Trade Size, Order Imbalance, and the Volatility-Volume Relation

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Abstract

This paper examines the roles of the number of trades, size of trades, and order imbalance (buyer- versus seller- initiated trades) in explaining the volatility-volume relation for a sample of NYSE and NASDAQ stocks. Our results reconfirm the significance of the size of trades, beyond that of the number of trades, in the volatility-volume relation on both markets. After controlling for the return impact of order imbalance, the volatility-volume relation becomes much weaker. For NYSE stocks, the order imbalance in large trade size category affects the return more than smaller size categories do, whereas for NASDAQ stocks, the largest return impact comes from the order imbalance in maximum-sized Small Order Execution System (SOES) trades.

JEL **Classification Numbers**: G10, G12, G13

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1. Introduction

There is extensive evidence on the relation between price volatility and trading volume. Karpoff (1987), for example, cites many studies that document a positive relation between price volatility and trading volume in financial markets.[1] This relation is robust to various time intervals (hourly, daily, and weekly) and numerous financial markets (stocks, currency, and futures). While the empirical link between price volatility and volume appears strong, it is not obvious why this should be so. Various theoretical models are proposed to explain this relationship. These include "mixture of distributions" models (Epps and Epps (1976), Harris (1986), and Tauchen and Pitts (1983)), "asymmetric information" models (Kyle (1985) and Admati and Pfleiderer (1988)), and "differences in opinion" models (Varian (1985 and 1989) and Harris and Raviv (1993)).[2]

Despite so many empirical studies on the volatility-volume relation, there is no general consensus about what actually drives the relation. In particular, since trading volume for a time interval (e.g., daily volume) can be decomposed into two components, the number of trades and size of trades, the volatility-volume relation could in principle be driven by either one or both components. The theoretical models suggested thus far do not agree on the role of trade size in the volatility-volume relation. On the one hand, some models show that informed traders prefer to trade large amounts at any given price (Grundy and McNichols (1989), Holthausen and Verrecchia (1990), and Kim and Verrecchia (1991)).

[1] Recent studies provide additional evidence on the volatility-volume relationship. Schwert (1989) documents a positive relationship between estimated monthly volatility and volume growth rates. Gallant, Rossi, and Tauchen (1992) find that there is a positive correlation between conditional volatility and volume. Daigler and Wiley (1998) show that the volatility-volume relation in futures markets is driven by the public investors rather than the floor traders.

[2] In the "mixture of distributions" models, it is assumed that the price variance per transaction is monotonically related to the volume of that transaction. A mixing variable, typically the number of information arrivals, causes the volatility-volume relation. In the "asymmetric information" models, informed investors submit trades based on their private information. When informed investors trade more, volatility increases because of the generation of private information. In the "differences in opinion" models, when public information switches from favorable to unfavorable or vice versa, investors have different beliefs concerning the stock and this will generate trading among themselves. Hence, trading volume and absolute return are positively related because both are correlated with the arrival of public information.

Trade size is likely to be positively related to the quality of information possessed by them and will therefore be correlated with price volatility. On the other hand, other models indicate that a monopolist informed trader may camouflage his trading activity by splitting one large trade into several small trades (Kyle (1985) and Admati and Pfleiderer (1988)). Thus trade size will not necessarily convey adverse information. Few studies provide empirical evidence on the roles of the number of trades and size of trades in the volatility-volume relation. The most notable study is done by Jones, Kaul, and Lipson (1994) who investigate, based on a sample of NASDAQ stocks, how daily price volatility could be explained by daily number of trades and average trade size. They find that number of trades appears to provide virtually all the explanation for the volatility-volume relation, with average trade size playing a trivial role.

Despite Jones, Kaul, and Lipson's findings, it is premature to conclude that the size of trades has no information content beyond that contained in the number of trades. First, if informed traders prefer to break up trades so that they can camouflage their trades with liquidity traders, it might be optimal for them to submit medium-sized orders (Barclay and Warner (1993)). In that case, the volatility impact of medium-sized trades can be the greatest among trades of different sizes, and we may not be able to detect the volatility-trade size relation using average trade size.

Second, Jones et al. examine NASDAQ stocks only. It is unclear whether their results could also apply to NYSE stocks. There are differences in market microstructure between the NYSE and NASDAQ. Previous studies note that the adverse information associated with large trades seems to be more substantial on the NYSE than on NASDAQ. For example, Huang and Stoll (1996) argue that NASDAQ dealers know their institutional customers well, and many large trades are negotiated and contain a credible guarantee of being non-information motivated. On the other hand, on NASDAQ, since dealers must honor orders received over the Small Order Execution System (SOES), there may be substantial adverse information associated with the maximum-sized SOES trades (1000 shares per trade for major stocks). It is thus likely that the volatility-trade size relation varies across NASDAQ and the NYSE.

Besides the number of trades and size of trades, order imbalance or net order flow (the difference between buy and sell orders) may play a role in the volatility-volume relation. Yet previous empirical studies always investigate how volatility (measured by either absolute return or squared return) is correlated with trading volume or the number of trades. They simply ignore an important prediction of the market microstructure models (e.g., Kyle (1985) and Admati and Pfleiderer (1988)) that price volatility is induced by net order flow. In these models, the market makers cannot distinguish whether a specific buy or sell order is from an informed trader or a liquidity trader. The market makers will therefore infer information from the net order flow, and will revise the price upward (downward) when there are excess buy (sell) orders. Such behavior is supported by many empirical studies (e.g., Glosten and Harris (1988), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997)) that find trade indicator variables (buyer-initiated and seller-initiated trades) are quite successful in explaining intradaily movements in prices and quotes. Hence, the volatility-volume relation could be at least partially driven by the relation between stock returns and the daily order imbalance.

The objectives of this study are twofold. First, we provide a comprehensive analysis of the role of the size of trades beyond that of the number of trades in the volatility-volume relation. With transaction and quotation data available from the Trades and Quotes (TAQ) database, we rank the transactions into different trade size categories and regress the daily absolute return on the numbers of trades of different sizes. This is to examine whether daily price volatility increases more with the number of trades in a particular size category than with other size categories. Thus, unlike Jones et al., we can compare the volatility impacts of small-sized, medium-sized, and large-sized trades. Furthermore, we will examine the above relation for both NYSE and NASDAQ stocks. Given that these two markets have different market microstructures, it will be interesting to see whether the volatility-trade size relation is the same for the two markets. In particular, we will also examine the role of the maximum-sized SOES trades in the relation for NASDAQ.

Second, we examine whether daily order imbalance also plays a role in the volatility-volume relation. Although we do not observe actual order flow, the availability of transaction and quotation data allows us to distinguish between buyer-initiated trades and seller-initiated trades. The difference between the number of buyer-initiated trades and the number of seller-initiated trades over a day is used as a proxy for the daily order imbalance. We will perform a two-stage regression analysis. The first-stage regression is motivated by trade indicator models (e.g., Huang and Stoll (1997)), which predict that prices are adjusted in reaction to net buyer-initiated order flow. We will regress daily stock returns on daily order imbalances of different trade sizes. By incorporating the daily order imbalances of different trade sizes as the explanatory variables, we can determine if the order imbalance in a particular trade size category affects the return more than others do. In the second-stage regression, the absolute values of return residuals extracted from the first stage are regressed on the numbers of trades of different sizes. If daily order imbalance plays a role in the volatility-volume relation, we expect that the volatility-volume relation revealed by this second-stage regression will be weaker than the usual volatility-volume relation revealed by the regression of the daily absolute return on the numbers of trades of different sizes.

We find that daily absolute return increases more with the numbers of trades of medium size categories than with other size categories for both the NYSE and NASDAQ samples. This result suggests that both the number of trades and size of trades play significant roles in the volatility-volume relation.[3] We also find that daily return is well explained by the order imbalance. Once we control for

[3] A couple of contemporaneous but independent papers find similar results. Huang, Masulis, and Ng (1996) examine the relation between aggregate stock return volatility and trading activity on the London Stock Exchange, and find that order size can affect market volatility. Coughenour (1999) studies the intraday volatility-volume relation for 30 Dow Jones stocks, and finds that the relation depends on the frequency of medium-sized trades. Our work differs from these papers as we examine a more comprehensive sample (individual stocks traded on the NYSE and NASDAQ), and also consider the role of order imbalance in explaining the volatility-volume relation.

the return impact of the order imbalance in the first-stage regression, the volatility-volume relation becomes much weaker. This suggests that besides the number and size of trades, order imbalance plays a role in the volatility-volume relation. Furthermore, results from the first-stage regression suggest that the information content of trade size differs across the NYSE and NASDAQ. For NYSE stocks, the order imbalance in large trade size category affects the return more than smaller size categories do. On the other hand, there is no such relation for NASDAQ stocks. Instead, the 1000-share trades have the largest return impact. This is consistent with the notion that the maximum-sized SOES trades convey substantial adverse information.

