Transactions, Volume, and Volatility

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We should show that the positive volatility-volume relation documented by numerous researchers actually reflects the positive relations between volatility and the number of transactions. Thus, it is the occurrence of transactions per se, and not their size, that generates volatility; trade size has no information beyond that contained in the frequency of transactions. Our results suggest that theoretical research needs to entertain scenarios in which (i) both the frequency and size of trades are endogenously determined, yet (ii) the size of trades has no information content beyond that contained in the number of transactions.

The relation between volume of trade and stock prices has received increasing attention from academic researchers. Virtually all empirical investigations of the relation between stock-return volatility and volume have found a positive correlation between vol-

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atility (measured as absolute or squared price changes) and volume for both individual securities and portfolios. [See, for example, Schwert (1989) and Gallant, Rossi, and Tauchen (1992). Karpoff (1987) provides a detailed review of the empirical research.] In most theoretical models that have been developed to explore the relation between volume and stock-price dynamics, trading is generated due to asymmetric information (or differences in opinion), and the size of trades (or volume) reflects the extent of disagreement among traders about a security's value. Consequently, there is a positive relation between volume and absolute price changes.

The theoretical models fall into two groups, competitive and strategic. In competitive models with asymmetric information, the size of trades is positively related to the quality (or precision) of information possessed by informed traders. Therefore, trade size introduces an adverse-selection problem into security trading because informed traders prefer to trade large amounts at any given price [see Pfleiderer (1984), Grundy and McNichols (1989), Holthausen and Verrecchia (1990), and Kim and Verrecchia (1991)]. Consequently, as Pfleiderer (1984) and Kim and Verrecchia (1991) explicitly show, there is a positive relation between absolute price changes and volume, where volume is measured as the aggregate demand of all investors.[1]

In strategic models, asymmetric information also leads to trading, but a *monopolist* informed trader may camouflage his trading activity by making several small-sized trades rather than one large trade [see, for example, Kyle (1985), Admati and Pfleiderer (1988), and Foster and Vishwanathan (1990)]. Such strategic behavior may attenuate the positive relation between the size of transactions and the (monopolist) informed trader's information. In a recent paper, however, Holden and Subrahmanyam (1992) show that in a more realistic strategic model with multiple informed traders the distinction between strategic and competitive models is blurred. Even just two informed traders act noncooperatively and choose larger quantities to trade than a monopolist (or collusive agents). Therefore, in both competitive and strategic models the *size of trades or volume* of the informed agents is positively related to the quality of their information, thus resulting in a positive relation between volume and absolute price changes.

The objective of this article is very specific. We test whether number of transactions per se, or their size (or volume), generates volatility.

[1] More recently, Harris and Raviv (1993) show that, even if all traders were homogeneously informed, *differences in opinion* in a competitive market would result in trading and there would be a positive relation between volume and volatility [see also Varian (1985, 1989) and Kandel and Pearson 1991)].

This investigation is interesting purely as an empirical exercise, especially given the old Wall Street adage that "it takes volume to move prices." Our results, however, are also likely to have important implications for theoretical research on the role of volume in financial markets. This follows because of the apparent consensus even among academics that volume is related to volatility because it reflects the extent of disagreement about a security's value based on either differential information or differences in opinion. In fact, motivated by theoretical research, volume has increasingly been used as a measure of the "information content" of financial and macroeconomic events [see, for example, Beaver (1968), Bamber (1986), Jain (1988), Morse (1981), Richardson, Sefcik, and Thompson (1986), and Ziebart (1990)].

We use daily data of NASDAQ-NMS securities over the 1986-1991 period to investigate the relation between volatility, volume, and the frequency of trades. The tests reported in this article use average trade size (total number of shares traded divided by number of daily transactions) as the measure of "volume." Our results, however, are insensitive to the choice of the empirical measure of volume; alternative measures like dollar volume, number of shares traded, or turnover (number of shares traded divided by total number of shares outstanding) yield virtually identical inferences.

Our evidence shows that the volatility-volume relation typically disappears when we control for the relation between volatility and number of transactions. Specifically, daily volatility is significantly positively related to both average daily trade size and number of daily transactions. However, in regressions of volatility on average trade size *and* number of transactions, the volatility-volume relation is rendered statistically insignificant while the relation between volatility and number of transactions remains virtually unaltered. Average size of trades has a statistically significant positive relation with volatility only for small firms, but on average even this statistical relation seems to be of little economic significance. Thus, our evidence strongly suggests that the occurrence of transactions per se contains all the information pertinent to the pricing of securities.[2] This finding suggests that future theoretical research needs to develop scenarios in which (i) both the frequency and size of trades are endogenously determined and yet (ii) the size of trades has no information content beyond that contained in the number of transactions.

Section 1 contains a description of the data and the estimation procedures used in this study. In Section 2 we present and analyze

[2] Our investigation differs from studies that gauge the price response to large block trades [see, for example, Holthausen, Leftwich, and Mayers (1993) and Seppi (1992)]. The block-trade studies investigate the price-volume relation or the information content of such trades *conditional* on observing large trades, while we are interested in the unconditional relation between volatility and volume.

the empirical evidence. This section also contains some sensitivity tests to gauge the robustness of our results to alternative measures of volatility and volume and to alternative specifications of the regressions used in our analysis. Section 3 contains a brief summary and a discussion of the possible interpretations and implications of our results.

1. Data and Estimation Procedures

1.1 Data description

We use the Center for Research in Security Prices (CRSP) daily masterfile for NASDAQ-NMS firms to compute security returns. Trading on the NMS in the years immediately after its inception in 1982 was limited to only the most actively traded stocks. Consequently, we analyze all 853 securities that have an unbroken series of daily closing bid and asked prices between 1986 and 1991. Note that since CRSP provides closing quotes even on days when a security does not trade, a stock does not have to trade each day during the 1986-1991 period to be included in our sample. Finally, to gauge the effect of our sample selection criterion on our results and to expand the number of firms represented in our study, we also conduct a detailed subperiod analysis (see Section 2.1).

