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Two Essays on Liquidity Suppliers' Gross Profits.

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TWO ESSAYS ON LIQUIDITY SUPPLIERS' GROSS PROFITS

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

FIGURE

ABSTRACT

The purpose of this dissertation is to examine the strategic behavior of the specialist proposed by Glosten (1989) and its implications for price volatility and market liquidity. The extant literature suggests that the bid-ask spread is responsible, at least in part, for the greater volatility and more negative autocorrelation at the open than at the close. We find that these phenomena are not related to the bid-ask spread, but related to pricing errors quoted by the specialist or by limit order traders around the open.

We use George, Kaul, and Nimalendran's (1991) model, which is less biased than Roll's (1984) model, to estimate the implied spread. The results show that, on average, the implied spread earned by liquidity suppliers is less at the open than at the close. These results refute Stoll and Whaley's (1990) contention that the specialist exploits his monopoly position and earns a higher profit at the opening call.

Glosten (1989) posits that when information asymmetry is high, the specialist may reduce profits or even realize losses to induce informed traders to trade and to release their information. This reduces the adverse selection problem and makes subsequent trades more profitable. This hypothesis of averaging profits through time implies that the pattern in the specialist's gross profits is inversely

related to the pattern in information asymmetry. Since information asymmetry has been found to be higher at the beginning of the trading day, we predict that gross profits earned by the specialist will be lower at the beginning than during the rest of the trading day. Empirical results are consistent with this hypothesis.

CHAPTER 1

INTRODUCTION

In securities markets, market makers play several important roles such as suppliers of immediacy, information processors, price stabilizers, and auctioneers.[1] When market makers provide their services to traders, they incur costs that include order processing cost, inventory holding cost, and adverse selection cost.[2] Market makers charge the bid-ask spread to cover these market making costs.[3]

One of the major market structural issues is the effect of informational trading on liquidity of the market. The adverse information theory suggests that market makers widen the bid-ask spread to compensate for expected losses to informed traders when they perceive an increase in the degree of information asymmetry.[4] However, if market makers face an extremely high degree of information asymmetry, will they quote an extremely high spread? How will they resolve the high degree of information asymmetry? If market makers do quote an extremely high spread, the market will become

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[1]See Stoll (1985).

[2]See Stoll (1978, 1989).

[3]See Demsetz (1968) and Stoll (1989).

[4]See, for example, Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987).

illiquid and the cost of transacting will be very high.[5] In this case, private information may not be easily released through trading.

Glosten (1989) suggests that the monopolist specialist can average profits over time. When information asymmetry is high, the specialist may reduce profits or even realize losses to induce informed traders to trade and release their information, thus reducing the adverse selection problem and making subsequent trades profitable. Hence, the specialist may use this strategic behavior to mitigate the adverse selection problem and enhance the market liquidity. Glosten (1989) shows that this strategic behavior of the specialist's averaging profits over time is optimal under the condition of information asymmetry.

The strategic behavior of market makers is the primary focus of the dissertation. Specifically, this dissertation consists of two essays. The first essay examines whether greater return volatility and more negative serial correlation at the opening call, as documented by Amihud and Mendelson (1987) and Stoll and Whaley (1990), are due to the bid-ask spread. Stoll and Whaley (1990) conjecture that the specialist, in exploiting his monopoly position at the opening call, increases the effective bid-ask spread. However, according to Glosten (1989), the specialist, who charges a monopoly profit at the opening call, may not be

[5]See, for example, Admati and Pfleiderer (1988).

profit-maximizing. Instead, since the degree of information asymmetry is likely to be highest at the beginning of the trading day due to the long period of nontrading,[6] the specialist may lower his gross profits to induce informed traders to submit orders and release their information at the open. This may mitigate the adverse selection problem at the opening call and make subsequent trades in continuous market more profitable. Hence, unlike Stoll and Whaley (1990), we postulate that the specialist sets a smaller cost of immediacy in order to encourage trading at the opening call.

The second essay examines the implication of the strategic behavior of the specialist in intraday patterns of gross profits earned by NYSE specialists. Also, this essay empirically distinguishes the impacts of the bid-ask spread and of private information on intraday return volatility. If the strategic behavior of the specialist follows the model of Glosten (1989), gross profits earned by the specialist are expected to be lower at the beginning than during the rest of the trading day. In addition, the strategic behavior of the specialist suggests that the impacts on price volatility of the bid-ask spread and of private information may vary through time. Since gross profits earned by market makers are expected to be lower at the beginning, price volatility due to prices bouncing between the bid-ask spread should be

[6]See, for example, Hasbrouck (1991) and Foster and Viswanathan (1993).

less at the beginning than during the rest of the trading day. Conversely, since information asymmetry is expected to be higher at the beginning, price volatility due to private information should be larger at the beginning than during the rest of the trading day.

These two essays are addressed in Chapters 2 and 3, respectively. In these two chapters, we review the literature, identify the problems, formulate the hypotheses for empirical tests, and present the results. We then conclude the dissertation in Chapter 4 with a discussion of issues for further research.

CHAPTER 2

VOLATILITY AND LIQUIDITY AT THE OPENING CALL: A CLOSER LOOK

2.1. Introduction

Many stock exchanges, which operate as continuous markets, employ a call clearing procedure at the opening transaction.[7] The New York Stock Exchange (NYSE) is a typical example of this setting. Buy and sell orders are batched for execution at the opening call. After observing the accumulated buy and sell orders, the specialist may trade on his own account or solicit more orders from floor traders to offset order imbalances. With the assistance of the opening automated reporting system (OARS) that sorts the accumulated buy and sell orders, the specialist determines a price that clears the market. The price is applied to all executed buy and sell orders. In subsequent continuous trading, transactions are carried out through the specialist and other traders who quote bid and ask prices at which they are willing to buy or sell.[8] Hence, the trading mechanism at the open is different from that of the rest of the day.

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[7]Examples are the New York, American, Amsterdam, Brussels, Frankfurt, Luxembourg, Montreal, Paris, Tokyo, Toronto, and Vienna Stock Exchanges. See Cohen, Maier, Schwartz, and Whitcomb (1986, Ch. 2) for further discussions on trading systems in the main world exchange markets.

[8]The quoted prices may be from the specialist's own account or from traders who submit limit orders. Floor traders may also compete with the specialist for order flows.

Several studies have compared the volatility and liquidity of the call market at the open with those of the continuous market at the close and obtained intriguing results. For example, Amihud and Mendelson (1987) and Stoll and Whaley (1990) find that open-to-open returns of NYSE stocks exhibit greater volatility and more negative autocorrelation than close-to-close returns. Amihud and Mendelson (1989, 1991) examine the behavior of stock returns generated from the morning opening call and the closing transaction on the Tokyo Stock Exchange (TSE) and obtain similar results.

What may cause greater volatility and more negative autocorrelation at the open than at the close? Amihud and Mendelson (1987) and Stoll and Whaley (1990) suggest that the results are not attributable to the release of public information, since both the open-to-open return and the close-to-close return span the same time period (i.e., 24 hours). Amihud and Mendelson (1991) further show that the results are not attributable to the clearing transaction mechanism per se, because the afternoon clearing transaction on the TSE does not produce greater volatility than the continuous market.[9] They thus conclude that "the culprit in the higher volatility and negative autocorrelation of daily open-to-open returns is the preceding nontrading period ..." (p. 1787).

[9]The TSE employs a clearing mechanism in the opening transaction of both the morning and the afternoon trading sessions.

Amihud and Mendelson (1991) argue that during a long nontrading period traders cannot observe a sequence of recent transaction prices to infer the current value of the security. Hence, we should expect more noisy value discovery and larger pricing errors following the overnight trading halt. The larger pricing errors could lead to greater volatility and more negative autocorrelation at the open than at the close. Amihud and Mendelson (1991, p.1783) indicate that a simple interpretation of the relation between price reversals and pricing errors is due to the implicit bid-ask spread, as suggested by Roll (1984). Similarly, Stoll and Whaley (1990) contend that the specialist, in exploiting his monopoly position at the opening call, increases the effective bid-ask spread. Since transaction prices tend to bounce between bid and ask prices, the larger bid-ask spread increases the tendency of price reversals and makes prices more volatile at the open.

The first purpose of this study is to further examine whether the bid-ask spread is the main cause for higher volatility and more negative auto-correlation at the open. Using the bid price right after the opening transaction as the open bid, we find that open-to-open bid price returns also display higher volatility and more negative autocorrelation than close-to-close bid price returns. Furthermore, the transaction price reversal around the open is, to a large extent, related to the reversal in bid prices.

Since returns based on bid prices are not subject to bid-ask spread bounces, these findings cast doubts on the notion that the bid-ask spread is the main cause for greater volatility and more price reversals at the open than at the close.

We posit that informed trading around the opening causes bid prices to reverse. It is possible that new information is produced and accumulated during the overnight trading halt. All of the new private information may not be incorporated into prices at the opening call. (According to Kyle's (1985, p.1319) model, only one-half of the insider's private information is incorporated into prices through a single call auction.)[10] Hence, liquidity suppliers who quote bid and ask prices immediately after the opening call are still likely to face informed traders with private information. If the bid price at which liquidity suppliers are willing to buy is too high, informed traders sell and bring down the bid price later on. If the bid price is too low, informed traders could profit by setting a limit order with a slightly higher bid to buy. Thus, informed trading around the open could correct pricing errors quoted by the specialist or by limit order traders, resulting in the bid

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[10]Certainly, Kyle's (1985) model is derived under certain assumptions, which may not perfectly fit in with the NYSE. For example, informed traders can be market makers by submitting limit orders on the NYSE. Also, the quantity traded by noise traders may not follow a Brownian motion process. Hence, the proportion of private information incorporated into prices at the opening call on the NYSE may deviate from his prediction.

price reversal. Informed trading could similarly cause ask prices to reverse. The reversal in the bid and ask prices could lead to a reversal in transaction prices, which in turn could increase the volatility of open-to-open returns relative to close-to-close returns.

Although the specialist and limit order traders may lose to informed traders around the open, they may gain from liquidity traders in subsequent trades. Hence, the second purpose of this study is to examine the strategic behavior of the specialist at the opening call. Stoll and Whaley (1990) argue that the specialist charges a higher cost of immediacy and earns a monopoly profit at the open. Their estimated cost of immediacy at the open is about nine times as much as at the close.[11] As argued below, the specialist who charges a monopoly profit at the opening call may not be profit-maximizing.

Unlike Stoll and Whaley (1990), we postulate that the specialist encourages trading by setting a smaller cost of immediacy at the opening call. More trading would reveal more private information (about the value of the security),[12]

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[11]Their estimates indicate that the average implied spread is 0.8983 percent if based on open-to-open returns, whereas it is only 0.0971 percent if based on close-to-close returns.

[12]According to Admati and Pfleiderer (1988), the lower cost of immediacy can attract more discretionary liquidity traders. The concentration of liquidity trading induces more informed trading, which may release more information about the value of the security.

which has been accumulated since the closing transaction on the previous day. From learning at the opening call, the specialist reduces the adverse selection problem and makes subsequent trades in the continuous market more profitable.

This strategic behavior of the specialist at the opening call and at the continuous trading market follows the model of Glosten (1989). He suggests that the monopolist specialist can learn some of the information of the informed and can average profits over time. That is, the greater profits earned after a decrease in the information asymmetry offset the losses realized early on in the trading when the adverse selection problem was high. Certainly, the specialist on the NYSE is not a pure monopolist and hence his ability to average losses and profits over time may be limited. Nevertheless, the specialist has strong incentives to reduce the expected losses to informed traders for his own account and for limit order traders' accounts. As noted by Stoll and Whaley (1990, footnote 2), on average, the specialist participates in about 90 percent of the nonblock shares traded on the NYSE as either dealer for his own account or broker for the limit order book.

Without a call clearing at the open, the specialist could still learn from the informed in the continuous market. However, as shown by Madhavan (1992, p. 609), a periodic call market aggregates information more efficiently and is more robust to the problem of information asymmetry in that it could operate where a continuous market might fail. This may explain why most of exchanges with continuous trading adopt a periodic call procedure at the beginning of the trading day when the information asymmetry is likely to be highest.

The hypothesized strategic behavior of the specialist on the call market and the continuous market implies that the cost of immediacy is lower at the opening transaction than at the closing transaction. We test this hypothesis using George, Kaul, and Nimalendran's (GKN, 1991) approach to estimate the cost of immediacy. Their approach, which takes into consideration autocorrelations in expected returns, is less biased than Roll's (1984) model, which was used by Stoll and Whaley (1990).

2.2. Data

Amihud and Mendelson (1987) and Stoll and Whaley (1990) note that actively traded stocks are more likely to open using the call clearing procedure. Hence, to compare the volatility and liquidity of the call market at the open with those of the continuous market at the close, we select a sample of 452 actively traded common stocks. These stocks were (1) included in the Standard and Poor's 500 index, (2) listed on the NYSE, and (3) traded at a share price of no less than $3 at any time during 1991.[13]

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[13]Among the S&P 500 stocks, 457 stocks were listed on the NYSE. Five out of the 457 stocks were traded at a share price of less than $3 and discarded from our sample. The

We focus on opening and closing trades and quotes originated on the NYSE. On each trading day, we obtain the opening and closing transaction price and trading volume from the 1991 ISSM (the Institute for the Study of the Security Markets) files.[14] The opening bid and ask prices, which are the quotes immediately following the opening transaction, are also obtained from the ISSM files, along with the closing bid and ask prices. When computing stock returns, we adjust the prices for cash dividends, stock splits, and stock dividends. These distributions are obtained from the 1991 CRSP (the Center for Research in Security Prices) files.

Specifically, the open-to-open and close-to-close transaction price returns on day t, $PR_{o,t}$ and $PR_{c,t}$, are computed as

$$PR_{o,t} = \log(P_{o,t}+D_t) - \log(P_{o,t-1}), \text{ and}$$
$$PR_{c,t} = \log(P_{c,t}+D_t) - \log(P_{c,t-1}),$$

where $P_{o,t}$ and $P_{c,t}$ are the day-t opening and closing transaction prices, adjusted for splits and stock dividends, and D_t is the cash dividend if t is an ex-dividend day, and zero otherwise.

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ticker symbols of these five stocks are BLY, IK, NAV, UIS, and VAT.

[14]The ISSM develops error filters to flag a price or quote that is suspected of being incorrect. For example, if a stock traded around $40.0, an observed price of $4.0 would be flagged as a recording error. We discard from the sample any observation that is flagged as an error.

The open-to-open and close-to-close bid returns on day t, $BR_{o,t}$ and $BR_{c,t}$, are similarly calculated.

2.3. Variances at the Open and at the Close

In this section we extend Amihud and Mendelson's (1987) and Stoll and Whaley's (1990) analysis of open-to-open and close-to-close transaction price returns to returns based on quoted bid and ask prices. The advantage of using returns based on the bid price (or ask price) is that we can minimize the effect of bid-ask spread bounces on return variances. If the "true" variances at the open and at the close are the same, we should expect that the variance of open-to-open bid price returns is equal to the variance of close-to-close bid price returns. Alternatively, if we observe that the variance of open-to-open bid price returns is larger than the variance of close-to-close bid price returns, then factors other than the bid-ask spread bounce are responsible for the difference in variances of bid price returns.