This paper is organized as follows. Section 2 compares the potential role of trade size in the volatility-volume relation across the NYSE and NASDAQ. Section 3 discusses the data and sample selection. Section 4 presents the empirical results. This is followed by a conclusion in Section 5.

2. The Potential Role of Trade Size on the NYSE and NASDAQ

Although there is no general conclusion about the role of trade size in the volatility-volume relation, some important differences in the market microstructures across NASDAQ and the NYSE might affect the role of trade size on these two marketplaces.

The NYSE is an order-driven market, based on a centralized public limit order book, which is handled by a single specialist and floor brokers who "work" orders on the trading floor. The NASDAQ market is a quote-driven market, based on multiple dealers who compete for order flow and disseminate bid-ask quotes to brokers. On NASDAQ, dealers may have less information on the order flow as a whole since they cannot see the order flow of other dealers. Thus, while NYSE specialists operate in a centralized market and are better able to detect informed investors, NASDAQ dealers operate in a decentralized market, which may make it difficult to identify the presence of informed traders.

Nevertheless, adverse information is not necessarily more severe on NASDAQ than on the NYSE. On NASDAQ, much of the order flow is internalized or is preferenced to specific dealers. A broker-dealer internalizes the order flow by trading for its own account with the customer, with the provision that the trade takes place at the inside quote. The broker may also send a preferenced order flow to a particular dealer who guarantees execution at the best inside quote. Therefore, customers, such as a large institution, might be able to negotiate a trade inside the disseminated quotes. Because of these arrangements, NASDAQ dealers develop long-term relationships with their institutional customers, so that there is less adverse information from trading with them.

Indeed, previous empirical studies find that the adverse information in large trades differs across the NYSE and NASDAQ. Lin, Sanger, and Booth (1995) document a positive relation between the effective spread and trade size for the NYSE trades, but not for the non-NYSE trades. Huang and Stoll (1996) find that while the adverse information component in the effective spread decreases with trade size for NASDAQ stocks, it increases with trade size for NYSE stocks. Given that the information content of large trades differs on the two marketplaces, the volatility-trade size relation could also be different. We expect that large trades play a significant role in the volatility-volume relation on the NYSE, and less so on NASDAQ.

On the other hand, NASDAQ dealers are especially vulnerable to the orders received over the Small Order Execution System (SOES), since they must honor these orders. The SOES is intended for "non-professional" use, but, in practice, SOES trades are usually submitted by professional traders, sometimes refereed to as SOES "bandits" or "activists". To exploit their information advantage to the greatest extent, SOES "bandits" will usually submit the largest orders allowed on SOES (1000 shares per order for major stocks).[4] Several studies examine the relationship between price volatility and SOES trading. NASD (1993) finds significant SOES trading on days with large price changes, but it does not investigate the causality. Battalio, Hatch, and Jennings (1997) examine the bidirectional causality between maximum-sized SOES trades and intradaily price volatility. They find that higher intradaily volatility is followed by more frequent maximum-sized SOES trades, and that more maximum-sized SOES trades are also followed by higher intradaily volatility.[5] The evidence suggests that SOES "bandits" are informed traders so that their trades are correlated with intradaily volatility. Hence, we expect that the trades acceptable for execution through SOES, especially those maximum-sized trades (1000 shares), play a significant role in the volatility-volume relation on NASDAQ.

3. Sample and Descriptive Statistics

3.1. Sample

Data for this study are taken from the Trade and Quote (TAQ) database, which is made available by the NYSE. To mitigate the thin trading problem, we screen out those stocks that have less than an average of ten trades per day during the sample period of July to December 1993. We then construct a sample of NYSE-listed and NASDAQ-listed common stocks that are matched based on market capitalization.

First, based on the market capitalization data at the end of 1992, the NYSE common stocks are sorted into five size quintiles. A random sample of 60 stocks is then selected for each size quintile, and a total of 300 NYSE stocks are selected. NASDAQ stocks are sorted into each of these five quintiles based

[4] NASD (1993) reports that the average trade size in stocks having a 1000-share SOES maximum differs widely between activists and non-activists. Activists trade an average of 995 shares, and non-activist trade an average of only 366 shares.
[5] Another related study is by Harris and Schultz (1997) who examine how a decrease in the SOES maximum trade size from 1000 to 500 shares affects the distribution of trade size and the behavior of quotes and intradaily price movements.

on their market capitalization. For the largest and second largest quintiles, there are handfuls of eligible NASDAQ firms (18 and 58 respectively). In the other three quintiles, where there are many more eligible NASDAQ stocks, a random sample of 60 stocks is selected for each quintile.[6] Finally, we delete those stocks that have missing daily returns during the sample period,[7] and end up with 295 NYSE stocks and 231 NASDAQ stocks.

All trades during the sample period, except opening transactions on each day, are included for analysis. TAQ provides time-stamped trades and quotes observed on the NYSE, NASDAQ, and other regional exchanges. For the NYSE stocks, we include off-NYSE trades in the analysis as they contribute a substantial portion of trading activity. Furthermore, Bessembinder and Kaufman (1997) find that off-NYSE trades constitute more than 50% of small trades in large firms. This indicates that the trades executed outside the NYSE are not random, but rather vary systematically in dimensions that are potentially important to the determination of trading costs. Trades are omitted if they are coded in the TAQ database as out of time sequence, or involving an error or correction. We also omit trades and quotes that involve price changes of 20 percent or more if the prior price is more than $2 per share. Quotes are omitted if the ask or bid price is nonpositive or if the bid price is greater than the ask price.

3.2. Trade Classification

Each trade will be identified as buyer- or seller- initiated by comparing the trade price to the prevailing bid/ask quotes. To identify the prevailing quotes, all quotes eligible for the Best-Bid-Or-Offer (BBQ) calculation are included for consideration. Since trades and quotes could be recorded out of

[6] For the smallest NYSE size quintile, a random sample of 60 NASDAQ stocks would have the average firm size significantly smaller than the average firm size of the NYSE stocks. Thus, for this quintile, we divide eligible NASDAQ stocks into two groups: one being larger than the average firm size of the NYSE stocks and the other being smaller. We then take a random sample of 30 stocks from each of these two groups.

sequence, we follow Lee and Ready (1991) and discard the quotes that are less than five seconds before the trades. To avoid the stale quote problem, the prevailing quotes identified have to be within thirty minutes of the trades, or we will resort to the tick test. Following Lee and Ready (1991) and Harris (1989), when a trade takes place within the spread, it will be classified as buyer- (seller-) initiated if the trade price is closer to the prevailing ask (bid) price.[8] If a trade takes place at the midpoint of the quotes or outside the spread, we will resort to the tick test. The tick test classifies a trade as buyer-initiated if it occurs on an uptick or a zero-uptick, and as seller-initiated if it occurs on a downtick or a zero-downtick. In the case that a trade occurs on consecutive zero ticks, it will not be classified.

Each trade will also be classified in accordance with its size in shares. There is no common definition of large, medium, and small trades. In fact, a particular trade size considered large in one stock may not have the same designation in another. Moreover, since trading volume differs across stocks, the distribution of large and small trades differs as well. Many previous studies have their unique definitions of various trade size categories. Easley, Kiefer, and O'Hara (1997a and 1997b) classify the trades into large (at least 1000 shares) and small (fewer than 1000 shares). Barclay and Warner (1993) classify the trades into small (fewer than 500 shares), medium (500 - 9900 shares), and large (10,000 and more shares). Bessembinder and Kaufman (1997) classify the trades into three categories based on dollar volume: small trade (less than $10,000), medium trade ($10,000 - $199,999), and large trade (above $200,000). In this article, to detect whether a certain trade size will have more information content than the others, we fine tune the classification by partitioning all trades into five trade size categories: (i) size1: less than or equal to 500 shares; (ii) size2: 501 - 1000 shares; (iii) size3: 1001 - 5000 shares; (iv)

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[7] Daily returns are calculated using mid-quotes (with missing mid-quotes replaced by transaction prices). Two NYSE stocks and twenty-five NASDAQ stocks have missing daily returns during the sample period. Three other NYSE stocks have zero net trades in large trade-size categories in each sample day, and they are also dropped.

[8] Odders-White (1999) finds that the trade classification algorithm of Lee and Ready (1991) correctly classifies 85% of the transactions in her sample. The algorithm, however, tends to misclassify certain types of transactions,

size4: 5001 - 9999 shares; and (v) size5: 10,000 shares and above.[9] It might be argued that we should have different trade size category cutoffs for stocks of different firm sizes. Thus, to check whether our trade size classification introduces bias to our tests, we will separate our results for firm size-sorted subsamples.