Our tests are based on returns calculated from the average of closing bid-ask quotes, rather than transaction prices used in all previous studies, because transaction returns of individual securities contain measurement errors due to the bid-ask bounce which induce substantial spurious volatility in returns [see Roll (1984)]. Kaul and Nimalendran (1990) find that, even for the average NASDAQ-NMS firm that trades every day, the bid-ask bounce could account for 30 percent of the daily return variance, and for small firms this proportion is in excess of 50 percent. Returns calculated using the midpoints of closing quotes, on the other hand, contain no noise due to the bid-ask bounce.

To gauge the cross-sectional characteristics of the volatility-volume relation, we sort the sampled securities into five portfolios based on market value (number of shares outstanding times price per share) at the beginning of 1989 (the midpoint of the sample period). The portfolios have (approximately) equal number of securities, about 170. The motivation for sorting securities based on their market values is that firm size and volatility are positively correlated. It may, therefore, be important to extract size-related systematic components of volatility to better understand the empirical relation between volume and volatility. Also, sorting firms based on their market values may

Table 1
Daily descriptive statistics for NASDAQ-NMS stocks, 1986–1991

Portfolio	No. of firms	Market value ($ millions)	Average of bid-ask price (in dollars)	Share volume (in thousands)	Average trade size (in thousands)	Number of transactions	Corr (AV, N)	Corr (V, N)	Corr (V, AV)
1 (Smallest)	171	17.691	6.000	11.163	1.132	6.743	.156	.643	.639
2	170	40.722	10.609	17.528	1.254	10.939	.111	.637	.628
3	171	79.163	14.542	30.675	1.399	17.381	.099	.622	.638
4	170	176.401	22.416	38.061	1.445	21.355	.089	.613	.660
5 (Largest)	171	734.785	28.773	124.309	1.745	61.528	.046	.627	.639

This table contains the avenge market value (number of shares outstanding times price per share), the average of closing bid and asked prices, share volume *(V)*, average trade size (total number of shares traded divided by number of transactions) *(AV)*, number of transactions *(N)*. and the correlations between average trade size and number of transactions, share volume and number of transactions, and share volume and avenge trade size, respectively. The description statistics are based on daily data for the entire sample period and are reported for all 853 securities that have an unbroken series of closing bid and asked prices between 1986 and 1991 classified into five portfolios formed by rankings of market value of equity outstanding at the beginning of 1989 (the midpoint of 1986-1991 period). The individual-firm statistics arc averaged across firms in each portfolio. The second column reports the total number of firms in each portfolio.

be informative because of differences in the volatility-volume relation for firms of different capitalizations.

Finally, our analysis also requires daily volume and number of transactions for the sampled securities. Although volume data for NASDAQ securities have been available for the past few years, historical data on number of transactions have been made available only on the most recent tapes. The use of daily data is largely dictated by data availability considerations: daily volume and number of transactions are most readily available for a reasonably long time period and for a large cross-section of firms. Using weekly or lower frequency data was deemed unnecessary because it would reduce the sample size without any corresponding gains.

1.2 Descriptive statistics

Table 1 reports some descriptive statistics for the firms in our overall sample. The table contains average estimates of market value (in million dollars), average of closing bid-ask prices, share volume (in thousands), average trade size (total number of shares traded divided by number of daily transactions), number of transactions, and the correlations between average trade size and number of transactions, share volume and number of transactions, and share volume and average trade size, respectively. All reported numbers are obtained using daily observations. Each summary statistic is the cross-sectional average of the individual-firm values of firms within each portfolio.

The second column reports the total number of firms in each portfolio of our sample.

The numbers of Table 1 reflect the diverse sample of securities used in this study. For example, the average market values range between \$18 million for the smallest firms (portfolio 1) and \$735 million for the largest firms (portfolio 5). Similarly, the trading frequency exhibits substantial cross-sectional variation: the average number of transactions varies between 7 and 62 per day. Based on market values, our sample spans most of the firms on the NYSE and AMEX, except the 500 largest firms on these exchanges [see Keim (1989)]. However, since the firms in our sample are required to have bid-ask quotes on each day within the 1986-1991 period, a substantial number of small NASDAQ-NMS firms are excluded from the sample. The subperiod analysis in Section 2.1, however, provides insights into the behavior of such firms because the two subperiod samples contain firms that have an unbroken series of daily bid-ask quotes for three-year intervals, as opposed to the six-year interval for the overall sample.

The last three columns report the average correlations between average trade size, number of transactions, and share volume. Note that share volume *(V)* is simply the product of average trade size and number of transactions. The correlations between the two components of share volume—average trade size *(AV)* and number of transactions *(N)* —are small and exhibit a monotonic inverse relation with firm size, ranging between 0.156 and 0.046. On the other hand, both components are strongly positively correlated with share volume. The average correlations between both *V* and *N* and *V* and *AV* are similar and range between 0.60 and 0.70. The correlations between *AV, N,* and *V* together indicate that, although both components of volume are strongly correlated with it, they seem to contain different information about volume because they are not strongly correlated with each other.

1.3 Measures of volatility and estimation procedures

We measure daily volatility using a procedure similar to the one in Schwert (1990). Specifically, we use the absolute residuals of the following model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_j R_{it-j} + \hat{\epsilon}_{it} \tag{1}$$

where R_{it} is the return of security i on day t, D_{kt}'s are the five day-of-the-week dummies used to capture differences in mean returns [see, for example, French (1980) and Keim and Stambaugh (1984)]. The

12 lagged returns are used as regressors to estimate short-term movements in conditional expected returns.