Following Stoll and Whaley (1990), we first calculate variances of open-to-open returns and close-to-close returns for each sample stock in each month in 1991. Next, the ratio of the return variances is computed in each month, and then averaged over the 12 months for each stock.[15] Table 2-1

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[15]This procedure is slightly different from that used by Stoll and Whaley (1990). They compute the mean variance ratio by first averaging across all stocks in the sample and then averaging across the 60 months in the five-year sample

reports summary statistics of the average variance ratios across the sample stocks.

Panel A of Table 2-1 contains results based on transaction prices, with Panels B and C based on bid and ask prices, respectively. In addition to results for the full sample, we also report results for three subsamples, which are grouped by the average daily dollar volume in 1991. Since results for the subsamples are quite similar to those of the full sample, we focus our discussion on the full sample.

The mean open-to-open/close-to-close variance ratio based on transaction prices is 1.0939. This result suggests that open-to-open returns tend to be more volatile than close-to-close returns. The standard error of the ratio, as reported below the mean variance ratio, indicates that the mean variance ratio is significantly larger than one, consistent with previous studies.[16] However, the magnitude

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period. Hence, their test statistics are based on the distribution of the 60 monthly average values. Two reasons for the difference. First, we have only one year data. Second, our procedure is more appropriate for cross-sectional analysis, which is an important part of our study. Nevertheless, we tried both procedures and obtain very similar mean variance ratios.

[16]Based on Lo and Mackinlay (1988), open-to-open and close-to-close return variances are approximately normally distributed. Hence, open-to-open/close-to-close variance ratios for sample stocks should be also approximately normally distributed. The standard t-test can be used to exmine whether the mean variance ratio is greater than one.

TABLE 2-1

VARIANCE RATIOS

This table contains the mean and median ratios of variances of open-to-open returns relative to close-to-close returns, and mean and median differences of variances for 452 NYSE stocks in the sample. These results are also reported for three subsamples grouped by the average daily dollar volume in 1991. Panel A contains results based on transaction prices, Panels B and C based on bid and ask prices, respectively.

		By average daily dollar volume		
	All 452 stocks	Low 150 stocks	Medium 151 stocks	High 151 stocks
Panel A: Transaction Price				
Mean variance ratio[a]	1.0939	1.0935	1.0850	1.1031
Standard error of ratio[b]	0.0053	0.0091	0.0094	0.0092
Median variance ratio[a]	1.0854	1.0827	1.0785	1.0920
Mean difference of variance[a] (x 10,000)	0.1800	0.1500	0.1600	0.2200
Standard error of difference[b] (x 10,000)	0.0237	0.0459	0.0404	0.0362
Median difference of variance[a] (x 10,000)	0.3900	0.0981	0.0849	0.1800
Panel B: Bid Price				
Mean variance ratio	1.1678	1.1864	1.1520	1.1668
Standard error of ratio	0.0064	0.0124	0.0101	0.0104
Median variance ratio	1.1550	1.1708	1.1442	1.1556
Mean difference of variance (x 10,000)	0.4000	0.4600	0.3700	0.3900
Standard error of difference (x 10,000)	0.0277	0.0570	0.0419	0.0438
Median difference of variance (x 10,000)	0.3000	0.3600	0.2700	0.2700

[a]For each stock, the variance ratio is calculated in each month, and then averaged over the 12 months in 1991. The mean variance ratios are obtained by averaging across all stocks in the sample and all stocks within each average daily dollar volume group. The mean differences between the variances of open-to-open returns and the variances of close-to-close returns for all stocks in the sample and all stocks within each volume group are similarly obtained.

[b]The standard errors are based on the distributions of the average values for all stocks in the sample and all stocks within each volume group.

TABLE 2-1 (CONTINUED)

	All	By average daily dollar volume		
		Low	Medium	High
	452 stocks	150 stocks	151 stocks	151 stocks
	Panel C: Ask Price			
Mean variance ratio[a]	1.1650	1.1789	1.1511	1.1652
Standard error of ratio[b]	0.0063	0.0114	0.0099	0.0111
Median variance ratio[a]	1.1439	1.1553	1.1402	1.1404
Mean difference of variance[a] (x 10,000)	0.4000	0.4500	0.3700	0.3800
Standard error of difference[b] (x 10,000)	0.0268	0.0525	0.0430	0.0432
Median difference of variance[a] (x 10,000)	0.2800	0.3200	0.2800	0.2600

[a]For each stock, the variance ratio is calculated in each month, and then averaged over the 12 months in 1991. The mean variance ratios are obtained by averaging across all stocks in the sample and all stocks within each average daily dollar volume group. The mean differences between the variances of open-to-open returns and the variances of close-to-close returns for all stocks in the sample and all stocks within each volume group are similarly obtained.

[b]The standard errors are based on the distributions of the average values for all stocks in the sample and all stocks within each volume group.

is slightly smaller than the value of 1.1329 reported by Stoll and Whaley (1990) and 1.2 reported by Amihud and Mendelson (1987). Although the differences might be due to different sample firms,[17] we conjecture that the recent improvements in the efficiency of order processing on the NYSE, especially after the 1987 market crash, might also be a factor.

The mean variance ratio based on bid prices is 1.1678, and is 1.1650 based on ask prices. Both are significantly greater than one. These results imply that the open-to-open return volatility is larger than the close-to-close return volatility, even without the confounding effect of bid-ask spread bounce. In fact, the bid-ask spread bounce tends to dampen the difference in volatility at the open and at the close, since the mean variance ratio based on transaction prices is smaller than the mean variance ratio based on bid prices or ask prices. This is also evident from the mean difference between the open-to-open and the close-to-close variances. The mean difference in variances based on transaction prices is smaller than that based on bid prices or ask prices. In sum, Table 2-1 provides the first evidence that the greater volatility at the open than at the close may not be attributable to the bid-ask spread.

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[17]Amihud and Mendelson (1987) examine the 30 Dow Jones Industrial Average stocks over the period February 1982 through February 1983. Stoll and Whaley (1990) examine 1,374 NYSE stocks during the five-year period 1982-1986.

To see to what extent the variance ratio of transaction price returns is related to the variance ratio of bid price returns, we conduct a cross-sectional regression analysis with the variance ratio of bid price returns as an explanatory variable. In the analysis, we also include as an explanatory variable the ratio of the average quoted bid-ask spread at the open relative to the average quoted bid-ask spread at the close. McInish and Wood (1992) show that the quoted bid-ask spread tends to be larger at the beginning of the trading day than during the rest of the trading day. In our sample, the ratio of the average spread at the open relative to the average spread at the close is about 1.196. Since transaction prices tend to move between the bid and the ask, the larger spread at the open may induce greater volatility at the open.

The regression model is

$$\frac{\sigma^2(PR_{i,o})}{\sigma^2(PR_{i,c})} = a_0 + a_1 \frac{\sigma^2(BR_{i,o})}{\sigma^2(BR_{i,c})} + a_2 \frac{SP_{i,o}}{SP_{i,c}} + e_i, \quad (1)$$

where "i" indexes firm i, and "o" and "c" index at the open and at the close; "PR" is the transaction price return, "BR" is the bid price return, and "SP" is the quoted bid-ask spread. With eq.(1), we test two null hypotheses. First, H_o: $a_1=0$, i.e., the greater variance of transaction price returns at the open is not related to the greater variance of bid price returns at the open. Second, H_o: $a_2=0$, i.e., the greater variance of transaction price returns at the open is not attributable to the larger spread at the open. Table 2-2 contains the regression results.

According to Table 2-2, the variance ratio of transaction price returns is significantly related to the variance ratio of bid price returns, but is insignificantly related to the ratio of quoted spreads. The results are quite consistent across the three subsamples grouped by the average daily dollar volume. For the whole sample, the R^2 of the regression is 0.53, suggesting that the greater transaction price volatility at the open is, to a large extent, explainable by the greater bid price volatility at the open.[18]

Why are bid prices more volatile at the open than at the close? Hasbrouck (1991a) and Foster and Viswanathan (1993) show that trades at the beginning of the trading day tend to convey more information and move quote prices more. This suggests that the degree of information asymmetries between market makers and informed traders is greater at the open than at the close. Therefore, analogous to Amihud and Mendelson's (1991) arguments, pricing errors quoted by the specialist or by limit order traders are likely to be larger at the open than at the close, which could lead to a difference in volatility.

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[18]The results are very similar when ask prices are used in place of bid prices in the regressions.

TABLE 2-2

CROSS-SECTIONAL ANALYSIS OF VARIANCE RATIOS

This table contains cross-sectional regressions of average ratios of variance of open-to-open returns relative to close-to-close returns based on transaction prices on those based on bid prices and average ratios of opening quoted bid-ask spread relative to closing quoted bid-ask spread.[a] The regression model is

$$\frac{\sigma^2(PR_{i,o})}{\sigma^2(PR_{i,c})} = a_0 + a_1 \frac{\sigma^2(BR_{i,o})}{\sigma^2(BR_{i,c})} + a_2 \frac{SP_{i,o}}{SP_{i,c}} + e_i. \quad (1)$$

(t-statistics are in parentheses).

	All 452 stocks	By average daily dollar volume: Low 150 stocks	Medium 151 stocks	High 151 stocks
$\hat{a}_0$	0.3034	0.4432	0.2313	0.1739
	(4.76)	(3.68)	(2.04)	(1.89)
$\hat{a}_1$	0.6070	0.4813	0.6791	0.7254
	(22.52)	(10.47)	(13.21)	(17.61)
$\hat{a}_2$	0.0674	0.0665	0.0587	0.0681
	(1.43)	(0.72)	(0.68)	(1.08)
R^2	0.5340	0.4328	0.5502	0.6772

[a]For each stock, the variance ratio is calculated in each month, and then averaged over the 12 months in 1991. The bid-ask spread ratio is similarly calculated. The bid-ask spread is the relative spread computed as (ask-bid)/((ask+bid)/2).

$PR_{i,o}$ = the open-to-open return for stock i based on transaction price.
$PR_{i,c}$ = the close-to-close return for stock i based on transaction price.
$BR_{i,o}$ = the open-to-open return for stock i based on bid price.
$BR_{i,c}$ = the close-to-close return for stock i based on bid price.
$SP_{i,o}$ = the quoted spread for stock i at the open.
$SP_{i,c}$ = the quoted spread for stock i at the close.

2.4. Price Reversals

Stoll and Whaley (1990, p.56) show that "... prices established at the open tend to be reversed during the rest of the day, ... To the extent the specialist is an important provider of liquidity at the open, he benefits from the price reversals." If the price reversals are attributable to transaction prices bouncing between the bid-ask spread, then Stoll and Whaley's argument may be valid. However, if the transaction price reversals are due to bid price reversals, then liquidity suppliers (the specialist and limit order traders) may not benefit from the price reversals. To the extent that the bid price reversals are caused by pricing errors quoted by liquidity suppliers around the open, the price reversals may reflect liquidity suppliers' losses to informed traders. Therefore, the implications are quite different, depending on what really causes the transaction price reversals.

To analyze the causes of price reversals, we examine serial correlations between the overnight transaction price return, $PR_{n,t}$, and the following daytime transaction price return, $PR_{d,t}$. These returns are computed as

$$PR_{n,t} = \log(P_{o,t}+D_t) - \log(P_{c,t-1}), \text{ and}$$
$$PR_{d,t} = \log(P_{c,t}) - \log(P_{o,t}).$$

The correlation between the overnight bid price return, $BR_{n,t}$, and the daytime bid price return, $BR_{d,t}$, are also examined.

These bid price returns are computed in the same manner as the transaction price returns.

Unlike the transaction price returns, the bid price returns do not include the bid-ask spread bounce. Hence, GKN (1991) suggest that the transaction price return due to the bid-ask spread bounce can be extracted from the difference between the transaction price return and the bid price return. Following their suggestion, we measure the overnight and daytime transaction price returns due to the bid-ask spread bounce as

$$RD_{n,t} = PR_{n,t} - BR_{n,t}, \text{ and}$$

$$RD_{d,t} = PR_{d,t} - BR_{d,t}.$$

Table 2-3 reports autocorrelations for these three series of returns. Similar to Stoll and Whaley's (1990) results, we find that the overnight transaction price return and the following daytime transaction price return are negatively correlated. For the full sample, the mean correlation is -0.0334, which is significantly different from zero. Although the magnitude is small, these results do suggest that the opening prices tend to be reversed during the day.

Furthermore, we also observe reversals in bid price returns. For the full sample, the mean correlation between

TABLE 2-3

SERIAL CORRELATIONS

This table contains the mean and median serial correlations of returns in adjacent periods for 452 NYSE stocks in the sample and all stocks within the three average daily dollar volume groups in 1991. Panel A reports results based on transaction price returns, Panels B based on bid price returns, and Panel C based on transaction price returns due to bid-ask spread bounces, which are computed as differences between transaction price returns and bid price returns.

	All 452 stocks	By average daily dollar volume: Low 150 stocks	Medium 151 stocks	High 151 stocks
	Panel A: Transaction Price			
$\rho(PR_{n,t}, PR_{d,t})$				
Mean[a]	-0.0334	-0.0576	-0.0229	-0.0199
Standard error[b]	0.0041	0.0075	0.0069	0.0062
Median[a]	-0.0287	-0.0522	-0.0192	-0.0232
$\rho(PR_{d,t-1}, PR_{n,t})$				
Mean	-0.0064	-0.0338	-0.0050	0.0195
Standard error	0.0045	0.0079	0.0076	0.0070
Median	-0.0039	-0.0337	-0.0040	0.0231
$\rho(PR_{o,t-1}, PR_{o,t})$				
Mean	-0.0386	-0.0536	-0.0175	-0.0448
Standard error	0.0038	0.0069	0.0063	0.0063
Median	-0.0449	-0.0626	-0.0292	-0.0352
$\rho(PR_{c,t-1}, PR_{c,t})$				
Mean	-0.0058	-0.0318	0.0169	-0.0025
Standard error	0.0041	0.0076	0.0068	0.0061
Median	-0.0039	-0.0373	0.0216	-0.0026

[a]For each stock, the serial correlation is calculated in each month, and then averaged over the 12 months in 1991. The mean serial correlations are obtained by averaging across all stocks in the sample and all stocks within each average daily dollar volume group.

[b]The standard errors are based on the distributions of the average values for all stocks in the sample and all stocks within each volume group.

$PR_{n,t}$ - the overnight return at day t based on transaction price.
$PR_{d,t}$ - the daytime return at day t based on transaction price.
$PR_{d,t-1}$ - the daytime return at day t based on transaction price.
$PR_{o,t-1}$ - the open-to-open return at day t-1 based on transaction price.
$PR_{o,t}$ - the open-to-open return at day t based on transaction price.
$PR_{c,t-1}$ - the close-to-close return at day t-1 based on transaction price.
$PR_{c,t}$ - the close-to-close return at day t based on transaction price.