We construct two measures of daily order imbalance. The first measure is the daily net number of trades, which is calculated as the difference between the number of buyer-initiated trades and the number of seller-initiated trades for the day. The second is daily net share volume, which is computed as the difference between buyer-initiated share volume and seller-initiated share volume. Since some of the trades are not classified, the two measures are bound to be noisy proxies for the daily order imbalance. However, since there is no prior reason why buyer-initiated trades or seller-initiated trades would be more likely to be unclassified, our proxies should still be unbiased measures of the daily order imbalance.

3.3. Descriptive Statistics

Table 1 contains descriptive statistics for our sample of 295 NYSE and 231 NASDAQ stocks. Cross-sectional summary means of several variables of interest are reported for each firm-size quintile. These figures are computed by averaging across the trading days in the sample period for each firm and then averaging across firms within the quintile. The mean market capitalization is nearly identical across the matched NYSE and NASDAQ samples, but it varies substantially across the five quintiles, from more than $8 billion for quintile 1 (largest) to $100 million for quintile 5 (smallest).

We first discuss the statistics for the NYSE stocks. Stock price volatility, as measured by absolute daily returns (|R|) calculated with quotation midpoints, ranges from 1.1% for the largest firms to

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including transactions inside the bid-ask spread, small transactions, and transactions in large or frequently traded stocks. Nevertheless, there is no apparent reason that the misclassification will bias our results.

1.5% for the smallest firms. The average daily share volume (V) is an increasing function of the market capitalization of the stocks, decreasing from 410,900 shares for quintile 1 to 47,000 shares for quintile 5. Daily share volume could be decomposed into two components: daily number of trades (T) and average trade size (ATS), where ATS is calculated by dividing the daily share volume by T. Similar to daily share volume, both components are increasing in market capitalization. The average trade size decreases from 1,800 shares for quintile 1 to 1,400 shares for quintile 5, while the average daily number of trades decreases from 235.1 for quintile 1 to 34.5 for quintile 5. These numbers indicate that large firms are more actively traded than small firms, and suggest that many of the traders of large firms' stocks are institutional investors who trade larger quantities. The average daily numbers of buyer-initiated trades (BUY) and seller-initiated trades (SELL) are also reported. Since not all trades are classified,[10] the total of BUY and SELL is smaller than average daily number of trades (T). For example, while there is an average of 235.1 trades for quintile 1 per day, there are only 68.7 buyer-initiated trades and 67.6 seller-initiated trades. The average daily number of buyer-initiated trades is fairly close to the average daily number of seller-initiated trades, suggesting that there is no systematic buying or selling pressure across firms in the sample period. The average daily numbers of trades in the five trade-size categories (T_1, T_2, T_3, T_4, and T_5) are also reported. Generally speaking, the number of trades decreases when we move from the small size category to the large size category. For example, in firm-size quintile 1, the average daily numbers of trades are 150.0, 31.8, 39.3, 5.4, and 8.5 for the five trade-size categories. This pattern is also robust to other quintiles.

The NASDAQ stocks are generally more volatile than the NYSE stocks. The average daily price

[9] Originally, we followed previous studies and classified trades into three size categories. The results are qualitatively similar to results when the five size categories are used. The five size categories lead to a clearer picture of return impacts and volatility impacts of trades of different sizes, so they are used in our reporting.

[10] A trade will not be classified under the following conditions: (i) the trade does not find quotes in the recent 30 minutes, or the trade is outside the quotes, or the trade is at the midpoint of the quotes; and (ii) the trade is on consecutive zero ticks, so fails to be classified by the tick test.

volatility ranges from 1.7% for quintile 1 to 2.7% for quintile 5. Similar to the NYSE, both the average daily number of trades (T) and the average trade size (ATS) generally increase with firm size on NASDAQ. Also, the average daily number of trades generally declines with trade size on NASDAQ. However, compared with the NYSE, the decline on NASDAQ is steadier as there are still relatively large numbers of trades in the second and third trade-size categories. For instance, in quintile 1, the average daily numbers of trades are 366.0, 209.8, 139.5, 10.6, and 31.3 in the five trade-size categories. This indicates that traders tend to submit more small- or medium- sized trades on NASDAQ than on the NYSE. Whether the information content of these trades differs across the two marketplaces will be investigated in the next section.

4. Empirical Analysis

4.1. Relation of Daily Price Volatility with Volume and Number of Trades

Following Schwert (1990) and Jones, Kaul, and Lipson (1994), daily price volatility for each stock is estimated from the absolute residuals of the following model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \hat{\varepsilon}_{it} \qquad (1)$$

where R_{it} is the return of stock i on day t, the D_{kt}'s are the five day-of-the-week dummies to capture differences in mean returns. The 12 lagged returns are used to control for any serial dependence in daily returns. To examine the volatility-volume relation, we estimate the following two sets of regressions for each stock:

(2a) $$|\hat{\varepsilon}_{it}| = \phi_{i0} + \phi_{im} M_t + \sum_{j=1}^{12} \phi_{ij} |\hat{\varepsilon}_{it-j}| + \gamma_i V_{it} + \eta_{it}$$

(2b) $$|\hat{\varepsilon}_{it}| = \phi_{i0} + \phi_{im} M_t + \sum_{j=1}^{12} \phi_{ij} |\hat{\varepsilon}_{it-j}| + \gamma_i T_{it} + \eta_{it}$$

where $|\hat{\varepsilon}_{it}|$ is the absolute residual from (1), M_t is a dummy variable that is equal to 1 for Mondays and 0 otherwise, V_{it} and T_{it} are the share volume and number of trades for stock i on day t. The lagged values of $|\hat{\varepsilon}_{it}|$ are used to control for the persistence in volatility. We will compare the results for (2a) and (2b) to see whether share volume or number of trades better explains the price volatility.

Following Jones, Kaul, and Lipson (1994) and Bessembinder and Seguin (1992 and 1993), we use a two-step procedure to estimate (2a) and (2b).[11] After we estimate (1) using ordinary least squares, we extract the absolute residuals $|\hat{\varepsilon}_{it}|$, and use them as the dependent variables in (2a) and (2b). The regressions in (2a) and (2b) are estimated using ordinary least squares, which provide consistent estimators of the parameters. The estimators are not efficient, but, as Jones et al. point out, this will not pose inference problems. In fact, our results are very much similar when absolute simple returns are used in (2a) and (2b) directly.

Table 2 presents the results of regressions (2a) and (2b). Each regression is separately run for each stock, and the table reports the means of the coefficient estimates across all stocks in the whole sample and in firm-size quintiles. For brevity, only the coefficient estimates of share volume and the number of trades are reported. The standard errors of the mean coefficient estimates, which are reported in parentheses, are corrected for any cross-sectional correlation in the individual-stock coefficient

[11] Bessembinder and Seguin (1992 and 1993) use a similar two-stage procedure to estimate the volatility and examine the volatility-volume relation in the futures market.

estimators (see the appendix in Jones et al.). We also report the cross-sectional average of the $\overline{R^2}$'s of the regressions.

Table 2 demonstrates that there is a positive relation between price volatility and share volume. The average coefficient estimate of volume (in thousand shares) is statistically significant and equal to 0.007 for both the NYSE and NASDAQ samples. The average coefficient estimate of volume tends to decrease with firm size. The coefficient declines from 0.014 for the smallest firm-size quintile to 0.003 for the largest quintile on the NYSE, and from 0.018 for the smallest stocks to 0.001 for the largest stocks on NASDAQ. This suggests that smaller stocks have lower market depth. Table 2 also demonstrates that there is a positive relation between price volatility and the number of trades. For NYSE-listed stocks, the average coefficient estimate of the number of trades is 0.020 for the whole sample, ranging from 0.010 in quintile 1 to 0.033 in quintile 5. For NASDAQ-listed stocks, the average coefficient estimate is 0.026 for the whole sample, ranging from 0.006 in quintile 1 to 0.054 in quintile 5.

Although the above results indicate that the volatility-volume relation holds regardless of whether share volume or number of trades is used, it seems that number of trades explains the price volatility better than share volume does. In specification (2a), where share volume is used, the average $\overline{R^2}$ is 0.106 for NYSE and 0.149 for NASDAQ. In specification (2b), where the number of trades is used, the average $\overline{R^2}$ is higher - 0.147 for NYSE and 0.246 for NASDAQ. This finding is consistent with Jones, Kaul, and Lipson (1994) who find that the volatility-volume relation is driven mainly by the number of trades, rather than by the total volume. Since the number of trades is more successful than share volume in explaining price volatility, the rest of this paper will focus on using the number of trades.