To gauge the relative importance of number of transactions versus volume of trade, we estimate the following three sets of regressions for each security:

$$|\hat{\epsilon}_{it}| = \alpha_i + \alpha_{im}M_t + \beta_i AV_{it} + \sum_{j=1}^{12} \rho_{ij}|\hat{\epsilon}_{it-j}| + \eta_{it}, \tag{2a}$$

$$|\hat{\epsilon}_{it}| = \alpha_i + \alpha_{im}M_t + \gamma_i N_{it} + \sum_{j=1}^{12} \rho_{ij}|\hat{\epsilon}_{it-j}| + \eta_{it}, \tag{2b}$$

and

$$|\hat{\epsilon}_{it}| = \alpha_i + \alpha_{im}M_t + \beta_i AV_{it} + \gamma_i N_{it} + \sum_{j=1}^{12} \rho_{ij}|\hat{\epsilon}_{it-j}| + \eta_{it}, \tag{2c}$$

where $|\hat{\epsilon}_{it}|$ is the absolute residual from (1), M_t is a trading gap dummy variable that is equal to 1 for Mondays and 0 otherwise, AV_{it} is the average trade size (total number of shares traded divided by the number of transactions for security *i* or day *t*), N_{it} is the number of transactions for security *i* on day *t*, and the coefficients ρ_{ij}'s measure the persistence in the volatility of security *i*.

We use a two-step procedure to estimate (2a)-(2c): we first estimate (1), and then use the absolute residuals, $|\hat{\epsilon}_{it}|$'s, as the dependent variables in (2a)-(2c). We use ordinary least squares to estimate the regressions in (2), which provides consistent estimators of the parameters [see Pagan and Schwert (1990)]. The estimators, however, are not efficient. But the inefficiency of the two-step OLS estimators does not pose a significant inference problem because, when we replicate all our tests using absolute simple returns in (2a)-(2c) [that is, we estimate (2a)-(2c) directly without estimating (1)], our results remain unaltered (see Section 2.2).

Although we estimate regressions (2a)-(2c) for each security, for brevity we report and analyze estimates of Regression (2c) alone. Regression (2c) is chosen because it provides a natural decomposition of the effects of volume on volatility; volume is the product of average trade size and number of transactions. Estimates of (2c) can therefore help us determine whether the average size of trades, AV_{it}, or number of transactions, N_{it}, or both, are determinants of volatility.

2. Empirical Evidence

Table 2 presents estimates of Regression (2c) to test directly whether average trade size and/or number of daily transactions is related to daily volatility. For brevity, we do not report the estimates of the simple regressions of volatility on trade size and on number of transactions. We estimate Regression (2c) for each security in each portfolio using ordinary least squares (OLS), and panel A contains the means of the coefficient estimates of average trade size and number of daily transactions, with their standard errors in parentheses. Although it is infeasible to obtain seemingly unrelated regression (SUR) estimates of the systems of approximately 170 individual-security regressions in each portfolio, the standard errors of the means are corrected for any correlations in the individual-firm coefficient estimators (see Appendix for details).[3] Panel A also contains the means (with the fifth and ninety-fifth percentiles in parentheses) of the cross-sectional distributions of the individual-firm adjusted-R^2's. Finally, panel B contains some properties of the sampling distributions of the t-statistics of the individual-security coefficients of average trade size and number of transactions, $t(\hat{\beta}_i)$ and $t(\hat{\gamma}_i)$, respectively.

The most notable aspect of the evidence in Table 2 is that average trade size has virtually no marginal explanatory power when volatility is conditioned on number of transactions. This conclusion is based on several features of the data. First, for medium and large firms (specifically portfolios 3, 4, and 5) there is no positive relation *on* average between volatility and average trade size, AV_{it}. There is a statistically significant positive relation between volatility and average trade size for smaller firms in portfolios 1 and 2. However, the economic significance of these relations is questionable because AV_{it} adds little explanatory power over number of transactions, N_{it}. Specifically, the average $\bar{R}^2$'s of Regressions (2b) in which N_{it} is the only regressor are 0.236 and 0.258 for portfolios 1 and 2, and the inclusion of AV_{it} in Regression (2c) increases the average $\bar{R}^2$'s to 0.241 and 0.260 (increases of less than 2 percent).

On the other hand, there is strong evidence that volatility is primarily determined by the number of transactions, rather than their size. On average, there is a statistically positive relation between volatility and N_{it} for securities in all portfolios; the means of $\hat{\gamma}_i$'s are several (85 to 125) standard errors greater than zero. Moreover, inclusion of average trade size has virtually no effect on the coefficients of N_{it} or the $\bar{R}^2$'s of the regressions that have N_{it} as the sole regressor

[3] The infeasibility of the SUR estimation arises beause within each portfolio we have 170 regressions, with each regression containing 16 independent variables in (2c) (including a vector of ones for the intercept). As a result, the SUR estimator of the system of equations involves inverting a (2720 × 2720) matrix, which is infeasible. Fortunately, the efficiency gains from implementing the SUR procedure are unlikely to be large because the avenge pairwise correlations between the OLS residuals of (2c) are low, ranging between 0.059 and 0.112. On the other hand, since heteroskedasticity is a pervasive problem, we include 12 lagged $|\epsilon_{it}|$'s in Regressions (2a)-(2c) for each security (see Appendix for further details).