TABLE 2-3 (CONTINUED)

	All 452 stocks	By average daily dollar volume: Low 150 stocks	Medium 151 stocks	High 151 stocks
	Panel B: Bid Price			
$\rho(BR_{n,t},\ BR_{d,t})$				
Mean[a]	-0.0581	-0.0887	-0.0410	-0.0450
Standard error[b]	0.0042	0.0080	0.0065	0.0065
Median[a]	-0.0505	-0.0941	-0.0294	-0.0461
$\rho(BR_{d,t-1},\ BR_{n,t})$				
Mean	0.0330	0.0065	0.0375	0.0548
Standard error	0.0041	0.0077	0.0067	0.0065
Median	0.0323	0.0116	0.0319	0.0507
$\rho(BR_{o,t-1},\ BR_{o,t})$				
Mean	-0.0351	-0.0472	-0.0140	-0.0441
Standard error	0.0037	0.0067	0.0061	0.0062
Median	-0.0361	-0.0483	-0.0206	-0.0401
$\rho(BR_{c,t-1},\ BR_{c,t})$				
Mean	0.0195	-0.0025	0.0397	0.0213
Standard error	0.0037	0.0066	0.0063	0.0057
Median	0.0166	-0.0051	0.0407	0.0178

[a]For each stock, the serial correlation is calculated in each month, and then averaged over the 12 months in 1991. The mean serial correlations are obtained by averaging across all stocks in the sample and all stocks within each average daily dollar volume group.

[b]The standard errors are based on the distributions of the average values for all stocks in the sample and all stocks within each volume group.

$BR_{n,t}$ = the overnight return at day t based on bid price.
$BR_{d,t}$ = the daytime return at day t based on bid price.
$BR_{d,t-1}$ = the daytime return at day t based on bid price.
$BR_{o,t-1}$ = the open-to-open return at day t-1 based on bid price.
$BR_{o,t}$ = the open-to-open return at day t based on bid price.
$BR_{c,t-1}$ = the close-to-close return at day t-1 based on bid price.
$BR_{c,t}$ = the close-to-close return at day t based on bid price.

TABLE 2-3 (CONTINUED)

		By average daily dollar volume		
	All 452 stocks	Low 150 stocks	Medium 151 stocks	High 151 stocks
Panel C: Returns due to the bid-ask spread[c]				
$\rho(RD_{n,t}, RD_{d,t})$				
Mean[a]	-0.3532	-0.3838	-0.3720	-0.3041
Standard error[b]	0.0045	0.0071	0.0066	0.0080
Median[a]	-0.3607	-0.3860	-0.3838	-0.2980
$\rho(RD_{d,t-1}, RD_{n,t})$				
Mean	-0.5699	-0.5325	-0.5482	-0.6288
Standard error	0.0046	0.0071	0.0069	0.0077
Median	-0.5723	-0.5416	-0.5373	-0.6308
$\rho(RD_{o,t-1}, RD_{o,t})$				
Mean	-0.4684	-0.4713	-0.4634	-0.4706
Standard error	0.0021	0.0040	0.0034	0.0034
Median	-0.4681	-0.4730	-0.4605	-0.4718
$\rho(RD_{c,t-1}, RD_{c,t})$				
Mean	-0.4749	-0.4743	0.4788	-0.4717
Standard error	0.0022	0.0040	0.0033	0.0039
Median	-0.4777	-0.4790	-0.4806	-0.4737

[a]For each stock, the serial correlation is calculated in each month, and then averaged over the 12 months in 1991. The mean serial correlations are obtained by averaging across all stocks in the sample and all stocks within each average daily dollar volume group.

[b]The standard errors are based on the distributions of the average values for all stocks in the sample and all stocks within each volume group.

[c]The transaction price return due to the bid-ask spread is defined as the difference between the return based on transaction prices and the return based on bid prices [see GKN (1991)].

$RD_{n,t} = PR_{n,t} - BR_{n,t}$.
$RD_{d,t} = PR_{d,t} - BR_{d,t}$.
$RD_{d,t-1} = PR_{d,t-1} - BR_{d,t-1}$.
$RD_{o,t-1} = PR_{o,t-1} - BR_{o,t-1}$.
$RD_{o,t} = PR_{o,t} - BR_{o,t}$.
$RD_{c,t-1} = PR_{c,t-1} - BR_{c,t-1}$.
$RD_{c,t} = PR_{c,t} - BR_{c,t}$.

the overnight and the following daytime bid price returns is -0.0581, which is also significantly different from zero. Bid prices are the prices that liquidity suppliers are willing to pay for the security. The negative correlation implies that bid prices quoted by liquidity suppliers following the opening transaction tend to be too high or too low. The largest negative correlation occurs in the low trading volume group, suggesting that pricing errors are more likely to occur in thinly traded stocks. The pricing errors ought to be subsequently corrected through trading by the informed, resulting in bid price reversals. These reversals could lead to transaction price reversals.

The reversals in transaction price could also be related to the bid-ask spread bounce. As shown in Panel C of Table 2-3, the mean correlation between the overnight and the following daytime transaction price returns due to the bid-ask spread bounce, $RD_{n,t}$ and $RD_{d,t}$, is -0.3532. This magnitude of reversals is much larger than those of reversals in bid price returns and reversals in transaction price returns, as mentioned above.

To examine what really causes transaction price reversals, we rely on cross-sectional regression analysis. The regression equation is

$$\rho(PR_{i,n}, PR_{i,d}) = b_0 + b_1 \rho(BR_{i,n}, BR_{i,d}) + b_2 \rho(RD_{i,n}, RD_{i,d}) + u_i, \quad (2)$$

With eq.(2), we test two null hypotheses. First, H_o: $b_1=0$, i.e., the opening transaction price reversals are not related to the bid price reversals. Second, H_o: $b_2=0$, i.e., the opening transaction price reversals are not related to the bid-ask spread bounce. Table 2-4 reports the regression results.

According to Table 2-4, the null hypothesis that $b_2=0$ cannot be rejected in all four regressions: one for the full sample and three for the three subsamples. Since the reversals are not related to the bid-ask spread, the results imply that liquidity suppliers do not benefit from the opening transaction price reversals.

Conversely, we can easily reject the null hypothesis that $b_1=0$ in all four regressions. The results indicate that the stronger the bid price reversal, the stronger the transaction price reversal. This relation allows us to infer that pricing errors quoted by liquidity suppliers around the open are the main source of the opening transaction price reversals. Instead of benefiting from the reversals, as suggested by Stoll and Whaley (1990), it appears that the reversals may reflect liquidity suppliers' losses to informed traders.

While the overnight and the following daytime bid price returns, $BR_{n,t}$ and $BR_{d,t}$, tend to be negatively correlated, the overnight and the previous daytime bid price returns, $BR_{n,t}$ and $BR_{d,t-1}$, tend to be positively correlated, as shown in

TABLE 2-4

CROSS-SECTIONAL ANALYSIS OF SERIAL CORRELATIONS BETWEEN THE OVERNIGHT AND THE FOLLOWING DAYTIME RETURNS

This table contains results of cross-sectional regressions of the correlations between the overnight and following daytime returns based on transaction prices on those based on bid prices and the correlations between the overnight and following daytime transaction price returns due to bid-ask spread bounces.[a] The model is

$$\rho(PR_{i,n},\ PR_{i,d}) = b_0 + b_1\rho(BR_{i,n},\ BR_{i,d}) + b_2\rho(RD_{i,n},\ RD_{i,d}) + u_i. \qquad (2)$$

(t-statistics are in parentheses).

		By average daily dollar volume		
	All 452 stocks	Low 150 stocks	Medium 151 stocks	High 151 stocks
$\hat{b}_0$	0.0197 (2.25)	0.0261 (1.32)	0.0287 (1.39)	0.0085 (0.89)
$\hat{b}_1$	0.8004 (30.59)	0.7604 (16.58)	0.8170 (14.71)	0.8477 (22.58)
$\hat{b}_2$	0.0186 (0.77)	0.0425 (0.83)	0.0487 (0.89)	-0.0317 (-1.05)
R^2	0.6843	0.6659	0.6006	0.7795

[a]For each stock, the correlation between the overnight returns and the following daytime returns is calculated in each month, and then averaged over the 12 months in 1991. The transaction price return due to the bid-ask spread is defined as the difference between the return based on transaction prices and the return based on bid prices [see GKN (1991)].

$PR_{i,n}$ = the overnight return for stock i based on transaction price.
$PR_{i,d}$ = the following daytime return for stock i based on transaction price.
$BR_{i,n}$ = the overnight return for stock i based on bid price.
$BR_{i,d}$ = the following daytime return for stock i based on bid price.
$RD_{i,n}$ = $PR_{i,n}-BR_{i,n}$.
$RD_{i,d}$ = $PR_{i,d}-BR_{i,d}$.

TABLE 2-4a

CROSS-SECTIONAL ANALYSIS OF SERIAL CORRELATIONS BETWEEN THE OVERNIGHT AND THE FOLLOWING DAYTIME RETURNS

This table contains results of cross-sectional regressions of the correlation between the overnight and following daytime returns based on transaction prices on those based on bid prices.[a] The model is

$$\rho(PR_{i,n},\ PR_{i,d}) = b_0' + b_1'\rho(BR_{i,n},\ BR_{i,d}) + \mu_i.$$

(t-statistics are in parentheses).

		By average daily dollar volume		
	All 452 stocks	Low 150 stocks	Medium 151 stocks	High 151 stocks
$\hat{b}_0'$	0.0133	0.0105	0.0108	0.0180
	(4.87)	(1.78)	(2.19)	(5.35)
$\hat{b}_1'$	0.8039	0.7680	0.8222	0.8441
	(31.20)	(17.11)	(14.90)	(22.84)
R^2	0.6838	0.6620	0.5985	0.7778

[a]For each stock, the correlation between the overnight returns and the following daytime returns is calculated in each month, and then averaged over the 12 months in 1991.

$PR_{i,n}$ = the overnight return for stock i based on transaction price.
$PR_{i,d}$ = the following daytime return for stock i based on transaction price.
$BR_{i,n}$ = the overnight return for stock i based on bid price.
$BR_{i,d}$ = the following daytime return for stock i based on bid price.

TABLE 2-4b

CROSS-SECTIONAL ANALYSIS OF SERIAL CORRELATIONS BETWEEN THE OVERNIGHT AND THE FOLLOWING DAYTIME RETURNS

This table contains results of cross-sectional regressions of the correlation between the overnight and following daytime returns based on transaction prices on the correlations between the overnight and following daytime transaction price returns due to bid-ask spread bounces.[a] The model is

$$\rho(PR_{i,n},\ PR_{i,d}) = b_0'' + b_2''\rho(RD_{i,n},\ RD_{i,d}) + \epsilon_i.$$

(t-statistics are in parentheses).

		By average daily dollar volume		
	All 452 stocks	Low 150 stocks	Medium 151 stocks	High 151 stocks
$\hat{b}_0''$	0.0180	0.0245	0.0269	-0.0105
	(1.18)	(0.73)	(0.83)	(-0.52)
$\hat{b}_2''$	0.1457	0.2140	0.1341	0.0308
	(3.48)	(2.51)	(1.58)	(0.49)
R^2	0.0261	0.0409	0.0164	0.0016

[a]For each stock, the correlation between the overnight returns and the following daytime returns is calculated in each month, and then averaged over the 12 months in 1991. The transaction price return due to the bid-ask spread is defined as the difference between the return based on transaction prices and the return based on bid prices [see GKN (1991)].

$PR_{i,n}$ = the overnight return for stock i based on transaction price.
$PR_{i,d}$ = the following daytime return for stock i based on transaction price.
$RD_{i,n}$ = $PR_{i,n}-BR_{i,n}$.
$RD_{i,d}$ = $PR_{i,d}-BR_{i,d}$.

Table 2-3. For the full sample, the mean correlation between $BR_{n,t}$ and $BR_{d,t-1}$ is 0.033, suggesting a bid price continuation. As noted by Stoll and Whaley (1990, footnote 21), "One explanation for price continuations suggested by William Splitz is the pecking-order theory of research recommendations, which implies that favored clients receive recommendations before the general public." The bid price continuations could also reflect a partial adjustment of bid prices to information as suggested by Goldman and Beja (1979) and Hasbrouck and Ho (1987).[19]

This pattern of bid price continuations also have a significant effect on the transaction price behavior during the same time period, as reported in Table 2-5. The results may explain why the daytime transaction price return is less likely to be reversed in the following night. The results may also refute Stoll and Whaley's (1990, p. 54) argument that the price continuations around the closing imply that the closing transaction price is less likely to reflect the bid-ask spread bounce.

It is worth mentioning that price reversals around the open are not a result of the price continuations from the daytime into the following night. As shown in Table 2-3, the largest price reversal around the open occurs in the low

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[19]In particular, Hasbrouck and Ho (1987) suggest that because of costs of placing and canceling limit orders, we may observe a lagged adjustment of quote prices to information.

TABLE 2-5

CROSS-SECTIONAL ANALYSIS OF SERIAL CORRELATIONS BETWEEN THE OVERNIGHT AND THE PREVIOUS DAYTIME RETURNS

This table contains results of cross-sectional regressions of the correlations between the previous daytime and overnight returns based on transaction prices on those based on bid prices and the correlations between the previous daytime and overnight transaction price returns due to bid-ask spread bounces.[a] The model is

$$\rho(PR_{i,d-1},\ PR_{i,n}) = c_0 + c_1\rho(BR_{i,d-1},\ BR_{i,n}) + c_2\rho(RD_{i,d-1},\ RD_{i,n}) + \varepsilon_i.$$

(t-statistics are in parentheses).

		By average daily dollar volume		
	All 452 stocks	Small 150 stocks	Median 151 stocks	Large 151 stocks
$\hat{c}_0$	-0.04328 (-3.01)	-0.0504 (-1.77)	-0.0351 (-1.26)	-0.0127 (-0.48)
$\hat{c}_1$	0.9031 (32.14)	0.8449 (17.25)	0.9503 (18.33)	0.9024 (18.60)
$\hat{c}_2$	-0.0124 (-0.49)	-0.0207 (-0.39)	0.0102 (0.20)	0.0276 (0.67)
R^2	0.7028	0.6760	0.6962	0.7014

[a]For each stock, the correlation between the previous daytime returns and the overnight returns is calculated in each month, and then averaged over the 12 months in 1991. The transaction price return due to the bid-ask spread is defined as the difference between the return based on transaction prices and the return based on bid prices [see GKN (1991)].

$PR_{i,n}$ = the overnight return for stock i based on transaction price.
$PR_{i,d-1}$ = the previous daytime return for stock i based on transaction price.
$BR_{i,n}$ = the overnight return for stock i based on bid price.
$BR_{i,d-1}$ = the previous daytime return for stock i based on bid price.
$RD_{i,n}$ = $PR_{i,n}-BR_{i,n}$.
$RD_{i,d-1}$ = $PR_{i,d-1}-BR_{i,d-1}$.

TABLE 2-5a

CROSS-SECTIONAL ANALYSIS OF SERIAL CORRELATIONS
BETWEEN THE OVERNIGHT AND THE PREVIOUS DAYTIME RETURNS

This table contains results of cross-sectional regressions of the correlations between the previous daytime and overnight returns based on transaction prices on those based on bid prices.[a] The model is

$$\rho(PR_{i,d-1},\ PR_{i,n}) = c_0' + c_1' \rho(BR_{i,d-1},\ BR_{i,n}) + v_i.$$

(t-statistics are in parentheses).

	All	By average daily dollar volume		
		Small	Median	Large
	452 stocks	150 stocks	151 stocks	151 stocks
$\hat{c}_0'$	-0.0363	-0.0394	-0.0406	-0.0301
	(-13.98)	(-8.69)	(-8.75)	(-6.45)
$\hat{c}_1'$	0.9052	0.8478	0.9492	0.9035
	(32.61)	(17.56)	(18.48)	(18.67)
R^2	0.7027	0.6757	0.6961	0.7005

[a]For each stock, the correlation between the previous daytime returns and the overnight returns is calculated in each month, and then averaged over the 12 months in 1991.