4.2. Relation between Daily Price Volatility and Numbers of Trades of Different Sizes

In this section, we explore the relation between daily price volatility and the numbers of trades in the five trade-size categories. The empirical evidence on the role of size of trades in price movements is quite mixed. In a study based on a sample of takeover targets, Barclay and Warner (1993) find that most of the stocks' cumulative stock price changes occur on medium-sized trades, suggesting that informed traders tend to camouflage their information through medium trades. Jones, Kaul, and Lipson (1994) decompose daily volume into the number of trades and average trade size, and find that the number of trades appears to provide virtually all the explanation for the volatility-volume relation. Although they do not find a positive and significant relation between volatility and average trade size, it is premature to conclude that the size of trades is not important. If trades should be classified into small and large (Easley and O'Hara (1987)) and large trades move prices more than small trades do, we will expect a positive relation between price volatility and average trade size. On the other hand, if trades should be classified into small, medium, and large (Barclay and Warner (1993)) and medium trades move prices more than large and small trades do, the relation between price volatility and average trade size is unclear.[12]

To investigate the role of the size of trades beyond that of the number of trades in the volatility-volume relation, we modify regression (2b) by replacing the daily number of all trades with the daily numbers of trades in the five trade-size categories:

(2c) $$|\hat{\varepsilon}_{it}| = \phi_{i0} + \phi_{im} M_t + \sum_{j=1}^{12} \phi_{ij} |\hat{\varepsilon}_{it-j}| + \sum_{k=1}^{5} \gamma_{k,i} T_{k,it} + \eta_{it}$$

where $T_{k,it}$ is the number of trades in trade-size category k (k = 1,…, 5) for stock i on day t. The

[12] For example, let $N_t = \{N_{S,t}, N_{M,t}, N_{L,t}\}$ represent the numbers of trades for the small (S), medium (M), and large (L) trade size categories on day t. Suppose $N_1 = \{20, 0, 10\}$, $N_2 = \{10, 10, 10\}$, and $N_3 = \{10, 0, 20\}$. Therefore, the number of trades is equal to 30 on all three days, but the average trade size is smallest on day 1, followed by day 2, and is largest on day 3. Suppose the volatility impact of medium trades is the largest, say, the absolute return increases by 1% for 10 small trades, 3% for 10 medium trades, and 2% for 10 large trades. The daily absolute return

attractiveness of this regression is that we can compare the information content of trades of different sizes directly from the regression coefficients. Suppose trades in a medium size category (e.g., k = 3) are more likely to be information motivated, so they have greater impact on price volatility than trades of other sizes do. We will expect the coefficient to be the highest among all the γ_k coefficients. Thus, the role of sizes of trades beyond that of the number of trades in the volatility-volume relation would be reflected by the differences among the five γ_k coefficient estimates in equation (2c). On the other hand, if trade size does not matter, the volatility impact of the number of trades should be the same across the five size categories, and there should be no difference among the five γ_k coefficient estimates.

The equality of the five coefficients is tested using the *F*-test for each individual stock. The percentage of stocks that reject the equality of coefficients hypothesis at 5% level of significance is then computed. We also compute the aggregated *p*-value according to the chi-square method outlined in Gibbons and Shanken (1987) and Chung, Van Ness, and Van Ness (1999). We first obtain the *p*-value from the *F*-statistic for each stock. We then sum the $-2\log_e$ of the individual stock *p*-values across the overall sample or firm-size quintiles. Because the sum of these transformed *p*-values follows a chi-square distribution with twice the number of stocks as its degrees of freedom, we then obtain the aggregated *p*-value.[13]

Table 3 reports the results of regression (2c). The left-hand panel contains the results for the NYSE stocks. In the overall NYSE sample, the first four mean γ_k coefficient estimates are significantly positive, indicating that the well-documented positive relation between daily price volatility and the number of trades generally holds except for the largest trade-size category. There is also evidence that

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will be 4% on day 1, 6% on day 2, and 5% on day 3. Therefore, there is no linear relation between daily price volatility and average trade size.

[13] Note that this procedure ignores cross-correlations in the error terms. However, the aggregated *p*-values reported should suffer from little bias, since the cross-correlations in the error terms of regression (2c) are found to be trivial - the average pairwise cross-correlation is 0.005 and 0.008 for the NYSE stocks and NASDAQ stocks respectively. Similarly, the aggregated *p*-values reported for later regressions also suffer from little bias.

the γ_k coefficient varies across the trade-size categories, yet the mean coefficient does not increase monotonically from the smallest to the largest trade-size categories. The mean coefficient estimates for the five trade-size categories are 0.009, 0.027, 0.038, 0.048, and 0.028 respectively. More than 30% of the stocks reject the equality of the γ_k coefficients hypothesis at 5% level of significance, and the aggregated *p*-value is less than 0.001. There are some variations in the relative magnitudes of the mean γ_k coefficients across the firm-size quintiles. For example, in quintile 1 the mean γ_5 coefficient is the largest, in quintile 2 the mean γ_3 coefficient is the largest, and in quintiles 3, 4, and 5 the mean γ_4 coefficient is the largest. We are able to reject the equality of the γ_k coefficients hypothesis for all quintiles (with the aggregated *p*-values being less than 0.001).

The results for NASDAQ are even more surprising. In the overall sample, the mean γ_k coefficient estimates are 0.008, 0.075, -0.001, 0.017, and -0.007, with only the first two being significantly positive. More than 60% of the stocks reject the equality of the coefficients hypothesis at 5% level of significance, and the aggregated *p*-value is less than 0.001. While there are differences in terms of the relative magnitudes of the coefficients across the firm-size quintiles, the results generally suggest that only the number of trades for the second trade-size category (501-1000 shares) is significantly and positively correlated with daily volatility, while the number of trades for the first trade-size category (500 shares or less) is marginally so.

The above evidence indicates that trades of different sizes have different volatility impacts for both NASDAQ-listed stocks and NYSE-listed stocks. To evaluate the role of sizes of trades, we can also compare the $\overline{R^2}$'s in Tables 2 and 3. Based on the whole sample of NYSE-listed stocks, the average $\overline{R^2}$ is 0.147 when the total number of trades is used, and it increases slightly to 0.181 when the numbers of trades in the five trade-size categories are used. Based on the whole sample of NASDAQ-listed stocks, the average $\overline{R^2}$ is 0.246 when the total number of trades is used, and increases to 0.328 when the numbers of trades in the five trade-size categories are used. All in all, both the number and size of trades appear to play important roles in the volatility-volume relation. Yet, the volatility impacts of medium trades are greater than small trades and large trades. This may explain why Jones et al. find that average trade size plays a trivial role. Furthermore, the results for the NYSE and NASDAQ are different. On the NYSE, the volatility impacts of trades increase when the sizes of trades change from small to medium, but do not increase or even decrease when the sizes of trades change from medium to large. On NASDAQ, only trades of the second trade-size category (501-1000 shares) have substantial volatility impact.

4.3. Relation Between Daily Volatility and Order Imbalances of Different Trade Sizes

In this section, we investigate the role of the daily order imbalance in the volatility-volume relation. As discussed in the introduction, there is extensive evidence that trade indicator variables (buyer-initiated and seller-initiated trades) are quite successful in explaining intradaily movements in prices and quotes. It is thus likely that daily order imbalance, as measured by the difference between cumulative buyer-initiated trades and cumulative seller-initiated trades over a day, could explain the daily price movement. Furthermore, if the size of daily order imbalance is correlated with daily trading volume, this may result in the volatility-volume relation. There is a reason for the size of order imbalance to be positively correlated with trading volume. In Admati and Pfleiderer's (1988) model, informed traders would like to trade in a deep market so as to camouflage their information. Discretionary liquidity traders with trade timing flexibility also like to trade when the market is thick. Therefore, there is a concentration of orders submitted by informed traders and discretionary liquidity traders. Since informed traders would like to trade on a high-volume day, there are excess orders on one side (buy or sell), resulting in order imbalance and price volatility.

To estimate daily order imbalance, we calculate the daily net number of trades, which is the difference between the number of buyer-initiated trades and the number of seller-initiated trades over a day. As the price impacts may vary across trades of different sizes, the daily net number of trades is calculated for each of the five trade-size categories separately. Since some of the trades are either unclassifed or misclassified, the five daily net numbers of trades are obviously noisy proxy variables of the daily order imbalance. However, if there is measurement error, it should only bias against finding the relation between our order imbalance proxy variables and daily returns.

