section 3, the first factor is captured by the random variable e, and the second—by the adjustment coefficient g and by the random variable u. Studies of market microstructure suggest that the trading mechanism should affect the probability distribution—in particular, the dispersion—of observed returns. In this section we discuss the resulting hypotheses and test them empirically.

Theoretical studies and institutional knowledge suggest that market-makers stabilize prices and reduce the observed return variances.[11] The price stabilizing effect of the specialist in the context of his inventory-based pricing policy was suggested by Amihud and Mendelson (1980, 1982). When a change in the relative arrival intensity of buy or sell orders is not immediately perceived by the specialist, he absorbs part of the resulting imbalance into his stock inventory while partially inhibiting the market price change. Consequently, the bid-ask prices change gradually until the specialist, having perceived the change in value, shifts his whole inventory-based price vector, restoring his inventory position to its preferred level. As a result, a change in the stock's value is partially absorbed by the specialist's inventory, but this is only transitory in nature.[12]

Garbade and Silber (1979) and Goldman and Beja (1979) suggest that market-makers, observing the market buy and sell orders, try to estimate the stock value and set prices accordingly. They would attribute observed excess demand or supply partly to a change in value and partly to noise. They thus mitigate shifts in value by inducing partially offsetting changes in the transaction prices, resulting in reduced return variance.[13]

Institutional rules of conduct also induce price stabilization since NYSE

[10] Except for the small differences due to the first and last day, which should be negligible when the covered period is sufficiently long.

[11] The stabilizing role of the specialist was studied by West and Tinic (1971), Barnea (1974), Cohen, Maier, Schwartz and Whitcomb (1977), Schwartz and Whitcomb (1977a, 1977b) and Mendelson (1987a), and was surveyed by Stoll (1985).

[12] A similar pattern can be inferred from Ho and Stoll (1981).

[13] Garbade and Silber (1979) show that the optimal estimator of the equilibrium value from transaction prices, obtained by the Kalman Filtering algorithm, implies a partial-adjustment model.

specialists are explicitly required to act as "price stabilizers" and provide "price continuity". The specialist is expected to sell from his own account when prices go up and to buy into his own account when prices decline, so as to reduce price variations.[14] In fact, the surveillance systems of the NYSE continuously monitor compliance with these rules by the specialists. These price continuity requirements should induce a reduction in price dispersion.

Finally, in the daily transactions, traders can monitor prices continuously and infer from these prices on the impact of new information as soon as it arrives to the market. The market-maker's quotes signal current price information to all public traders (Mendelson (1987a)) and reduce errors of interpretation since traders have at their disposal the most recently available information set. In contrast, at the opening, there is likely to be a greater amount of information which has accumulated since the last transaction and has not yet been reflected in market prices. Although not necessarily so, there may be a relationship between the size of the error in determining the price and the amount of accumulated information, leading to greater price dispersion in the opening.

While the above arguments suggest that the return variance is higher in a clearing house compared to the dealership market, there are a few factors which operate in the opposite direction. In a dealership market, transactions fluctuate between the bid and ask prices—an effect which introduces noise in stock returns, and does not exist in the clearing house. In terms of our model, the greater the bid-ask spread, the greater the noise-induced variance σ^2 (see (3.5); this is further discussed in Section VIII). In addition, the batching of orders in the clearing house tends to reduce the resulting price variance (cf. Mendelson (1982, 1985, 1986, 1987a)). If these effects dominate, the return variance in a dealership market will be greater than in a clearing house. The comparison between the two mechanisms is thus an empirical question.

The results in Table 2 suggest that the trading mechanism has a distinct effect on the dispersion of stock returns: $\mathrm{Var}(R_{o,t})$ exceeds $\mathrm{Var}(R_{c,t})$. For 29 out of 30 stocks (Table 2, column 3) and, on average, the variance of the open-to-open returns is 20% greater than that of the close-to-close returns.[15] This suggests that traders who choose to transact at the opening are usually exposed to a higher variance than those who trade at the closing. Put differently, the return volatility is greater in the clearing house than in the dealership market.