$PR_{i,n}$ = the overnight return for stock i based on transaction price.
$PR_{i,d-1}$ = the previous daytime return for stock i based on transaction price.
$BR_{i,n}$ = the overnight return for stock i based on bid price.
$BR_{i,d-1}$ = the previous daytime return for stock i based on bid price.

Table 2-5b

CROSS-SECTIONAL ANALYSIS OF SERIAL CORRELATIONS BETWEEN THE OVERNIGHT AND THE PREVIOUS DAYTIME RETURNS

This table contains results of cross-sectional regressions of the correlations between the previous daytime and overnight returns based on transaction prices on the correlations between the previous daytime and overnight transaction price returns due to bid-ask spread bounces.[a] The model is

$$\rho(PR_{i,d-1},\ PR_{i,n}) = c_0'' + c_2''\rho(RD_{i,d-1},\ RD_{i,n}) + \zeta_i.$$

(t-statistics are in parentheses).

		By average daily dollar volume		
	All 452 stocks	Small 150 stocks	Median 151 stocks	Large 151 stocks
$\hat{c}_0''$	-0.0829 (-3.19)	-0.1175 (-2.41)	-0.0544 (-1.08)	0.0530 (1.12)
$\hat{c}_2''$	-0.1343 (-2.98)	-0.1571 (-1.74)	-0.0900 (-1.00)	0.0533 (0.72)
R^2	0.0172	0.0200	0.0066	0.0034

[a]For each stock, the correlation between the previous daytime returns and the overnight returns is calculated in each month, and then averaged over the 12 months in 1991. The transaction price return due to the bid-ask spread is defined as the difference between the return based on transaction prices and the return based on bid prices [see GKN (1991)].

$PR_{i,n}$ = the overnight return for stock i based on transaction price.
$PR_{i,d-1}$ = the previous daytime return for stock i based on transaction price.
$RD_{i,n}$ = $PR_{i,n} - BR_{i,n}$.
$RD_{i,d-1}$ = $PR_{i,d-1} - BR_{i,d-1}$.

trading volume group, which tends to have the least price continuation from the daytime into the following night.

2.5. Implied Bid-Ask Spread

Amihud and Mendelson (1987) and Stoll and Whaley (1990) observe that the serial covariance of open-to-open transaction price returns are more negative than the serial covariance of close-to-close transaction price returns. Based on Roll's (1984) model, Stoll and Whaley (1990) show that the implied spread at the open is larger than at the close. They thus conclude that liquidity suppliers charge a higher cost of immediacy at the open than at the close. In this section we re-examine this issue.

According to Stoll and Whaley's analytical framework,[20] the serial covariance of open-to-open returns to some extent depends on the covariance between the overnight and the

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[20] Stoll and Whaley (1990, footnotes 19 and 20) suggest that the open-to-open transaction price return on day t, $PR_{o,t}$, can be written as the sum of the overnight return, $PR_{n,t}$, and the daytime return during the previous day, $PR_{d,t-1}$:

$$PR_{o,t} = PR_{d,t-1} + PR_{n,t}.$$

Hence, $COV(PR_{o,t-1}, PR_{o,t}) = COV(PR_{d,t-2}, PR_{d,t-1}) + COV(PR_{n,t-1}, PR_{d,t-1}) + COV(PR_{d,t-2}, PR_{n,t}) + COV(PR_{n,t-1}, PR_{n,t})$. The only term involving returns in the adjacent time period is $COV(PR_{n,t-1}, PR_{d,t-1})$. Similarly, the close-to-close return can be written as

$$PR_{c,t} = PR_{n,t} + PR_{d,t}.$$

Hence, $COV(PR_{c,t-1}, PR_{c,t}) = COV(PR_{n,t-1}, PR_{n,t}) + COV(PR_{d,t-1}, PR_{d,t}) + COV(PR_{d,t-1}, PR_{n,t}) + COV(PR_{n,t-1}, PR_{d,t})$. The only term involving returns in the adjacent time period is $COV(PR_{d,t-1}, PR_{n,t})$.

following daytime returns, $PR_{n,t}$ and $PR_{d,t}$, which tend to be negatively correlated. However, our analysis reported in Table 2-4 suggests that the negative correlation between $PR_{n,t}$ and $PR_{d,t}$ is not related to the bid-ask spread bounce. Therefore, the fact that open-to-open transaction price returns are more likely to be reversed than are close-to-close transaction price returns does not necessarily indicate a larger implied spread at the open.

Furthermore, charging a larger spread at the open may not be the optimal behavior for the specialist. If the degree of information asymmetry is greater at the open than during the rest of the day, the specialist may encourage trading by charging a lower spread at the open. More trading could release more private information and, hence, reduce information asymmetry. This could make subsequent trades more profitable. Glosten (1989) shows that, under the condition of information asymmetry, this strategic behavior of averaging profits over time is optimal. If the specialist's behavior is consistent with this hypothesis, we should expect a lower implied spread at the open than at the close.

We use GKN's (1991) approach to estimate the implied spread, which is based on the difference between the transaction price return and the bid price return. Following their approach, the implied spreads using open-to-open returns and close-to-close returns are computed as

$$S_o = 2\sqrt{-\mathrm{cov}(RD_{o,t-1},\ RD_{o,t})}\text{, and}$$

$$S_c = 2\sqrt{-\mathrm{cov}(RD_{c,t-1},\ RD_{c,t})}, \tag{3}$$

where $RD_{o,t}=PR_{o,t}-BR_{o,t}$ and $RD_{c,t}=PR_{c,t}-BR_{c,t}$.

Stoll and Whaley (1990) use Roll's model to estimate the implied spreads, which are

$$S_o = 2\sqrt{-\mathrm{cov}(PR_{o,t-1},\ PR_{o,t})}\text{, and}$$

$$S_c = 2\sqrt{-\mathrm{cov}(PR_{c,t-1},\ PR_{c,t})}. \tag{4}$$

GKN(1991) show that their approach is less biased since the effect of bid price fluctuations on transaction prices is removed from their estimator.

It should be pointed out that the implied spread is the average gross profits earned by liquidity suppliers in two transactions, a buy and a sell. The implied spread is therefore the gross profit component of the quoted spread. According to Stoll (1989), the other component of the quoted spread is the adverse selection component, which covers liquidity suppliers' expected losses to informed traders.

Table 2-6 contains the implied spreads estimated from Roll's model and the implied spreads estimated from GKN's model. Based on Roll's model, the mean implied spread computed from open-to-open returns is 0.506% for the full sample, and is 0.012% from close-to-close returns. These estimates are consistent with Stoll and Whaley's (1990)

TABLE 2-6

IMPLIED BID-ASK SPREADS

This table contains the mean and median implied and quoted bid-ask spread for 452 NYSE stocks in the sample and all stocks within the three average daily dollar volume groups in 1991. Panel A reports the estimates of implied bid-ask spread based on Roll's (1984), and Panel B based on George, Kaul, and Nimalendran's (GKN, 1991) model.

Panel A: Roll's (1984) Model

	Implied bid-ask spread(%)[a]				Quoted spread(%)[b]	
	($PR_{n,t}$, $PR_{d,t}$)	($PR_{d,t-1}$, $PR_{n,t}$)	($PR_{o,t}$, $PR_{o,t-1}$)	($PR_{c,t}$, $PR_{c,t-1}$)	SP_o	SP_c
All (452 stocks)						
Mean spread	0.3266	-0.0222	0.5061	0.0119	0.8986	0.7512
Standard error	0.0321	0.0354	0.0517	0.0557	0.0002	0.0002
Median spread	0.4371	-0.2104	0.7605	0.1145	0.7789	0.6400
Proportion positive	0.7058	0.4646	0.7058	0.5044	1.0000	1.0000
Low volume stocks						
Mean spread	0.5035	0.2502	0.6764	0.3814	1.2887	1.0880
Standard error	0.0618	0.0685	0.0981	0.1052	0.0005	0.0004
Median spread	0.5845	0.4564	0.9276	0.6677	1.1020	0.9197
Proportion positive	0.7733	0.5800	0.7533	0.6467	1.0000	1.0000
Medium volume stocks						
Mean spread	0.2352	-0.0715	0.2598	-0.2790	0.8444	0.7012
Standard error	0.0532	0.0555	0.0906	0.0915	0.0003	0.0002
Median spread	0.3613	-0.2559	0.5818	-0.5006	0.7727	0.6401
Proportion positive	0.6689	0.4570	0.6026	0.3775	1.0000	1.0000
High volume stocks						
Mean spread	0.2421	-0.2435	0.5832	-0.0642	0.5651	0.4668
Standard error	0.0488	0.0521	0.0753	0.0844	0.0002	0.0001
Median spread	0.3478	-0.4180	0.7841	-0.1562	0.5337	0.4365
Proportion positive	0.6755	0.3576	0.7616	0.4901	1.0000	1.0000

[a]Based on Roll's (1984) model, implied bid-ask spread is calculated as $2\sqrt{-cov}$, where cov is the serial covariances of returns. For each stock, the covariance is computed in each month, and then averaged over the 12 months in 1991. The implied bid-ask for each stock is then calculated based on the average monthly serial covariance. The mean spreads are obtained by averaging across all stocks in the sample and all stocks within each dollar volume group. If the average serial covariance is positive, the square root of the absolute value of the covariance is calculated and the negative sign is reattached.

[b]The percentage quoted spread = (ask-bid)/((ask+bid)/2).

$PR_{n,t}$ = the overnight return at day t based on transaction price.
$PR_{d,t}$ = the daytime return at day t based on transaction price.
$PR_{d,t-1}$ = the daytime return at day t-1 based on transaction price.
$PR_{o,t-1}$ = the open-to-open return at day t-1 based on transaction price.
$PR_{o,t}$ = the open-to-open return at day t based on transaction price.
$PR_{c,t-1}$ = the close-to-close return at day t-1 based on transaction price.
$PR_{c,t}$ = the close-to-close return at day t based on transaction price.
SP_o = the percentage quoted spread at the open.
SP_c = the percentage quoted spread at the close.

TABLE 2-6 (CONTINUED)

Panel B: GKN's (1991) Model

	Implied bid-ask spread(%)[a]				Quoted spread(%)[b]	
	$(RD_{a,t}, RD_{d,t})$	$(RD_{d,t-1}, RD_{a,t})$	$(RD_{o,t}, RD_{o,t-1})$	$(RD_{c,t}, RD_{c,t-1})$	SP_o	SP_c
All (452 stocks)						
Mean spread	0.6348	0.7018	0.6843	0.7425	0.8986	0.7512
Standard error	0.0190	0.0178	0.0207	0.0207	0.0002	0.0002
Median spread	0.5254	0.5990	0.5644	0.6421	0.7789	0.6400
Proportion positive	1.0000	1.0000	1.0000	0.9934	1.0000	1.0000
Low volume stocks						
Mean spread	0.8829	0.9473	0.9593	0.9920	1.2887	1.0880
Standard error	0.0368	0.0385	0.0411	0.0470	0.0005	0.0004
Median spread	0.7676	0.8166	0.7989	0.8319	1.1020	0.9197
Proportion positive	1.0000	1.0000	1.0000	0.9867	1.0000	1.0000
Medium volume stocks						
Mean spread	0.6201	0.6582	0.6604	0.6997	0.8444	0.7012
Standard error	0.0245	0.0214	0.0264	0.0226	0.0003	0.0002
Median spread	0.5450	0.5935	0.5810	0.6369	0.7727	0.6401
Proportion positive	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
High volume stocks						
Mean spread	0.4031	0.5015	0.4350	0.5374	0.5651	0.4668
Standard error	0.0229	0.0157	0.0242	0.0212	0.0002	0.0001
Median spread	0.3233	0.4672	0.3554	0.4872	0.5337	0.4365
Proportion positive	1.0000	1.0000	1.0000	0.9934	1.0000	1.0000

[a]Based on GKN's (1991) model, implied bid-ask spread is calculated as $2\sqrt{-cov}$, where cov is the serial covariances of return differences. For each stock, the covariance is computed in each month, and then averaged over the 12 months in 1991. The implied bid-ask for each stock is then calculated based on the average monthly serial covariance. The mean spreads are obtained by averaging across all stocks in the sample and all stocks within each dollar volume group. If the average serial covariance is positive, the square root of the absolute value of the covariance is calculated and the negative sign is reattached.

[b]The percentage quoted spread = (ask-bid)/((ask+bid)/2).

$RD_{a,t}$ = $PR_{a,t}-BR_{a,t}$.
$RD_{d,t}$ = $PR_{d,t}-BR_{d,t}$.
$RD_{d,t-1}$ = $PR_{d,t-1}-BR_{d,t-1}$.
$RD_{a,t-1}$ = $PR_{a,t-1}-BR_{a,t-1}$.
$RD_{o,t}$ = $PR_{o,t}-BR_{o,t}$.
$RD_{c,t-1}$ = $PR_{c,t-1}-BR_{c,t-1}$.
$RD_{c,t}$ = $PR_{c,t}-BR_{c,t}$.
SP_o = the percentage quoted spread at the open.
SP_c = the percentage quoted spread at the close.

results that the implied spread based on opening prices is much larger than the implied spread based on closing prices. However, large proportions of implied spreads, especially for medium and high trading volume stocks, are negative, which are unreasonable and may somewhat reflect biases in Roll's model.[21]

Based on GKN's model, we obtain the opposite results. The mean implied spread computed from open-to-open returns is 0.68%, and is 0.74% from close-to-close returns. The null hypothesis that these mean implied spreads are the same can be rejected at the 1% level of significance, as shown in Table 2-7. The result that the mean implied spread based on opening prices is less than the mean implied spread based on closing prices is especially evident for more actively traded stocks. These findings imply that liquidity suppliers charge a lower cost of immediacy at the open than at the close. The evidence is therefore consistent with Glosten's (1989) hypothesis of the specialist averaging profits over time.

Since the implied spread reflects the gross profit component, we estimate the adverse selection component of the quoted spread as the difference between the quoted spread and the implied spread. For the full sample, the mean quoted spread at the open is 0.899%, and is 0.751% at the close.

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[21]GKN (1991) show that Roll's (1984) measure can be downward biased and may be negative due to the effect of positive autocovariance induced by time-varying expected returns and/or frictions in the trading process.

TABLE 2-7

IMPLIED SPREAD COMPARISONS

This table contains results of the paired-comparison between the implied bid-ask spreads based on open-to-open returns, S_o, and based on close-to-close returns, S_c. The implied spreads are computed by GKN's (1991) model.

	N	Mean S_o	Mean S_c	Mean S_o-S_c	t-statistic
All sample	452	0.6843	0.7425	-0.0582	-4.36
Low volume stocks	150	0.9593	0.9920	-0.0327	-1.19
Medium volume stocks	151	0.6604	0.6997	-0.0393	-2.10
High volume stocks	151	0.4350	0.5374	-0.1024	-4.59

TABLE 2-8

COMPARISONS OF THE ADVERSE SELECTION COMPONENTS

This table contains results of the paired-comparison between the adverse selection components of the spreads at the open, Y_o, and at the close, Y_c. $Y_o = SP_o - S_o$, and $Y_c = SP_c - S_c$, where SP_o and SP_c are the average quoted relative spreads at the open and at the close. S_o and S_c are the implied spread at the open and at the close based on GKN's (1991) model.

