Institutional Trading, Trading Volume, and Spread

Malay K. Dey
University of Massachusetts at Amherst
and
Northern Illinois University

B. Radhakrishna
University of Minnesota

[This Draft: March 2001]

We are grateful to NYSE for providing us with the TORQ data and to Ben Branch, Shanta Hegde, and Robert Miller for their comments and numerous helpful suggestions. All comments are welcome.

Please address correspondence to: Malay K. Dey, Dept. of Finance, Northern Illinois University, Dekalb, IL 60115, Tel. (815) 753-6395, Email: mdey@niu.edu, OR B. Radhakrishna, Department of Accounting, Carlson School of Management, University of Minnesota, 321, 19th Avenue S., #3-122, Minneapolis, MN 55455, Tel. (612) 624-0302, Fax (612) 626-1335, Email: bradha@umn.edu.

Institutional trading, Trading Volume, and Spread

Abstract

Besides its academic interest, the effect of institutional trading on the bid-ask spread is of interest to regulators and market makers. It is often (casually) argued that greater institutional participation results in increased volatility in the market. On the other hand, some argue that greater liquidity trading by institutions reduces spread. There is no direct empirical evidence and little theoretical knowledge to suggest a convincing relation between institutional trading and spread. In this paper, we present some evidence on the nature and effect of institutional trading on spreads. We argue that institutional trading is not completely information driven, part of it is liquidity trading in nature. We find evidence that information induced institutional trading increases the adverse selection component. However, large volume (liquidity) trading reduces the order processing costs. We find the net effect of institutional trading on spread is consistently negative. Moreover, institutional buys have differential information from sells. Institutional trades per se reduce spreads, but only sells increase the adverse selection component. Both effective and relative spreads impound the differential nature of institutional buys and sells.

Keywords: Institutional Trading, Spread decomposition, information, liquidity.

JEL Classification: G19.

Institutional trading, Trading Volume, and Spread

I. Introduction

Since Demsetz (1968) bid-ask spread is recognized as the price of liquidity provided by the dealers in an equity market. A number of studies have investigated what determines spread (Branch and Freed [1977], McInish and Wood [1992], Klock and McCormick [1999], Heflin and Shaw [2000]). Some of the significant determinants of spread found in the literature are order size, number of trades, competition in the dealers' market, ownership structure, and the native characteristics of a stock e.g., price, and volatility. Trading rules and mechanics of trading that proxy for information flow are also found to affect the spread.

There is very little empirical evidence on institutional trading and spread and their interrelationship. Keim and Madhavan (1997) find execution costs for institutional trades are different between listed and NASDAQ stocks. Conrad, Johnson and Wahal (2001) report an asymmetric relation between institutional buys and sells and soft-dollar execution. However, there is some evidence of the effect of institutional trading on securities prices. Empirical studies using order size or trading volume as a proxy for institutional trading[1] suggest an increased price effect associated with institutional trading. Using proprietary data on institutional trading, Chan and Lakonishok (1993) find the average price effect to be small for institutional trades, but the price effect for buys and sells to be asymmetric; and Sias and Starks (1997) find that institutional trading contributes to serial correlation of returns.

[1] Lakonishok and Maberly (1990) use block trades as a proxy for institutional trades, and odd lot trades plus non-margin account trades as a proxy for individual trades.

The role of institutional trading in the determination of spread is interesting since it is often argued (casually) that increased institutional participation in the U.S. equity market during the past decade has led to an increase in the volatility, and has widened the bid-ask spread in the equity market. On the other hand, some argue that institutional trades provide liquidity, and hence decrease spread. Bertisimas and Lo (1998) show how optimal trading strategies may be devised by execution cost minimizing investment mangers. In any case, there is very little empirical evidence or theoretical knowledge to conclude how institutional trading affects spread. Further since spread is considered to be a sum of two different components, adverse selection, and order processing[2] it is unclear how institutional trading affects the individual components of the spread.

In this paper, we investigate if institutional trading has any information content beyond what has been documented as a size or volume effect. In a multivariate, panel regression framework, we determine if there exists a relation between bid-ask spread and institutional trading after adjusting for size and price effects. Most studies on the determinants of spread focus on the supply side of dealership market i.e., competition in the dealer market, and use a cross sectional regression approach. Our approach is different from previous studies in two important ways. First, we focus on the demand side (investors' characteristics) to determine the relation between spread and institutional trading[3]; and second, we use a panel data approach accounting specifically for both serial and contemporaneous correlation in the error terms[4]. We report regression results using

[2] Arguably there is also inventory effect in spread. In this paper, we use a decomposition technique that ignores inventory effect.

[3] Recently, some other papers have studied the demand side, particularly the ownership structure. For example, Heflin and Shaw (2000) document a relation between block holding and spread, and Chung and Charoenwong (1998) look at insider holding as a determinant of spread.

[4] Dey (2000) introduces a similar but reduced form panel data regression model for effective spread.

both effective ($) and relative spread as the dependent variable in a set of regression equations.

