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NUMBER OF TRANSACTIONS AND VOLATILITY: AN EMPIRICAL STUDY USING HIGH-FREQUENCY DATA FROM NASDAQ STOCKS

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Abstract

Our empirical evidence based on transactions data of a sample of Nasdaq stocks indicates that trades of large firms are related to the proxies of marketwide and firm-specific information. For large firms, an increase in the number of trades seems to have a beneficial effect on liquidity as measured by bid-ask spreads. On the other hand, trades of small and medium firms are associated with firm-specific information and are not related to marketwide information. For small and medium firms, the frequency of trades is positively associated with bid-ask spreads, apparently because of the adverse information content of trades.

JEL classification: G10, G12, G13

I. Introduction

The familiar Wall Street adage that it takes volume to move prices is confirmed by empirical research. However, trading volume measured over a given period, such as a trading day, can be decomposed into two components: number of trades and the average size of each trade. Jones, Kaul, and Lipson (1994) conduct further research into this issue to see whether it is the number of transactions or the trade size that moves prices more. They study the volatility of closing prices of Nasdaq stocks and show there is a reliably positive relation between volatility and number of transactions. However, the volume-volatility relation vanishes when the association between volatility and the number of transactions is controlled for. Jones, Kaul, and Lipson consider the number of daily transactions to be the most

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appropriate measure of the rate of flow of information. We can now modify the Wall Street adage to state that it takes transactions to move prices.[1] However, Jones, Kaul, and Lipson do not provide a formal explanation for the informativeness of the number of transactions variable. We address this issue explicitly in this article.

We use high-frequency data from stocks traded on the Nasdaq market to conduct our empirical tests. Our approach focuses on the relation between volatility and trading frequency in an intraday setting. We look at factors affecting trading frequency. Specifically, we look at the relative roles of marketwide information and firm-specific information in determining trading frequency. We draw on the work of Bessembinder, Chan, and Seguin (1996) that explains trading volume by using proxies of marketwide and firm-specific information. We use a similar framework to explain the number of transactions.

Bessembinder, Chan, and Seguin find that public marketwide information drives the trading volumes of large firms. They also suggest that for small firms, price reaction to marketwide information occurs without a perceptible increase in trading volume.[2] If so, prices can change even in the absence of trades for small firms, as market makers adjust their quotes in response to price changes of large firms or index movements. Another implication of this explanation is that when trades of small firms do occur, it is mostly because traders are acting on the basis of firm-specific information. Bessembinder, Chan, and Seguin present evidence that the trading volume of small firm stocks bears no relation to common marketwide information and that most trading occurs in response to firm-specific information. It is reasonable to expect that some of the traders of small stocks possess material, nonpublic information. We conjecture that the dealers faced with a large number of trades for small firms face more information asymmetry as compared with frequent trades of big firms. If so, the dealers, to protect themselves from potential adverse information costs, would increase the bid-ask spread. We thus propose that the effect of trading frequency on bid-ask spread is conditioned on firm size. For large firms, we surmise that a higher trading frequency, ostensibly because of trading in response to marketwide information, should lower the bid-ask spread. In contrast, for small firms, we expect a direct positive relation between spread and trading frequency, because trading frequency is directly associated with firm-specific information.

Our study contributes to the literature on two fronts. First, we extend earlier work on the association between trading volume and categories of information flow. We use several measures of trading activity and find that for large firms trading frequency is most clearly associated with marketwide information. Second, we document that when trading is motivated by public marketwide information it

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[1]Easley and O'Hara (1990) and Harris and Raviv (1993) provide theoretical support for the effect of number of trades in the determination of asset prices.

[2]This is consistent with the explanations presented by Brennan, Jegadeesh, and Swaminathan (1993) and Jones, Kaul, and Lipson (1994).

TABLE 1. Descriptive Statistics for Size Portfolios.