	N	Mean Y_o	Mean Y_c	Mean Y_o-Y_c	t-statistic
All sample	452	0.2143	0.0087	0.2056	14.83
Low volume stocks	150	0.3294	0.0960	0.2334	7.85
Medium volume stocks	151	0.0408	0.0015	0.0393	9.54
High volume stocks	151	0.0318	-0.0706	0.1024	9.15

Hence, the mean adverse selection component of the spread at the open is about 0.214%, and is about 0.009% at the close. As shown in Table 2-8, the mean adverse selection component at the open is significantly larger than that at the close. These results suggest that liquidity suppliers do expect larger losses to informed traders at the open when the degree of information asymmetry is likely to be higher.

2.6. Conclusions

The purpose of this study is two-fold. First, following Amihud and Mendelson (1987, 1991) and Stoll and Whaley (1990), we examine whether the greater volatility and more negative serial correlation at the open than at the close is attributable to the larger bid-ask spread at the open. Although transaction prices moving between the bid and the ask could increase the price volatility, the greater volatility at the open could not be attributed to the bid-ask spread bounce. Instead, we find that the greater transaction price volatility at the open is related to greater bid price volatility at the open. Furthermore, the transaction price reversals around the open are also related to bid price reversals around the open. Since information asymmetry is likely to be higher at the open, the greater bid price volatility and bid price reversals around the open may reflect larger pricing errors quoted by liquidity suppliers. Therefore, unlike Stoll and Whaley's suggestion that liquidity suppliers benefit from price reversals around the open, the reversals may reflect liquidity suppliers' losses to informed traders.

Second, we examine the strategic behavior of the specialist at the opening call. Stoll and Whaley (1990) suggest that the specialist exploits his monopoly position at the opening call and charges a higher cost of immediacy. However, according to Glosten's model, when information asymmetry is high, the specialist who charges a higher cost of trading, may not be profit-maximizing. Hence, we argue that, the specialist may set a lower cost of immediacy to encourage trading and to release more information at the opening call. This could reduce information asymmetry and make subsequent trades more profitable.

We use George, Kaul, and Nimalendran's (1991) model, which is less biased than Roll's (1984) model, to estimate the implied spreads at the open and at the close. Consistent with our argument, the results show that, on average, the implied spread earned by liquidity suppliers is less at the open than at the close. This finding, therefore, refutes Stoll and Whaley's contention that the specialist exploits the monopoly position and earns a higher profit at the opening call.

CHAPTER 3

INTRADAY PATTERNS IN GROSS PROFITS EARNED BY NYSE SPECIALISTS

3.1. Introduction

The specialist who makes a market for a security on the New York Stock Exchange (NYSE) tends to buy low (at bid price) and sell high (at ask price). The difference between the selling price and the purchasing price reflects the gross profit per share earned by the specialist.[22] Stoll (1989) suggests that the specialist will not earn the whole quoted bid-ask spread when there is information asymmetry between the specialist and informed traders. In this paper we consider the strategic behavior of the specialist in resolving information asymmetry and its implication for intraday patterns in gross profits.

Glosten (1989) hypothesizes that when information asymmetry is high, a monopolist specialist may reduce profits or even realize losses to induce informed traders to trade and to release their information. This reduces the adverse selection problem and makes subsequent trades more profitable. The specialist can earn greater profits to

[22]The profit is gross in the sense that it should cover order processing costs, inventory holding costs, and other operating expenses incurred in market making.

offset the losses realized early on in the trading.[23] This hypothesis of averaging profits over time implies that the pattern in gross profits earned by the specialist is inversely related to the pattern in information asymmetry. The first objective of this paper is to examine empirically whether the intraday pattern in gross profits earned by the specialist is consistent with this hypothesis.

Private information is likely to be accumulated over the nontrading period and released via trading. Hence, Brock and Kleidon (1990) note that information asymmetry is highest at the beginning of the trading day because of a long period of nontrading since the closing on the previous day. Indeed, Foster and Viswanathan (1993) and Hasbrouck (1991a) show that trades are more informative and move quote prices more at the beginning than during the rest of the trading day. If the specialist loses on some trades at the beginning of trading and learns some information of informed traders, the gross profits could be increased in subsequent trades as information asymmetry is reduced. Therefore, the hypothesis of averaging profits through time predicts that the specialist's gross profits are lower at the beginning than during the rest of the trading day.

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[23]Glosten (1989, p.213) notes that "It is reasonable to assume that there are times in which the specialist enjoys a monopolist position and times in which this monopolist power is curtailed by other traders. Thus, the ability of the specialist to average profits over time may be restricted."

Roll (1984) points out that successive transaction price changes tend to be inversely correlated because of transaction prices bouncing between bid and ask prices. This bouncing between the bid-ask spread creates a temporary price effect, which allows the specialist to generate gross profits to cover costs in market making. Thus, a portion of price volatility is attributable to the bid-ask spread. Price volatility can also be generated from private information released via trading, as theoretically demonstrated by Kyle (1985) and empirically shown by French and Roll (1986), among others. The strategic behavior of the specialist to reduce information asymmetry suggests that the impacts on price volatility of the bid-ask spread and of private information may vary through time. The second objective of this paper is to empirically distinguish the impacts of these two factors on intraday volatility.

Since the hypothesis of averaging profits over time predicts lower gross profits at the beginning, price volatility due to prices bouncing between the bid-ask spread should be lower at the beginning than during the rest of the trading day. Conversely, since information asymmetry is expected to be higher at the beginning, price volatility due to private information should be larger at the beginning than during the rest of the trading day.

Our study is related to a number of previous studies, which examine the U-shaped intraday patterns in trading volume and price volatility.[24] In particular, Admati and Pfleiderer (1988) suggest that the concentration of liquidity trading induces information trading. Since trading volume tends to concentrate at the beginning and at the end of the trading day, their model implies that trades are more informative at the beginning and at the end of the trading day than during the rest of the day. Also, the higher volatility at the beginning and at the end of the trading day are both attributable to private information revealed by informed traders. Our predictions differ from theirs. While they assume a passive role for the market maker,[25] we emphasize the strategic behavior of the market maker in reducing information asymmetry through time, and suggest possible different sources of intraday volatility.

Wei (1992) considers an inverted U-shaped pattern for the transitory cost component of the bid-ask spread. He conjectures that the lower transitory cost component may induce some informed trading, leading to higher price volatility at the beginning and at the end of the trading day. Although the gross profits earned by the specialist are related to the transitory cost component of the bid-ask

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[24]See, for example, Wood, McInish, and Ord (1985) and Harris (1986).

[25]Admati and Pfleiderer (1988) assume the market maker sets prices so that his expected profits are zero in every trade. The hypothesis of averaging profits over time is based on Glosten's (1989) model in that the market maker sets prices to maximize expected profits.

spread, our prediction for the intraday pattern in gross profits is not an inverted U-shaped pattern. Instead, the gross profit is predicted to be lower at the beginning than during the rest of the day.

McInish and Wood (1992) show that the bid-ask spread is largest at the beginning of the trading day. A large bid-ask spread tends to induce high price volatility. However, the hypothesis of averaging profits over time suggests that the higher volatility at the beginning of trading is not due to the larger bid-ask spread. The hypothesis also suggests that the specialist does not earn higher gross profits, even though the quoted spread is larger, at the beginning compared to the rest of the trading day. This is because, if information asymmetry is highest at the beginning of the trading day, then adjusting the quotes to reflect private information from trades increases price volatility, but reduces the realized spread earned by the specialist.

Another factor that may affect gross profits earned by the specialist is the pattern in order arrivals. Hasbrouck and Ho (1987), Choi, Salandro, and Shastri (1988), and Hasbrouck (1991b) document that buy orders tend to follow buy orders, and sell orders tend to follow sell orders. Since a buy order following a sell order allows the specialist to earn the bid-ask spread, order persistence reduces the specialist's chance of earning the bid-ask spread. Furthermore, the specialist's gross profit is generated from the effective bid-ask spread. However, because a large portion of trades take place inside the quoted bid-ask spread, the average effective spread is smaller than the average quoted spread. Therefore, to properly estimate the intraday pattern in gross profits earned by the specialist, we also need to take order persistence and inside-the-quote transactions into consideration.

In the next section we present an empirical model to estimate the specialist's gross profits. The model is very similar to that used by Huang and Stoll (1992). Section 3.3 discusses intraday transaction data. Section 3.4 reports estimation results of gross profits. Section 3.5 compares the sources of intraday volatility. The final section contains our conclusions.

3.2. The Empirical Model

Let X_t denote the specialist's estimated value of the security at time t, conditional on the information available to the specialist at time t-1. Since the conditional expectation is unobservable, a convenient assumption is that the quote midpoint reflects this conditional value of the security.

One objection to this assumption, as argued by the inventory control theory, is that the quotes may be temporarily perturbed away from the specialist's estimated value of the security. However, Hasbrouck (1988, p.251) uses a sophisticated VAR model and finds that "effects of dealer inventory-control behavior on quotes, as ascertained from the transient impact of trades on quote revisions, are insignificant." Madhavan and Smidt (1991, p.120) use the actual specialist inventory data and show that "specialist inventory control has a weak effect on intradaily prices." George, Kaul, and Nimalendran (1991, p.649) further show "no evidence for the existence of an inventory cost component." Hence, we assume that the prevailing quote midpoint at time t, denoted as Q_t, is the specialist's estimated value of the security, prior to the trade at time t.[26]

Denote P_t as the trade price at time t. Following Huang and Stoll (1992), the trade price is related to the quote midpoint as

$$P_t = Q_t + z_t. \tag{5}$$

Huang and Stoll (1992) suggest that z_t can be regarded as half of the (signed) effective bid/ask spread. The effective spread is equal to the quoted spread for trades that are executed at the quoted ask or bid price. However, the effective spread is less than the quoted spread for trades that are executed inside the quoted spread.

[26]In reality, since the specialist maintains the book of limit orders, the price quotations may be those of either the specialist or public limit orders.

Hasbrouck and Ho (1987) and Hasbrouck (1991a) classify a trade as a buy (sell) order if the trade price is greater (less) than the prevailing quote midpoint. Hence, the trade at time t can be classified as a buy order if $z_t > 0$, and a sell order if $z_t < 0$.

The adverse information theory suggests that the specialist will adjust the quote midpoint upward following a buy order, and downward following a sale order [see Stoll (1989)]. Similar to Huang and Stoll (1992), the quote revision process due to trades is written as[27]

$$\Delta Q_{t+1} = \lambda z_t + e_{t+1}, \tag{6}$$

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[27]In this study, we assume no inventory holding cost. However, this assumption can be easily relaxed as follows. Let α be the inventory holding cost component of the spread. Given the conditional value X_t, the dealer sets the quote midpoint as

$$Q_t = X_t + \alpha z_{t-1}$$

That is, the dealer sets the quote midpoint higher (lower) following a public buy (sale) in order to induce public sale (buy) orders to even out his inventory position. As in eq.(6), the change in the conditional value is

$$\Delta X_{t+1} = \lambda z_t + e_{t+1}$$

The change in the quote midpoint can then be expressed as

$$\begin{aligned} \Delta Q_{t+1} &= \Delta X_{t+1} + \alpha z_t - \alpha z_{t-1} \\ &= (\lambda+\alpha) z_t - \alpha z_{t-1} + e_{t+1} \end{aligned}$$

Empirically, we find that α is very close to zero, consistent with previous studies that show weak inventory-control effect on dealer pricing.

where $\Delta Q_{t+1}=Q_{t+1}-Q_t$; λ is the proportion of the effective spread due to adverse selection; and the error term e_{t+1} reflects arrivals of public information and market frictions such as price discreteness and the lag in price adjustment due to limit orders. These market frictions may cause serial dependence in the error term. However, we find that, for most of our sample firms, the autocorrelations in the error term are small and that adjusting for these autocorrelations does not have a material effect on the estimate of λ.

Empirically, Lin (1992) shows that the quote revision process in eq. (6) tends to perform better than the quote revision process with the trade indicator variable and signed trading volume proposed by Hasbrouck (1991b). There are two possible reasons that the effective spread can efficiently capture the impact of trading volume on the quote midpoint. First, trades with large volume tend to have large effective spreads [see Choe, McInish, and Wood (1991)]. Second, while the relation between quote revision and trading volume may be complex and nonlinear, the relation between quote revision and effective spread appears to be linear.

The intuition underlying eq. (6) is that λz_t is the amount of quote revision attributable to private information revealed from the trade at time t. If the trade carries no private information, i.e., $\lambda=0$, as in Roll's (1984) model, then the quote midpoint follows a random walk. Conversely, if the whole effective spread is due to adverse selection, i.e., $\lambda=1$, as in Glosten and Milgrom's (1985) model, then the quote midpoint is immediately adjusted to the trade price. These are the two extreme cases. Normally, we expect $0<\lambda<1$ because the specialist has to earn a portion of the effective spread to cover market making costs.

The portion of the effective spread earned by the specialist is inferred as follows. Given the updated quote midpoint, Q_{t+1}, the trade price at time t+1, P_{t+1}, can also be expressed as $P_{t+1}=Q_{t+1}+z_{t+1}$. The transaction-to-transaction price change from time t to t+1 can thus be decomposed as:

$$\Delta P_{t+1} = \Delta Q_{t+1} + z_{t+1} - z_t, \tag{7}$$

where $\Delta P_{t+1}=P_{t+1}-P_t$. In this expression, the first part of the transaction price change is due to the adjustment in quote midpoint, which reflects a change in the specialist's conditional value of the security from time t to t+1. The second and third parts are due to the effective bid/ask spreads.

As discussed previously, a buy (sell) order is associated with a positive (negative) z_t. That buy orders tend to follow buy orders, and sell orders tend to follow sell orders implies that z_t will be serially correlated. Following Hasbrouck and Ho's (1987, p.1042) suggestion, the pattern of order arrivals is modelled as an AR(1) process:

$$z_{t+1}=\theta z_t + \eta_{t+1} \tag{8}$$

where $|\theta|<1$, and η_{t+1} is the error term. The error term is assumed to be serially uncorrelated, and uncorrelated with e_{t+1} in eq. (6). As shown by Hasbrouck and Ho (1987), under the assumption of a constant effective spread, i.e., $|z_t|=k$ for all t, eq. (8) implies that, if the transaction at time t is a buy (sell) order, there is a probability of $(1+\theta)/2$ that the next transaction will be a buy (sell) order. The conditional probability of order reversal is then equal to $(1-\theta)/2$. The probability structure will be more complex if the effective spread changes over time. However, in our model, the parameter, θ, is a sufficient statistic for the pattern of order arrivals.

With the relations in eqs. (6) and (8), eq. (7) can be simplified to

$$\Delta P_{t+1} = -\beta z_t + u_{t+1}, \tag{9}$$

where $\Delta P_{t+1}=P_{t+1}-P_t$; $\beta=1-\lambda-\theta$; and $u_{t+1}=e_{t+1}+\eta_{t+1}$ is the error term. Eq. (9) is a predictive model. Since a portion of the effective spread is needed to compensate the market maker, the model predicts a temporary price effect. That is, if traders sell shares of the security to the specialist at time t at P_t with $z_t<0$, then the price at time t+1 is expected to increase by

$$E(\Delta P_{t+1}|z_t<0) = \beta|z_t|. \tag{10}$$

The expected increase in price after a specialist buy is the expected amount earned by the specialist for providing liquidity services. Hence, β may be interpreted as the gross profit component of the effective spread.