Another measure of dispersion is the range of the return distribution. Comparing the extreme values of the observed returns in the opening and the closing, we found (Table 2, columns 4 and 5) that on average, the minimum of $R_{o,t}$ is 17% smaller than the minimum of $R_{c,t}$ and the maximum of $R_{o,t}$ is 14% greater than the maximum of $R_{c,t}$. This further shows that open-to-open returns have greater dispersion than close-to-close returns.[16]

Despite its greater return volatility, we observe that trading is heavy at the

[14] See *Report of the Committee to Study the Stock Allocation System*, The New York Stock Exchange, January 27, 1976, Exhibit A-5.

[15] We also ran a similar test on a much smaller sample, using mid-day to mid-day returns (at 12:00 and at 14:00 hours) instead of close-to-close returns, and obtained similar results.

[16] It can also be shown that for most stocks in our sample, the empirical distribution of opening returns is a median-preserving spread (Mendelson (1987b)) of the closing return distribution.

Table 2

Comparison of the Dispersion and Deviations from Normality for the Open-To-Open Returns, R_o, and Close-To-Close Returns, R_c

Stock (1)	Stock Symbol (2)	$Var(R_o)/Var(R_c)$ (3)	$Min(R_o)/Min(R_c)$ (4)	$Max(R_o)/Max(R_c)$ (5)	$CRT(R_o)/CRT(R_c)$ (6)	$SR(R_o)/SR(R_c)$ (7)
1	AA	1.25	1.85	1.05	2.80	1.24
2	AC	1.11	.94	.97	1.01	.91
3	ALD	1.23	1.20	1.31	1.61	1.12
4	AMB	1.43	1.26	1.71	3.57	1.25
5	AXP	1.20	1.02	1.29	1.28	1.08
6	BS	1.07	1.30	.82	1.06	1.00
7	DD	1.33	1.08	.99	.56	.89
8	EK	1.18	1.14	.96	.71	.94
9	GE	1.23	1.42	.99	.95	1.02
10	GF	1.30	1.07	1.40	2.45	1.10
11	GM	1.16	1.06	.90	.61	.89
12	GT	1.09	1.10	1.01	1.19	1.02
13	HR	0.80	.88	1.14	1.12	1.01
14	IBM	1.30	1.83	1.14	2.51	1.25
15	IP	1.32	1.08	1.02	1.19	.91
16	MMM	1.21	1.42	.99	1.12	1.04
17	MRK	1.21	1.31	1.20	1.39	1.13
18	N	1.16	1.23	1.09	1.32	1.07
19	OI	1.27	1.23	.93	.67	.94
20	PG	1.12	1.07	1.09	1.34	1.02
21	S	1.32	.90	1.26	1.26	.97
22	SD	1.10	1.06	1.11	.64	1.04
23	T	1.15	1.53	.93	.98	1.08
24	TX	1.22	.76	1.13	.60	.84
25	UK	1.15	1.34	1.05	1.43	1.09
26	UTX	1.22	1.04	1.44	9.63	1.12
27	WX	1.23	1.04	1.19	.75	1.19
28	X	1.00	.80	.93	.78	.93
29	XON	1.48	1.08	1.51	1.13	1.51
30	Z	1.13	.99	1.73	4.56	1.73
Mean		1.20	1.17	1.14	1.67	1.04
Std. Error		.02	.05	.04	.32	.07
Number of cases where ratio > 1		29	24	20	20	21

Notes: Var(R) is the variance of the returns; Min and Max are the minimum (always negative) and maximum (always positive) values of the returns in the sample.

CRT is the estimated curtosis; SR is the estimated studentized range of the distribution.

opening, implying that the latter has some advantages. A trader placing a limit order in the opening can expect an execution price which is *better* than his limit price, generating an expected surplus (cf. Mendelson (1982, 1985)), whereas daytime limit orders are executed at their limit price with no such surplus. Also, daytime traders may face a greater adverse selection problem due to the risk of their limit orders being executed by better-informed traders. This problem is mitigated at the opening by the batching of orders, which reduces the likelihood that an uninformed trader's order will determine the execution price. Finally, market traders in the opening can avoid the cost of the bid-ask spread, which may be viewed in part as the cost traders pay to reduce uncertainty. As a result, there are those who prefer to trade at the opening, whereas others opt for continuous daytime execution.

VI. Deviations from the Normal Distribution

The normality of stock returns is a widely applied hypothesis in the theory of investment finance. In his well-known study, Fama (1965, 1976) found that the distribution of daily stock returns deviates from normality. In Fama's study, returns were computed from closing prices and are similar to our $R_{c,t}$. Here, we shall compare the deviations of $R_{o,t}$ and $R_{c,t}$ from normality. If not for the effect of the trading mechanism, we should hardly expect differences in this respect.

