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Short-Horizon Return Reversals and the Bid–Ask Spread

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We show that the pattern of short-term negative serial covariances for stock returns over different return measurement intervals is consistent with the implications of inventory-based market microstructure models. We develop additional testable implications of these models and document supporting evidence. Our findings indicate that to a large extent the short-horizon return reversals can be explained by dealer-inventory-related market microstructure effects. *Journal of Economic Literature* Classification Numbers: G14, G20. © 1995 Academic Press, Inc.

1. INTRODUCTION

Since the seminal works of Cootner (1964) and Fama (1965) economists have been aware that individual stock returns tend to exhibit negative serial correlation over short horizons. Although these early studies did not consider the magnitude of the observed serial correlation to be economically important, more recent work suggests that these return reversals provide opportunities for significant abnormal profits. In particular,

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recent research indicates that contrarian strategies designed to exploit these return reversals provide investors with opportunities to achieve abnormal returns of about 2% per month (see Jegadeesh, 1990; Lehmann, 1990).

Both Jegadeesh and Lehmann consider the possibility that the observed return reversals are induced by prices bouncing between bid and ask quotes. Appealing to Roll's (1984) model, where the bid–ask spread induces negative serial correlation in returns measured over adjacent intervals only, Jegadeesh and Lehmann examine modified strategies where contrarian portfolios are formed 2 days after the dates when the returns used to form the portfolios are measured. The authors argue that since the profits to these modified strategies are still reliably positive, the observed return reversals are not due to bid–ask bounce and are suggestive of an inefficient market where stock prices overreact to information. It should be noted, however, that Roll's results follow from the implicit assumption that the bid–ask spread is determined entirely by the specialists' or market makers' order processing costs. In more general models that also account for inventory costs, higher-order serial correlations can in fact be induced by bid–ask bounce and this effect is not fully accounted for by the Jegadeesh and Lehmann modified strategies that skip a day.

The focus in this paper is on the component of the spread that is due to the inventory costs imposed on risk-averse specialists when they deviate from their preferred portfolio.[1] We develop a simple model that builds on the theoretical results of Ho and Stoll (1981). This model allows us to decompose the serial covariance of stock returns into four components: a component that relates to the decay of the temporary component of stock prices caused by the specialist's (or other liquidity providers') inventory imbalances, a component that accounts for the effect on serial covariances of the bid–ask bounce, and two additional components that relate to interactions between the order flow and the temporary components of stock prices caused by inventory imbalances.

In our model, serial covariances of returns induced by the bid–ask bounce are less negative for returns measured over short intervals than for returns measured over long intervals. Our results imply that Roll's measure of implicit spread is downward-biased when serial covariances of returns are measured over short intervals (e.g., daily) and upward-biased when they are measured over sufficiently long intervals (e.g., weekly). Furthermore, we show that the slope coefficient in a regression of the

[1] This component of the spread is analyzed in Amihud and Mendelson (1980), Ho and Stoll (1981), and Stoll (1989). An additional component of the spread that has received a great deal of attention arises because of adverse selection (see Gloston and Milgrom, 1985; Copeland and Galai, 1983). This component of the spread, however, does not have an effect on the serial correlation of returns and is not explicitly considered in this paper.

serial covariance of returns on squared bid–ask spread is larger in absolute value for long return measurement intervals than for short intervals.

The results of our empirical tests are consistent with these predictions. Specifically, quoted spreads are on average larger than Roll's implicit spread estimates based on 1-day returns and they are smaller than the implicit spread estimates based on 10-day returns. In addition, the slope coefficient of a cross-sectional regression of estimated serial covariance of returns on squared spread increases monotonically as the return measurement interval is increased from 1 to 10 days. Our results also indicate that squared spread explains a large fraction of the observed serial covariances.

The rest of the paper is organized as follows: The next section relates the serial covariances at different return measurement intervals to the bid–ask spread. The empirical tests and the results are presented in Section 3. Section 4 discusses the results of additional tests and Section 5 contains our conclusions.

2. THE RELATION BETWEEN SERIAL COVARIANCES AND THE BID–ASK SPREAD

Ho and Stoll (1981) theoretically examine the determination of prices in a dealer market with risk-averse dealers.[2] In this model, because of fixed costs and inventory considerations, dealers require a spread between their bid and ask prices. Ho and Stoll show that the midpoint between the dealer bid and ask prices will deviate from the intrinsic value of the shares when there are dealer inventory imbalances. When their inventories are large, the dealers set the midpoints of the bid and ask quotes below the intrinsic values so that the probability of attracting buy orders increases. The midpoint deviates from the intrinsic value as long as the inventory imbalance persists.