If the trade at time t is a specialist sale with $z_t>0$, the expected decrease in price at time t+1 will be

$$E(\Delta P_{t+1} | z_t>0) = - \beta |z_t|, \quad (11)$$

and the gross profit per share the specialist is expected to earn from the trade is $\beta|z_t|$. Since $\beta=1-\lambda-\theta$, the derivation suggests that the specialist's gross profit per share is affected by three factors: adverse selection (λ), order persistence (θ), and the effective spread (z_t).

The hypothesis of averaging profits through time suggests that the gross profit component of the effective spread in eq. (9) and the adverse selection component of the effective spread in eq. (6) may vary through time. To examine their intraday patterns, we divide each trading day into 13 thirty-minute intervals. The first interval is from 9:30 A.M. to 10:00 A.M. and the last interval from 3:30 P.M. to 4:00 P.M.. The division of the trading day into 13 intervals is similar to that used by McInish and Wood (1992). Estimation results in these 13 intraday intervals allows us to observe how quickly the high level of information asymmetry at the beginning is reduced to the level of information asymmetry at the closing of the trading day.

Since the explanatory variable is the same for eqs. (6) and (9), there is no efficiency gain from seemingly unrelated regressions. Furthermore, because the variances of the error terms in eqs. (6) and (9) are likely to vary through time, the approach with dummy variables may not be appropriate. We thus separately estimate eqs. (6) and (9) for each sample firm in each of the 13 intervals. The sample firms are discussed in the next section. In the empirical tests reported in Section 4, we use the logarithms of the trade price and of the quote midpoint. The log transformation produces continuously compounded returns and reduces the problem of price discreteness.

Based on eq. (6), the variance of trade-to-trade returns based on quote midpoints, σ_Q^2, in each intraday interval can be decomposed into

$$\sigma_Q^2 = \lambda^2\sigma_z^2 + \sigma_e^2, \tag{12}$$

where $\lambda^2\sigma_z^2$ can be regarded as the price volatility due to private information revealed from trades and σ_e^2 as the price volatility due to the error term.

Similarly, based on eq. (9), the variance of trade-to-trade returns based on trade prices, σ_P^2, in each intraday interval can be decomposed into

$$\sigma_P^2 = \beta^2\sigma_z^2 + \sigma_u^2, \tag{13}$$

where $\beta^2\sigma_z^2$ can be regarded as the price volatility due to trade price bouncing between the bid-ask spread. Thus, the estimates of λ in eq. (6) and β in eq. (9) along with the variance of the effective spread in each of the 13 intraday intervals allow us to compare the sources of intraday volatility.

3.3. Data

To test the hypothesis of the specialist averaging profits over time, we select a sample of 100 common stocks from the 1988 Institute for the Study of Security Markets (ISSM) files. These 100 common stocks are the first 100 NYSE common stocks on the files that have an average price above $10.0, more than 2,000 trades, and no stock splits in 1988.[28] The average stock prices in 1988 for the sample firms range from $10.09 to $91.19 with the mean equal to $28.74 and the median equal to $24.16. The number of trades in 1988 ranges from 2,001 to 63,365 with the mean 12,893 and the median 7,667.

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[28]The requirement of an average price above $10.0 is to reduce the impact of discreteness. The requirement of more than 2,000 transactions in the sample period is to assure sufficient observations to carry out reliable estimations of the components of the spread in each intraday interval. We discard firms with stock splits because several studies show empirically that stock splits tend to change firms' variances of stock returns and bid/ask spreads [see, for example, Ohlson and Penman (1985), Dravid (1987), and Conroy, Harris, and Benet (1990)].

All trades in 1988, except for opening transactions on each day, are included for analysis.[29] For each trade, the transaction time, the trade price, and the prevailing bid and ask prices are identified. Lee and Ready (1991) find that prevailing quotes may sometimes be recorded ahead of trades. Following their suggestion, we identify the prevailing quotes for each transaction as the quotes that are in effect five seconds earlier and are BBO-eligible (i.e., eligible for inclusion in the National and NASD Best Bid and Offer calculation). The prevailing quote midpoint is then computed as the average of the prevailing bid and ask prices.[30]

Table 3-1 reports intraday patterns in quoted and effective bid-ask spreads. Consistent with previous studies, the quoted spread for our sample firms exhibits a U-shaped pattern. The average quoted percentage spread declines from 1.13% in the 9:30-10:00 interval to 1.00% in the

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[29]Opening transactions are excluded from the sample because they are conducted in the call market, while transactions after the opening are generally conducted in the continuous market.

[30]Occasionally, trades with exactly the same time, price, and trading volume are observed on the ISSM files. If there are several trades reported at exactly the same time, price, and volume, we take the first trade and discard the remaining trades. We also discard trades and quotes that are initiated on regional exchanges. Hasbrouck and Ho (1987) point out that a single trade may be reported as multiple trades if different parts of a market order clear at different prices. They thus take into the sample for analysis only those trades that are separated by at least two minutes. We apply the two-minute requirement to our sample and find that the requirement does not alter the results much.

TABLE 3-1

INTRADAY PATTERNS IN BID-ASK SPREADS

Average quoted and effective bid-ask spreads for the 100 NYSE sample stocks in 1988.

Time interval	Quoted[a] spread (%)	Effective spread (%)	Quoted spread ($)	Effective spread ($)
9:30-10:00	1.13	0.77	0.256	0.174
10:00-10:30	1.06^{--}	0.71^{--}	0.236^{--}	0.156^{--}
10:30-11:00	1.04^{--}	0.70^{-}	0.232^{--}	0.154
11:00-11:30	1.03^{--}	0.68^{--}	0.228^{--}	0.149^{--}
11:30-12:00	1.02^{-}	0.68	0.226^{-}	0.150
12:00-12:30	1.01	0.67	0.225	0.149
12:30-1:00	1.00	0.68	0.223^{-}	0.151
1:00-1:30	1.02	0.68	0.225	0.149
1:30-2:00	1.00^{--}	0.67^{-}	0.222^{-}	0.147
2:00-2:30	1.00	0.68^{+}	0.223	0.149^{+}
2:30-3:00	1.00	0.68	0.223	0.150
3:00-3:30	1.02^{++}	0.69^{+}	0.226^{++}	0.152^{+}
3:30-4:00	1.04^{++}	0.71^{++}	0.230^{++}	0.158^{++}

[a]Denote A_t, B_t, and p_t as the ask, bid and trade prices at time t. The quoted dollar spread is A_t-B_t; the quoted percentage spread is $(A_t-B_t)/q_t$, where $q_t=(A_t+B_t)/2$; the effective dollar spread is $2|p_t-q_t|$; and the effective percentage spread is $2|\log(p_t)-\log(q_t)|$.

The signs -- and - (++ and +) indicate that the average spread in the interval is significant smaller (larger) than the average spread in the preceding interval at the 1% level and 5% level of significance, respectively.

2:30-3:00 interval, and then increases to 1.04% in the last half hour of trading.

The effective percentage spread is computed as $2|P_t-Q_t|$, where P_t is the logarithm of the trade price at time t and Q_t is the logarithm of the quote midpoint between the bid and ask prices at time t.[31] Similar to the quoted spread, the effective spread also exhibits a U-shaped intraday pattern. However, the average effective spread is smaller than the average quoted spread in each intraday interval. On average, the effective spread is only about 68% of the quoted spread. The effective spread is the basis of our estimates of gross profits earned by the specialist.

Table 3-2 reports intraday patterns in the average half-hour trading volume and variance of half-hour returns. Both trading volume and return variance show the usual U-shaped pattern. These results suggest that our sample firms have characteristics similar to those in previous studies. However, the intraday patterns in information asymmetry and gross profits earned by the market maker are not U-shaped, as will be shown next.

[31]This measure of the effective percentage spread is approximately equal to $2|(p_t-q_t)/q_t|$, where p_t is the trade price and q_t is the quote midpoint in dollar terms.

TABLE 3-2

INTRADAY PATTERNS IN TRADING VOLUME AND VOLATILITY

Average half-hour trading volumes, variances of half-hour trade price returns, and variances of half-hour quote midpoint returns for the 100 NYSE sample stocks in 1988.

Time interval	Average trading volume (100)	Average return variance based on prices (10^{-5})	Average return variance based on quotes (10^{-5})
9:30-10:00	151.73	7.34	11.26
10:00-10:30	145.66	6.01^{--}	5.63^{--}
10:30-11:00	129.18^{-}	5.56^{-}	4.38^{--}
11:00-11:30	115.23^{--}	4.85^{--}	3.46^{--}
11:30-12:00	103.74^{--}	4.91	3.37
12:00-12:30	92.12^{-}	4.78	3.03
12:30-1:00	79.03^{--}	4.52	3.05
1:00-1:30	76.59	4.45	3.00
1:30-2:00	72.56	3.81^{--}	2.44^{--}
2:00-2:30	83.22^{++}	4.21^{++}	2.48
2:30-3:00	88.64^{++}	4.44	2.72
3:00-3:30	99.49^{++}	4.91^{++}	3.13^{++}
3:30-4:00	144.30^{++}	6.38^{++}	4.21^{++}

The signs -- and - (++ and +) indicate that the variable in the interval is significant smaller (larger) than the same variable in the preceding interval at the 1% level and 5% level of significance, respectively.

3.4. Evidence of an Intraday Pattern in Gross Profits

Trades in the period of high information asymmetry will have large impacts on quote prices. Because of a long nontrading period preceding the opening, we expect that, on average, the level of information asymmetry is higher in the first trading period than during the rest of the trading day. Based on eq. (6), we first examine the intraday pattern in information asymmetry. Eq. (6) is estimated for each of the 100 sample firms in each of the 13 intraday intervals. We report in Table 3-3 the mean results of the 100 estimates in each interval.[32]

According to Table 3-3, trades in the first half-hour interval show the highest information asymmetry in the sense that they move the quote prices the most. On average, the quote price revision in response to trades in the first half-hour interval is about 61% of the effective spread, as indicated by the estimates of λ. This suggests that, on average, the adverse selection component accounts for 61% of the effective spread in the first half hour of trading. The adverse selection component declines to 46% of the effective spread in the second half-hour interval. In the third half-hour interval, the adverse selection component decreases to 39% of the effective spread, and remains stable around that level for the rest of the trading day. In the last half-hour

[32]The median estimates are very similar to the mean estimates reported in Table 3-3. The results based on the median estimates are available upon request.

Table 3-3

ESTIMATES OF AVERAGE QUOTE REVISIONS DUE TO TRADES

The quote revision model is estimated for each of the 100 sample firm in each of the 13 intraday intervals. The model is

$$\Delta Q_{t+1} = a + \lambda z_t + e_{t+1}, \qquad (6)$$

where $\Delta Q_{t+1}=Q_{t+1}-Q_t$; $a=0$; $z_t=P_t-Q_t$, P_t is the log trade price at time t and Q_t is the log midpoint between the bid and ask prices at time t; λ is the proportion of the effective spread due to adverse selection; and e_{t+1} is the error term.

Time interval	Average estimate λ	Average t-stat on λ	Average R^2	Variance Decomposition σ_Q^2 (10^{-5})	$\lambda^2\sigma_z^2$ (10^{-5})	σ_c^2 (10^{-5})
9:30-10:00	0.61	34.22	0.55	3.02	1.80	1.22
10:00-10:30	0.46^{--}	22.71	0.38	1.71^{--}	0.76^{--}	0.95^{--}
10:30-11:00	0.39^{--}	18.79	0.31	1.33^{--}	0.51^{--}	0.82^{--}
11:00-11:30	0.38	17.93	0.30	1.18^{--}	0.41^{--}	0.77^{-}
11:30-12:00	0.37	17.28	0.30	1.09^{-}	0.39	0.70^{-}
12:00-12:30	0.37	16.00	0.29	1.11	0.37	0.74
12:30-1:00	0.37	15.16	0.29	1.15	0.42	0.73
1:00-1:30	0.38	15.20	0.30	1.15	0.43	0.73
1:30-2:00	0.36	14.74	0.29	1.00^{--}	0.33^{--}	0.67^{-}
2:00-2:30	0.36	16.04	0.29	0.98	0.33	0.65
2:30-3:00	0.36	17.09	0.29	1.00	0.33	0.67
3:00-3:30	0.35	18.25	0.29	1.00	0.32	0.68
3:30-4:00	0.35	21.09	0.28	1.00	0.31	0.68

The signs -- and - (++ and +) indicate that the variable in the interval is significant smaller (larger) than the same variable in the preceding interval at the 1% level and 5% level of significance, respectively.

interval, the adverse selection component is about 35% of the effective spread.

The estimates of λ are all very significant; the average t-statistics on λ in the 13 intraday intervals range from 14.74 to 34.22. The average R^2's for the model range from 0.28 to 0.55, suggesting that the effective spread, z_t, explains a substantial portion of variation in quote revisions in each intraday interval.

Figure 3-1 exhibits the dynamics of the adverse selection component of the effective spread. The results are consistent with Foster and Viswanathan's (1993) and Hasbrouck's (1990a) findings that information asymmetry is higher at the beginning than during the rest of the trading day. Our results further indicate that the high level of information asymmetry at the opening is reduced to the level of information asymmetry at the closing in about one hour of trading.

The hypothesis of the specialist averaging profits through time predicts that the intraday pattern in gross profits should be inversely related to the pattern in information asymmetry. To examine this prediction, we estimate the gross profit component of the effective spread using eq. (9). Similarly, eq. (9) is estimated for each of the 100 sample firms in each of the 13 intraday intervals. The summary results in each interval are reported in Table 3-4.

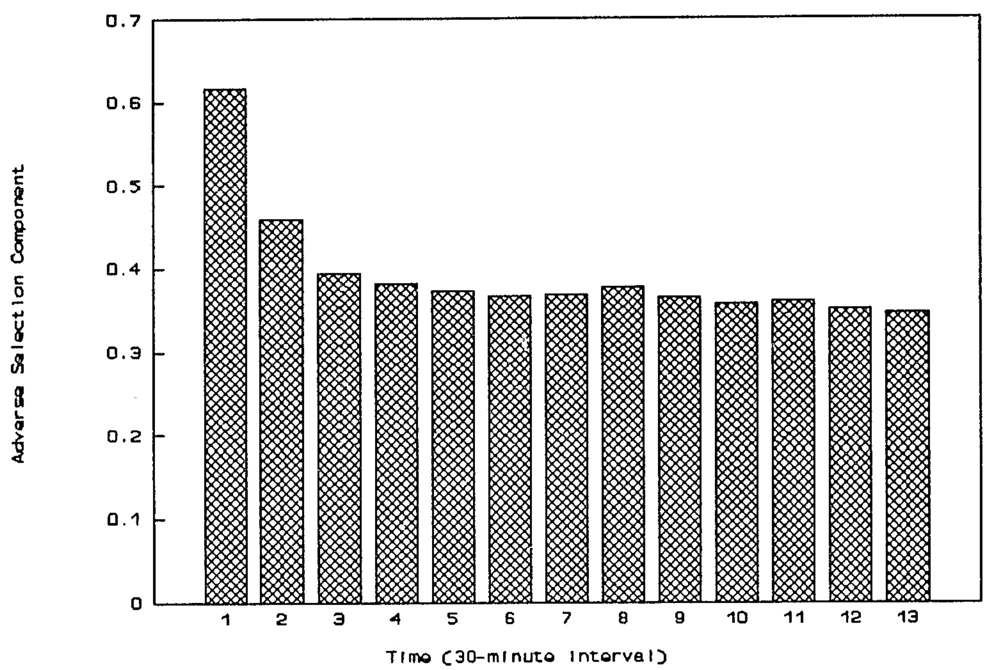

FIGURE 3-1

The INTRADAY PATTERN IN THE ADVERSE SELECTION COMPONENT OF THE EFFECTIVE SPREAD

The trading day is divided into 13 thirty-minute intervals with the first interval 9:30-10:00 A.M. and the last interval 3:30-4:00 P.M.. The adverse selection component λ is estimated for each of the 100 NYSE sample firms in each of the 13 intervals with the model

$$\Delta Q_{t+1} = a + \lambda z_t + e_{t+1.} \tag{6}$$

The mean of the 100 estimates of λ in each interval is depicted in the figure and reported in Table 3-3.