Under the normality hypothesis, the third central moment of the return distribution, measured by the skewness coefficient, should be equal to zero. In our sample (as in Fama) the skewness was positive in most cases, both for R_o (29 out of 30 cases) and for R_c (27 out of 30 cases), and there was no appreciable difference in the magnitudes of the skewness coefficients between the open-to-open and close-to-close returns.

The coefficient of curtosis is also expected to be zero under the hypothesis of normal return distribution, whereas, in reality, daily stock returns have positive curtosis, indicating greater peakedness than under normality. While this was also the case for all the stocks in our sample, the curtosis of the open-to-open returns R_o was greater than that of the close-to-close returns R_c for 20 out of the 30 stocks in our sample, and on average the curtosis of R_o was 67% greater than the curtosis of R_c (Table 2, column 6).[17]

Finally, we compared the studentized range (SR, the sample range divided by the sample standard deviation) of the two distributions. As in Fama (1976), most cases exhibited statistically significant deviations from normality: The average studentized range of R_o was 7.27 and it deviated from normality (at the .9 fractile) in 29 out of 30 cases; the average studentized range of R_c was 7.02 and it deviated from normality in 24 out of 30 cases. In comparison, the studentized range of the opening returns is usually greater than the studentized range of the closing returns (21 out of 30 cases; see Table 2, column 7).

Looking at the evidence as a whole, the distribution of open-to-open returns has greater dispersion, fatter tails and more peakedness than the distribution of close-to-close returns. We thus find that trading at the opening is associated

[17] If we omit the extreme ratio of stock 26, we obtain that the average curtosis of R_o is 40% greater than that of R_c.

with greater deviations from normality than at the closing, suggesting that the method of trading affects the probability distribution of stock returns.

VII. Market Efficiency: Tests of Serial Correlation

Market efficiency implies that security prices fully reflect all available information at any point in time. Fama (1976) suggested that "if the market is efficient, there is no way to use any information available at time $t-1$ as the basis for a correct assessment of an expected value of R_t which is different from the assumed constant equilibrium expected return, $E(R)$. Since part of the information available at $t-1$ is the time series of past returns, there is no way to use the past returns as the basis for a correct assessment of the expected return from $t-1$ to t which is other than $E(R)$" (p. 44). This gives rise to Fama's random walk form of the market efficiency hypothesis,

$$E[R_t \mid R_{t-1}] = E[R], \tag{7.1}$$

that is, the expected conditional return is equal to the unconditional mean. Then, if past returns have no information content, the return autocorrelations should be zero. Testing this hypothesis using close-to-close returns, Fama (1965) found that the first-order autocorrelation coefficient was positive for most stocks in his sample, averaging 0.026, and that in eleven cases out of 30 the correlation coefficients were significantly different from zero (10 out of these 11 coefficients were positive).

The market efficiency hypothesis may be applied to market prices observed at any point in time under any trading mechanism. This calls for examining whether the opening price contains all the information available in the sequence of opening prices which preceded it, and whether the closing price reflects all the information contained in the sequence of preceding closing prices. The above form of the market efficiency hypothesis implies that the serial correlations of both open-to-open and close-to-close returns should be equal to zero.[18] On the other hand, if different trading mechanisms give rise to different price adjustment processes, we may observe a different serial autocorrelation pattern for the open-to-open and close-to-close returns.

To test the above hypothesis, we first replicated Fama's tests of first-order autocorrelation using both close-to-close and open-to-open returns. The closing return series (see Table 3) exhibit the same pattern as in Fama (1965). Most correlation coefficients are positive (24 out of 30), their average is .0464 (compared with Fama's .026), and a few are significantly different from zero. The open-to-open returns, however, exhibit an opposite pattern altogether: most of the autocorrelation coefficients of open-to-open returns are negative (23 out of 30), and their mean is −.0635; the few significant coefficients are all negative. By

[18] One may argue that there is more information available to traders at the closing than at the opening, since the former is preceded by a sequence of transactions whereas the latter follows a period of no trade. However, the returns utilized in our tests, R_o and R_c, are both computed over 24-hour periods. Hence, in both cases we test efficiency not with respect to information contained in the immediately preceding stock price, but with respect to information contained in the stock price observed 24 hours earlier.