This section presents a simple model that captures the spirit of Ho and Stoll and other inventory-based microstructure models. We then use this model to examine whether the observed negative serial covariance in stock returns that gives rise to contrarian profits can be explained by the price setting behavior of dealers and other providers of market liquidity.

Let p_t' and p_t be the natural logarithm of the "true" price (a hypothetical price that would occur in the absence of transaction costs and inventory considerations) and the transaction price at time t, respectively. Let

$$p_t = p_t' + z_t, \tag{1}$$

[2] The term "dealer" in this model should be viewed as a composite of the specialist and other investors who offer market liquidity.

where z_t, the temporary component of the transaction price, is determined by the bid–ask spread and is assumed to be independent of the true price.

In the context of the inventory model of Ho and Stoll, z_t can be decomposed into the sum of two components,

$$z_t = \frac{S}{2}\theta_t + \delta_t,$$

where $\theta_t = 1$ if the transaction at t is a buy and $\theta_t = -1$ if the transaction at t is a sell, S is the total spread (the difference between bid and ask prices), and δ_t is the adjustment to the quoted prices made by the dealer in response to inventory imbalances. When the dealer has positive excess inventory, δ_t is set to be negative in order to encourage purchases and discourage sales. In Ho and Stoll, δ_t depends upon a number of unobservable parameters such as the wealth, the risk aversion parameter, and the planning horizon of the specialist. However, in their model, these parameters affect δ_t in the same way as they affect the size of the spread so that δ_t can be specified as a simple linear function of the inventory level and the size of the spread

$$\delta_t = -\alpha' I_{t-1}(S - C),$$

where α' is a positive constant that is related to the average order size, I_t is the level of inventory imbalance after the trade at time t, and C represents those components of the spread that are not directly related to inventory costs (such as monopoly profits and fixed costs). In what follows, we will use a simplified version of the above expression that assumes that C is proportional to S cross-sectionally, allowing us to specify δ_t as[3]

$$\delta_t = -\alpha I_{t-1} S. \tag{2}$$

Under the hypothesis that the "true" prices follow a random walk, the serial covariance of the changes in observed prices across a measurement interval of k periods is given by the sum of four terms

[3] This specification of δ_t is similar to that in Stoll (1989) where the specialist temporarily increases the bid and ask prices by an amount proportional to the spread after each transaction.

$$
\begin{aligned}
&\operatorname{cov}(p_{t+k} - p_t, p_t - p_{t-k}) \\
&\quad = \operatorname{cov}(z_{t+k} - z_t, z_t - z_{t-k}) \\
&\quad = \operatorname{cov}(\delta_{t+k} - \delta_t, \delta_t - \delta_{t-k}) + \frac{S^2}{4}\operatorname{cov}(\theta_{t+k} - \theta_t, \theta_t - \theta_{t-k}) \\
&\qquad + \frac{S}{2}\operatorname{cov}(\delta_{t+k} - \delta_t, \theta_t - \theta_{t-k}) + \frac{S}{2}\operatorname{cov}(\theta_{t+k} - \theta_t, \delta_t - \delta_{t-k}),
\end{aligned} \tag{3}
$$

each of which can be considered separately.

The first term is related to the decay of the inventory component of the bid and ask prices. Using Eq. (2), this term can be expressed as

$$\operatorname{cov}(\delta_{t+k} - \delta_t, \delta_t - \delta_{t-k}) = -\alpha^2 S^2(\sigma_I^2 + \gamma_{2k} - 2\gamma_k),$$

where σ_I^2 is the unconditional variance of I_t and γ_k and γ_{2k} are its kth- and $2k$th-order serial covariances. Unlike the serial covariance in returns due to the bounce between the bid and ask prices, the serial covariance due to the decay of δ will persist beyond a single transaction. In Ho and Stoll, $\gamma_k \to 0$ as k becomes large since the inventory imbalance of the specialist is stationary. Therefore,

$$\lim_{k\to\infty} \operatorname{cov}(\delta_{t+k} - \delta_t, \delta_t - \delta_{t-k}) = -\alpha^2 S^2 \sigma_I^2.$$

For small k, however, $\gamma_k > \gamma_{2k}$ and hence $\operatorname{cov}(\delta_{t+k} - \delta_t, \delta_t - \delta_{t-k}) > -\alpha^2 S^2 \sigma_I^2$. In other words, the serial covariance in returns due to the decay of δ will be more negative for large k than for small k.

The second term in (3) can be expressed as

$$\frac{S^2}{4}\operatorname{cov}(\theta_{t+k} - \theta_t, \theta_t - \theta_{t-k}) = -S^2(1 - \pi_k)^2,$$

where π_k is the unconditional probability that a buy (sell) order at time t will be followed by a buy (sell) order at time $t + k$. The derivation of this expression is similar to that in the generalization of Roll's model considered by Choi *et al.* (1988). In Ho and Stoll the specialist changes δ_t between transactions in order to encourage offsetting transactions so that π_k is less than 0.5 for low k, making this component of the serial covariance more negative than $-0.25S^2$ for small k.[4] However, this component tends to $-0.25S^2$ for large k as in Roll.