Table 2
Estimates of regressions of daily percentage volatility of returns calculated from the average of bid and asked prices on daily average trade size and number of daily transactions for NASDAQ-NMS stocks, 1986-1991

Portfolio	A: Parameter estimates $\hat{\beta}$	$\hat{\gamma}$	$\bar{R}^2$	B: Distributions of $t(\hat{\beta}_i)$ and $t(\hat{\gamma}_i)$ Percentage of $t(\hat{\beta}_i) > 2.0$	Percentage of $t(\hat{\gamma}_i) > 2.0$
1 (Smallest)	0.077 (0.0043)	0.191 (0.0017)	0.241 (0.125, 0.359)	36.25	100.00
2	0.032 (0.004)	0.116 (0.0011)	0.260 (0.145, 0.372)	12.87	100.00
3	0.001 (0.0037)	0.091 (0.0008)	0.272 (0.164, 0.410)	8.77	100.00
4	−0.010 (0.0035)	0.073 (0.0007)	0.298 (0.174, 0.428)	4.09	100.00
5 (Largest)	−0.030 (0.0046)	0.042 (0.0005)	0.326 (0.200, 0.454)	3.51	100.00

Panel A contains estimates of the following regression:

$$|\hat{\epsilon}_{it}| = \alpha_i + \alpha_{im} M_t + \beta_i AV_{it} + \gamma_i N_{it} + \sum_{j=1}^{12} \rho_{ij} |\hat{\epsilon}_{it-j}| + \eta_{it}$$

where $|\hat{\epsilon}_{it}|$ Is the absolute value of the return of security i in period t conditional on Its own 12 lags and day-of-the-week dummies, M, is a dummy variable that is equal to 1 for Mondays and 0 otherwise, AV_{it} is the average trade size (total number of shares traded divided by number of transactions for security i on day t), N_{it} is the number of transactions for security i on day t, and the coefficients ρ_{ij} measure the persistence in volatility of security i. We estimate the regression using daily returns calculated from the average of closing bid and asked prices of all 853 securities that have an unbroken series of closing bid and asked prices between 1986 and 1991. These securities arc classified into five portfolios formed by rankings of market value at the beginning of 1989 (the midpoint of the 1986-1991 period). All regression parameters are estimated for each firm, and we report the means of the individual security parameter estimates for each portfolio. The numbers in parentheses below the means are their standard errors. which take into account any cross-sectional correlation in the individual-firm estimators (see Appendix). Panel A also contains the means (with the fifth and ninety-fifth percentiles in parentheses) of the cross-sectional sampling distributions of the individual-firm $\bar{R}^2$'s. For brevity we do not report the $\hat{\alpha}$'s, $\hat{\alpha}_m$'s, and $\hat{\rho}_{ij}$'s. Panel B contains the percentage of $\hat{\beta}_i$'s and $\hat{\gamma}_i$'s with t- statistics greater than 2.0.

[see (2b)]. Specifically, the average $\hat{\gamma}_i$'s in (2b) range between 0.193 and 0.042 for portfolios 1 through 5, while the corresponding average values range between 0.191 and 0.042 in Table 2. Similarly, the average $\bar{R}^2$'s of (2c), which range between 0.241 and 0.326, are only trivially higher than the average $\bar{R}^2$'s of (2b), which vary between 0.236 and 0.323.

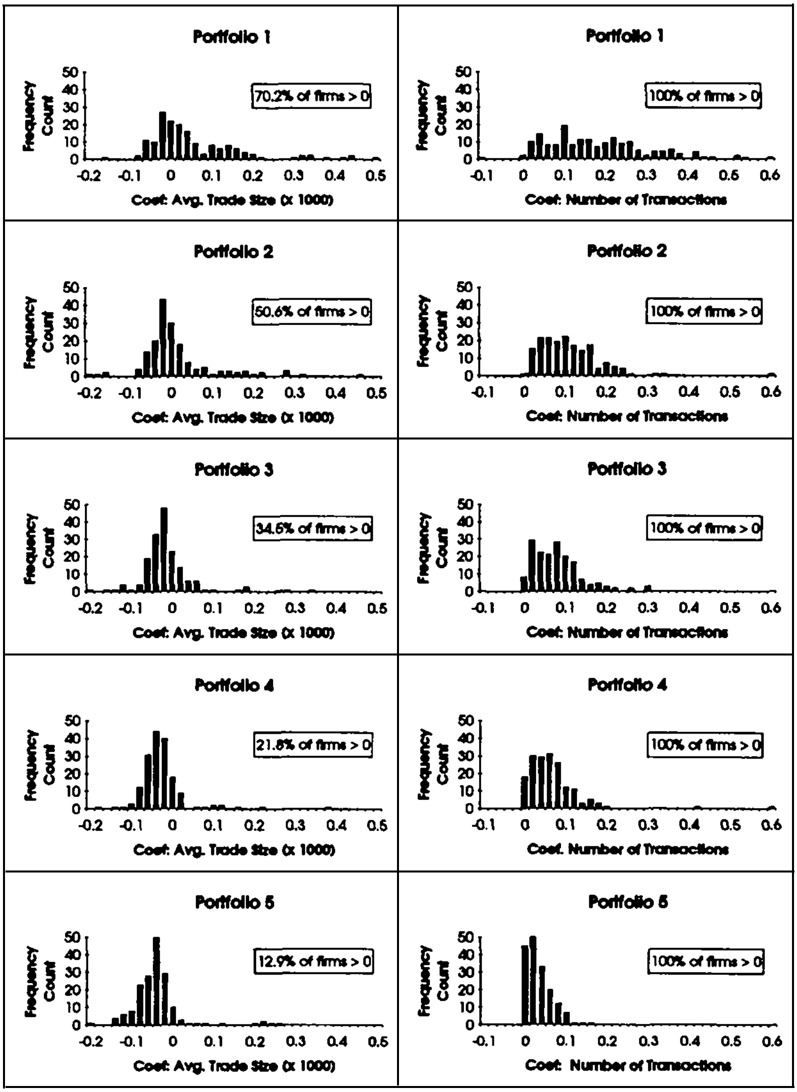
The relative importance of the number of transactions and the unimportance of the size of trades are also reflected in the characteristics of the sampling distributions of individual-firm coefficients and t- statistics of N_{it}, and AV_{it}. Figure 1 contains the frequency distributions of the estimated coefficients of average trade size and number of transactions, $\hat{\beta}_i$ and $\hat{\gamma}_i$, from Regression (2c) for each portfolio, while panel B of Table 2 contains the percentage of $t(\hat{\beta}_i)$'s and $t(\hat{\gamma}_i)$'s that are greater than 2.0. The most striking aspect of Figure 1 and Table 2, panel B, is that, not only is there a positive relation between volatility and N_{it} for *all* firms in our sample, but that *all* these relations are also statistically significant [that is, 100 percent of the $t(\hat{\gamma}_i)$'s are greater than 2.0 within each portfolio].