We first investigate the correlation between daily total number of trades and the size of daily order imbalance, which is measured by daily absolute net number of trades. Table 4 reports the correlation between daily total number of trades and daily absolute net numbers of trades of the five trade-size categories. The correlation coefficients are positive for both NYSE and NASDAQ stocks. In the overall NYSE sample, the mean correlation coefficients between the total number of trades and the absolute net numbers of trades of the five trade-size categories are 0.365, 0.319, 0.357, 0.258, and 0.276. In the overall NASDAQ sample, the mean correlation coefficients are even higher: 0.580, 0.520, 0.444, 0.312, and 0.385. Therefore, daily total number of trades appears to be strongly correlated with the size of daily order imbalance, suggesting that the volatility-volume relation could be potentially explained by the order imbalance. Now, we examine whether daily order imbalance could subsume the explanatory power of daily number of trades in explaining the price volatility by incorporating the return impacts of order imbalance in the first-stage regression.

We modify the first-stage regression (1) by including the net number of trades as one of the regressors. To examine whether the size of trades has information content beyond that of the net number of trades, we will include the net numbers of trades in the five size categories to capture differential price impacts. Specifically, we estimate the following regression in the first stage:

(3) $$R_{it} = \sum_{k=1}^{5}\hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_{ij} R_{it-j} + \sum_{h=1}^{5}\lambda_{h,i} NT_{h,it} + \hat{\varepsilon}_{it}$$

where $NT_{h,it}$ is the net number of trades in size category h for stock i on day t. This regression is motivated by trade indicator models (e.g., Huang and Stoll (1997)), which predict that intradaily price movements are caused by net buyer-initiated order flow. After we estimate (3), we extract the absolute residual returns $|\hat{\varepsilon}_{it}|$ and use them as the dependent variables in the second-stage regression (2c). If the daily order imbalance plays a role in the volatility-volume relation, we expect that the volatility-volume relation revealed by this second-stage regression would be weaker than the volatility-volume relation revealed in Table 3.

Table 5A reports the results for the NYSE stocks. The first-stage regression results, reported in the left-hand panel, show the net numbers of trades in all five trade-size categories have positive and significant impacts on daily returns. The cross-sectional average of the $\overline{R^2}$'s is 0.425, indicating that a substantial portion of the daily price movement is explained by the order imbalance. There is also evidence that the mean *NT* coefficient estimate increases monotonically from the smallest to the largest trade-size categories. For instance, in the overall NYSE sample, the mean coefficient estimates for the five trade-size categories are 0.163, 0.201, 0.233, 0.335, and 0.375 respectively. About 54% of the stocks reject the equality of the coefficients hypothesis at 5% level of significance, and the aggregated *p*-value is less than 0.001. Furthermore, the results are generally robust for different firm-size quintiles. These contrast with the results in Table 3 that volatility impacts of trades increase from small trades to medium trades, but do not increase or even decrease from medium trades to large trades. Therefore, the information content of trade size seems to be more pronounced for the return impacts of the net number of trades than for the volatility impacts of the number of trades.

The right-hand panel of Table 5A reports the results for the second-stage regression where the absolute residual returns are regressed on the numbers of trades in the five trade-size categories. Since the order imbalance proxy variables already explain a substantial portion of daily price movements, not surprisingly, the mean coefficient estimates from the second-stage regression are generally much smaller than those in Table 3 where the order imbalance proxy variables are not included in the first-stage regression. The cross-sectional average of the $\overline{R^2}$'s also declines from 0.181 in Table 3 to 0.081 in Table 5A. Therefore, after controlling for the return impacts of the order imbalances, the volatility-volume relation becomes much weaker.

Table 5B reports the results for the NASDAQ stocks. In the first-stage regression for the overall sample, the cross-sectional average of the $\overline{R^2}$'s is 0.394, and there is a significantly positive relation between daily returns and the net numbers of trades in all size categories. This is interesting considering that when we investigate the role of the numbers of trades of different sizes in Table 3, only the trades of the second size category appear to have substantial impacts on price volatility. These results suggest that trades of other size categories will also move prices, although their impacts might not be detected in the numbers of trades. Thus, similar to NYSE stocks, the information content of trade size seems to be more pronounced for the return impacts of the net number of trades than for the volatility impacts of the number of trades. However, unlike NYSE stocks, the return impacts of the net number of trades do not increase monotonically from the smallest to the largest trade-size categories. In the overall sample, the mean *NT* coefficient estimates of the five size categories are 0.023, 0.268, 0.122, 0.128, and 0.121. Therefore, it seems that there is more information content associated with trades in the second size category (501-1000 shares). About 87% of the stocks reject the equality of the coefficients hypothesis at 5% level of significance using the *F*-test, and the aggregated *p*-value is less than 0.001. In firm-size quintiles 1 and 2, the differential return impacts pattern across trades of the five size categories is even sharper: the categories other than the second one are generally insignificant.

In the second-stage regression, although the number of trades in the second size category still has a positive and statistically significant impact on absolute residual returns, the mean coefficient estimate is much smaller than that in Table 3 where the order imbalance proxy variables are not included in the first-stage regression. For example, in the overall sample, the mean coefficient estimate for the second size category drops from 0.075 in Table 3 to 0.033 in Table 5B. Furthermore, the cross-sectional average of the $\overline{R^2}$'s also declines from 0.328 in Table 3 to 0.130 in Table 5B. Therefore, after controlling for the return impacts of the order imbalances, the volatility-volume relation becomes much weaker.[14]

Both the NYSE and NASDAQ results imply that although there is still a significant volatility-volume relation as revealed in the right-hand panels of Tables 5A and 5B,[15] it is much weaker than the usual volatility-volume relation as revealed in Table 3. Therefore, the order imbalance proxy variables do not appear to subsume all the explanatory power of the numbers of trades in explaining the daily price volatility, yet we can at least claim that one major driving force for the volatility-volume relation is related to the impact of the daily order imbalance on stock returns. In other words, the number of trades, size of trades, and order imbalance all play roles in the volatility-volume relation.

4.4. Role of Maximum-Sized SOES Trades in the Volatility-Volume Relation

The results from regression (3) suggest that the information content of trade size is different across the NYSE and NASDAQ. While the return impact of net number of trades increases

[14] Another method to control for the impacts of order imbalance is to directly include order imbalance in the second-stage regression. In the first stage, we estimate regression (1) without including order imbalance proxy variables as the regressors. In the second stage, we modify regression (2c) by including the absolute net number of trades as one regressor to explain the absolute residual returns $|\hat{\varepsilon}_{it}|$ extracted from regression (1). Results, which are available upon request, also show that the absolute net number of trades subsumes part of the explanatory power of the numbers of trades in explaining volatility.

[15] It should be noted that some of the residual volatility-volume relation in the second-stage regression could still be related to the impacts of the order imbalance. For example, if the relation between returns and order imbalances is not exactly linear as in equation (3), the residual volatility could be correlated with the numbers of trades.

monotonically from the smallest to the largest trade-size categories for NYSE-listed stocks, it appears that the trades of the second size category (501-1000 shares) have the largest return impact for NASDAQ-listed stocks. These results are consistent with previous studies. For example, Huang and Stoll (1996) find that the adverse information component in the effective spread decreases with trade size on NASDAQ, but it increases with trade size on the NYSE. One reason for the difference is that NASDAQ dealers know their institutional customers well, so the adverse information effect is relatively small for large trades. On the other hand, NASDAQ dealers must honor the trades received over the Small Order Execution System (trade-size categories 1 and 2), so that they are more vulnerable to these small trades. This section provides additional insight on these trades.

As NASDAQ dealers must honor SOES orders, informed traders, or SOES "bandits", will tend to submit the maximum-sized SOES orders (1000 shares) to exploit their information advantage to the greatest extent. Consequently, we conjecture that the large price impacts in trade-size category 2 actually come from the 1000-share trades. To investigate this, we split trade-size category 2 further into two subcategories: one for trades of 501-999 shares and one for trades of 1000 shares. Using the new trade size classification, we re-estimate regressions (2c) and (3) for the NASDAQ sample.

Table 6 presents the results. The left panel contains the results for regression (2c), where we examine the relation between volatility and the numbers of trades of different size categories. The mean coefficient estimate of number of trades of 501-999 shares (T_{2A}) is insignificant for most of the firm-size quintiles. On the other hand, the number of trades of 1000 shares (T_{2B}) is significantly positive for all the quintiles. A comparison of these results with Table 3 indicates that the large volatility impacts in trade-size category 2 actually come from the 1000-share trades. The right panel of Table 6 contains the results for regression (3), where we examine the relation between daily returns and the net numbers of trades of different size categories. The mean coefficient estimate of net number of trades of 501-999 shares (NT_{2A}) is small and generally insignificant for most of the firm-size quintiles. On the other hand, the mean coefficient estimate of net number of trades of 1000 shares (NT_{2B}) is significantly positive and is higher than the mean coefficient estimates for all the other size categories. Comparing these results with the left panel of Table 5B, it appears that the large return impacts in trade-size category 2 actually come from the 1000-share trades. Overall, the evidence supports the reasoning that maximum-sized SOES trades convey a lot of information and play the most significant role among all trade sizes in the volatility-volume relation on NASDAQ.