[4] However, if the order flow over short intervals is positively serially correlated over short intervals for reasons outside the model, as found by Choi *et al.* (1988) in the options market, then this component of serial covariance will be less than $-0.25S^2$.

The third component of serial covariance in (3) is related to the average adjustment to δ made by the specialist in response to a buy or a sell order. Specifically,

$$\frac{S}{2}\operatorname{cov}(\delta_{t+k} - \delta_t, \theta_t - \theta_{t-k})$$

$$= -\alpha \frac{S^2}{2}\operatorname{cov}(I_{t+k-1} - I_{t-1}, \theta_t - \theta_{t-k})$$

$$= -\alpha \frac{S^2}{2}\{\operatorname{cov}(I_{t+k-1} - I_{t-1}, \theta_t) - \operatorname{cov}(I_{t+k-1} - I_{t-1}, \theta_{t-k})\}.$$

Note that θ_t is positive when the transaction at time t is a buy and that a buy order leads to a reduction in the specialist's inventory level. Therefore, the first term within brackets in the above expression is negative for small k. As k increases this term becomes smaller since any inventory imbalance is worked off in the long run. The second term in the above expression is also negative since the transaction at time $t - k$ has a bigger effect on the inventory position at time $t - 1$ than at time $t + k - 1$. The above discussion implies that the third component can be written as

$$\operatorname{cov}(\delta_{t+k} - \delta_t, \theta_t - \theta_{t-k}) = S^2 f_{1k}, \tag{4}$$

where f_{1k}, which equals $-\alpha/2$ times the bracketed term in the above equation, is positive and becomes small as k becomes large. This term remains positive even for large k due to the term $\operatorname{cov}(I_{t-1}, \theta_t)$, which does not depend on k. This covariance is positive since a positive inventory imbalance leads to negative δ, which in turn encourages buy orders (positive θ).

The last term in (3) is

$$\frac{S}{2}\operatorname{cov}(\theta_{t+k} - \theta_t, \delta_t - \delta_{t-k})$$

$$= -\alpha \frac{S^2}{2}\operatorname{cov}(\theta_{t+k} - \theta_t, I_{t-1} - I_{t-k-1}),$$

$$= -\alpha \frac{S^2}{2}\{\operatorname{cov}(\theta_{t+k}, I_{t-1} - I_{t-k-1}) - \operatorname{cov}(\theta_t, I_{t-1} - I_{t-k-1})\}.$$

Since positive changes in inventory lead to a decrease in δ which in turn increases the probability that the transaction at time t is a buy order, both the covariances within the brackets are negative. The effect of the second term within the brackets dominates that of the first term because the changes in the specialist's inventory from time $t - k - 1$ to $t - 1$ is likely to have a bigger effect on the order flow at time t than that at time $t + k$. Therefore, the last component can be expressed as

$$\frac{S}{2}\operatorname{cov}(\theta_{t+k} - \theta_t, \delta_t - \delta_{t-k}) = S^2 f_{2k},$$

where f_{2k} is positive. This term also remains positive for large k due to the term $\operatorname{cov}(I_{t-1}, \theta_t)$.

The preceding analysis indicates that Eq. (3) can be written as

$$\begin{aligned}\operatorname{cov}(p_{t+k} - p_t, p_t - p_{t-k}) = {} & -\alpha^2 S^2(\sigma_I^2 + \gamma_{2k} - 2\gamma_k) - S^2(1 - \pi_k)^2 \\ & + S^2 f_{1k} + S^2 f_{2k},\end{aligned} \tag{5}$$

and the first two terms in this expression become more negative and the last two expressions become less positive as k increases. Therefore, our results predict that the serial covariance of stock returns will become more negative as we increase the return measurement interval k. In addition, as k is increased the serial covariance of returns becomes a larger multiple of the squared spread.

This representation of the serial covariances of stock returns can be compared with Roll's (1984) predictions for both large and small k's. In the case considered by Roll, only the second term in the above expression is relevant and π_k is assumed to equal 0.5. Thus, in Roll's model,

$$\operatorname{cov}(p_{t+k} - p_t, p_t - p_{t-k}) = -0.25S^2. \tag{6}$$

Our analysis implies that when inventory considerations affect the bid and ask quotes the serial covariance of returns will in general differ from $-0.25S^2$. When k is large, the sum of the first two terms in Eq. (5) is less than $-0.25S^2$. Since the positive terms (the third and fourth terms in this expression) become smaller as k increases, the sum of the four terms could result in the serial covariance of returns being smaller than $-0.25S^2$. For small k, the decay of the temporary component is likely to be small, which would make the first term less important. In addition, the third and fourth components are positive and larger for small k than for large k. Depending on the relative magnitudes of these terms, for small k the serial covariance in observed returns could be greater than $-0.25S^2$.