Further we decompose the spread into order processing and adverse selection components and investigate how those components vary with changes in trading volume, net order flow (buy vs. sell), and institutional trading. We assume contemporaneous correlation between the disturbances and use an SUR (Seemingly Unrelated Regression) analysis to find the significant determinants of the adverse selection and the order processing components of the spread for our sample firms. We use a unique data set (TORQ) that identifies institutional trading. Prior studies proxy institutional participation by using measures based on trade size that are subject to measurement error.

Our results show that institutional trading proportion is inversely related to both effective and relative spreads. We also find that the negative slope (suggestive of the inverse relation) is not constant and flattens out at higher concentrations of institutional trading. We find that this negative slope is provided by both institutional buys and sells alike. Results from a SUR analysis show that the adverse selection costs tend to increase and the order processing costs tend to decrease with increases in institutional trades.

The rest of this paper is organized as follows. In section II, we present the motivation for this study. In section III, we describe an empirical model for spread using panel regressions, provide data description, and explain the results. Further, we describe the decomposition of the spread into order processing and adverse selection costs components and report results from a SUR analysis of the determinants of those components. Section IV concludes the paper.

II. Motivation

II.A. Relation between Spread and Institutional trading

Schwartz (1988) identifies four classes of variables, namely, activity, risk, information, and competition as determinants of spread. Existing literature find trade size, number of trades, ownership structure, and extent of market power in the dealership market to be the key determinants of bid-ask spread (McInish and Wood [1992], Laux [1993, 1995], Klock and McCormick [2000], Heflin and Shaw [2000]). Dealer market competition represents the supply side of the market for liquidity services[5]. On the other hand, trade size, ownership structure, and frequency of trading measure the activity in securities markets and represent the demand side of the market for liquidity services.

Prior research suggests an inverse relationship between spread and trading activity measured by order size, and number of trades (McInish and Wood [1992]). Institutions trade large sizes, and also trade frequently.[6] Thus institutional trading will induce low spread. However, trading activity also contributes to both information and risk associated with a security[7]. Hasbrouck (1991) provides evidence that large trades contain more information than small trades and cause spreads to widen. Lin, Sanger and Booth – hereafter LSB (1995) find evidence of an increasing (although not continuously), non-linear relation between spread and trade size. Jones, Kaul, and Lipson (1994) report that

[5] In a securities market, dealers provide liquidity (both buying and selling of securities) services, while investors demand those services.

[6] Lee and Radhakrishna (2000) confirm earlier evidence that institutions tend to trade in larger volumes. They present a technique of classifying trades into institutional and non-institutional based on size in a way that reduces the error in classification to statistically manageable levels.

[7] See, for example, the summary of the empirical evidence on the price effect of block trades in Dey (2000).

the number of trades captures the essence of volatility in financial markets even in the presence of volume and trade size.[8]

Seppi (1990) argues that institutions use trade size strategically; they trade large orders when they can signal to the market that their trades are not information motivated and hence large institutional trades may not have information content. Dey and Kazemi (2000) distinguish between large, pure information trades and large institutional trades and argue that institutional trades are driven by both “pure information” and liquidity needs. Dey and Kazemi (2000) predict the “pure information” component of equilibrium spread to be an increasing, while the liquidity component of the spread to be a decreasing function of institutional trading.

Chan and Lakonishok (1993), and Keim and Madhavan (1994) find that the price effect and cost implications of institutional buys and sells are not symmetric. Koski and Michaely (2000) find that buys and sells provide different information for different trade sizes. Saar (2000) provides a theoretical framework based on a dynamic portfolio rebalancing process of institutions to explain the documented asymmetry in the price effect of institutional buys and sells.

In this paper, in a multivariate regression framework, we determine whether institutional trading has information content beyond that provided by trade size denoted by trading volume, and number of trades. Specifically, we hypothesize that the variation in bid-ask spread can be explained by trading volume, number of trades, price, and institutional trading. Further, we hypothesize that institutional trading *per se* and not the

[8] Recently, Chan and Fong (1999) find that after adjusting for order imbalance, trade size is important for the volume-volatility relation.

direction of institutional trading - buy or sell affects the bid-ask spread. Stated in alternate form, we hypothesize:

> **H1: The bid-ask spread should vary significantly with institutional trading after controlling for number of trades, price, and trading volume. Further, institutional trades per se affect bid ask spread, and thus institutional buys and sells do not have any differential effect on the bid-ask spread after controlling for number of trades, price, and trading volume.**

II.B. Components of the spread

We extend our analysis of the relation between institutional trading and spread by decomposing the spread into its order processing and adverse selection components and investigating the effect of institutional trading on the individual components. We use a technique from LSB (1995) to decompose the spread into order processing and adverse selection components and hypothesize a relation between the individual components and institutional trading.

Sias (1996) reports positive correlation between institutional activity and market volatility; however, Cohen et al (1987) suggest that institutions trade frequently because of their low order processing costs. Bertisimas and Lo (1998) derive optimal trading strategies of institutions based on minimum execution cost. LSB (1995) find the order processing cost to be decreasing and adverse selection cost to be increasing in trade size. We conjecture that if institutional trading is a mix of information and liquidity trading then the information effect should increase the adverse selection component and the liquidity effect should decrease the order processing costs. We also recognize that while gross volume is important for the determination of order processing cost, trade direction or net volume (buy volume - sell volume), is important in the determination of adverse selection costs. We therefore include log (buy/sell) as a variable in the regression model for the adverse selection component.