TABLE 3-4

ESTIMATES OF AVERAGE TRADE PRICE CHANGES DUE TO SPREADS

The trade price change model is estimated for each of the 100 sample firm in each of the 13 intraday intervals. The model is

$$\Delta P_{t+1} = b - \beta z_t + u_{t+1}, \tag{9}$$

where $\Delta P_{t+1}=P_{t+1}-P_t$; $b=0$; $z_t=P_t-Q_t$, P_t is the log trade price at time t and Q_t is the log midpoint between the bid and ask prices at time t; β is the gross profit component of the effective spread; and u_{t+1} is the error term.

Time interval	Average estimate β	Average t-stat on β	Average R^2	Variance Decomposition σ_P^2 (10^{-5})	Variance Decomposition $\beta^2\sigma_z^2$ (10^{-5})	Variance Decomposition σ_u^2 (10^{-5})
9:30-10:00	0.16	6.24	0.05	2.66	0.18	2.49
10:00-10:30	0.28^{++}	9.70	0.09	2.61	0.24^{++}	2.38^{-}
10:30-11:00	0.32^{++}	10.23	0.11	2.60	0.33	2.28
11:00-11:30	0.34^{+}	10.86	0.12	2.44	0.30	2.15
11:30-12:00	0.34	10.44	0.12	2.46	0.31	2.16
12:00-12:30	0.34	9.74	0.12	2.45	0.31	2.14
12:30-1:00	0.34	9.00	0.12	2.47	0.32	2.16
1:00-1:30	0.33	8.53	0.12	2.51	0.32	2.20
1:30-2:00	0.35	9.30	0.12	2.31^{-}	0.32	2.00^{-}
2:00-2:30	0.34	9.64	0.12	2.40	0.33	2.07
2:30-3:00	0.34	9.96	0.12	2.51	0.35	2.17
3:00-3:30	0.35	10.67	0.12	2.49	0.38	2.12
3:30-4:00	0.33	11.85	0.11	2.63	0.31	2.33^{++}

The signs -- and - (++ and +) indicate that the variable in the interval is significant smaller (larger) than the same variable in the preceding interval at the 1% level and 5% level of significance, respectively.

Consistent with our prediction, the gross profit component of the effective spread is lowest at the first half-hour interval. On average, it accounts for only 16% of the effective spread. The gross profit component increases to 28% of the effective spread in the second half-hour interval. In the third half-hour interval, the gross profit component increases to 32% of the effective spread, and stays stable around that level for the rest of the day. In the last half-hour interval, the gross profit component is about 33% of the effective spread, on average.

Figure 3-2 exhibits the gross profit components of the effective spread in the 13 intraday intervals. Comparing Figures 3-1 and 3-2, the intraday pattern in gross profits is clearly inversely related to the intraday pattern in information asymmetry. These results support Glosten's (1989) hypothesis of averaging profits over time. Since information asymmetry is highest at the beginning of trading, the specialist appears to stimulate trading by reducing his gross profits at the beginning of trading. In this way the specialist learns some information of the informed and reduces the adverse selection problem. This makes subsequent trades more profitable. Figures 3-2 also indicates that it takes about one hour of trading for the specialist to increase the level of profitability to the level at the closing of the trading day.

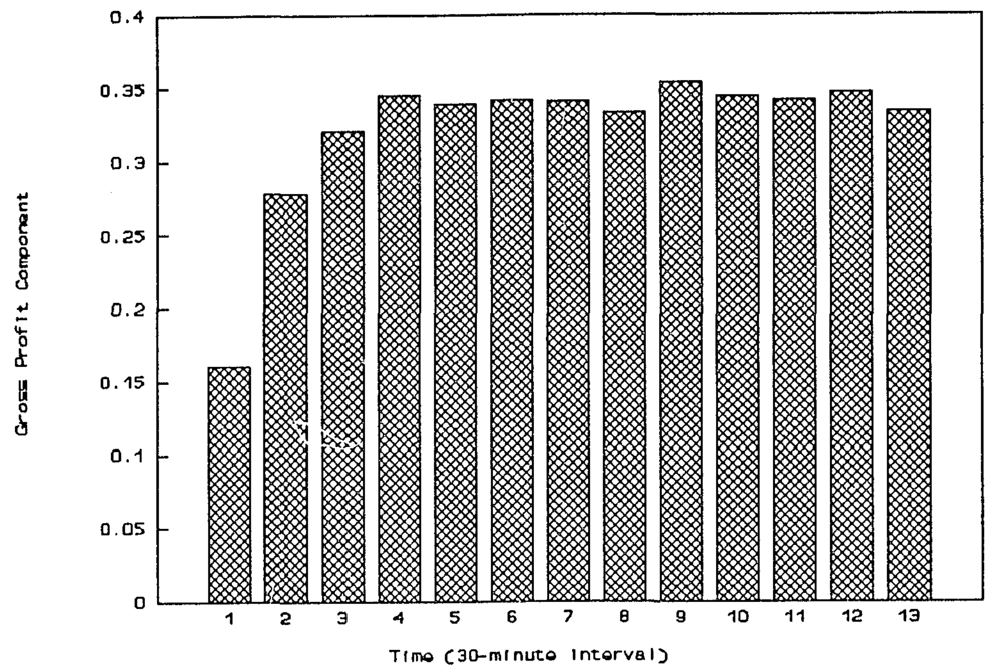

FIGURE 3-2

The INTRADAY PATTERN IN THE GROSS PROFIT COMPONENT OF THE EFFECTIVE SPREAD

The trading day is divided into 13 thirty-minute intervals with the first interval 9:30-10:00 A.M. and the last interval 3:30-4:00 P.M.. The gross profit component β is estimated for each of the 100 NYSE sample firms in each of the 13 intervals with the model

$$\Delta P_{t+1} = b - \beta z_t + u_{t+1}. \qquad (9)$$

The mean of the 100 estimates of β in each interval is depicted in the figure and reported in Table 3-4.

Table 3-5 and Figure 3-3 report the average gross profit per share in cents for each of the 13 intraday intervals. The number for each firm in each interval is computed as β x mean($|z_t|$) x mean(q_t), i.e., the gross profit component times half of the average effective relative spread times the average quote midpoint (in dollar terms) in the interval. The results indicate that the specialist earns about 1.23 cents per share from each trade in the first half-hour interval, and 2.03 cents per share in the second half-hour interval, and around 2.45 cents per share during the rest of the trading day.[33]

Certainly, because of limit order traders, floor traders, and upstairs traders, the specialist does not participate in all trades. From NYSE and SEC data, Smidt (1988) estimates the gross profits earned by NYSE specialists based on specialist transactions for the 11 year period from 1970 through 1980. He reports that "on each transaction the average gain of the specialist is about 2.25 cents" (p.13). In measuring transaction costs on the NYSE, Berkowitz, Logue, and Noser (1988, p.104) show that, on average, the market impact costs for trades in 1985 are "slightly less than two

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[33]As shown in Table 3-5, the average trade sizes are 2,337 shares and 2,335 shares in the first and second half-hour intervals. These trade sizes imply that the specialist earns about $28.74 and $47.40 per trade in the first and second half-hour intervals, respectively. The average trade size in the rest of the trading day is about 1,992 shares, implying $48.80 per trade earned by the specialist.

TABLE 3-5

THE AVERAGE GROSS PROFIT PER SHARE IN CENTS

The average gross profit per share from each trade earned by the specialist in each interval is computed as the average of β x mean($|z_t|$) x mean(q_t) across the 100 sample firms, where β is the gross profit component of the effective spread and is obtained from Table 4; $z_t=P_t-Q_t$, P_t is the log trade price and Q_t is the log midpoint between the bid and ask prices at time t; q_t is the quote midpoint in dollar terms.

Time interval	Average gross profit per share (cents)	Average trade size (shares)	Average number of trades in 1988
9:30-10:00	1.23	2,337	1,198
10:00-10:30	2.03^{++}	2,335	1,189
10:30-11:00	2.34^{++}	2,396	$1,067^{--}$
11:00-11:30	2.44	$2,180^{-}$	$1,019^{--}$
11:30-12:00	2.41	2,072	968^{--}
12:00-12:30	2.44	2,107	861^{--}
12:30-1:00	2.43	$1,939^{-}$	744^{--}
1:00-1:30	2.36	1,934	716^{--}
1:30-2:00	2.49	1,833	737^{++}
2:00-2:30	2.48	1,848	865^{++}
2:30-3:00	2.51	1,843	950^{++}
3:00-3:30	2.55	1,834	$1,093^{++}$
3:30-4:00	2.55	1,922	$1,481^{++}$

The signs -- and - (++ and +) indicate that the variable in the interval is significant smaller (larger) than the same variable in the preceding interval at the 1% level and 5% level of significance, respectively.

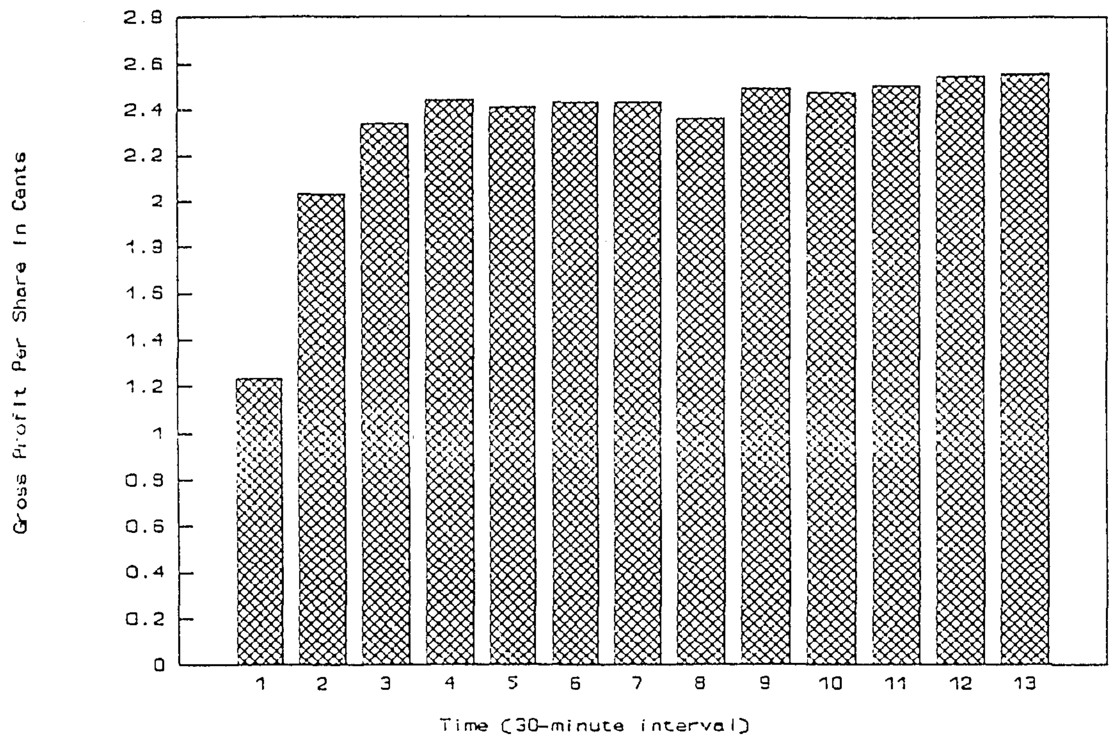

FIGURE 3-3

THE INTRADAY PATTERN IN THE AVERAGE GROSS PROFIT PER SHARE IN CENTS EARNED BY THE SPECIALIST

The trading day is divided into 13 thirty-minute intervals with the first interval 9:30-10:00 A.M. and the last interval 3:30-4:00 P.M.. The average gross profit per share from each trade earned by the specialist in each interval is computed as the average of β x mean($|z_t|$) x mean(q_t), where β is the gross profit component of the effective spread and is obtained from Table 3-4; $z_t=P_t-Q_t$, P_t is the log trade price at time t and Q_t is the log midpoint between the bid and ask prices at time t; q_t is the quote midpoint in dollar terms.

cents per share." The market impact costs paid by traders should correspond to the gross profits earned by market makers who provide liquidity services to traders. The results in these two studies suggest that our estimates of the gross profit per share, ranging from 1.23 to 2.55 cents, in the intraday intervals are not unreasonable. In fact, our estimates are very close to the estimates in these two studies. Furthermore, our estimates of the gross profit per share indicate an intraday pattern, which is consistent with the hypothesis of specialist averaging profits over time.

3.5. Sources of Intraday Volatility

The literature on the market microstructure has speculated on possible causes of the U-shaped pattern in price volatility. Several studies have described private information as the main cause of this empirical regularity. In this section we examine the intraday patterns in price volatility due to private information from trades and price volatility due to trade price bouncing between the bid-ask spread.

In Table 3-3, we decompose the trade-to-trade return variance calculated from quote midpoints, σ_Q^2, into volatility due to private information from trades, $\lambda^2\sigma_z^2$, and volatility due to the error term, σ_ε^2. The average return volatility due to private information revealed from trades is highest in the first half-hour interval. It accounts for about 55% of the quote return variance in the first half-hour interval, and 38% of the quote return variance in the second half-hour interval, on average. The volatility due to private information from trades then decreases toward the end of the trading day. In the last half-hour interval, the volatility due to private information from trades accounts for only 28% of the quote return variance.

The results are depicted in Figure 3-4. This clearly illustrates that the volatility due to private information from trades in the first two intervals are larger than the volatility in the rest of the trading day. This intraday pattern suggests that information revealed from trades declines very fast in the first hour of trading. This is consistent with the hypothesis that the specialist reduces information asymmetry in early hours of trading and makes subsequent trades more profitable. The evidence implies that private information revealed from trades is not the cause of the high volatility at the end of the trading day.