On the other hand, the relation between volatility and average trade size is tenuous at best. Figure 1 shows that, for medium and large firms (portfolios 3-5), only 13 percent to 35 percent of the coefficient estimates are positive, and the proportions of $t(\hat{\beta}_i)$'s > 2.0 are only 8.77, 4.09, and 3.51 percent for portfolios 3, 4, and 5, respectively.[4] However, there seems to be some evidence of a statistically significant relation between volume and volatility for smaller firms. Over 50 percent of the firms in portfolios 1 and 2 have positive $\hat{\beta}_i$'s, and a nontrivial fraction of these coefficients is statistically significant. In particular, it is unlikely that about 36 percent of the $t(\hat{\beta}_i)$ > 2.0 for portfolio 1 is a chance occurrence.

We argued earlier that, although on average there is a statistically positive relation between volume and volatility for the smaller firms in portfolios 1 and 2, this relation seems to be of little economic significance. We also attempt to gauge the economic significance of the volume-volatility relation for the subset of 36 percent and 13 percent of the firms in portfolios 1 and 2 with $t(\hat{\beta}_i)$'s > 2.0. We again find that AV_{it} seems to add little to the explanatory power of the multiple regression (2c): the mean R^2's of the regressions that have N_{it} as the only explanatory variable [see (2b)] are 0.207 and 0.220 for firms in portfolios 1 and 2, respectively, and inclusion of the trade size variable AV_{it} increases the mean R^2's to only 0.218 and 0.232. Also, the mean R^2's of these firms from regressions that contain AV_{it} as the sole regressor [see (2a)] are only 0.088 and 0.096, respectively.

We conclude, therefore, that even for the subset of firms in portfolios 1 and 2 with $t(\hat{\beta}_i)$'s > 2.0 in the multiple regression (2c) the volume-volatility relation on average seems to be of little economic significance (especially when compared to the relation between volatility and number of transactions). Of course, there clearly is evidence that volume has at least some "information content" for some of the smaller NASDAQ-NMS firms. This finding, in turn, has an appealing interpretation; it suggests that private-information-based

[4] Note that even if there is no positive relation between volatility and average trade size, some $t(\hat{\beta}_i)$'s will be greater than 2.0 purely by chance. Suppose that, under the null hypothesis of no relation between volatility and AV_{it}, the outcomes of the hypothesis tests for 170 securities in a particular portfolio are independent. Then, at the 0.05 test level. the proportion of rejections for such a Bernoulli process has a mean of 0.05 and a standard deviation of 0.017. If the proportion of rejections is normally distributed, then the percentage of rejections (i.e., $t(\hat{\beta}_i)$'s > 2.0) in Table 2 should be between 1.50 and 8.50 percent (under the null hypothesis) approximately 95 percent of-the time, when testing at the 0.05 significance level. Of course, the 170 regression estimators b_i are not independent. However, due to the infeasibility of estimating a SUR system we cannot provide more formal tests of the restriction that $b_i = 0 \ \forall \ i$ in a particular portfolio (see Appendix).



trading may be important only for the smallest firms on the stock market. This interpretation has intuitive appeal because there is likely to be relatively little public information about these firms and, therefore, it may "pay" some traders to incur the costs of gathering private information about them.

2.1 Subperiod evidence

Since the results in Table 2 are limited to only a subsample of securities that trade on the NMS, we conduct a detailed subperiod analysis to gauge the robustness of our results. Specifically, we break up our six-year sample period into two equal-sized (three-year) subperiods. In each subperiod we sample all firms that have an unbroken series of daily closing bid and asked quotes. There are three main advantages of conducting the subperiod analysis. First, by requiring firms to have unbroken series of closing quotes for only three years (as opposed to all six years), we dramatically increase the number of sampled firms in each subperiod. Compared to 853 firms in our overall sample, subperiod I (1986-1988) contains 1385 firms and subperiod II (1989-1991) has 1553 firms. A second, and related, advantage is that the subperiod sampling procedures ensure the inclusion (in both subperiods) of small firms that are excluded from the overall sample. This feature of the subperiod data is important because the size of trades exhibits some marginal statistical significance for the smaller firms in the overall sample. By including even smaller firms in our subperiod samples, we can further investigate this aspect of the volatility-volume relation. Finally, the subperiod analysis, by breaking the overall sample into the 1986-1988 and 1989-1991 periods, allows us to check the robustness of our results to the 1987 Crash.

Table 3 contains subperiod estimates of the multiple regression of volatility on trade size and number of transactions [see (2c)]. We again do not report the subperiod estimates of the simple regressions of volatility on trade size and on number of transactions. The subperiod results in Table 3 generally confirm our earlier evidence, and the 1987 Crash seems to have little effect on our findings. For larger firms (in portfolios 3-5) the positive relation between volume (or trade size) and volatility disappears in both subperiods when the latter is conditioned on number of transactions as well. There again is some evidence that, for small firms, volume may have some information content beyond that contained in the number of transactions. The means of the trade size coefficients (β_i) for securities in portfolios 1 and 2 are several standard errors greater than zero in both subperiods. As in the case of the overall period's results, however, at least *on* average the economic significance of these statistical relations is questionable. Specifically, even for the smallest firms in the two subperiod samples the distributional characteristics of the $\bar{R}^2$'s in (2c), that is, their means and percentiles, are similar to the distributional characteristics of the $\bar{R}^2$'s of regressions of volatility on number of transactions alone. In other words, the size of trades has little marginal explanatory power when volatility is conditioned on both AV_{it} and N_{it}.