Our analysis can be contrasted with some earlier papers that also argue that there may be a temporary component in prices that gives rise to predictable changes in short-horizon returns.[5] In Amihud and Mendelson

[5] See, for example, Amihud and Mendelson (1987, 1989) and Damodaran (1993).

(1987), for example, a temporary component, which eventually decays, is exogenously specified to account for noise in prices. In contrast, the temporary component (δ) in our model arises endogenously and therefore we are able to derive predictions about how the decay of the temporary component (measured by the serial covariance of returns at different measurement intervals) relates to the squared spread. One could interpret the noise in prices in Amihud and Mendelson as coming from the bid–ask spread, in which case the decay of this component over time will give rise to a relation between the serial covariance of returns and the squared spreads similar to that presented in our model.

3. EMPIRICAL TESTS

Empirical tests of the above inventory model are presented in this section. Our data consist of quoted year-end closing spreads for securities traded on the New York Stock Exchange (NYSE) over the period 1963 to 1979 and daily stock returns from CRSP. The bid–ask spread data were originally obtained from the Fitch Quotations for a study by Stoll and Whaley (1983).[6] As in Stoll and Whaley (1983) the averages of the quoted spreads at the end of years t and $t - 1$ are used as the spreads for year t. All securities that had spread data available and had at least 100 observations to estimate the means and the serial covariances were included in the sample.[7]

A. *Estimates of Serial Covariances*

It is well known that the standard estimate of the serial covariance has a negative bias in small samples (see Marriot and Pope, 1954). To circumvent this bias we estimate serial covariances separately for each year using an estimate of the expected returns from the previous year. Specifically, our serial covariance estimate for year t is

$$\widehat{\mathrm{Scov}}^{t}_{ik} = \frac{1}{T}\sum_{n=1}^{T}\left(\sum_{m=1}^{k} R_{in+m-1} - k\bar{R}_{it-1}\right)\left(\sum_{m=1}^{k} R_{in-m}\right), \tag{7}$$

where T is the number of overlapping sample points in year t, R_{in} is the continuously compounded return on day n, and $\bar{R}_{it-1}$ is the sample mean daily return estimated from the data in year $t - 1$. As shown in the Appendix, the serial covariance estimate given by (7) is unbiased.

[6] We would like to thank Hans Stoll for providing these data.

[7] On average, there were 1214 securities per year in the sample.

The serial covariance from Eq. (7) is separately estimated for each security for each calendar year. These estimates for the individual securities are averaged across the cross section every year. The estimates of the average serial covariances and the standard errors are computed from the time-series of the cross-sectional estimates. These estimates for return measurement intervals of 1, 3, 5, 7, and 10 days are presented in Table I. Consistent with our analysis, the estimate of average serial covariance

TABLE I
ESTIMATES OF SERIAL COVARIANCES OF RETURNS MEASURED OVER DIFFERENT OBSERVATION INTERVALS

k =	1	3	5	7	10
S1	−0.563[b]	−1.687	−2.568	−3.746	−4.885
	(−2.86)	(−5.48)	(−4.98)	(−4.26)	(−3.40)
S2	−0.069	−0.794	−1.472	−2.209	−2.725
	(−0.78)	(−5.62)	(−4.13)	(−3.64)	(−2.85)
S3	0.081	−0.450	−0.947	−1.445	−1.651
	(1.60)	(−4.56)	(−3.13)	(−2.92)	(−2.37)
S4	0.170	−0.157	−0.601	−1.024	−1.013
	(4.15)	(−3.39)	(−2.64)	(−2.13)	(−1.28)
S5	0.197	−0.040	−0.587	−1.154	−1.234
	(4.57)	(−0.93)	(−3.29)	(−3.24)	(−2.73)
All	0.002	−0.571	−1.182	−1.830	−2.117
	(0.05)	(−7.91)	(−4.40)	(−3.72)	(−3.02)

Note. Unbiased estimates of k-day return serial covariance are obtained using the estimator

$$\widehat{\mathrm{Scov}}'_{ik} = \frac{1}{T}\sum_{n=1}^{T}\left(\sum_{m=1}^{K} R_{in+m-1} - k\bar{R}_{it-1}\right)\left(\sum_{m=1}^{k} R_{in-m}\right),$$

where$T$ is the number of overlapping in year t, R_{in} is the continuously compounded return on day n, and $\bar{R}_{it-1}$ is the sample mean daily return estimated from the data in year $t-1$. The estimates are obtained for each security i within the calendar year t and these estimates are averaged across the cross section. The mean of the time-series of the cross-sectional averages and the associated t-statistics are presented below. S1 through S5 are quintiles of the smallest through the largest firms in the sample.[a] The t-statistics are presented in parentheses. The sample period is 1963–1979.