5. Conclusion

Although there are many empirical studies on the volatility-volume relation, there is still no general consensus about what actually drives the relation. To enrich the understanding of the trading dynamics behind the relation, we examine the roles of the number of trades, size of trades, and order imbalance. Using transaction and quotation data for a sample of NYSE and NASDAQ stocks, we rank the trades into different trade size categories and examine the relation between daily price volatility and the numbers of trades of different trade sizes. We also construct proxies of order imbalance based on the net number of trades - the difference between the numbers of buyer-initiated trades and seller-initiated trades - and examine whether the return impact of the net number of trades of a particular size category differs from other size categories.

Contrary to some previous studies, our results reconfirm the significance of the size of trades beyond that of the number of trades in the volatility-volume relation. The volatility impacts of trades do not increase monotonically from the smallest to the largest trade-size categories on both the NYSE and NASDAQ. Yet it appears that the role of sizes of trades is more pronounced for the return impacts of net number of trades than for the volatility impacts of number of trades. Further, the pattern of differential return impacts of net trades of the five size categories varies across the NYSE and NASDAQ. The return impacts of net trades increase monotonically from the smallest to the largest trade-size categories for

NYSE-listed stocks. There is no such monotonic relation for NASDAQ-listed stocks. On NASDAQ, the largest return impacts come not from medium- or large-sized trades (more than 1000 shares), but from maximum-sized SOES trades (1000 shares). These results suggest that on NASDAQ, maximum-sized SOES trades convey more adverse information than institutional trades.

We also find that our order imbalance proxy variables explain a substantial portion of daily price movements. After controlling for the return impacts of order imbalance, the volatility-volume relation becomes much weaker. This suggests that one major driving force behind the volatility-volume relation stems from the daily return impacts of order imbalance.

Our results have important implications for theoretical work in explaining the volatility-volume relation. In the “mixture of distributions” models, it is typically assumed that the number of transactions is related to the number of information events and causes the volatility-volume relation. In the “differences in opinion” models, trading volume and price volatility are positively related because the trading interest of investors increases at the time when price volatility is higher. These two types of models consider neither the return impact of order imbalance nor the role of trade size. On the other hand, the “asymmetric information” models allow for the impacts of order imbalance and trade size on price volatility. Even these models, however, do not consider the differential roles of trading frequency and trade size, so they are still unlikely to capture the full dynamics behind the volatility-volume relation. Future theoretical models should seek to accommodate trading frequency, trade size, and order imbalance in explaining the volatility-volume relation.

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TABLE 1: Average market capitalization, daily price volatility, daily volume, trade size, and daily numbers of trades, buys & sells of different sizes for stocks in the NYSE and the NASDAQ samples.

Market capitalization (CAP) is in thousand dollars. Each of the numbers reported for CAP is the firm-size quintile's mean of individual stocks' CAP. Absolute daily returns ($|R|$, continuous compounding, in percent) are calculated using mid-quotes (with missing mid-quotes replaced by transaction prices). Daily volume (V) is in thousand shares. Average trade size (ATS) = V ÷ daily number of trades (T). Daily number of buys is denoted BUY. Daily number of sells is denoted SELL. Trades are classified into five size categories: size1 ≤ 500 shares < size2 ≤ 1000 shares < size3 ≤ 5000 shares < size4 ≤ 9999 shares < size5; thus T_1 is daily number of trades of size1, etc. Each of the numbers reported for a variable, except CAP, is the firm-size quintile's mean of individual stocks' averages of that variable (e.g., each of the numbers reported for V is the firm-size quintile's mean of individual stocks' average daily volume).

	295 NYSE stocks					231 NASDAQ stocks				
Firm-size Quintile	1 (largest)	2	3	4	5 (smallest)	1 (largest)	2	3	4	5 (smallest)
No. of stocks	60	60	60	58	57	18	58	59	53	43
CAP	8,548,474	1,587,585	668,818	304,143	100,282	8,172,344	1,599,191	633,814	293,543	100,270
$\|R\|$	1.1	1.3	1.2	1.2	1.5	1.7	1.6	1.9	2.0	2.7
V	410.9	148.8	102.6	60.6	47.0	5,163.4	325.6	252.6	112.5	71.1
ATS	1.8	1.8	1.6	1.5	1.4	2.3	1.9	1.8	1.7	1.8
T	235.1	83.4	59.0	34.2	34.5	757.1	182.1	147.1	68.3	39.6
BUY	68.7	24.2	16.8	10.0	10.1	280.1	68.3	54.6	25.8	14.8
SELL	67.6	23.3	16.1	9.7	9.3	262.6	65.8	52.9	24.8	14.0
T_1	150.0	50.8	34.3	18.7	19.2	366.0	71.6	60.6	28.4	15.3
T_2	31.8	12.9	10.3	6.7	7.4	209.8	66.8	51.9	23.4	11.9
T_3	39.3	14.6	11.0	7.0	6.5	139.5	34.0	27.3	13.4	10.2
T_4	5.4	2.0	1.3	0.7	0.6	10.6	2.6	2.1	1.0	0.8
T_5	8.5	3.1	2.0	1.0	0.7	31.3	7.1	5.3	2.2	1.3

TABLE 2: Estimates of regressions of daily price volatility on daily volume and number of trades.

There are two sets of regressions. In the first regression, daily return (continuous compounding, in percent, calculated using mid-quotes, with missing mid-quotes replaced by transaction prices) is regressed on its own 12 lags and day-of-week dummies. In the second regression, absolute value of residual return from the first regression is regressed on its own 12 lags, Monday dummy, and daily volume (or daily number of trades). Daily volume is in thousand shares. The regression is separately run for each stock using OLS estimation. Each of the numbers reported for volume (or number of trades) is the cross-sectional mean of stocks' regression coefficients for volume (or number of trades). Figures in parentheses below the means are their standard errors, which take into account any cross-sectional correlation in the individual-stock coefficient estimators. Also reported are the means of the cross-sectional sampling distributions of the individual-stock $\overline{R^2}$. For brevity, the results of the first regression, the coefficients for the 12 lags of absolute residual and Monday dummy of the second regression are not reported below.

295 NYSE stocks				231 NASDAQ stocks			
Volume	$\overline{R^2}$	*No. of Trades*	$\overline{R^2}$	*Volume*	$\overline{R^2}$	*No. of Trades*	$\overline{R^2}$
			All Stocks				
0.007 (0.0005)	0.106	0.020 (0.0006)	0.147	0.007 (0.0003)	0.149	0.026 (0.0007)	0.246
			Firm-size Quintile 1 (Largest)				
0.003 (0.0002)	0.119	0.010 (0.0007)	0.172	0.001 (0.0001)	0.199	0.006 (0.0003)	0.316
			Firm-size Quintile 2				
0.003 (0.0004)	0.094	0.016 (0.0011)	0.155	0.003 (0.0003)	0.104	0.014 (0.0008)	0.226
			Firm-size Quintile 3				
0.006 (0.0006)	0.102	0.019 (0.0011)	0.141	0.004 (0.0003)	0.184	0.017 (0.0008)	0.272
			Firm-size Quintile 4				
0.009 (0.0020)	0.088	0.025 (0.0022)	0.116	0.008 (0.0005)	0.146	0.032 (0.0013)	0.247
			Firm-size Quintile 5 (Smallest)				
0.014 (0.0008)	0.127	0.033 (0.0015)	0.150	0.018 (0.0011)	0.146	0.054 (0.0031)	0.209

TABLE 3: Estimates of regressions of daily price volatility on daily numbers of trades of different sizes

Trades are classified into five size categories: size1 ≤ 500 shares < size2 ≤ 1000 shares < size3 ≤ 5000 shares < size4 ≤ 9999 shares < size5; thus T_1 is daily number of trades of size1, etc. There are two sets of regressions. In the first regression, daily return (continuous compounding, in percent, calculated using mid-quotes, with missing mid-quotes replaced by transaction prices) is regressed on its own 12 lags and day-of-week dummies. In the second regression, absolute value of residual return from the first regression is regressed on its own 12 lags, Monday dummy, and T_1 through T_5. The regression is separately run for each stock using OLS estimation. Each of the numbers reported for T_1 (or T_2 through T_5) is the cross-sectional mean of stocks' regression coefficients for T_1 (or T_2 through T_5). The numbers in parentheses below the means are their standard errors, which take into account any cross-sectional correlation in the individual-stock coefficient estimators. The equality of the coefficients of T_1 through T_5 is tested by *F*-test for individual stock. The percentage of stocks that reject the equality hypothesis at 5% level of significance is reported, and the number in parentheses below is the aggregated *p*-value. Also reported are the means of the cross-sectional sampling distributions of the individual-stock $\overline{R^2}$. For brevity, the results of the first regression, the coefficients for the 12 lags of absolute residual and Monday dummy of the second regression are not reported below.