Table 3

First-order Autocorrelation Coefficients for the Open-To-Open and Close-To-Close Returns

Stock	Open	Close
1	−.1078	.0403
2	.0104	.0672
3	−.0647	.0458
4	−.1448*	−.0066
5	−.0804	.0280
6	.0561	.0776
7	−.1924**	.0019
8	−.1924**	−.0921
9	−.1420*	−.0186
10	−.0072	.1423*
11	−.1172	.0070
12	−.0101	.0420
13	.0687	−.0006
14	−.1738**	−.0412
15	−.0670	.1381
16	−.0795	.0449
17	−.0819	.0500
18	−.0427	.0938
19	−.0415	.0827
20	−.0898	.0036
21	−.1055	.0497
22	.0180	.1121
23	−.0863	−.0086
24	−.0695	.0464
25	.1026	.1933**
26	−.0900	.0042
27	−.1112	.0085
28	.0878	.1992**
29	−.1588*	.0010
30	.0084	.0788
Mean	−.0635	.0464
Standard Error	.0146	.0119
No. of Negative	23	6

* = Significant at the 0.05 level.
** = Significant at the 0.01 level.

expression (3.7) for the autocorrelation coefficient, these results suggest that in the opening, $\sigma^2 > (1-g)\nu^2$, whereas in the close the inequality is reversed. This is consistent with larger values of the noise variance σ^2 and of the adjustment coefficient g in the opening. Note that this implies that an overshooting effect (i.e., $g > 1$) is unlikely at the close but possible in the opening.[19]

As a further test of the random-walk form of the market efficiency hypothesis, we estimated the standard autoregressive moving-average process of the form

$$R_t = \alpha + \beta R_{t-1} + \epsilon_t + \theta \epsilon_{t-1}, \tag{7.2}$$

[19] Hasbrouck and Schwartz (1986) suggested to estimate a T-period Market Efficiency Coefficient given by $\mathrm{MEC}_T = \mathrm{Var}(\sum R_t)/T \cdot Var(R_t)$, similar to French and Roll (1986). MEC_T deviates from unity when the return autocorrelation is nonzero. We estimated MEC_T for $T = 1, 2, 3, 4$, and obtained that they were greater than 1 for R_c and smaller than 1 for R_o, consistent with our other findings.

where $\{\epsilon_t\}$ are i.i.d. random variables with zero mean. This ARMA (1, 1) model was estimated for our opening and closing return series. By (7.1), we should obtain $\beta = \theta = 0$.

The results in Table 4 show significant violations of the hypothesis $\beta = \theta = 0$ for the open-to-open returns, whereas the results for the close-to-close return series were mostly insignificant.[20] Twenty-five of the open-to-open return series were invertible, and 12 of them had autoregressive *and* moving average coefficients that were significantly different from zero (three additional ones were marginal). The dominant pattern was a negative autoregressive coefficient β and a positive moving average coefficient θ (in 11 out of the 12 significant series and 18 out of the 25 series estimated). On average, $\beta = -.400$ and $\theta = .330$.

As for the close-to-close return series, five produced significant estimates and one was marginal. Out of these six, four followed the same pattern as the open-to-open series; but in general, the pattern of the estimated coefficients was mixed.

Our results suggest that simple autocorrelation tests may be insufficient to detect market inefficiencies, since they disguise the pattern given by equation (7.2). For opening returns, the results of the ARMA (1, 1) model imply more significant deviations from the random-walk form of the market efficiency hypothesis than those obtained under serial correlation tests. The autocorrelation of the ARMA (1, 1) process (7.2) is given by

$$\mathrm{Corr}(R_t, R_{t-1}) = \frac{(1 + \beta\theta)(\beta + \theta)}{1 + \theta^2 + 2\beta\theta}$$

(see Judge et al. (1980), p. 172). When $\beta \approx -\theta$, as for most stocks in our sample (the mean value of β in the opening is $-.4$, and that of θ is .33), the correlation coefficients will be small even though $|\beta|$ and $|\theta|$ themselves are relatively high. Thus, simple autocorrelation tests may not detect a pattern rejecting the random-walk hypothesis when one exists.

Finally, we still observed that the residual noise in R_o was greater than that of R_c, even after having accounted for the variance explained by past returns, and despite the better fit of the open-to-open return series (see last three columns of Table 4). It should be noted that unlike the comparison of the raw return variances in Table 2, here we are comparing only the variances of the unexpected residual disturbances. These differences between the residual variances represent more forcefully the difference in the return volatility associated with the clearing house as compared to the dealership market.