[a] The cutoffs for the size-quintiles are based on all the firms traded on the NYSE at the beginning of a given year out of which some are excluded from our sample. Therefore, the number of firms in the groups S1 through S5 are different and hence the estimates of the serial covariance of returns for the entire sample need not equal the average of the estimates within the five groups.

[b] The estimates of average serial covariances are multiplied by 10^4 and reported in this table.

(t-statistic) for the entire sample monotonically decreases from 0.002×10^{-4} (0.05) for $k = 1$ to -2.12×10^{-4} (-3.02) for $k = 10$.[8]

The serial covariance estimates within the size quintiles are also presented in Table I.[9] Virtually the same pattern of serial covariances is observed for all size-based groups. The small firms generally exhibit more negative serial covariance than the large firms at almost all lags. For instance, the average 10-day return serial covariance for the quintile of smallest firms is -4.9×10^{-4} while the corresponding estimate for the quintile of largest firms is -1.2×10^{-4}.

B. Quoted Spread vs Roll's Implicit Measure

As shown in Section 2, if inventory considerations affect bid and ask prices, Roll's implicit measure of the spread will overstate the spread when the serial covariance is measured over a sufficiently long interval and may understate the spread at very short intervals. This section examines these predictions.

Roll's implicit measure of the spread is derived by solving Eq. (6) for S, and substituting an estimate of the serial covariance. For example, if the serial covariance is estimated with k-period returns, Roll's implicit measure is given by

$$\begin{aligned} S^k_{\text{imp}} &= 2\sqrt{-\widehat{\text{Scov}}_k} \qquad \text{if } -\widehat{\text{Scov}}_k > 0 \\ &= -2\sqrt{\widehat{\text{Scov}}_k} \qquad \text{if } -\widehat{\text{Scov}}_k < 0. \end{aligned}$$

In small samples the estimate of serial covariance, and hence Roll's implicit spread measure, is severely biased downward when the variance of returns is large.[10] To minimize this bias we estimate Roll's implicit spread using serial covariance estimates that are averaged across size-based groups of securities. Based on (6), the relation between the estimate

[8] The estimates of average serial covariance using the standard serial covariance estimator ranged from -0.008×10^{-4} for $k = 1$ to -3.74×10^{-4} for $k = 10$. Consistent with the results in Marriot and Pope, 1954, all these conventional estimates are more negative than the corresponding unbiased estimates reported in Table I and also, the extent of measured bias is increasing in the measurement interval k.

However, the evidence of positive serial covariances for the two large-firm quintiles at $k = 1$ is not consistent with our predictions. This result could possibly be explained by a more general inventory-based market-microstructure model that allows for positively correlated order flows. It is also possible that the positive serial correlation is induced by partially delayed stock price reaction (see Amihud and Mendelson, 1987; Damodaran, 1993).

[9] Securities are assigned to different size-quintiles at the beginning of each year.

[10] By Jensen's inequality, the expected value of the square root of a random variable is less than the square root of its expected value. Since the estimate of serial covariance is unbiased Roll's implicit measure of spread is biased downward.

of average serial covariance within a given group, denoted by $\overline{\text{Scov}}_k$, and the quoted spread is given by

$$E(\overline{\text{Scov}}_k) = -0.25(\bar{S}^2 + \sigma_s^2),$$

where $\bar{S}$ is the average within-group spread and σ_s^2 is the within-group variance of the quoted spread.

Based on this expression, the modified version of Roll's implicit measure of the average spread within a group is given by

$$\begin{aligned} \bar{S}_{\text{imp}}^k &= 2\sqrt{-\overline{\text{Scov}}_k + 0.25\sigma_s^2} && \text{if } (-\overline{\text{Scov}}_k + 0.25\sigma_s^2) > 0 \\ &= -2\sqrt{\overline{\text{Scov}}_k - 0.25\sigma_s^2} && \text{if } (-\overline{\text{Scov}}_k + 0.25\sigma_s^2) < 0. \end{aligned}$$

Estimates of average implicit spreads within size-based groups over the sample period 1963–1979 along with the average quoted spreads are given in Table II. The estimates of the implicit spreads are negative when calculated with a return measurement interval of 1 day and they are smaller than the average quoted spreads for $k = 3$. However, as our model predicts, these estimates are larger than the average quoted spreads for longer return measurement intervals. For example, the average quoted