Size Portfolio	No. of Stocks	Market Capitalization ('000 dollars)	Trading Characteristics: No. of Transactions (*N*)	Average Trade Size (AV)	Average Trading Volume (V)	Average Closing Spread (SP)
1	160	1,070	12.48	1283.64	17,714	0.0629
2	160	2,947	16.34	1154.85	18,695	0.0225
3	160	6,764	26.06	1156.22	28,240	0.0186
4	160	15,322	27.59	1088.66	23,570	0.0135
5	160	36,580	42.22	1090.31	33,846	0.0095
6	158	184,680	90.80	803.13	55,946	0.0065

Note: This table contains average market capitalization, number of transactions (*N*), average trade size (AV), average trading volume per day (V), and average closing spread (SP). Closing spread is calculated as: (ask price − bid price)/bid price. The descriptive statistics are based on transaction data from the TAQ database of the NYSE. All Nasdaq stocks that traded for at least ten days in April 1996 and that have no dividend and stock-split declaration dates in the month are included in the sample. The statistics are based on 958 Nasdaq stocks. Individual firm statistics are averaged across firms in each portfolio.

improves liquidity. Large firms experience this beneficial effect of trading. Our findings are similar to the conclusion of Bessembinder and Seguin (1992), who report that trading imparts depth and liquidity to the marketplace. Although Bessembinder and Seguin focus on aggregate trading volume of stocks trading on the New York Stock Exchange (NYSE), we focus on trading activity of Nasdaq stocks organized into market-capitalization-based portfolios. Our additional finding is that trading activity has a deleterious effect on liquidity of small and medium firms in the short run.

II. Data

Our empirical analysis of Nasdaq stocks covers April 1996. We include all stocks that traded for at least ten days during that month and that had no dividend or split declaration dates. Our data source is the Trades and Quotes (TAQ) database of the NYSE. Our sample is composed of 958 stocks and is broken down into six portfolios on the basis of market capitalization as of the beginning of April 1996.

In Table 1, we provide the descriptive statistics. Stocks in the smallest firm portfolio trade about 12.5 times per day. This value increases with market capitalization and reaches a value of 91 trades per day for the largest firm portfolio. Average trade size decreases from 1,284 shares to 803 as we move from the smallest to the largest firm portfolios. The average trading volume per day increases monotonically, from 17,714 shares to 55,946 shares, with market capitalization. The average closing percentage spread decreases monotonically with market capitalization, from 6.29 percent for smallest firms to 0.65 percent for the largest

firms. Although trading volume increases three-fold as we move from the smallest portfolio to the largest portfolio, the percentage spread declines to one-tenth of the value for small firms. Perhaps, the increased trading activity of large firms bestows a beneficial effect on liquidity as measured by percentage spread. Our conjecture is empirically supported by Harris (1994), who finds that higher trading volumes are associated with lower spreads for a sample of NYSE and American Stock Exchange stocks. Huang and Stoll (1996) also report empirical evidence of the inverse association between trading volumes and execution costs of Nasdaq stocks.

III. Transactions and Volatility

Bessembinder and Seguin (1993) and Gallant, Rossi, and Tauchen (1992) document a positive relation between volatility and volume. But trading volume is a compound variable that can be decomposed into number of transactions and average size per transaction. Although most of the earlier literature focuses on trading volume, recent work centers on number of trades. Theoreticians posit that trading is generated by agents facing information asymmetry and that trading volume conveys information on the magnitude of discord among traders concerning the value of a security. In competitive models with asymmetric information, trading volume is directly related to the accuracy of information possessed by informed traders. Informed traders therefore prefer to trade large quantities at a given price. This leads to an adverse-selection problem in the trading process. Pfleiderer (1984) and Kim and Verrecchia (1991) discuss this problem in detail.

In another set of models classified as strategic models, a monopolist informed trader may conceal his or her trading activity by doing several small trades instead of a large trade. The models of Admati and Pfleiderer (1988) and Foster and Vishwanathan (1990) fall in this category. Thus, the number of trades rather than size may convey more information to the market participants.