In sum, Table 4 reveals a number of results:

1. There are numerous violations of the random-walk form of the market efficiency hypothesis, primarily at the opening, with many of the open-to-open return series being well-explained by the ARMA (1, 1) model.
2. The pattern of first-order serial correlation is generally negative in the opening and positive in the closing.

[20] Smidt (1979) tested market efficiency using intraday data and accounting explicitly for the spread. His results reject the weak-form market efficiency hypothesis. An autoregressive-moving-average test using intraday data was carried out by Hasbrouck and Ho (1986). Their results reject the hypothesis that price behaves as a random walk plus bid/ask spread and affirm the existence of a lagged adjustment effect.

3. The residual variance of the open-to-open returns is greater than that of the close-to-close returns, reflecting less noise in the dealership market than in the clearing house.

The trading mechanism thus has a distinct impact on the stochastic process governing the behavior of observed returns.

VIII. The Effect of the Bid-Ask Spread

Our analysis provides an insight into the effect of the bid-ask spread on the variance and covariance of closing stock returns. Assume that the noise in the closing price is due to the fluctuations between the bid and the ask, with a partial-adjustment equation of the form

$$P_t^* = P_{t-1} + g \cdot (V_t - P_{t-1}), \tag{8.1}$$

where P_t^* denotes the (log) price as estimated by market participants and P_t is the actually observed (log) price. Denote the relative (percentage) spread by $2s$, and assume that the observed price satisfies

$$P_t = P_t^* + \epsilon_t, \tag{8.2}$$

where

$$\epsilon_t = \begin{cases} \log(1+s) & \text{w.p. } 1/2 \\ \log(1-s) & \text{w.p. } 1/2 \end{cases}$$

(see Roll (1984)). Using a first-order approximation (as in Roll (1984)), we obtain (3.1) with[21]

$$u = \begin{cases} +s & \text{w.p. } 1/2 \\ -s & \text{w.p. } 1/2 \end{cases}$$

and $\sigma^2 = s^2$. By equation (3.6) we obtain

$$s = \sqrt{(1 - 2/g)\mathrm{Cov}(R_t, R_{t-1}) + (1-g)\nu^2} \tag{8.4}$$

which, for $g = 1$ (i.e., full price adjustment) gives Roll's (1984) result[22]

$$s = \sqrt{-\mathrm{Cov}(R_t, R_{t-1})}. \tag{8.5}$$

Roll's (1984) analysis implies that $\mathrm{Cov}(R_t, R_{t-1})$ must be *negative* for all stocks. However, his findings (as well as our own results) cast doubt on the validity of the assumption that $g = 1$. Contrary to (8.5), the first-order autocorrelations between closing returns are predominantly positive in our sample, suggesting that $0 < g < 1$ for close-to-close returns. Further, Roll (1984) pointed out that

(i) the magnitudes of the spreads implied by the estimated covariances are less than reasonable values of the spread;
(ii) the spreads implied from weekly covariances are higher and more reasonable than those estimated from daily covariances.

Both of these observations are consistent with the hypothesis that in model

[21] As pointed out earlier, there may be additional sources of noise which can simply be added to u.
[22] See also Hawawini (1978), Cohen, Maier, Schwartz and Whitcomb (1980).

Table 4

Results of ARMA (1, 1) Estimation for Open-To-Open and Close-To-Close Returns
(t-values are in parentheses)