Table 3
Estimates of regressions of daily percentage volatility of returns calculated from average of bid and asked prices on daily average trade size and number of daily transacti for NASDAQ-NMS stocks over two subperiods: I (1986–1988) and II (1989–1991)

Portfolio	A: Subperiod I (1986–1988) $\hat{\beta}$	$\hat{\gamma}$	$\bar{R}^2$	B: Subperiod II (1989–1991) $\hat{\beta}$	$\hat{\gamma}$	$\bar{R}^2$
1	0.070	0.263	0.274	0.067	0.297	0.234
(Smallest)	(0.0063)	(0.0031)	(0.139, 0.428)	(0.0050)	(0.0030)	(0.101, 0.395)
2	0.034	0.150	0.289	0.028	0.175	0.255
	(0.0063)	(0.0019)	(0.132, 0.432)	(0.0044)	(0.0017)	(0.106, 0.413)
3	−0.008	0.113	0.299	0.008	0.120	0.274
	(0.0054)	(0.0015)	(0.175, 0.422)	(0.0041)	(0.0012)	(0.126, 0.417)
4	−0.020	0.081	0.320	−0.009	0.086	0.290
	(0.0067)	(0.0012)	(0.167, 0.472)	(0.0045)	(0.0010)	(0.137, 0.456)
5	−0.040	0.048	0.359	−0.020	0.049	0.318
(Largest)	(0.0082)	(0.0009)	(0.236, 0.489)	(0.0050)	(0.0007)	(0.159, 0.475)

Panel A contains estimates of the following regression:

$$|\hat{\epsilon}_{it}| = \alpha_i + \alpha_{im} M_t + \beta_i AV_{it} + \gamma_i N_{it} + \sum_{j=1}^{12} \rho_{ij} |\hat{\epsilon}_{it-j}| + \eta_{it}$$

where $|\hat{\epsilon}_{it}|$ is the absolute value of the return of security *i* in period *t* conditional on its own 12 lags and day-of-the-week dummies, M_t is a dummy variable that is equal to 1 for Mondays and 0 otherwise, AV_{it} is the average trade size (total number of shares traded divided by the number of transactions for security *i* on day *t*), N_{it} is the number of transactions for security *i* on day *t*, and the coefficients ρ_{ij} measure the persistence in volatility of security *i*. *We* estimate the regression using daily returns calculated from the average of closing bid and asked prices of all 1385 and 1553 securities that have an unbroken series of closing bid and asked prices for the 1986-1988 and 1989-1991 subperiods, respectively. These securities are classified into five portfolios formed by rankings of market value at the midpoint of each subperiod. All regression parameters are estimated for each firm, and we report the means of the individual-security parameter estimates for each portfolio in both subperiods. The numbers in parentheses below the means are their standard errors, which take into account any cross-sectional correlation in the individual-firm estimators (see Appendix). Panels A and B contain the mean estimates of the regression coefficients for the 1986-1988 and 1989-1991 subperiods, respectively. Each panel also contains the means (with the fifth and ninety-fifth percentiles in parentheses) of the cross-sectional sampling distributions of the individual-firm $\bar{R}^2$'s. For brevity we do not report the $\hat{\alpha}$'s, $\hat{\alpha}_m$'s, and $\hat{\rho}_{ij}$'s.

Of course, as in the overall sample, there are a number of small firms that have a significantly positive relation between volatility and trade size. For example, more than 20 percent of the firms in the smallest portfolio have $t(\hat{\gamma}_i)$'s greater than 2.0 in both subperiods. Consequently, volume may have some information content for these smallest of NASDAQ-NMS firms, which again suggests that private-information-based trading may be important for only (very) small firms.

2.2 Some sensitivity tests

Since our results may have potentially important implications for future research concerning the relation between stock prices and volume, we evaluate their robustness by conducting a variety of sensitivity tests.

2.2.1 Tests based on transaction returns. All our results in Tables 2 and 3 are based on returns calculated from the average of closing bid and asked prices. For completeness, we replicate the tests using returns calculated from daily closing transactions prices. The results (not reported) lead to identical inferences about the relative roles of volume versus frequency of trading in explaining volatility. In fact, even for the smallest portfolio of securities there is no positive relation between volatility and trade size when number of transactions is included as an explanatory variable in Regression (2c). This, however, is not surprising because the "noise" in transaction returns leads to a loss in power of our tests.

2.2.2 **Alternative measures of volatility and volume.** We replicate our tests using the squared residuals from Regression (1) instead of the absolute residuals. We also estimate Regressions (2a)-(2c) directly using absolute and squared simple returns without conditioning on day-of-the-week dummies or past returns in (1). Our results are insensitive to the alternative measures of volatility and the estimation procedures (two-step or one-step): the volatility-volume relation is entirely driven by the strong positive relation between volatility and number of transactions.

Similarly, our conclusions seem invariant with respect to alternative measures of volume. In the results reported, we use average trade size because AV_{it} and N_{it} provide a natural decomposition of volume. However, use of share volume, dollar volume, or turnover (total number of shares traded divided by the total number of shares outstanding) leads to similar inferences. Also, since we use the absolute value of returns (rather than squared returns) as our measure of volatility, we used square root transformations of both AV_{it} and N_{it} as regressors in (2a)-(2c); again the results remained unaltered.