Easley and O'Hara (1990) provide a theoretical market microstructure model that explicitly considers the role of time in the adjustment process of prices. Their model shows that total number of trades is informative with respect to price changes because the market maker infers information from both trades and a lack of trades. Harris and Raviv (1993) derive a model that predicts a positive relation between the number of trades and absolute price changes. Their model assumes that traders receive the same information but differ in their interpretation of the information. Trading occurs because of the divergent opinions regarding the value of the security generated by the same information. Shalen (1993) also provides a model in which traders differ in their interpretation of common signals.

Although the theoretical literature provides sufficient arguments to expect a positive relation between trading frequency and stock price volatility, they do not provide specific, testable implications that help us understand the phenomenon further. Therefore, we probe the issue by using an empirical approach.

TABLE 2. Ordinary Least Squares Regression of the Absolute Value of Closing-Price Returns.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Panel A. Number of Transactions (N) As Independent Variable						
Intercept	0.0216	0.0149	0.0147	0.0151	0.0134	0.0126
N	0.000940	0.000582	0.000339	$8.97*10^{-5}$	$4.97*10^{-5}$	$1.56*10^{-5}$
	(9.92)	(11.35)	(11.92)	(10.03)	(6.84)	(8.58)
Adj. R^2	0.0515	0.0753	0.0763	0.0501	0.0240	0.0280
Panel B. Number of Transactions and Average Trade Size (AV) As Independent Variables						
Intercept	0.0214	0.0148	0.0147	0.0153	0.0133	0.0126
N	0.000930	0.000580	0.000340	$8.96*10^{-5}$	$4.92*10^{-5}$	$1.56*10^{-5}$
	(9.89)	(11.35)	(11.92)	(10.01)	(6.76)	(8.54)
AV	$1.60*10^{-7}$	$2.86*10^{-8}$	$1.66*10^{-8}$	$-6.00*10^{-8}$	$-7.00*10^{-8}$	$-3.60*10^{-8}$
	(0.77)	(0.41)	(0.54)	(-0.76)	(-1.60)	(-0.49)
Adj. R^2	0.0520	0.0750	0.0764	0.0504	0.0250	0.0280

Notes: In Panel A, we estimate the equation: $r_{it} = \alpha + \beta N_{it} + \varepsilon_{it}$, where r_{it} is the absolute value of closing-price returns of stock i on day t, and N_{it} is the number of daily transactions for stock i on day t. In Panel B, we estimate the equation: $r_{it} = \alpha + \beta_{AV} AV_{it} + \beta_N N_{it} + \varepsilon_{it}$, where AV_{it} is the average trade size for stock i on day t. We estimate the regression for each portfolio using daily observations for each stock.

Jones, Kaul, and Lipson (1994), using a sample of Nasdaq stocks, show that the occurrence of transactions as such, and not their size, generates volatility. Their evidence shows that trade size has no additional information content beyond that provided by trading frequency. Using a high-frequency database we explore further the relation between the number of transactions and stock price volatility.

In Table 2 we show the estimates of regressions of price volatility on the number of transactions. Price volatility is measured by the absolute value of daily (close-to-close) return. Daily observations of price volatility for each stock within a portfolio are regressed on the number of daily transactions of that stock for that day. The regressions are performed for each portfolio. The results are shown in Table 2, Panel A. We find that the number of transactions variable has a reliably positive effect on stock price volatility as shown by the t-statistics. We also find that the effect of number of transactions on stock price volatility decreases monotonically as we move from the smallest to the largest firm portfolios. Our results are in conformity with Jones, Kaul, and Lipson (1994).