— Indicates that the Process is non-invertible

Stock Number (1)	Open AR(1) (2)	Open MA(1) (3)	Close AR(1) (4)	Close MA(1) (5)	Residual Variance (×10000) Open (6)	Residual Variance (×10000) Close (7)	Variance Ratio (6)/(7) (8)
1	−.682	.586	.391	−.349	6.716	5.439	1.235
	(2.56)	(1.97)	(.48)	(.42)			
2	—	—	.881	−.959		2.834	
			(32.39)	(45.28)			
3	−.857	.802	.445	−.375	5.239	4.285	1.223
	(6.91)	(5.49)	(.76)	(.62)			
4	.405	−.553	—	—	2.993		
	(1.36)	(2.04)					
5	−.660	.570	.462	−.418	5.937	4.991	1.190
	(2.45)	(1.94)	(.56)	(.50)			
6	.200	−.134	.690	−.585	5.034	4.726	1.065
	(.57)	(.37)	(2.87)	(2.17)			
7	−.864	.742	—	—	4.254		
	(9.95)	(6.39)					
8	−.388	.198	−.192	.096	3.381	2.936	1.152
	(1.45)	(.70)	(.45)	(.22)			
9	−.761	.630	−.684	.634	2.697	2.231	1.209
	(4.98)	(3.45)	(3.42)	(2.94)			
10	—	—	.259	−.117		2.306	
			(.64)	(.28)			
11	−.460	.340	—	—	4.248		
	(1.47)	(1.01)					
12	—	—	−.833	.820		5.019	
			(2.57)	(2.42)			
13	.280	−.200	−.166	.164	27.087	34.006	0.800
	(.43)	(.30)	(.049)	(.048)			
14	−.147	−.028	—	—	2.890		
	(.46)	(.09)					

15	−.477	.404	.019	.123	4.795	3.599	1.332
	(1.26)	(1.02)	(.044)	(.283)			
16	−.713	.620	—	—	3.381		
	(3.13)	(2.44)					
17	−.570	.483	.155	−.100	2.883	2.406	1.198
	(1.72)	(1.37)	(.14)	(.09)			
18	−.875	.805	.485	−.391	8.227	7.201	1.142
	(9.50)	(7.05)	(1.05)	(0.81)			
19	−.496	.458	.056	.027	3.623	2.847	1.273
	(.60)	(.54)	(0.08)	(.038)			
20	−.636	.546	−.915	.876	2.144	1.938	1.106
	(2.68)	(2.10)	(9.98)	(7.97)			
21	−.860	.770	−.032	0.082	5.510	4.284	1.286
	(9.17)	(6.51)	(.027)	(.069)			
22	.800	−.837	−.395	.510	6.711	5.965	1.125
	(5.52)	(6.16)	(1.46)	(1.99)			
23	−.945	.905	—	—	1.874		
	(17.4)	(12.68)					
24	—	—	.105	−.060		2.080	
			(.14)	(.08)			
25	.065	.038	.257	−.066	3.086	2.684	1.150
	(.20)	(.12)	(.83)	(.21)			
26	−.350	.260	.427	−.407	4.805	3.968	1.211
	(.65)	(.47)	(.20)	(.18)			
27	−.675	.573	—	—	5.545		
	(4.17)	(3.13)					
28	.043	.047	−.140	.374	4.921	4.789	1.028
	(.13)	(.14)	(.57)	(1.62)			
29	−.372	.220	—	—	2.443		
	(1.13)	(.64)					
30	—	—	.222	−.143		5.212	
			(.31)	(.20)			
Mean	−.400	.330	.068	−.012	4.306*	3.892*	1.183
Standard Error	.092	.087	.100	.097			.020
No. of Obs.	25	25	22	22	25*	22*	16*
No. Positive	6	20	14	10			

* Excluding stock 13 (HR), which is an outlier.

(8.1), $0 < g < 1$ for close-to-close returns. Then, Roll's finding (i) is consistent with the fact that (8.4) implies $-\text{Cov}(R_t, R_{t-1}) < s^2$, and hence use of the return covariances in (8.5) underestimates the spread. The second finding is consistent with the fact that the effective value of the adjustment coefficient g should tend to unity as the return-measurement interval increases. This implies that the five-day return covariance (and hence also the resulting spread estimate) should be greater (in absolute value) than the corresponding single-day estimate.

The bid-ask spread effect should also be considered when estimating the return variance. Under (8.3), equation (3.5) reads

$$\text{Var}(R_t) = \frac{g}{2-g}\nu^2 + \frac{2}{2-g}s^2, \tag{8.6}$$

implying that the larger the spread, the larger the measured return variance for any given level of the value return variance ν^2. This suggests a positive cross-sectional relationship between the measured closing return variance and the spread. We thus estimated the regression equation

$$\begin{array}{ll} \text{Var}(R_{c,j}) = 0.000279 + & 0.000986\, s_j, \\ (t=) & (4.01) \end{array}$$

where $\text{Var}(R_{c,j})$ is the close-to-close return variance for stock j and s_j is the average spread of stock j over our sample period (relative to its price). The result supports the hypothesis that the greater the spread, the greater the close-to-close return variance. Further, since the opening price has no spread, we should also expect a negative relationship between the spread and the ratio of the open-to-open return variance to the close-to-close return variance. Indeed, we obtained the following relationship

$$\begin{array}{ll} \dfrac{\text{Var}(R_{o,j})}{\text{Var}(R_{c,j})} = 1.29 - & 13.62\, s_j, \\ (t=) & (3.68) \end{array}$$

thus supporting our hypothesis.