295 NYSE stocks							231 NASDAQ stocks						
Coefficients of daily numbers of trades in five size categories							*Coefficients of daily numbers of trades in five size categories*						
T_1	T_2	T_3	T_4	T_5	Equality test (*p*-value)	$\overline{R^2}$	T_1	T_2	T_3	T_4	T_5	Equality test (*p*-value)	$\overline{R^2}$
All Stocks													
0.009	0.027	0.038	0.048	0.028	32%	0.181	0.008	0.075	-0.001	0.017	-0.007	62%	0.328
(0.001)	(0.003)	(0.003)	(0.014)	(0.015)	(<0.1%)		(0.003)	(0.003)	(0.003)	(0.015)	(0.013)	(<0.1%)	
Firm-size Quintile 1 (Largest)													
0.004	0.013	0.016	-0.002	0.056	45%	0.219	0.001	0.016	0.002	0.025	-0.011	56%	0.381
(0.002)	(0.004)	(0.003)	(0.012)	(0.010)	(<0.1%)		(0.001)	(0.001)	(0.002)	(0.014)	(0.006)	(<0.1%)	
Firm-size Quintile 2													
0.003	0.030	0.032	-0.001	0.006	27%	0.194	0.004	0.037	-0.006	-0.012	0.000	55%	0.297
(0.003)	(0.006)	(0.005)	(0.019)	(0.016)	(<0.1%)		(0.002)	(0.002)	(0.004)	(0.020)	(0.012)	(<0.1%)	
Firm-size Quintile 3													
0.010	0.020	0.041	0.053	0.034	32%	0.171	0.001	0.051	-0.003	0.013	-0.006	68%	0.369
(0.002)	(0.005)	(0.006)	(0.021)	(0.024)	(<0.1%)		(0.002)	(0.003)	(0.005)	(0.024)	(0.011)	(<0.1%)	
Firm-size Quintile 4													
0.014	0.039	0.052	0.113	-0.016	24%	0.144	0.009	0.079	0.009	0.038	0.000	68%	0.331
(0.004)	(0.012)	(0.012)	(0.057)	(0.058)	(<0.1%)		(0.004)	(0.004)	(0.007)	(0.032)	(0.018)	(<0.1%)	
Firm-size Quintile 5 (Smallest)													
0.016	0.032	0.053	0.080	0.063	30%	0.176	0.027	0.179	-0.006	0.035	-0.026	60%	0.287
(0.005)	(0.007)	(0.007)	(0.032)	(0.038)	(<0.1%)		(0.015)	(0.013)	(0.011)	(0.057)	(0.059)	(<0.1%)	

TABLE 4: Correlation of daily number of trades with daily absolute net numbers of trades of different sizes for the NYSE stocks and the NASDAQ stocks.

Trades are classified into five size classes: size1 ≤ 500 shares < size2 ≤ 1000 shares < size3 ≤ 5000 shares < size4 ≤ 9999 shares < size5. Absolute net number of trades ($|NT|$) is defined as the absolute value of number of buy trades minus number of sell trades; thus $|NT_1|$ is daily absolute net number of trades of size1, etc. Each of the numbers reported represents the mean of individual stocks' correlation coefficients between the corresponding variable and daily number of trades.

295 NYSE stocks					231 NASDAQ stocks				
Daily absolute net numbers of trades in five size categories					*Daily absolute net numbers of trades in five size categories*				
$\|NT_1\|$	$\|NT_2\|$	$\|NT_3\|$	$\|NT_4\|$	$\|NT_5\|$	$\|NT_1\|$	$\|NT_2\|$	$\|NT_3\|$	$\|NT_4\|$	$\|NT_5\|$
All Stocks									
0.365	0.319	0.357	0.258	0.276	0.580	0.520	0.444	0.312	0.385
Firm-size Quintile 1 (Largest)									
0.374	0.287	0.327	0.281	0.313	0.632	0.489	0.475	0.305	0.471
Firm-size Quintile 2									
0.330	0.276	0.353	0.272	0.303	0.586	0.527	0.406	0.258	0.354
Firm-size Quintile 3									
0.356	0.321	0.331	0.264	0.259	0.603	0.537	0.455	0.331	0.397
Firm-size Quintile 4									
0.347	0.332	0.371	0.227	0.235	0.577	0.524	0.436	0.344	0.395
Firm-size Quintile 5 (Smallest)									
0.418	0.382	0.405	0.247	0.267	0.524	0.496	0.478	0.321	0.361

TABLE 5A: Estimates of regressions of daily price movement on daily net numbers of trades of different sizes and regressions of daily residual price volatility on daily numbers of trades of different sizes for the NYSE stocks.

Trades are classified into five size categories: size1 ≤ 500 shares < size2 ≤ 1000 shares < size3 ≤ 5000 shares < size4 ≤ 9999 shares < size5; thus T_1 is daily number of trades of size1, etc. Daily net numbers of trades of size1 to size5 (denoted NT_1 to NT_5) are defined as numbers of buy trades of size1 to size5 minus numbers of sell trades of size1 to size5. There are two sets of regressions. In the first regression, daily return (continuous compounding, in percent, calculated using mid-quotes, with missing mid-quotes replaced by transaction prices) is regressed on its own 12 lags, day-of-week dummies, and NT_1 through NT_5. In the second regression, absolute value of residual return from the first regression is regressed on its own 12 lags, Monday dummy, and T_1 through T_5. The regression is separately run for each stock using OLS estimation. Each of the numbers reported for NT_1 (or other regressors) is the cross-sectional mean of stocks' regression coefficients for NT_1 (or other regressors). The numbers in parentheses below the means are their standard errors, which take into account any cross-sectional correlation in the individual-stock coefficient estimators. The equality of the coefficients of NT_1 through NT_5 (or T_1 through T_5) is tested by *F*-test for individual stock. The percentage of stocks that reject the equality hypothesis at 5% level of significance is reported, and the number in parentheses below is the aggregated *p*-value. Also reported are the means of the cross-sectional sampling distributions of the individual-stock $\overline{R^2}$. For brevity, the coefficients for the 12 lags of daily return and day-of-week dummies of the first regression, the 12 lags of absolute residual and Monday dummy of the second regression are not reported below.

First-stage regression: Coefficients of daily net numbers of trades in five size categories							*Second-stage regression: Coefficients of daily numbers of trades in five size categories*						
NT_1	NT_2	NT_3	NT_4	NT_5	Equality test (*p*-value)	$\overline{R^2}$	T_1	T_2	T_3	T_4	T_5	Equality test (*p*-value)	$\overline{R^2}$
All Stocks													
0.163	0.201	0.233	0.335	0.375	54%	0.425	0.005	0.011	0.019	0.043	0.006	18%	0.081
(0.004)	(0.006)	(0.006)	(0.022)	(0.022)	(<0.1%)		(0.001)	(0.003)	(0.003)	(0.013)	(0.013)	(<0.1%)	
Firm-size Quintile 1 (Largest)													
0.062	0.087	0.104	0.158	0.221	65%	0.451	0.002	0.006	0.005	-0.003	0.026	20%	0.079
(0.004)	(0.007)	(0.005)	(0.017)	(0.017)	(<0.1%)		(0.001)	(0.003)	(0.003)	(0.010)	(0.008)	(<0.1%)	
Firm-size Quintile 2													
0.127	0.178	0.192	0.259	0.300	57%	0.430	0.001	0.013	0.016	-0.005	0.012	20%	0.112
(0.007)	(0.012)	(0.010)	(0.032)	(0.028)	(<0.1%)		(0.002)	(0.006)	(0.004)	(0.017)	(0.015)	(<0.1%)	
Firm-size Quintile 3													
0.158	0.166	0.216	0.210	0.335	57%	0.430	0.005	0.007	0.018	0.078	0.003	22%	0.084
(0.006)	(0.010)	(0.011)	(0.042)	(0.045)	(<0.1%)		(0.001)	(0.004)	(0.005)	(0.017)	(0.020)	(<0.1%)	
Firm-size Quintile 4													
0.211	0.246	0.269	0.436	0.374	43%	0.416	0.007	0.015	0.032	0.109	-0.038	16%	0.056
(0.009)	(0.018)	(0.019)	(0.080)	(0.071)	(<0.1%)		(0.004)	(0.011)	(0.012)	(0.054)	(0.056)	(<0.1%)	
Firm-size Quintile 5 (Smallest)													
0.265	0.336	0.393	0.629	0.659	46%	0.399	0.011	0.014	0.025	0.038	0.024	11%	0.076
(0.013)	(0.015)	(0.015)	(0.056)	(0.066)	(<0.1%)		(0.004)	(0.006)	(0.005)	(0.026)	(0.031)	(0.14%)	

TABLE 5B: Estimates of regressions of daily price movement on daily net numbers of trades of different sizes and regressions of daily residual price volatility on daily numbers of trades of different sizes for the NASDAQ stocks.