Jones, Kaul, and Lipson's work also shows the absence of information content of the trade size variable. We confirm their conclusion and display the evidence in Panel B of Table 2, which includes an additional independent variable in the regression, namely, average trade size (AV).[3] The results indicate no reliable relation between trade size and price volatility. The relation between number of

[3]We observe low cross-correlation between N and AV. This signifies that N and AV contain different information. Also, the results are not tainted by multicollinearity.

transactions and volatility remains intact. We therefore conclude that trade size does not have a significant effect on price volatility.[4] We show empirically, using a different sample and a different period, the primary result of Jones, Kaul, and Lipson, that the number of transactions is directly related to the price volatility of securities.

Jones, Kaul, and Lipson (1994) do not examine, empirically, the likely reasons for the transactions—volatility association. It may be fruitful to investigate the kinds of information that seem to be associated with trades in securities markets. Conceivably, this probe may provide possible explanations for the transactions—volatility association. We thus focus our attention on the information-trading frequency link in the following section.

IV. Trading Frequency and Information

Several theoretical studies seem to suggest that information is associated with trading. Some models require asymmetric information to induce trading, although others merely rely on a different interpretation of the same information to bring about trades. Bessembinder, Chan, and Seguin (1996) characterize all information into two types: common or marketwide information and firm-specific information. They establish that trading may occur because of informed traders dealing with firm-specific information or traders transacting on the basis of marketwide information. In addition there may be noise traders or liquidity traders who trade for noninformational reasons. Trades based on firm-specific information are more likely to rely on asymmetric inside information possessed by certain traders. On the other hand, trades induced by marketwide information are more likely to be caused by different interpretation of the same information. Bessembinder, Chan, and Seguin find that both types of information determine aggregate trading volume in stock markets. They also find that trading volume of large stocks is more strongly related to marketwide information than trading volume of small stocks. Moreoever, they find that firm-specific information has less effect on the trading volume of large firms than it does on trading volume of small firms. Their evidence shows that trading volume of small firms is primarily determined by firm-specific information.

The relation between trading volume and marketwide information may occur either because of the effect of marketwide information on trading frequency or because of its effect on trade size. Bessembinder, Chan, and Seguin (1996) do not specifically address this issue. We believe that trading frequency is more informative than trading volume. Trade size is jointly determined by trader

[4]Using data for the thirty stocks contained in the Dow Jones Industrial Average, Coughenour (1999) shows that the relation between trade frequency and volatility is mainly due to medium size trades. It is possible that the same effect occurs in our sample, too. However, we do not explore this issue in our article.

TABLE 3. Ordinary Least Squares Estimates of Number of Transactions (N) on Absolute Value of Market Index Returns.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Panel A. Absolute Value of Daily NYSE Index Returns As Independent Variable						
Intercept	11.49	14.39	23.08	26.29	34.89	77.92
$\|R\|$	-7.94	-171.22	-137.49	-116.05	395.31	1547.04
	(-0.16)	(-2.38)	(-0.20)	(-0.68)	(1.43)	(2.86)
Panel B. Absolute Value of Daily Nasdaq Index Returns As Independent Variable						
Intercept	11.58	14.21	22.89	23.40	33.23	77.76
$\|R\|$	-19.33	-101.00	59.23	374.36	316.21	1200.76
	(-0.35)	(-1.24)	(0.28)	(1.93)	(1.69)	(1.95)

Notes: In Panel A, we estimate the equation: $N_{it} = \alpha + \beta|R_t| + \varepsilon_{it}$, where N_{it} is the number of daily transactions for stock i on day t, and $|R_t|$ is the absolute value of the return of the NYSE composite index for day t. In Panel B, we estimate the same equation, with $|R_t|$ now representing the absolute value of the return of the Nasdaq composite index for day t. We estimate the regression for each portfolio using daily observations for each stock.

motivation to trade (liquidity versus informational), type of information (firm specific versus marketwide), attitude to risk (hedging versus speculation), and market microstructure (dealer versus order driven). We believe trade size is strategically determined by the factors mentioned earlier. Trading frequency on the other hand is a cleaner variable and may reflect more clearly the information flows in the market.