Equation (8.6) suggests a spread effect whereby the measured return variance $\text{Var}(R_t)$ is a biased estimator of the value return variance, ν^2. This bias is an increasing function of the spread, and its overall impact also depends on the adjustment coefficient g (see Section 3). Given the empirical regularity of a negative relation between the bid-ask spread and both firm size and stock price (cf. Stoll and Whaley (1983)), the upward bias in the computed return variance due to the spread is more severe for small firms and for low-priced stocks. This relationship between the bid-ask spread and the bias in the estimate of the value return variance complements the analysis of Blume and Stambaugh (1983) on biases in computed mean returns due to the spread, which are more severe in small firms.

The above analysis can be applied to the use of estimated return variances in the pricing of options. The standard Black-Scholes option pricing model assumes that stock prices evolve as a continuous diffusion process (or a discrete random walk), where the (value) return variance increases linearly with time. In practical applications, the measured return variance of the underlying stock is often used as an estimator of the value return variance to calculate the option price. However, by (8.6) (or (3.5)) it is clear that this practice may be erroneous. This may explain the systematic difference found between measured return variances and the variances implied from option prices.[23]

The positive effect of the bid-ask spread on the observed return variance may explain part of the increase in the measured return variance following stock splits, documented by Ohlson and Penman (1985), if the percentage bid-ask spread increases when the stock price decreases. This is also consistent with Ohlson and Penman's (1985) finding that it is the actual split rather than the split announcement which affects volatility.

We also suggest that caution is called for when observed return variances are used in empirical studies in finance. For example, in "event studies", the objective is to examine the value effects of an event, i.e., the changes in V_t. While the appropriate variance for testing the related hypotheses is the value return variance ν^2, the variance actually used is $\mathrm{Var}(R_t)$, which is quite different.

IX. Conclusion

This paper examines the effects of two prevalent trading mechanisms—the periodic clearing house and the continuous dealership market—on the behavior of stock returns. The empirical investigation employed price data from the opening and closing transactions in active NYSE stocks, utilizing the fact that each of these transaction series is generated by a different trading mechanism. The clearing house mechanism was represented by the opening transaction, whereas the closing transaction represented the dealership market. This enabled us to compare the effects of the trading mechanism on the behavior of the returns on the same stocks in the same market during the same time period. We interpreted the results using a model where prices follow a lagged partial-adjustment process with noise.

Our results show that the trading mechanism has a significant effect on a number of characteristics of stock returns. First, the distribution of open-to-open returns has greater variance than that of close-to-close returns. And while both show deviations from normality, the opening return distribution exhibits greater peakedness and fatter tails than that of the closing returns. Second, the serial correlation pattern is quite different in the two return series. Further, employing an ARMA (1, 1) model we find that in the opening, returns exhibit higher residual noise and stronger dependence on past returns, reflecting stronger deviations

[23] A possible test of our hypothesis is to relate the difference between the measured return variance and the variance implied from the option price with the underlying stock's bid-ask spread and its estimated adjustment coefficient. Note that since the percentage spread usually decreases when stock prices increase, the noise may be decreasing in the stock price. This was observed by Black (1976) and in more recent studies of option pricing.

from the random-walk form of the market efficiency hypothesis.[24] Finally, we analyze the effects of the bid-ask spread and the adjustment process on the estimated serial covariance and variance of stock returns. We show that the practice of estimating the parameters of the value return distribution using observed returns can produce misleading results.

Taken as a whole, the evidence suggests that trading at the opening exposes traders to a greater variance than in the close, reflecting the differences between the trading mechanisms. Both the nature of lagged price adjustment and the level of transitory noise are different. Thus, when considering the implications of changing the method of trading in a market, the effects on return behavior should not be overlooked.

[24] It is interesting to entertain the thought of how Finance textbooks would have treated the issue of market efficiency had the first empirical studies been carried out using open-to-open rather than close-to-close returns.

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