We determine through a set of simultaneous equations how institutional trading affects the order processing and the adverse selection components of the spread after controlling for number of trades, volume, and trade direction. The simultaneous equations approach uses the cross correlation between the two regression equations to improve the estimates. Further we determine how the asymmetric information content and the liquidity motive in institutional buys and institutional sells affects the adverse selection (information) component of the spread. Stated in alternate form, our hypotheses are:

H2a. The adverse-selection component should increase with institutional trading, and the order-processing component should decrease with institutional trading.

H2b. Institutional buys should have a differential effect on the adverse selection component of the spread from institutional sells.

III. Regression Models, Data Description, and Results

III.A.1. Panel Data Regression Model

We use a multivariate, panel (time series – cross sectional) regression framework to investigate the effect of institutional trading on the bid-ask spread. We use a unique data set (TORQ) that allows us to identify the order origination for a trade as institutional or otherwise. Most studies on the determinants of spread use pooled OLS estimates of the parameters of a regression model. OLS estimates ignore the covariance structure of the error term both across firms and over time.

We assume disturbances are both serially and contemporaneously correlated. Specifically, we assume an AR(1) process with contemporaneous correlation for the disturbance term. In our model for the spread, the serial correlation may be due to lagged spread or lagged values of the independent variables or their interactions. Kim and Ogden (1996) find higher order serial correlation for the spread, and Peles (1992) report contemporaneous correlation among equity trading of institutional investors. Parks (1967) provide consistent and efficient estimates of the parameters when disturbances follow a first order auto regressive process - AR(1) with contemporaneous correlation.

We run the following regression model for our panel data:

$$Spread_{nt} = a + b_1 NtradePct_{nt} + b_2 Dly\_Avg_{nt} + b_3 \mathrm{Pr}ice + b_4 Instprop_{nt} + e_{nt} \quad (1)$$

where:

n = 1…N; number of firms in sample, t = 1…T; number of trading days

$Spread_{nt}$ = Effective or Relative spread for the *nth* firm on day t

$NtradePct_{nt}$ = Number of trades on day t for firm n expressed as a proportion of average number of daily trades over the entire sample period

Dly_Avg_{nt} = Volume of trade on day t for firm n expressed as a proportion of average daily trading volume over the entire sample period

$Price_{nt}$ = Closing price on day t for firm n

$Instprop_{nt}$ = Institutional trading (number of trades) as a proportion of total trading for the *nth* firm on day t.

Further, the error structure is assumed as follows:

$E\left(e_{nt}^2\right) = s_{nn}$,

$E\left(e_{it} e_{jt}\right) = s_{ij}$ where $i \in n,$ and $j \in n$ (due to contemporaneous correlation),

$e_{nt} = r_n e_{n,t-1} + m_{nt}$ (disturbance term is AR(1)),

$m_{nt} \sim N\left(0, f_{nn}\right)$,

$$E\left(e_{i,t-1}m_{jt}\right) = 0$$

$$E\left(m_{it}m_{js}\right) = 0 \text{ where } t \neq s \text{ (cross correlation is zero).}$$

$$E\left(m_{it}m_{jt}\right) = f_{ij} \text{ (contemporaneous correlation),}$$

III.A.2. Data

To estimate the parameters of our regression model, we use data from the TORQ data set. The TORQ files released by NYSE were prepared under the supervision of Professor Joel Hasbrouck during his tenure as a Visiting Economist to the NYSE. This dataset contains trades, quotes, order processing, and audit trail data for a sample of 144 NYSE stocks for the three months (63 trading days) from November 1990 through January 1991.[9] These firms represent a size stratified random sample of firms in the NYSE and thus cover the broad spectrum of NYSE firms.

As noted by Lee and Radhakrishna (2000), the marginal contribution of TORQ data over ISSM or TAQ data is in providing identification for traders' classes, as institutions, individuals, and dealers. Most studies using other trades/quotes databases use size as a proxy for institutional trades.

We impose a restriction that is common among studies that study effective spreads or the components of the spread to ensure adequacy of data in estimation. We select all firms in the data set that have on average 20 trades per day or more during the sample period. Further, in classifying the trades, whenever there are executions of multiple orders on the active side of a trade, we take the trader class of the largest order

[9]For more details on the TORQ database and on trading procedures at the NYSE, see Hasbrouck (1992).

on the active side as the initiator of that trade. The active side of the trade is determined using the Lee-Ready (1991) algorithm.[10] This reduces our sample to 65 firms.

Of the 65 firms that survived our initial cutoff, 14 firms have one or more days of missing observations or days with trading halts. We leave out the firms with trading halt days from our study since the effect of trading halts on spreads and the price discovery process is unique and beyond the realm of this paper. We chose to omit the firms with missing observations, since there are questions about the reliability of estimates using an unbalanced panel[11]. Thus we have a balanced panel of 51 firms with 63 days data that we use in our panel regression.