Bessembinder, Chan, and Seguin present empirical evidence to show that traders transact a basket of stocks, such as the futures contract on a stock market index, when they trade on the basis of marketwide information. Trades of individual stocks are mostly determined by firm-specific information flows. However, the value of the index futures cannot deviate substantially from the underlying index without triggering arbitrage. Arbitrageurs, who exploit the price discrepancy between the index futures and stock prices in the spot market trade, tend to concentrate their trades on stocks whose transaction costs are low. Typically, large firms have lower trading costs and are therefore ideal candidates for such arbitrage trades. We thus conjecture a positive relation between marketwide information and trading frequency for large firms. This argument is predicated on the basis of transactions cost measures such as the percentage spread, which for large firms is shown to be about one-tenth the value of that of the smallest firms. Small firms are less likely to trade for arbitrage reasons. Most trades of small firms may be based on firm-specific information. An implication of this premise is that trades of small firms contain more adverse information from the perspective of the market maker. We empirically examine this conjecture.

In Table 3, Panel A, we present results of regressing the number of transactions (N) on the absolute value of NYSE composite index returns. We

TABLE 4. Ordinary Least Squares Regressions of Total Daily Volume (TV) on Absolute Value of Market Index Returns.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Panel A. Absolute Value of Daily NYSE Index Returns As Independent Variable						
Intercept	5,633	6,915	7,789	12,742	16,528	37,293
$\|R\|$	−18,794	−94,065	−8,602	−30,414	−17,716	364,406
	(−0.27)	(−1.16)	(−0.10)	(−0.21)	(−0.11)	(1.45)
Panel B. Absolute Value of Daily Nasdaq Index Returns As Independent Variable						
Intercept	5,819	6,619	7,316	13,430	18,202	35,945
$\|R\|$	−10,212	−64,096	78,136	−167,970	−337,828	725,547
	(−0.07)	(−0.37)	(0.45)	(−0.56)	(−0.99)	(1.36)

Note: In Panel A, we estimate the equation: $TV_{it} = \alpha + \beta|R_t| + \varepsilon_{it}$, where TV_{it} is the total trading volume for stock i on day t, and $|R_t|$ is the absolute value of the return of the NYSE composite index for day t. In Panel B, we estimate the same equation with $|R_t|$ now representing the absolute value of the return of the Nasdaq composite index for day t. We estimate the regression for each portfolio using daily observations for each stock.

consider the NYSE return as a proxy for the amount of publicly available marketwide information. Our proxy is similar to the one used by Bessembinder, Chan, and Seguin (1996). The results of Panel A show that marketwide information has a substantially positive effect on the number of transactions for large firms. We also find that the absolute value of the NYSE return is negatively related to N for small firms. Bessembinder, Chan, and Seguin arrive at similar conclusions when they regress trading volume on a proxy for marketwide information.

However, in general the results are not statistically significant for small and medium firms. The results imply that on days of substantial marketwide information, small and medium firms do not trade more. In fact, they may face lower trading activity on such days. This is in contrast to large firms, which experience greater trading activity on days of substantial marketwide information. It appears traders concentrate their trading activity on large firms on days when major marketwide information is disseminated and neglect small and medium firms on those days.

In Panel B of Table 3, we use the Nasdaq index return as the proxy for marketwide information. The results are not significantly altered. This confirms our conjecture that trades of large firms are significantly related to a proxy of public marketwide information. The evidence also supports our premise that for smaller firms there should be no meaningful relation between trading frequency and public marketwide information proxy. Bessembinder, Chan, and Seguin (1996) arrive at similar conclusions when they regress trading volume on a proxy for marketwide information. We, therefore, replicate our regressions using total trading volume (TV) in place of the trading frequency variable for comparison.