TABLE II
ROLL'S IMPLICIT MEASURES OF SPREAD AND THE QUOTED SPREADS

	Implicit spread					Quoted
$k =$	1	3	5	7	10	spread
S1	−0.006	0.020	0.027	0.034	0.039	0.025
S2	−0.009	0.015	0.022	0.028	0.032	0.018
S3	−0.009	0.012	0.019	0.024	0.025	0.014
S4	−0.010	0.006	0.015	0.020	0.019	0.011
S5	−0.010	0.001	0.016	0.023	0.022	0.008
Column average	−0.009	0.011	0.020	0.026	0.027	0.015

Note. The within-size-group pooled cross-sectional time-series average estimates of serial covariances of k-day returns are inverted to obtain Roll's implicit measure of bid–ask spread. Specifically the implicit spread is obtained using the expression

$$\begin{aligned} \bar{S}_{\text{imp}}^k &= 2\sqrt{-\overline{\text{Scov}}_k + 0.25\sigma_s^2} && \text{if } (-\overline{\text{Scov}}_k + 0.25\sigma_s^2) > 0 \\ &= -2\sqrt{\overline{\text{Scov}}_k - 0.25\sigma_s^2} && \text{if } (-\overline{\text{Scov}}_k + 0.25\sigma_s^2) < 0, \end{aligned}$$

where $\bar{S}_{\text{imp}}^k$ is the implicit estimate of the average spread with a given-size group, $\overline{\text{Scov}}_k$ is the within-size-group average of the estimates of serial covariance of k-day returns, and σ_s^2 is the within-size-group variance of quoted spread. S1 through S5 are quintiles of the smallest through the largest firms in the sample. The sample period is 1963–1979.

spread for all the securities in our sample is 1.5% of the price. In comparison, the implicit spread from serial covariances measured over 3- and 10-day intervals are 1.1 and 2.7%, respectively. The results are qualitatively similar within each of the size-based subsamples.

C. *Regression Tests*

To test the relation between serial covariances and bid–ask spreads predicted from our analysis in the last section (see Eq. (5)) we substitute estimates of the serial covariances for the actual serial covariances and fit the regression

$$\widehat{\mathrm{Scov}}^t_{ik} = a^t_k + b^t_k S^2_{it} + e^t_{ik}, \tag{8}$$

where $\widehat{\mathrm{Scov}}^t_{ik}$ is the estimated serial covariance of k-period returns on security i in year t. The analysis in the last section suggests that $|b_k|$ should be smaller than 0.25 for small k and larger than 0.25 for large k.

Regression (8) is fitted separately for each of the 17 years in the sample period. The average of the yearly coefficient estimates and the corresponding t-statistics obtained from the time-series of the yearly coefficient estimates are presented in Table III. The slope coefficient estimates (t-statistics) reported in this table decrease monotonically with an increase in the measurement interval from -0.096 (-8.3) for $k = 1$ to -0.251 (-3.04) for $k = 10$ days and are all significant at the 1% level. The t-statistics at the bottom of this table indicate that the slope coefficient in

TABLE III

RELATION BETWEEN THE SQUARE OF THE SPREAD AND THE SERIAL COVARIANCE OF RETURNS MEASURED OVER DIFFERENT INTERVALS

$k =$	1	3	5	7	10
$\hat{a}_k \times 10^4$	0.311	0.004	−0.507	−1.035	−1.144
	(7.36)	(0.06)	(−2.40)	(−2.65)	(−2.00)
$\hat{b}_k$	−0.096	−0.189	−0.225	−0.243	−0.251
	(−8.30)	(−11.52)	(−8.95)	(−5.40)	(−3.04)
$\bar{R}^2_{\mathrm{adj}}$	0.298	0.194	0.103	0.073	0.052
$\hat{b}_k - \hat{b}_1$	—	−0.093	−0.129	−0.147	−0.155
	—	(−6.49)	(−5.48)	(−3.53)	(−1.99)

Note.

$$\text{Regression Model } \widehat{\mathrm{Scov}}_{ik} = a_k + b_k S^2_i + e_{ik},$$

where $\widehat{\mathrm{Scov}}_{ik}$ is the estimate of k-day return serial covariance of security i and S^2_i is the squared spread. The above cross-sectional regression is fitted each year and the average estimates of the regression parameters are obtained from the time-series of these estimates. The t-statistics are presented in parentheses. $\bar{R}^2_{\mathrm{adj}}$ is the average of the adjusted R^2 in the individual cross-sectional regressions. The sample period is 1963–1979.