2.2.3 **Alternative regression specifications.** As a final check of the robustness of our results, we estimate a regression with AV_{it}, N_{it}, and share volume, V_{it}. Our results are even stronger in that the estimated mean coefficients of AV_{it} and V_{it} are significantly positive only for portfolio 1 (and not for portfolios 2-5), while the mean coefficients of N_{it} remain largely unaltered and statistically greater than zero for all portfolios. We do not report these results because we are interested in the effects of the two components of volume, average trade size, and number of transactions. Including volume detracts from this fundamental objective of the article. From a statistical standpoint also (2c) may be preferable because of the low correlations between the two regressors, AV_{it} and N_{it} (see Table 1). On the other hand, the strong positive correlations of over .60 between both AV_{it} and V_{it} and

N_{it} and V_{it} for each portfolio may potentially create multicollinearity problems for the regression of volatility on AV_{it}, N_{it}, and V_{it}.

3. A Summary and the Implications of the Evidence

In this article, we show that the positive volatility-volume relation documented by numerous researchers simply reflects the positive relation between volatility and number of transactions. The most notable implication of this finding is that *on average* the size of trades has virtually no incremental information content; any information in the trading behavior of agents is almost entirely contained in the frequency of trades during a particular interval. Average trade size has a marginally significant positive relation with volatility only for the smallest NASDAQ-NMS firms, but even this relation (at least on average) seems to be of little economic significance.

Our findings are quite contrary to the old Wall Street adage that "it takes volume to move prices." Our investigation can be viewed as a *direct* test of the Mixture of Distribution Hypothesis (MDH), which asserts that volatility and volume are positively correlated *only* because both are positively related to the number of daily information arrivals (the mixing variable). With a fixed number of traders who all trade a fixed number of times in response to new information, the number of daily transactions will be proportional to the number of information arrivals [see, for example, Clark (1973) Harris (1987) and Tauchen and Pitts (1983)]. Therefore, the volatility-volume relation should be rendered statistically insignificant when volatility is conditioned on the number of transactions as well.[5] Although the MDH interpretation of our findings is valid, it is unappealing from an "economic" standpoint. The MDH is primarily statistical in nature; it does not provide any insights into the (equilibrium) economic behavior of agents which, in turn, affects volume and volatility of stock returns.

From an economic standpoint, our results are quite intriguing. The

[5] Similarly, Ross (1989) shows that the variance of price changes is directly related to the rate of Row of information and, under certain conditions, the two are identical. Our results suggest that the number of daily transactions, and not volume, may be the more appropriate measure of the rate of flow of information.

Based on a sample of 50 NYSE stocks sampled over the period from December 1, 1981, to January 31, 1983, Harris (1987) also shows that daily transaction count may be a useful instrumental variable for the number of information events. However, the investigation by Harris (1987) only tests whether the MDH can explain the characteristics of the distribution of security returns (namely, the non-normality of returns and the autocorrelation in returns and squared returns).

Also, just before this paper went to press, Terry Marsh made us aware of an interesting and related finding in Marsh and Rock (1986). They find that net number of trades (i.e., number of seller-initiated minus buyer-initiated trades) explains as much (if not more), as does net volume, of even the *level* of percentage changes in bid-ask prices in separate regressions of the latter on the (former) two variables. This finding suggests that both changes in returns and their volatility are more strongly related to number of trades, as opposed to volume, even though the former "throws away" information contained in the latter.

fact that volume, or the size of trades, has virtually no marginal explanatory power vis a vis changes in absolute prices seems surprising given that the size of trades is positively correlated with the quality (or precision) of information of informed traders in competitive models of trading. Also, in more realistic models of strategic behavior that allow for imperfect competition among multiple informed traders there is aggressive trading of large quantities by them [see Holden and Subrahmanyam (1992)].

Two recent articles by Easley and O'Hara (1990) and Harris and Raviv (1993), however, do highlight the role of number of trades in the determination of asset prices. Easley and O'Hara (1990) develop a market microstructure model that explicitly incorporates the role of time in the price-adjustment process. In their model, total number of trades is informative with respect to price changes because both trades and a *lack of trades* are informative to the market maker. Using a different approach, Harris and Raviv (1993) also show that the number of trades will be positively correlated with absolute price changes. They assume that all traders receive the same information but differ in the way in which they interpret this information. Specifically, all traders agree on whether a particular piece of information is favorable or unfavorable but disagree on the extent to which the information is important. Trading in their models occurs if, and only if, cumulative information for a particular type of trader switches from favorable to unfavorable or vice versa.

Both the articles by Easley and O'Hara (1990) and Harris and Raviv (1993), therefore, explicitly demonstrate that the number of transactions will be positively related to absolute price changes. However, neither of these models can completely "explain" our evidence because in both of these models (presumably for tractability reasons) all trades are standardized to be of unit size. Therefore, in the context of these models we cannot distinguish between volume (or size of trades) and frequency of trades, and hence we cannot address the issue of why the size of trades typically has no information content beyond that contained in the number of transactions. Our results suggest that theoretical models need to endogenize both the frequency and size of trades. Perhaps a more nontrivial task is to explicitly parameterize scenarios in which the number of trades contains all the information relevant to the pricing of securities, with the size of trades containing little or no additional information.

Appendix: Calculation of Standard Errors

In this Appendix, we describe the procedure used to calculate the standard errors of the cross-sectional means of the estimated regression coefficients of (2a)-(2c). In calculating the standard errors, we take into account any cross-sectional correlation in the individual-firm regression coefficient estimators. Our procedure, however, is not necessarily efficient because it is based on ordinary least squares estimates of individual-firm regression parameters. As explained below, we found it infeasible to obtain the efficient seemingly unrelated regression estimates of the regression coefficients.

Consider the general regression for security m ($m = 1, \ldots, M$):

$$y_m = X_m\beta_m + \eta_m \tag{A1}$$

where y_m is the (1450×1) vector of volatilities (or $|\epsilon_t|$'s) and X_m is the (1450×16) matrix of independent variables for each security in (2c) (including the 12 lagged dependent variables).