TABLE 5. Ordinary Least Squares Estimates of Average Trade Size (AV) on Absolute Value of Market Index Returns.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Panel A. Absolute Value of Daily NYSE Index Returns As Independent Variable						
Intercept	1,255	1,952	1,428	1,708	1,850	1,104
$\|R\|$	-6,587	-43,597	26,901	-39,683	-24,812	-19,037
	(-0.52)	(-1.15)	(0.62)	(-1.83)	(-1.02)	(-1.91)
Panel B. Absolute Value of Daily Nasdaq Index Returns As Independent Variable						
Intercept	1,552	2,018	1,027	1,746	2,228	1,129
$\|R\|$	-63,968	-64,428	110,297	-58,100	-103,127	-19,037
	(-2.41)	(-0.79)	(1.19)	(-1.26)	(-2.00)	(-1.91)

Note: In Panel A, we estimate the equation: $AV_{it} = \alpha + \beta|R_t| + \varepsilon_{it}$, where AV_{it} is the average size of trade for stock i on day t and $|R_t|$ is the absolute value of the return of the NYSE composite index for day t. We estimate the regression for each portfolio using daily observations for each stock. In Panel B, we estimate the same equation with $|R_t|$ now representing the absolute value of the return of the Nasdaq composite index for day t. We estimate the regression for each portfolio using daily observations for each stock.

In Table 4 we report results of regressing trading volume on absolute value of NYSE and Nasdaq index returns. As before, for small firms, there is no reliable relation between the marketwide information proxy and trading volume. For large firms, there is a positive but insignificant association between market information and trading volume. Because trading volume is a composite of trading frequency and average trade size, we expect to gain additional insights by examining the relation between average trade size and public marketwide information proxy.

In Table 5 we present our results of regressing average size of trade (AV) on the absolute value of index returns. The results indicate that the size of trades is negatively associated with market information. However, the association is generally not statistically significant. Our evidence indicates that public marketwide information has no significant effect on average trade size for stocks of all market capitalization. There is a tendency for trade sizes to be smaller on days of large market movements. When considering the results from Tables 3 and 5 for large firms, it appears that on days of substantial marketwide information, there is a tendency for traders to make more frequent but smaller trades. For small and medium firms, trading activity is not significantly associated with public marketwide information. Our conclusions are unaltered regardless of how the trading activity is measured.

For large firms, considering the regression results of Tables 3 through 5, we observe that the strong positive relation between trading frequency and public marketwide information is attenuated by the weak negative association between trade size and market information proxy. Therefore, trading volume, which is a

TABLE 6. Ordinary Least Squares Regression Estimates of Number of Transactions (*N*) on Absolute Value of Firm-Specific Information (FI) and Marketwide Information (MI).

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Intercept	5.41	5.31	6.26	6.42	10.46	22.65
FI	-13.28	-11.19	53.43	124.29	126.17	356.27
	(-0.34)	(-0.85)	(1.85)	(3.61)	(3.71)	(8.21)
MI	38.99	81.15	11.84	-64.67	34.40	457.15
	(0.73)	(5.09)	(0.26)	(-1.03)	(0.49)	(2.51)
Adj. R^2	0.13	0.90	0.67	0.77	0.87	0.98

Note: The regression is performed using the model: $N_{pt} = \alpha + \beta_{FI}FI_{pt} + \beta_{MI}MI_t + \varepsilon_{pt}$, where N_{pt} is the average number of transactions of firms in portfolio p on day t, MI_t is the marketwide information on day t, given by $|R_{mt}|$ where R_{mt} is the NYSE index return; and FI_{pt} is the cross-sectional average of the firm-specific information of firms in portfolio p on day t. The firm-specific information for firm i on day t is computed as: $(|R_{it} - R_{mt}|)$, where R_{it} is the return for firm i on day t.

composite of trading frequency and trade size, is weakly and positively related to marketwide information.