Trades are classified into five size categories: size1 ≤ 500 shares < size2 ≤ 1000 shares < size3 ≤ 5000 shares < size4 ≤ 9999 shares < size5; thus T_1 is daily number of trades of size1, etc. Daily net numbers of trades of size1 to size5 (denoted NT_1 to NT_5) are defined as numbers of buy trades of size1 to size5 minus numbers of sell trades of size1 to size5. There are two sets of regressions. In the first regression, daily return (continuous compounding, in percent, calculated using mid-quotes, with missing mid-quotes replaced by transaction prices) is regressed on its own 12 lags, day-of-week dummies, and NT_1 through NT_5. In the second regression, absolute value of residual return from the first regression is regressed on its own 12 lags, Monday dummy, and T_1 through T_5. The regression is separately run for each stock using OLS estimation. Each of the numbers reported for NT_1 (or other regressors) is the cross-sectional mean of stocks' regression coefficients for NT_1 (or other regressors). The numbers in parentheses below the means are their standard errors, which take into account any cross-sectional correlation in the individual-stock coefficient estimators. The equality of the coefficients of NT_1 through NT_5 (or T_1 through T_5) is tested by *F*-test for individual stock. The percentage of stocks that reject the equality hypothesis at 5% level of significance is reported, and the number in parentheses below is the aggregated *p*-value. Also reported are the means of the cross-sectional sampling distributions of the individual-stock $\overline{R^2}$. For brevity, the coefficients for the 12 lags of daily return and day-of-week dummies of the first regression, the 12 lags of absolute residual and Monday dummy of the second regression are not reported below.

First-stage regression: Coefficients of daily net numbers of trades in five size categories							*Second-stage regression: Coefficients of daily numbers of trades in five size categories*						
NT_1	NT_2	NT_3	NT_4	NT_5	Equality test (*p*-value)	$\overline{R^2}$	T_1	T_2	T_3	T_4	T_5	Equality test (*p*-value)	$\overline{R^2}$
All Stocks													
0.023	0.268	0.122	0.128	0.121	87%	0.394	0.013	0.033	0.007	0.005	-0.027	24%	0.130
(0.007)	(0.006)	(0.008)	(0.026)	(0.026)	(<0.1%)		(0.003)	(0.003)	(0.003)	(0.014)	(0.011)	(<0.1%)	
Firm-size Quintile 1 (Largest)													
-0.005	0.077	-0.008	0.040	0.019	100%	0.493	0.001	0.006	0.002	0.022	-0.008	28%	0.124
(0.003)	(0.004)	(0.006)	(0.022)	(0.014)	(<0.1%)		(0.001)	(0.001)	(0.002)	(0.012)	(0.005)	(<0.1%)	
Firm-size Quintile 2													
-0.006	0.151	0.050	0.016	-0.047	88%	0.461	0.006	0.010	0.004	-0.019	-0.018	12%	0.097
(0.005)	(0.006)	(0.009)	(0.032)	(0.022)	(<0.1%)		(0.002)	(0.002)	(0.004)	(0.018)	(0.011)	(<0.1%)	
Firm-size Quintile 3													
0.014	0.210	0.055	0.047	0.072	88%	0.453	0.001	0.019	0.011	-0.010	-0.005	29%	0.147
(0.006)	(0.007)	(0.011)	(0.034)	(0.023)	(<0.1%)		(0.002)	(0.003)	(0.004)	(0.022)	(0.010)	(<0.1%)	
Firm-size Quintile 4													
0.028	0.323	0.162	0.166	0.165	87%	0.346	0.012	0.029	0.018	0.044	-0.046	26%	0.148
(0.011)	(0.011)	(0.016)	(0.051)	(0.039)	(<0.1%)		(0.004)	(0.003)	(0.006)	(0.028)	(0.016)	(<0.1%)	
Firm-size Quintile 5 (Smallest)													
0.079	0.519	0.315	0.380	0.402	77%	0.241	0.045	0.099	-0.008	0.002	-0.055	30%	0.129
(0.033)	(0.029)	(0.030)	(0.103)	(0.122)	(<0.1%)		(0.014)	(0.012)	(0.010)	(0.051)	(0.052)	(<0.1%)	

TABLE 6: The impacts of daily number of 1000-share trades on volatility and return for the NASDAQ stocks.

Trades are classified into six size categories: size1 ≤ 500 shares < size2A < 1000 shares = size2B < size3 ≤ 5000 shares < size4 ≤ 9999 shares < size5; thus T_1 is daily number of trades of size1, T_{2B} is daily number of 1000-share trades, etc. Daily net numbers of trades of size1 to size5 (denoted NT_1 to NT_5) are defined as numbers of buy trades of size1 to size5 minus numbers of sell trades of size1 to size5. To study the volatility impact, we first regress daily return (continuous compounding, in percent, calculated using mid-quotes, with missing mid-quotes replaced by transaction prices) on its own 12 lags, day-of-week dummies. The absolute value of residual return is then regressed on its own 12 lags, Monday dummy, and T_1 through T_5. To study the return impact, we regress daily return on its own 12 lags, day-of-week dummies, and NT_1 through NT_5. The regression is separately run for each stock using OLS estimation. Each of the numbers reported for T_1 (or other regressors) is the cross-sectional mean of stocks' regression coefficients for T_1 (or other regressors). The numbers in parentheses below the means are their standard errors, which take into account any cross-sectional correlation in the individual-stock coefficient estimators. Also reported are the means of the cross-sectional sampling distributions of the individual-stock $\overline{R^2}$. For brevity, the coefficients for the 12 lags of regressees and day-of-week dummies are not reported below.

Impact on Volatility: Daily numbers of trades in six size categories							*Impact on Return: Daily net numbers of trades in six size categories*						
T_1	T_{2A}	T_{2B}	T_3	T_4	T_5	$\overline{R^2}$	NT_1	NT_{2A}	NT_{2B}	NT_3	NT_4	NT_5	$\overline{R^2}$
							All Stocks						
0.012	0.000	0.086	-0.002	0.017	-0.007	0.341	0.023	0.049	0.300	0.118	0.126	0.117	0.418
(0.003)	(0.009)	(0.003)	(0.003)	(0.015)	(0.012)		(0.007)	(0.016)	(0.007)	(0.008)	(0.025)	(0.025)	
							Firm-size Quintile 1 (Largest)						
0.001	0.022	0.016	0.002	0.029	-0.010	0.393	-0.008	-0.006	0.086	-0.011	0.034	0.005	0.524
(0.001)	(0.007)	(0.001)	(0.002)	(0.013)	(0.006)		(0.003)	(0.012)	(0.004)	(0.006)	(0.021)	(0.014)	
							Firm-size Quintile 2						
0.006	0.001	0.041	-0.007	-0.013	0.005	0.309	-0.010	0.029	0.166	0.044	0.010	-0.049	0.483
(0.002)	(0.011)	(0.003)	(0.004)	(0.020)	(0.012)		(0.005)	(0.016)	(0.006)	(0.009)	(0.032)	(0.022)	
							Firm-size Quintile 3						
0.004	-0.007	0.057	-0.002	0.017	-0.008	0.377	0.014	0.019	0.235	0.056	0.056	0.078	0.474
(0.003)	(0.012)	(0.003)	(0.005)	(0.024)	(0.011)		(0.006)	(0.020)	(0.008)	(0.011)	(0.034)	(0.023)	
							Firm-size Quintile 4						
0.012	-0.015	0.090	0.009	0.044	-0.004	0.347	0.026	0.027	0.365	0.151	0.180	0.154	0.375
(0.004)	(0.018)	(0.004)	(0.007)	(0.032)	(0.018)		(0.011)	(0.031)	(0.012)	(0.016)	(0.051)	(0.038)	
							Firm-size Quintile 5 (Smallest)						
0.039	0.018	0.209	-0.009	0.021	-0.027	0.307	0.090	0.171	0.581	0.314	0.347	0.397	0.264
(0.015)	(0.036)	(0.014)	(0.011)	(0.057)	(0.059)		(0.033)	(0.071)	(0.031)	(0.030)	(0.102)	(0.121)	