The panel data set includes daily data for the firms in the data set. For each firm, we calculate the mean daily effective bid-ask spread, and the proportion of buy and sell orders initiated by institutions for each day. We compute the effective spread for each trade defined as twice the absolute value of the difference between trade price and the prevailing mid-quote. The mean effective spread is the average of effective spreads across all trades in a day. To determine the mean proportion of trades by institutions in that firm, we calculate, for each day, the proportion of trades by institutions on the buy and sell side.

Besides proportion of institutional trading, there are three other independent variables in the panel regression. The "number of trades" variable is computed as the number of trades each day divided by the average number of trades for the firm over the

[10] Lee and Radhakrishna (2000) show the effectiveness of Lee-Ready algorithm for classifying trades into buys and sells.

[11] We explored another alternative i.e., to consider all the firms (65) but for fewer days (61). However, there was a problem in deciding which 2 days to delete for firms that have full 63 days data. Since any choice on this was likely to be arbitrary, we chose to use a balanced panel of 51 firms over 63 days.

sample period. Thus this is a measure of abnormal trading in each day. Trading above (below) mean would give this variable a value higher (lower) than one. The "trading volume" variable is computed by dividing the daily share volume for the firm by the average daily share volume over the sample period. Therefore, this variable also has values above (below) one when trading volume is higher (lower) than the average daily share volume. The price variable is the closing price of the stock.[12]

In Table 1, we present means of the computed statistics of the variables used in the panel regression. We first compute the relevant statistics for the sample firms over the sample period and then compute the means of those statistics. Thus we report the means of the cross sections of firm means, medians, and standard deviations. The inter-firm mean (median) spread is .126 (.12) that is about an eighth. The inter-firm mean standard deviation is quite low at .02. The largest spread in our sample is .514, approximately one-half, and the lowest .019 or approximately one-sixty-fourth. The inter-firm mean (and median) institutional trading in our sample is around 30%. Although institutions generally trade on a regular basis, in some trading days there is no institutional trading. Of the 3,213 (51×63) firm trading days covered in our sample there were 10 firm-days when there was no institutional trading, and one firm-day when all the trading was initiated by institutions. There is also sufficient variability in the number of trades and volume. The low trading (volume) in our sample was 9% (3%) of average daily trades (volume). The high trading (volume) was 392% (1235%) of average daily volume. In Table 2, we present Pearson correlations for variables in the regression.

[12] Using average price over a day instead of closing price does not change the results.

Panel A presents pooled correlations computed from 3,213 observations. In Panel B, we present the means of correlations computed in time series for each firm.

III.A.3 Regression Results of Panel Model

Table 3 reports the regression results for the panel data regressions with effective spread (in dollars) and relative spread as dependent variables. For our first model (1-ES), the independent variables are number of trades, trading volume, price, and the proportion of institutional trades. All four variables are significant in determining effective spread. The significant coefficients show that effective spread increases as trading (number of trade) and price increase and decreases as trading volume and institutional trading increase. The coefficient for institutional proportion is negative (-.0111) and significant at less than 1% level. Thus an increase in institutional proportion reduces the spread. The R^2 for this model is 22%. However, for a similar model with relative spread (1-RS) as the dependent variable, number of trades fails to be a significant determinant of spread. All other variables, namely average trading volume (-.0137), price (-.028), and institutional proportion (-.024) remain significant at less than 1% level, and the R^2 for the model is 90%. The change in the effect of price on relative spread (decreasing in price) from that on effective spread (increasing in price) is expected since relative spread is computed as effective spread over mid quote. This change in the effect of price on effective and relative spreads is consistent across all the four models.

For our second model, we introduce two dummy variables for high and medium institutional proportions. The high (medium) institutional proportion variable has a value of 1 when the level of institutional trading is in the top (middle) 33% percentile, and zero otherwise. The coefficients of the dummy variables are both positive and significant in the regression. The high dummy has a larger coefficient (.0016) than the medium dummy variable (.0007). Taken in conjunction with the significant negative (-0.0153) coefficient of the institutional proportion variable, this suggests that the negative slope of the institutional proportion variable flattens out at higher levels of institutional trading. This conjecture is confirmed with model 3.

In model 3, the institutional proportion variable is replaced by three variables – high, medium and low proportion. The high (medium, low) proportion variable has the same value as institutional proportion if institutional trading proportion is in the top (middle, bottom) 33 percentile, and zero otherwise. The coefficients of all three variables are negative and significant in the regression, but while the coefficient for low proportion is -.0144, that for the high proportion is significantly (14%) less at -.0122. We interpret these results as follows. On average, there may be a mean positive effect on institutional trading embodied in the positive intercept. However, when there is an increase in institutional trading within a level, the spread declines, but the rate of decrease is lower at higher levels of institutional proportion. Between low and medium levels, the rate of decrease is similar indicating these are perhaps two discrete levels of institutional proportions.

Finally, for our fourth model, we break up the institutional proportion into institutional buy and institutional sell to test for a difference in their effect on the spread. Results from the fourth model show that spread reduces as institutional trading increases, be it buy or sell. The coefficients for buy and sell are significantly negative for both effective spread and relative spread.