the regression with $k = 1$ is significantly less negative than the corresponding estimate for $k = 3$ which is in turn less negative than the corresponding estimate for $k = 5$. Although the slope coefficients continue to increase in magnitude for larger k the increases are not statistically significant. These findings are consistent with our prediction and support the hypothesis that at least part of the observed higher-order negative serial correlation in stock returns is attributable to inventory costs.[11]

D. *Instrumental Variable Regressions*

This section examines the extent to which the average serial covariance of returns can be explained by the bid–ask spread. This can be evaluated by examining the intercept in regression (8), which provides an estimate of the serial covariance that is not explained by bid–ask spreads. These intercepts, reported in Table III, are about half the average serial covariance of returns measured over intervals longer than a day. For instance, the estimate of average serial covariance with a 5-day measurement interval is -1.182×10^{-4} while the intercept in regression (8) with $k = 5$ is -0.507×10^{-4}. These point estimates suggest that only about half of the average serial covariance can be explained by the spread.

These estimated intercepts may, however, be biased because of errors in the estimated bid–ask spreads.[12] To overcome this error-in-variables problem we estimate an instrumental variable version of regression (8). The instruments used for squared spread are LOGSIZE, the average price during the year, and the variance of daily returns.[13]

Table IV presents the estimates of the first and second stages of the instrumental variable regressions. Consistent with the presence of errors-in-variables, the estimated slope coefficients from these instrumental variable regressions, except for the case where $k = 1$, are more negative than

[11] To check the robustness of the results in this subsection, we also estimated the regression

$$\widehat{\text{Scov}}_{ik}^{t} = a_k^t + b_{1k}^t S_{it}^2 + b_{2k}^t \,\text{LOGSIZE}_{it} + u_{ik}^t,$$

where LOGSIZE_{it} is the natural logarithm of the market value of equity of firm i at time t. The estimated slope coefficient on S^2, b_{1k}, remained roughly the same as the corresponding slope coefficients in the univariate regression (8).

[12] Measurement errors in the bid–ask spread can arise either from the fact that the bid and ask prices are quoted in eighths or because the spread data are point sampled while the serial covariance is estimated using returns over the entire year.

[13] We estimated the variance for year t using data in year $t - 1$ in order to avoid picking up in-sample correlation between the estimated variance and serial covariance.

The instruments used here were chosen because previous literature (e.g., Stoll, 1989; Jegadeesh and Subrahmanyam, 1993) documents that they are related to the spread.

TABLE IV
INSTRUMENTAL VARIABLE REGRESSION ESTIMATES

$k =$	1	3	5	7	10
$\hat{\alpha}_k \times 10^4$	0.252	0.123	−0.227	−0.548	−0.531
	(4.86)	(1.63)	(−2.45)	(−2.21)	(−1.12)
$\hat{\beta}_k$	−0.065	−0.200	−0.260	−0.336	−0.378
	(−4.36)	(−10.34)	(−7.33)	(−5.16)	(−3.33)
$\bar{R}^2_{\text{adj}}$	0.067	0.108	0.076	0.070	0.050
$\hat{\beta}_k - \hat{\beta}_1$	—	−0.135	−0.195	−0.271	−0.313
	—	(−14.36)	(−6.99)	(−4.69)	(−2.99)

Note. The first stage regression is fitted using pooled cross-section time-series data, obtaining the estimates

$$S^2_{it} = 0.00177 - 0.00000166\text{PRC}_{it} - 0.000138\text{LOGSIZE}_{it} + 0.5354\text{VAR}_{it} + u_{it}$$

$$R^2_{\text{adj}} = 0.275,$$

where S^2 is the squared spread and the instrumental variable PRC is the average price, LOGSIZE is the natural logarithm of the market value of equity at the beginning of the year, and VAR is the variance of daily return.

The second stage regression is

$$\widehat{\text{Scov}}^t_{ik} = \alpha^t_k + \beta^t_k \hat{S}^2_{it} + e^t_{ik},$$

where $\hat{S}^2_{it}$ is the fitted value from the first stage regression, $\widehat{\text{Scov}}^t_{ik}$ is the estimated k-day return serial covariance of security i in year t. The cross-sectional regressions are fitted each year and the average estimates of the regression parameters are obtained from the time-series of these estimates. The t-statistics are reported in parentheses. $\bar{R}^2_{\text{adj}}$ is the average of the adjusted R^2 in the individual cross-sectional regressions. The sample period is 1963–1979.

the estimates obtained in the corresponding OLS regressions. For $k > 3$ these coefficients are marginally less than -0.25. As with the OLS regressions, the slope coefficients in the instrumental variables regression vary with the measurement interval, again supporting the inventory model. The estimates of the intercepts are generally closer to zero in the instrumental variable regressions than in the corresponding OLS regressions. For example, in the regression with $k = 5$, the intercept is -0.227×10^{-4} while the corresponding estimate of average serial covariance is -1.182×10^{-4}. The point estimate of the intercept is, therefore, less than 20% of the estimate of the average serial covariance suggesting that a large part of the observed serial covariances can be explained by the bid–ask spread.