Having established the association between market information proxy and trading frequency for large firms, we now provide empirical evidence on the relative importance of firm-specific and marketwide information for portfolios of stocks classified on the basis of market capitalization. In Table 6, we show results of regressing the number of transactions on a measure of firm-specific information (FI) and marketwide information (MI). We estimate the following equation:

$$N_{pt} = \alpha + \beta_{FI}FI_{pt} + \beta_{MI}MI_t + \varepsilon_{pt} \quad (1)$$

where N_{pt} is the average number of transactions of stocks in portfolio p on day t, FI_{pt} is the average firm-specific information of stocks in portfolio p on day t, and MI_t is the marketwide information on day t. The firm-specific information for the portfolio is calculated as the equally weighted average of firm-specific information of all stocks contained in the portfolio.

The firm-specific information of stock i is computed as:

$$FI_{it} = ABS(R_{it} - R_{mt}),$$

where R_{mt} is the return on the NYSE composite index on day t.[5] R_{it} is the continuously compounded return of stock i on day t given by:

$$R_{it} = \ln(P_{it} - P_{it-1}).$$

[5]Our measure parallels the proxy for firm-specific information used by Bessembinder, Chan, and Seguin (1996).

The results shown in Table 6 indicate that for largest firms, both firm-specific and marketwide information determine the trades. Both the firm-specific information and marketwide information variables are statistically significant in explaining the number of transactions. For small and medium firms, firm-specific information seems to be the major determinant of trades. Except for the largest firms, marketwide information does not appear to affect the number of trades. An exception is portfolio 2, for which marketwide information is significant. There are no clear patterns in the smallest firm portfolio. The correlation between marketwide information and firm-specific information averages about 0.65. Possibly, the statistical significance of some of the variables is affected by multicollinearity. For large firms, both marketwide information and firm-specific information are significant, and a high proportion of the variability in the number of transactions is explained by the two information variables. We interpret these results to mean that the pattern of trading activity of large firm stocks differs considerably from that of small firm stocks. Although both marketwide information and firm-specific information are associated with the trades of very large firms, only firm-specific information seems to be driving the trades for other firms.

V. Trading Activity and Bid-Ask Spreads

In the previous section we show evidence relating trading activity to marketwide and firm-specific information. Our results show that firm-specific information is the dominant motive behind the trading activity of small and medium firms. Trading because of firm-specific information is likely to be influenced more by traders with inside information. Thus, trades of small and medium firms are likely to result in a higher spread because of the adverse selection problem. Therefore, we expect the number of transactions to be positively related to the bid-ask spread for small and medium firms. This effect is likely to be attenuated for very large firms for which trading activity is motivated by both marketwide and firm-specific information. In this context, the marketwide information pertains to publicly disseminated information, for instance, macroeconomic announcements. For large firms, trading in response to publicly disseminated marketwide information does not expose the market maker to adverse information costs.[6] For very large firms, bid-ask spreads are expected to be inversely related to trades motivated by marketwide information and positively associated with trades motivated by firm-specific information. The resultant net effect of trades on bid-ask spread is an empirical issue that needs to be resolved.

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[6]In this context, we are disregarding the possibility that traders having private access to broad macroeconomic information exploit their advantage, causing market makers to widen their spreads. We wish to thank the referee for pointing out this distinction.

TABLE 7. Ordinary Least Squares Estimates of Regressions of End-of-Day Closing Spread on Number of Transactions.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Intercept	0.064	0.026	0.019	0.015	0.010	0.007
N	$-7.20*10^{-5}$	$-7.80*10^{-6}$	$1.35*10^{-6}$	$-1.30*10^{-5}$	$2.06*10^{-6}$	$-2.70*10^{-6}$
	(−4.02)	(−0.63)	(2.05)	(−4.89)	(1.70)	(−4.16)
Adj. R^2	0.017	0.003	0.003	0.016	0.001	0.005

Note: We estimate the equation: $SP_{it} = \alpha + \beta N_{it} + \varepsilon_{it}$, where SP_{it} is the closing spread computed as the proportionate spread for stock i on day t, and N_{it} is the number of daily transactions for stock i on day t. We estimate the regression for each portfolio using daily observations for each stock.