These results support our hypotheses. We show (H1) that institutional trading is a significant variable in the determination of both effective and relative spreads. We also show that this relation has a downward slope that gradually flattens out. Finally, we show that institutional trading *per se* drives the relation between spread and institutional trading, and not the direction of institutional trade - buy or sell.

III.B.1 Decomposition of Spread

In order to test our third hypothesis, we decompose the quoted spread for the firms in our sample to determine the adverse selection and order processing components[13]. We follow a decomposition technique originally proposed by Stoll (1989)[14] and used recently by LSB (1995). The parameters $\hat{l}$, and $\hat{g}$ of the following regression models are estimates of the adverse selection and the order processing components of the spread.

$$\Delta Q_{t+1} = l\, z_t + e_{t+1} \qquad (2)$$

$$\Delta P_{t+1} = -g\, z_t + u_{t+1} \qquad (3)$$

where, P_t = log trade price at time t

Q_t = log quote mid point at time t

Δ = Change in the relative variable from t to $t+1$

Δ $z_t = P_t - Q_t$ and

e_{t+1}, u_{t+1} = Random error terms with zero mean and constant variance

---

[13] We don't do any analysis with inventory holding cost component.

[14] There are several decomposition methodologies other than Stoll (1989) that are available in the literature. Huang and Stoll (1997), Glosten and Harris (1988), and George, Kaul and Nirmalendran (1991) provide estimates of the different components of the spread including adverse selection, order processing and inventory holding cost. Studies using different methodologies find the components of the spread to be different. There is no consensus about any one of the methodologies being more robust than the others.

$$E\left(e_{t+1}u_{t+1}\right)=0\,.$$

The assumption about zero correlation between the error terms is based on the reported findings in LSB (1995).

Table 4 reports descriptive statistics about the spread decomposition for the 65 firms in the sample. We find that the order processing costs for our sample firms are higher, and adverse selection costs lower than that reported in LSB 1995. The means and medians of the components are similar indicating a symmetric (low skewness) distribution for the component costs. Not surprisingly the descriptive statistics from our sample correspond closely with those from the largest volume sub-sample in LSB (1995) confirming the notion that institutions generally trade in large sizes and in high volume, liquid stocks.

III.B.2. SUR model

We use a cross sectional SUR (Seemingly Unrelated Regression) model to estimate the parameters of the following system of equations for the adverse selection and the order processing components of the daily spread for our sample firms.

$$OPC = a_1 + b_{11}NumTrd + b_{12}InstitutionTrading + b_{13}AvgVol + e_o \qquad (4)$$

$$ADV = a_2 + b_{21}NumTrd + b_{22}InstitutionTrading + b_{23}AvNetVol + e_a \qquad (5)$$

where,

OPC = Order Processing cost

ADV = Adverse Selection cost

NumTrd = Mean daily number of trades for firm

InstitutionTrading = Mean institutional trading proportion for firm

AvgVol = Log(Average daily trade volume for firm)

AvNetVol = Log(Average buy volume per trade/average sell volume per trade)

The SUR model assumes that

$E\left(e_o\right) = E\left(e_a\right) = 0$.

$E\left(e_{oi}e_{aj}\right) = \sigma_{oa}$ if $i = j$ and 0 otherwise for $i,j \in (1..65)$.

III.B.3. Results of the SUR model

Table 5 reports the results of the SUR model. The number of observations for each system of equations estimated is 65 – one observation for each firm in the sample. Our results show that institutional trading significantly increases the adverse selection component of the spread but reduces the order processing cost component. This suggests that the market views institutional trading to have a dual character, both information and liquidity trading and prices both in the determination of the spread. The order flow variable (AvNetVol) is significantly negative, thus an increase in buys has the effect of reducing the spread. The "number of trades" variable is significantly negative in the adverse selection equation and positive in the order processing equation – indicating its dichotomous effect on the spread components. The volume variable is negative in the order processing equation as expected. As volume increases, order processing costs decrease. We interpret this result as supporting Bertisimas and Lo (1998) that higher trading by institutions are motivated by lower order processing costs.

For our second model, we estimate the system of equations with institutional buys and sells in place of total institutional proportion. We find that institutional sells are positive and significant (at 8% level) in determining the adverse component. Buys are insignificant in the adverse selection equation.

IV. Conclusion

The role of institutional trading in the determination of spread is of interest to regulators and market makers. It is often argued that institutional investors have superior information, better processing power to assimilate the information, and greater access to markets.[15] Institutions have low transaction costs and thus trade frequently. The increased institutional participation is often considered an attribution for the increased volatility in the U.S. equity market. However there is no empirical evidence suggesting a relation between institutional trading and spread. We present empirical evidence to suggest a non-linear inverse relation between the bid ask spread and institutional trading in the equity market. Our analysis shows that institutional trading is not just information driven – a part of their trading is liquidity trading in nature. Institutional trading affects both the adverse selection and order processing components of the spread. Increased institutional trading increases the adverse selection component, while it reduces the order processing costs through large volume trading. We find the net effect of increased institutional trading to be a reduction spread. Increased institutional buys seem to reduce spreads, but sells seem to increase the adverse selection component. The market makers recognize this and accordingly adjust the effective spreads.

[15] Radhakrishna (1995) shows the swiftness with which institutional traders enter the market after a news event like an earnings announcement.