4. ADDITIONAL EVIDENCE

The results described to this point are consistent with our predictions based on the market microstructure models and they support the hypothesis that return reversals are induced by inventory imbalances. This section presents a discussion of additional tests that examined whether the pattern of return reversals are related to the volume of trading. Extant empirical evidence suggests that serial covariances are likely to be more negative during times of high volume since larger inventory imbalances can be expected at such times.[14]

We found that the serial covariances were more negative during high volume periods for return measurement intervals of 3, 5, 7, and 10 days.[15] In contrast, the serial covariances of 1-day returns were closer to zero on high volume days. This result, however, is consistent with our earlier findings and it probably implies that the order flows tend to be more positively serially correlated during times of high volume. We also found that the differences in serial covariances estimated during high and low volume periods were greater for smaller firms than for the larger firms. Overall, the relation between serial covariances and volume of trading that we found provided additional support for the hypothesis that these serial covariances are induced by specialists' inventory imbalances.

5. CONCLUSION

The evidence presented in this paper suggests that most of the short-horizon return reversals can be explained by the way dealers set bid and ask prices, taking into account their inventory imbalances. The results support the implications of Ho and Stoll (1981) and others that examine the dynamics of the bid and ask prices quoted by risk-averse dealers. Our results, together with these market microstructure models, imply that the decay of dealer-inventory imbalances takes several days. This is consistent with Madhavan and Smidt (1993) who found that the dealers on the NYSE take several days to work down their inventory imbalances.

This evidence further suggests that the apparent contrarian trading profits documented by Jegadeesh (1990) and Lehmann (1990) are compensation for bearing inventory risk and cannot be realized by traders transacting at bid and ask prices. Hence, these prior findings are not necessarily inconsistent with an informationally efficient market. However, the evidence indicates that the stock market may not be as liquid or resilient as has been generally believed.

[14] For example, Kraus and Stoll (1972) examined price behavior following large block sells and found significant positive returns. Blume *et al.* (1989) examined the relation between price changes following the October 1987 stock market crash and volume on the day of the crash. They found that the stocks with the heaviest volume on the day of the crash, recovered the most on the following day, suggesting that part of the decline on the day of the crash was due to order imbalance.

[15] These results are not reported here but are available from the authors.

APPENDIX A

The standard estimator of serial covariance (denoted as $\widehat{\mathrm{SC}}$) of returns using T observations is

$$\widehat{\mathrm{SC}}(R_t, R_{t-1}) = \frac{1}{T-1}\sum_{i=2}^{T} R_i R_{i-1} - \left(\frac{1}{T}\sum_{i=1}^{T} R_i\right)^2. \tag{A1}$$

Taking the expectations of the terms in (A1) we get

$$E(\widehat{\mathrm{SC}}(R_t, R_{t-1})) = E(R_t R_{t-1}) - \mu^2 - \frac{\sigma^2}{T} - \frac{2}{T^2}\sum_{i=1}^{T}(T-i)\gamma_i, \tag{A2}$$

where μ, σ^2, and γ_i are the mean, the variance, and the ith order serial covariance of returns respectively. Under the hypothesis that the returns are serially uncorrelated the last term in (A2) is zero and the small sample bias in the serial covariance estimator (A1) is $-\sigma^2/T$.

Note that when returns are serially correlated, as suggested by our results in Section 1, the last term in (A2) is nonzero and hence the small sample bias contains terms involving the return serial covariances.

The estimator of serial covariance that we propose can be written as

$$\widehat{\mathrm{Scov}}(R_t, R_{t-1}) = \frac{1}{T-1}\sum_{i=2}^{T} R_i R_{i-1} - \left(\frac{1}{T}\sum_{i=1}^{T} R_i\right)\left(\frac{1}{T}\sum_{i=-T+1}^{0} R_i\right). \tag{A3}$$

Taking the expectations of the terms in (A3) we get

$$E(\widehat{\mathrm{Scov}}(R_t, R_{t-1})) = E(R_t R_{t-1}) - \mu^2 - \frac{1}{T^2}\left(\sum_{i=1}^{T} i\gamma_i + \sum_{i=T+1}^{2T}(2T-i)\gamma_i\right). \tag{A4}$$

Note that the term σ^2/T, which is the major source of bias in (A2), is not contained in (A4). The last term in (A4) is zero when returns are serially uncorrelated. Even when the daily returns are serially correlated as observed, the last term on the right-hand side is trivial for actual values of serial covariance detected in the data.

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