In Table 3-4, we decompose the trade-to-trade return variance calculated from trade prices, σ_P^2, into volatility due to price bouncing between the bid-ask spread, $\beta^2\sigma_z^2$, and volatility due to the error term, σ_u^2. The price volatility due to prices bouncing between the bid-ask spread is lower in the first half-hour interval than during the rest of the day. The pattern is illustrated in Figure 3-5. Since prices bouncing between the bid-ask spread allow the specialist to

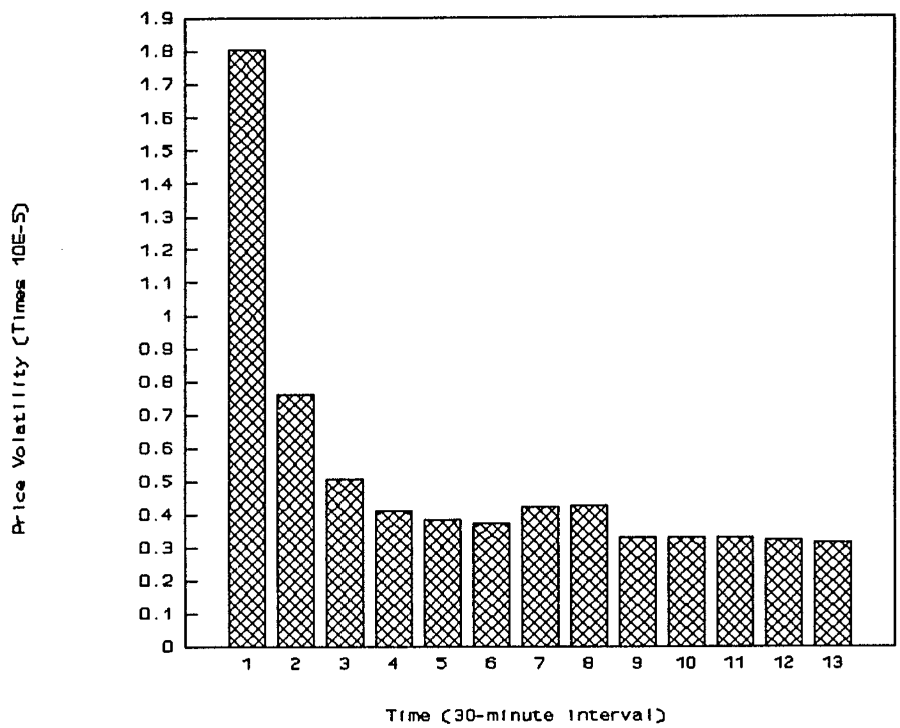

FIGURE 3-4

THE INTRADAY PATTERN IN PRICE VOLATILITY DUE TO PRIVATE INFORMATION REVEALED FROM TRADE

The trading day is divided into 13 thirty-minute intervals with the first interval 9:30-10:00 A.M. and the last interval 3:30-4:00 P.M.. Price volatility due to private information revealed from trades for each of the 100 sample firms in each of the 13 intervals is estimated as $\lambda^2\sigma_z^2$, where λ is the adverse selection component of the effective spread and σ_z^2 is the variance of z_t. The mean of the 100 estimates in each interval is depicted in the figure and reported in Table 3-3.

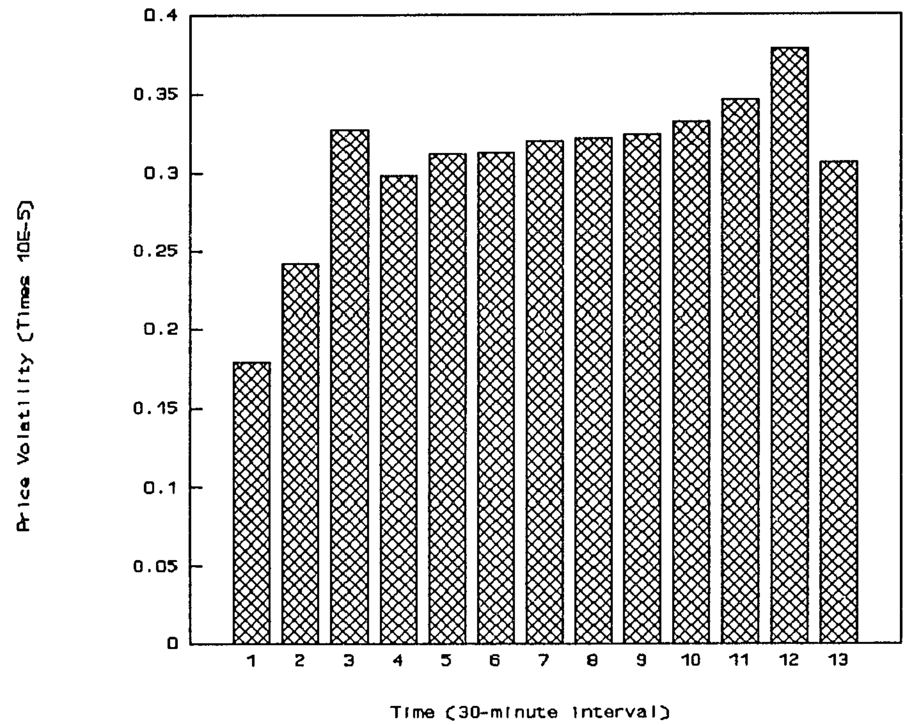

FIGURE 3-5

THE INTRADAY PATTERN IN PRICE VOLATILITY DUE TO PRICES BOUNCING BETWEEN THE BID-ASK SPREAD

The trading day is divided into 13 thirty-minute intervals with the first interval 9:30-10:00 A.M. and the last interval 3:30-4:00 P.M.. Price volatility due to prices bouncing between the bid-ask spread for each of the 100 sample firms in each of the 13 intervals is estimated as $\beta^2\sigma_z^2$, where β is the gross profit component of the effective spread and σ_z^2 is the variance of z_t. The mean of the 100 estimates in each interval is depicted in the figure and reported in Table 3-4.

generate profits, the pattern is consistent with the hypothesis of the specialist averaging profits over time. Furthermore, although the bid-ask spread exhibits a U-shaped intraday pattern, the price volatility due to the bid-ask spread does not show a U-shaped pattern.

3.6. Conclusions

This paper examines intraday patterns in gross profits earned by NYSE specialists. Based on Glosten's (1989) hypothesis of specialists' averaging profits over time, we argue that the pattern in gross profits should be inversely related to the pattern in information asymmetry. The intraday pattern in information asymmetry is found to be higher at the beginning than during the rest of the trading day. This pattern is consistent with Foster and Viswanathan's (1993) and Hasbrouck's (1990a) findings. Conversely, gross profits earned by the specialist are lower at the beginning than during the rest of the trading day. The evidence supports the hypothesis that the specialist reduces information asymmetry in early hours of trading and makes subsequent trades more profitable.

Our analysis does not attempt to answer the question of what may cause the U-shaped patterns in trading volume and price volatility. Nevertheless, our results imply that private information is not the cause of high trading volume and high price volatility at the end of the trading day.

Furthermore, although the bid-ask spread exhibits a U-shaped pattern, we find that the price volatility due to prices bouncing between the bid-ask spread does not have a U-shaped pattern. As suggested by Brock and Kleidon (1990), the puzzle of the U-shaped patterns in market microstructure may be related to exogenous demand. Further research in this area is certainly warranted.

CHAPTER 4

CONCLUDING REMARKS

In this dissertation, we examine the strategic behavior of the specialist proposed by Glosten (1989) and its implications for price volatility and market liquidity. To conclude this study, we provide a brief summary of the findings and suggest several issues for further research.

The extant literature suggests that the bid-ask spread is responsible, at least in part, for the greater volatility and more negative autocorrelation at the open than at the close. We find that these phenomena are not related to the bid-ask spread, but related to pricing errors quoted by the specialist or by limit order traders around the open. We use George, Kaul, and Nimalendran's (1991) model, which is less biased than Roll's (1984) model, to estimate the implied spread. The results show that, on average, the implied spread earned by liquidity suppliers is less at the open than at the close. These results refute Stoll and Whaley's (1990) contention that the specialist exploits his monopoly position and earns a higher profit at the opening call.

Glosten (1989) posits that when information asymmetry is high, the specialist may reduce profits or even realize losses to induce informed traders to trade and to release their information. This reduces the adverse selection problem and makes subsequent trades more profitable. This hypothesis of averaging profits through time implies that the pattern in the specialist's gross profits is inversely related to the pattern in information asymmetry. Since information asymmetry has been found to be higher at the beginning of the trading day, we predict that gross profits earned by the specialist will be lower at the beginning than during the rest of the trading day. Empirical results are consistent with this hypothesis.

For future research, this dissertation can be extended in several directions. First, in Chapter 2, we suggest that the larger return volatility and pricing reversal at the open may reflect pricing errors quoted by suppliers of liquidity. Posted quotes can be from the quotation of the specialist or the public limit order book. Future research may examine whether pricing errors at the open come from the specialist or limit order traders. Second, future study may examine the opening price behavior on the OTC market. Unlike the NYSE specialist, the dealers on the OTC quote competitive quoted prices to elicit the order flow at the open. Whether the competitive multiple-dealership system may provide an efficient value discovery process for the opening transaction would be an interesting issue. Furthermore, Glosten (1989) suggests that competition restricts market makers' ability to average gross profits over time. Hence, it is expected that there is no clear intraday pattern in gross profits earned by OTC market makers.

Third, Morse and Ushman (1983) and Venkatesh and Chiang (1986) examine the bid-ask spread around information releases and find no difference in the size of the spread. The hypothesized strategic behavior of the specialist implies that gross profits earned by the specialist is inversely related to the degree of information asymmetry. When the degree of information asymmetry increases, the specialist may charge lower profits to encourage trading, and hence, the size of the spread may not increase with the degree of information asymmetry. Hence, the same size of the bid-ask spread does not necessarily mean no change in asymmetry information around information releases. To examine whether the degree of information asymmetry increases prior to the releases of new information, it is more appropriate to investigate the components of the bid-ask spread, instead of the spread itself.

REFERENCES

Admati, A. and P. Pfleiderer, 1988, A theory of intraday pattern: Volume and price variability, Review of Financial Studies 1, 3-40.

Amihud, Y. and H. Mendelson, 1987, Trading mechanisms and stock returns: An empirical investigation, Journal of Finance 42, 533-553.

Amihud, Y. and H. Mendelson, 1989, Market microstructure and price discovery in the Tokyo Stock Exchange, Japan and the World Economy 1, 341-370.

Amihud, Y. and H. Mendelson, 1991, Volatility, efficiency, and trading: Evidence from the Japanese stock market, Journal of Finance 46, 1765-1789.

Berkowitz, S.A., D.E. Logue, and E.A. Noser, Jr., 1988, The Total cost of Transactions on the NYSE, Journal of Finance 43, 97-112.

Bagehot, W., 1971, The only game in town, Financial Analysts Journal 27, 12-14, 22.

Brock, W. and A. Kleidon, 1990, Exogenous demand shocks and trading volume: A model of intraday bids and asks, Working Paper, Stanford University.

Choe, H., T.H. McInish, and R.A. Wood, 1991, Market microstructure effects on the measurement of the impact of block trades.

Choi,J.Y., D. Salandro, and K. Shastri, 1988, On the estimation of bid-ask spreads: Theory and evidence, Journal of Financial and Quantitative Analysis 23, 219-230.

Cohen, K., S.F. Maier, R.A. Schwartz, and D.K. Whitcomb, 1986, The Microstructure of Securities Markets, Englewood Cliffs, NJ:Prentice Hall, 1986.

Conroy, R.M., R.S. Harris, and B.A. Benet, 1990, The effect of stock splits on bid-ask spreads, Journal of Finance 45, 1285-1295.

Copeland, T. and D. Galai, 1983, Information effects and the bid-ask spread, Journal of Finance 38, 1457-69.

Demsetz, H., 1968, The cost of transacting, Quarterly Journal of Economics 82, 33-53.

Dravid, A., 1987, A note on the behavior of stock returns around ex-dates of stock distributions, Journal of Finance 42, 163-168.

Easley, D. and M. O'Hara, 1987, Price, trade size, and information in securities markets, Journal of Financial Economics 19, 69-90.

Foster, F.D., and S. Viswanathan, 1993, Variations in trading volume, return volatility, and trading costs: Evidence on recent price formation models, Journal of Finance 48, 187-210.

French, K. and R. Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, Journal of Financial Economics 17, 5-26.

George, T.J., G. Kaul, and M. Nimalendran, 1991, Estimation of the bid-ask spread and its components: A new approach, Review of Financial Studies 4, 623-656.

Glosten, L., 1989, Insider trading, liquidity, and the role of the monopolist specialist, Journal of Business, vol. 62, 211-235.

Glosten, L. and P. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, Journal of Financial Economics 14, 71-100.

Goldman, B. and A. Beja, 1979, Market prices versus equilibrium prices: Return's variance, serial correlation, and the role of the specialist, Journal of Finance 34, 595-607.

Harris, L., 1986, A transaction data study of weekly and intradaily patterns in stock returns, Journal of Financial Economics 16, 99-118.

Hasbrouck, J., 1988, Trades, quotes, inventories and information, Journal of Financial Economics 22, 229-252.

Hasbrouck, J., 1991a, The summary informativeness of stock trades: An econometric analysis, Review of Financial Studies 4, 571-595.

Hasbrouck, J., 1991b, Measuring the information content of stock trades, Journal of Finance 46, 179-207.

Hasbrouck, J. and T.S.Y. Ho, 1987, Order arrival, quote behavior, and the return-generating process, Journal of Finance 42, 1035-1048.

Huang, R.D. and H.R. Stoll, 1992, Market microstructure and stock return predictions, working paper, Owen Graduate School of Management, Vanderbilt University.

Kyle, A.S., 1985, Continuous auctions and insider trading, Econometrica 53, 1315-1335.

Lee, C.M.C. and M.J. Ready, 1991, Inferring trade direction from intraday data, Journal of Finance 46, 733-746.

Lin, J.C., 1992, Order persistence, adverse selection, and gross profits earned by NYSE specialists, working paper, Louisiana State University.

Lo, A.W. and A.C. Mackinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, The Review of Financial Studies 1, 41-66.

Madhavan, A., and S. Smidt, 1991, A bayesian model of intraday specialist pricing, Journal of Financial Economics 30, 99-134.

Madhavan, A., 1992, Trading mechanisms in securities markets, Journal of Finance 47, 607-641.

McInish, T.H. and R.A. Wood, 1992, An analysis of intraday patterns in bid/ask spreads for NYSE stocks, Journal of Finance 47, 753-764.

Ohlson, J.A. and S. Penman, 1985, Volatility increases subsequent to stock splits: An empirical aberration, Journal of Financial Economics 14, 251-266.

Roll, R., 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, Journal of Finance 39, 1127-1139.

Smidt, S., 1988, The bid ask spread and the cost of transacting, working paper, Johnson Graduate School of Management, Cornell University.

Stoll, H.R., 1978, The supply of dealer service in securities markets, Journal of Finance 33, 1135-1151.

Stoll, H.R., 1985, Alternative views of market making, Paper presented at the Conference on Market Making and the Changing Structure of the Securities Industry, Chapter 4.

Stoll, H.R., 1989, Inferring the components of the bid-ask spread: Theory and empirical tests, Journal of Finance 44, 115-134.

Stoll, H.R. and R.E. Whaley, 1990, Stock market structure and volatility, Review of Financial Studies 3, 37-71.

Wei, P.H., 1992, Intraday variations in trading activity, price variability, and the bid-ask spread, The Journal of financial Research 15, 265-276.

Wood, R.A., T.H. McInish, and J.K. Ord, 1985, An investigation of transaction data for NYSE stocks, Journal of Finance 40, 723-739.

VITA

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DOCTORAL EXAMINATION AND DISSERTATION REPORT

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Title of Dissertation: Two Essays on Liquidity Suppliers' Gross Profits

Approved:

Major Professor and Chairman

Dean of the Graduate School

EXAMINING COMMITTEE:

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