Bibliography

Branch, Ben, and Walter Freed, 1977, Bid-Asked Spreads on the AMEX and the Big Board, *Journal of Finance*, v32, n1, 159-163

Bertisimas, Dimitris, and Andrew Lo, 1998, Optimal Control of Execution Costs, *Journal of Financial Markets*, v1, n1, 1-50

Chan, Kalok, and Wai-Ming Fong, 2000, Trade Size, Order Imbalance, and the Volume - Volatility Relation, *Journal of Financial Economics*, v57, n2, 247-73

Chan, Louis K. C., and Josef Lakonishok, 1993, Institutional Trades and Intraday Stock Price Behavior, *Journal of Financial Economics*, v33, n2, 173-99

Cohen, Jerome, Edward Zinbarg, and Arthur Ziekel, 1987, *Investment Analysis and Portfolio Management*, Fifth Edition, Irwin

Conrad, J., K. Johnson, and S. Wahal, 2001, Institutional Trading and Soft Dollars, *Journal of Finance*, v56, n1, 397-416

Chung, Kee, and C. Charoenwong, 1998, Insider Trading and the Bid-Ask Spread, *Financial Review*, v33, n3, 1-20

Demsetz, H., 1968, The Cost of Transacting, *Quarterly Journal of Economics*, v82, 33-53

Dey, Malay K., 2000, Essays on Information Asymmetry and Microstructure of Equity Markets, *Ph.D. Dissertation*, University of Massachusetts Amherst

Dey, Malay K. and H. Kazemi, 2000, Bid-ask Spread in a Competitive Market with Institutions and Order Size, University of Massachusetts, *Working Paper*

George Thomas, G. Kaul, and Nirmalendran, 1991, Estimation of the Bid-Ask Spread and its Components, A New Approach, *Review of Financial Studies*, v4, n4, 623-56

Glosten, Larry, and Lawrence Harris, 1988, Estimating the Components of Bid /Ask Spread, *Journal of Financial Economics*, v21, n1, 123-42

Greene, Willam, 1997, Econometric Analysis, Third Edition, Prentice Hall

Hasbrouck, Joel, 1991, Measuring the Information Content of Stock Trades, *Journal of Finance*, v46, n1, 179-207

Hasbrouck, Joel, 1992, Using the TORQ Database, *NYSE Working Paper*

Heflin, Frank, and Kenneth Shaw, 2000, Blockholder Ownership and Market Liquidity, *Journal of Financial and Quantitative Analysis*, v35, n4, 621-33

Huang, Roger and Hans Stoll, 1997, The Components of the Bid-Ask spread: A General Approach, *Review of Financial Studies*, v10, n4, 995-1034

Jones, Charles, G. Kaul, and M. Lipson, 1994, Transactions, Volume and Volatility, *Review of Financial Studies*, v7, n4,

Keim, Donald, and A. Madhavan, 1997, Transactions Costs and Investment Style: An Inter-exchange Analysis of Institutional Trades, *Journal of Financial Economics*, v46, n3, 265-92

Keim, Donald, and A. Madhavan, 1994, Execution Costs and Investment Performance: An Empirical Analysis of Institutional Equity Trades, *Working Paper*, Wharton School, University of Pennsylvania

Kim, Sung-Hun, and Joseph Ogden, 1996, Determinants of the Components of Bid-Ask Spreads on Stock, *European Financial Management*, v1, n1, 127-45

Klock, Mark, and Timothy McCormick, 1999, The Impact of Market Maker Competition on Nasdaq Spreads, *The Financial Review*, v34, 55-74

Koski, Jennifer L. and R Michaely, 2000, Prices, Liquidity, and the Information Content of Trades, *Review of Financial Studies*, v13, n3, 659-96

Lakonishok, Joseph, and Edwin Maberly, 1990, The Weekend Effect: Trading Patterns of Individual and Institutional Investors, *The Journal of Finance*, v45, n1, 231-43

Laux, Paul, 1993, Trade Sizes and Theories of the Bid-Ask Spread, *Journal of Financial Research*, v16, n3, 237-49.

Laux, Paul, 1995, Trade Sizes and Theories of the Bid-Ask Spread, *Journal of Economic Dynamics and Control*, v16, n3, 237-49.

Lee, Charles, and B. Radhakrishna, 2000, Inferring Investor Behavior: Evidence from TORQ Data, *Journal of Financial Markets*, v3, 2, 183-204

Lee, Charles, and M. Ready, 1991, Inferring Trade Directions from Intraday Data, *Journal of Finance*, v46, n3, 733-46

Lin, Ji-chai, Gary Sanger, and Geoffrey Booth, 1995, Trade Size and Components of the Bid-Ask Spread, *Review of Financial Studies*, v8, n4, 1153-83

McInish Thomas, and Robert Wood, 1992, An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE stocks, *The Journal of Finance*, v47, n2, 753-64

Parks, R.W., (1967), Efficient Estimation of a System of Regression Equations when Disturbances are Both Serially and Contemporaneously Correlated, *Journal of American Statistical Association*, v62, 500-509