We test the implications of our premise by examining the number of trades and bid-ask spreads for the various market-capitalization-based portfolios. We expect to see different patterns of association between spreads and number of transactions across the market-capitalization-based portfolios because marketwide information has a positive effect on trading frequency only for large firms and not for small and medium firms. We show the results of regressing the number of transactions on the closing spread (at the end of the trading day) in Table 7. For all but two of the portfolios N is negatively related to spreads. There is no clear pattern of association between spreads and number of transactions. This is not consistent with our expectations. By way of explanation, Chan, Christie, and Schultz (1995) suggest that closing spreads on Nasdaq stocks at the end of the trading day are narrower because of the inventory-control behavior of dealers. This aspect of dealer behavior may have precluded us from finding support in favor of our conjecture.

To investigate this issue further, we conduct regressions of closing spreads on number of transactions computed on an hourly basis. For this regression, we measure the number of transactions at the end of each hourly period and use the closing spread values at the end of each hourly period. We hope to reduce any effect the end-of-day inventory-control behavior of dealers may have on observed closing spreads. The results are reported in Table 8. For small and medium firms, the direct association between trading frequency and closing spreads is presumably a consequence of perceived adverse selection costs faced by the dealers who observe increased trading activity in their stocks. It is likely that for these stocks, dealers attribute most of the motivation for trading activity to firm-specific information. The number of transactions variable has a direct and positive effect on closing spreads for all but the largest firm portfolio.[7] Our finding implies that an increase in the number of trades for large firms enhances the liquidity as measured by closing spreads. Our conclusion is similar in spirit to the result of Bessembinder and Seguin

[7]Even within the largest firm group, the results of the lower half are similar to smaller firms. Only in the top half of the largest firm portfolio are closing spreads negatively related to the number of transactions. These results are not reported for the sake of brevity.

TABLE 8. Ordinary Least Squares Estimates of Hourly Closing Spreads on Number of Transactions.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Intercept	0.073	0.033	0.021	0.017	0.012	0.007
N	0.0096	0.0014	0.0003	$2.56*10^{-5}$	$4.75*10^{-5}$	$-5.50*10^{-6}$
	(2.91)	(7.18)	(5.48)	(2.27)	(6.54)	(−6.63)
Adj. R^2	0.034	0.032	0.014	0.002	0.007	0.002

Note: We estimate the following equation: $SP_{idt} = \alpha + \beta N_{idt} + \varepsilon_{idt}$, where SP_{idt} is the closing spread computed as the proportionate spread for stock i during period d on day t, and N_{idt} is the number of transactions for stock i during period d on day t. We estimate the regression for each portfolio using hourly observations for each stock.

(1992) who find that forecastable futures trading activity in the S&P 500 contract enhances liquidity and reduces stock market volatility.

VI. Summary and Conclusions

We confirm the positive relation between number of transactions and stock price volatility for Nasdaq stocks using a high-frequency transactions database. We also find a significant difference between large and small firms with respect to motivation of trades. The number of trades for large firms is positively associated with marketwide and firm-specific information. The number of trades for small and medium firms is positively associated with firm-specific information. Our findings help explain the association between trading activity and stock price volatility.

The effect of trading activity on bid-ask spread depends on the market capitalization of the firm. Closing spreads of large firms are negatively associated with the number of transactions. For small and medium firms, we find a positive association between number of trades and closing spreads when we examine hourly observations of number of transactions and closing spreads. We attribute this positive association between trading activity and liquidity for small and medium firms to an increase in the adverse information perceived by market makers.

The differential effect of trading frequency on closing spreads for large and small firms has several implications for traders. Discretionary traders wishing to transact shares of small firms are likely to incur lower trading costs by choosing periods of relative inactivity. On the other hand, discretionary traders of large firms are better off choosing periods of high trading activity.

Our research points to the fact that small and medium firms assimilate marketwide information differently from large firms. Further research on this aspect of price-formation process is likely to enrich our understanding of the complex interrelation among trades, volatility and information flows.

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