Peles, Nadav (1992), Contemporaneous Correlations Within Equity Trading of Institutional Investors, *Working Paper*, Columbia University

Radhakrishna, B., 1995, Investor Heterogeneity and Earnings Announcement, *Ph.D. Dissertation*, University of Michigan, Ann Arbor

Saar, Gideon (2000), Price Impact Asymmetry of Block Trades: An Institutional Trading Explanation, Forthcoming in *Review of Financial Studies*

Schwartz, (1988), Robert, *Equity Markets*, Harper and Row, New York

Seppi, D. (1990), Equilibrium Block Trading and Asymmetric Information, Journal of Finance, v45, n1, 73-94

Sias, Richard, 1996,Volatility and the Institutional Investor, *Financial Analyst Journal*, v52, n2, 13-20

Sias, Richard, and Laura Starks, 1997, Return Autocorrelation and Institutional Investors, *Journal of Financial Economics*, v46, n1, 103-31

Stoll, Hans, 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance*, v44, n1, 115-34

Table 1

Descriptive Statistics of Variables Used in Panel Regressions

	Mean	Median	Quartile Range	Minimum	Maximum	Standard Deviation[5]
Spread[1]	0.126	0.120	0.020	0.019	0.514	0.023
Relative Spread Percent[1]	0.773	0.613	0.167	0.115	6.022	0.167
Institutional Trading Proportion[2]	0.299	0.296	0.060	0.000	1.000	0.100
Number of Trades[3]	1.000	0.942	0.188	0.095	3.924	0.415
Trade Volume[4]	1.000	0.793	0.177	0.027	12.351	0.821

[1]Effective spread is defined as Abs[(Price – Mid Quote)*2]. The variable used in the panel regressions is average spread per day for each firm. Relative Spread Percent is computed as effective spread/mid quote *100.

[2]Institutional trading proportion is computed as trades by institutions as a proportion of total trades for a day.

[3]Number of trades is computed as the number of trades for firm each day divided by average trades per day over the entire trading period. Thus, the mean of this variable on a firm-by-firm basis is by design equal to 1.

[4]Trade Volume is computed as share volume of firm for each day divided by average share volume per day over the entire trading period. Thus, the mean of this variable on a firm-by-firm basis is by design equal to 1. The standard deviation presented here is the mean of the within firm standard deviations.

[5]The standard deviation presented here is the mean of the within firm standard deviations.

Table 2
Correlation Analysis

PANEL A: Pooled sample Pearson Correlations (N=3213) [a]

Variables	Spread	Relative Spread %	NTradePct	InstProp	Dly_Avg	Price[5]
Spread[1]	1.000					
Relative Spread %	.0905 (<.0001)	1.000				
NTradePct [2]	.0297 (.092)	-.0163 (.355)	1.000			
InstProp[3]	-.0005 (.979)	-.2617 (<.0001)	-.0880 (<.0001)	1.000		
Dly_Avg[4]	-.0384 (.029)	-.0184 (.297)	.5164 (<.0001)	.0994 (<.0001)	1.000	
Price[5]	.1319 (<.0001)	-.6296 (<.0001)	-.0003 (.854)	.3032 (<.0001)	-.0025 (.8858)	1.000

PANEL B: Mean of firm Correlations [a]

Variables	Spread	Relative Spread %	NtradePct	InstProp	Dly_Avg	Price[5]
Spread[1]	1.000					
Relative Spread %	.8377 (49)	1.000				
NTradePct[2]	.0298 (9)	-.0186 (16)	1.000			
InstProp[3]	-.0954 (13)	-.0593 (14)	-.1047 (14)	1.000		
Dly_Avg[4]	-.0725 (12)	-.0711 (10)	.5605 (46)	.1231 (15)	1.000	
Price[5]	.0164 (13)	-.2725 (30)	.0244 (23)	-.0186 (10)	-.0163 (19)	1.000

[a]Panel A table values are 1) Parameter estimates, and 2) P-Values in parentheses. Panel B table values are 1) Parameter estimates based on mean of firm estimates, 2) the number of firms for which coefficients are significant at p-values of less than 10%. The mean coefficient is computed from the 51 firms in the sample.

Variable Descriptions:
[1]**Spread** = Effective spread is defined as Abs[(Price – Mid Quote)*2]. The variable used in the panel regressions is average spread per day for each firm.
[2]**NTradePct** = Number of trades **-** This is computed as the number of trades for firm each day divided by average trades per day over the entire trading period.
[3]**InstProp** = Institutional trading proportion – This is computed as trades by institutions as a proportion of total trades for a day.
[4]**Dly_Avg** = Daily Trade Volume **-** This is computed as share volume of firm for each day divided by average share volume per day over the entire trading period.
[5]**Price** = Closing Price.

Table 3
Panel Regression Results

Dependent Variable: Spread and Relative Spread (for all models)

Model	1-ES	2-ES	3-ES	4-ES	1-RS	2-RS	3-RS	4-RS
Intercept	.1174 (<.0001)	.1181 (<.0001)	.1183 (<.0001)	.1171 (<.0001)	1.4428 (<.0001)	1.4374 (<.0001)	1.442 (<.0001)	1.4532 (<.0001)
Nos.trade Pct	.0051 (<.0001)	.0050 (<.0001)	.0050 (<.0001)	.0052 (<.0001)	.0003 (.8482)	.0008 (.6519)	-.0006 (.7241)	-.0012 (.4145)
Dly_Avg	-.0025 (<.0001)	-.0025 (<.0001)	-.0025 (<.0001)	-.0026 (<.0001)	-.0137 (<.0001)	-.0133 (<.0001)	-.013 (<.0001)	-.0127 (<.0001)
Price	.0004 (<.0001)	.0004 (<.0001)	.0004 (<.0001)	.0004 (<.0001)	-.028 (<.0001)	-.0282 (<.0001)	-.0281 (<.0001)	-.0278 (<.0001)
InstProp	-.0111 (<.0001)	-.0153 (<.0001)			-.0563 (<.0001)	-.024 (.001)		
InstBuy				-.0055 (<.0001)				-.0506 (<.0001)
InstSell				-.0042 (<.0001)				-.0523 (<.0001)
High-Dum		.0016 (.0049)				-.012 (<.0001)		
Med-Dum		.0007 (.0530)				-.0063 (<.0001)		
High InstProp			-.0122 (<.0001)				-.056 (<.0001)	
Med Instprop			-.0146 (<.0001)				-.0702 (<.0001)	
Low Instprop			-.0144 (<.0001)				-.0631 (<.0001)	
Adj. R^2	.223	.220	.219	.220	.899	.892	.889	.914

All regression models in Table 3 above are run with a panel data set that has 51 firms each with 63 trading days. The Parks (1967) method with AR(1) and contemporaneously correlated error term is used for estimation. Table values are parameter estimates with p-values in parentheses.

Variable Descriptions:
Spread = Effective spread is defined as Abs[(Price – Mid Quote)*2]. The variable used in the panel regressions is average spread per day for each firm.
NTradePct = Number of trades **-** This is computed as the number of trades for firm each day divided by average trades per day over the entire trading period.
Dly_Avg = Daily Trade Volume **-** This is computed as share volume of firm for each day divided by average share volume per day over the entire trading period
InstProp = Institutional trading proportion – This is computed as trades by institutions as a proportion of total trades for a day. **HighInstProp** has the value of InstProp if the institutional proportion is in the top third percentile of institutional proportions, and 0 otherwise. **MedInstprop** has the value of InstProp if the institutional proportion is in the middle third percentile of institutional proportions, and 0 otherwise. **LowInstprop** has the value of InstProp if the institutional proportion is in the bottom third percentile of institutional proportions, and 0 otherwise.
HighDum has the value 1 if the institutional proportion is in the top third percentile of institutional proportions, and 0 otherwise. **MedDum** has the value 1 if the institutional proportion is in the middle third percentile of institutional proportions, and 0 otherwise.
InstBuy = Institutional Buy trading proportion – This is computed as #buys by institutions as a proportion of total trades for a day.
InstSell = Institutional Sell trading proportion – This is computed as #sells by institutions as a proportion of total trades for a day.

Table 4

Descriptive Statistics: Components of the spread expressed as percentage of total spread

	Mean	Median	Minimum	Maximum	Standard Deviation
Adverse Selection Component[1]	25.3%	25.2%	2.8 %	46.1%	11.5%
Order Processing Component	40.1%	39.2%	13.4%	79.8%	15.9%

[1]The effective spread is decomposed into its components using methodology originally proposed by Stoll (1989) and used recently by Lin, Sanger and Booth (1995). The descriptive statistics presented above is for the cross-section of 65 firms in the sample and is calculated from the mean proportion for each firm in our sample, of the adverse selection component and order processing component of the spread.

Table 5
Regression Results of System of Equations with Adverse Selection and Order Processing Costs on Trades, Volume and Institutional Trading

Dependent Variable	Intercept	NumTrd	Institution Trading	Institution Buy	Institution Sell	AvNetVol	AvgVol
OPC	.1817 (<.0001)	.00007 (.005)	-.0507 (.0798)				-.0107 (.0008)
ADV	.0137 (.0671)	-.00005 (.0007)	.0740 (.0022)			-.0131 (.0172)	
OPC	.1804 (<.0001)	.00007 (.005)	-.0511 (.0776)				-.0106 (.001)
ADV	.0125 (.1079)	-.00005 (.0008)		.0494 (.2969)	.1079 (.0814)	-.0135 (.0157)	

All regressions are run as seemingly unrelated regressions (SUR). The data set has observations for 65 firms for which data is available. Table values are parameter estimates with p-values in parentheses.

Variable Descriptions:
(All averages are computed over the entire 3-month trading period in the TORQ data set on a firm-by-firm basis.)
OPV = Order Processing component of the average effective spread for firm.
ADV = Adverse Selection component of the average effective spread for firm.
NumTrd = Average trades per day.
Institutional Trading =Average institutional proportion of trades.
Institution Buy = Average institutional buy proportion of trades.
institution Sell = Average institutional sell proportion of trades.
AvNetVol = Natural Log of [Average Buy Volume per trade/Average Sell Volume per trade]
AvgVol = Natural Log of Average Daily Trade Volume.