Let us assume that each security m's errors, η_m, follow standard OLS properties, that is, $E(\eta_m) = 0$ and $E(\eta_m\eta'_m) = \sigma^2_m I$. However, since the returns of individual securities are measured over the same calendar intervals, the errors of the individual-security regressions (2a)-(2c) are likely to be contemporaneously correlated. Following Zellner (1962) let us, therefore, assume that

$$E(\eta_{mt}\eta_{ns}) = \sigma_{nm} \qquad \text{if } t = s \text{ and 0 otherwise.}$$

The "stacked" regression for all M securities then becomes

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & & X_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_M \end{bmatrix} \tag{A2}$$

where $E(\eta\eta') = \Omega = \Sigma \otimes I$.

We estimate (A2) using OLS, which provides consistent estimators. The sampling distribution of $\hat{\beta}_{OLS}$ is given by [see Greene (1990)]

$$E(\hat{\beta}_{OLS}) = \beta$$

and

$$\mathrm{Var}(\hat{\beta}_{OLS}) = (X'X)^{-1}(X'\Omega X)(X'X)^{-1}.$$

Let $\hat{\theta}$ be the vector of cross-sectional means of the OLS estimates $\hat{\beta}_m$, that is, $\hat{\theta} = 1/M \sum_{m=1}^{M} \hat{\beta}_m$. The OLS estimator of the cross-sectional mean, $\hat{\theta}$, is also a consistent estimator of θ, and its variance is given by

$$\mathrm{Var}(\hat{\theta}) = \frac{1}{M^2}(1 \otimes I)'(X'X)^{-1}(X'\Omega X)(X'X)^{-1}(1 \otimes I) \tag{A4}$$

where 1 is a suitably defined vector of ones.

To calculate $\mathrm{Var}(\hat{\theta})$ we need to estimate Ω, or equivalently 2. Given the OLS regressions, the elements of Σ can be estimated as

$$\hat{\sigma}_{mn} = \hat{\eta}'_m \hat{\eta}_n / (T - k)$$

where $T - k$ are the degrees of freedom in the OLS estimation.

Although the derivation of the above variance-covariance matrices is straightforward, our large sample size makes their computation tedious. For example, the matrices $X'X$ and $X'WX$ in the stacked regression (2c) are each of dimension 2720 × 2720 because we have 16 independent variables for approximately 170 firms in each portfolio.

To manipulate these large matrices, we utilize the unique properties of their structure to estimate the variance of $\hat{\theta}$ in (A4). Specifically, since $\Omega = \Sigma \otimes I$, and using the block diagonality of the $X'X$ matrix, the variance-covariance matrix of β_{OLS} in (A3) can be rewritten as

$$\begin{bmatrix} (X_1'X_1)^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & (X_M'X_M)^{-1} \end{bmatrix} \begin{bmatrix} \sigma_{11}X_1'X_1 & \cdots & \sigma_{M1}X_1'X_M \\ \vdots & \ddots & \vdots \\ \sigma_{1M}X_M'X_1 & \cdots & \sigma_{MM}X_M'X_M \end{bmatrix}$$
$$\times \begin{bmatrix} (X_1'X_1)^{-1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & (X_M'X_M)^{-1} \end{bmatrix} \tag{A5}$$

and multiplication of these partitioned matrices yields

$$\begin{bmatrix} \sigma_{11}(X_1'X_1)^{-1} & \cdots & \sigma_{M1}(X_1'X_1)^{-1}(X_1'X_M)(X_M'X_M)^{-1} \\ \vdots & \ddots & \vdots \\ \sigma_{1M}(X_M'X_M)^{-1}(X_M'X_1)(X_1'X_1)^{-1} & \cdots & \sigma_{MM}(X_M'X_M)^{-1} \end{bmatrix}. \tag{A6}$$

Define V_{kl} as the $(k, l)th$ subblock given by

$$\sigma_{kl}(X_l'X_l)^{-1}(X_l'X_k)(X_k'X_k)^{-1} \tag{A7}$$

and $V_{kl}(i, j)$ as the $(i, j)th$ element of this subblock.

Fortunately, the structure of Var $(\hat{\theta})$ is such that we can exploit the above partitioning. A similar partitioning of the $1 \otimes I$ matrix and a simplification of quadratic form in (A4), though tedious, reveals that the estimator of the variance of a particular cross-sectional mean, that is, Var$(\hat{\theta}_i)$, is equal to the average of the $(i, i)th$ elements of each of the M^2 subblocks above. More formally,

$$\mathrm{Var}(\hat{\theta}_i) = \frac{1}{M^2} \sum_{k=1}^{M} \sum_{l=1}^{M} V_{kl}(i, i). \tag{A8}$$

Therefore, the computational task, though nontrivial, is feasible. In particular, to calculate the diagonal elements of Var $(\hat{\theta})$, which are reported in the article, we separately calculate each subblock of $\hat{\beta}_{OLS}$ and average the diagonals across all of the subblocks. Although this procedure requires substantial computer time, the memory requirements are low because all matrix manipulations are performed on 16 × 16 matrices.

Note that our technique for calculating the standard errors of the cross-sectional means of individual-firm regression coefficients takes into account cross-sectional correlation between the coefficient estimators. However, since our technique is based on OLS it is not necessarily efficient [see Zellner (1962)]. Unfortunately, efficient joint generalized least squares (GLS) estimation is not feasible in the context of our study.

Recall that the joint GLS or SUR estimator of the set of *M* regression coefficients is given by

$$\hat{\beta}_{GLS} = (X'\Omega^{-1}X)^{-1}X'X'\Omega^{-1}y \tag{A9}$$

and the feasible GLS estimator simply involves replacing Ω by $\hat{\Omega}$ in (A9). Similarly, the variance-covariance matrix of b_{GLS} is given by

$$\mathrm{Var}(\hat{\beta}) = (X'\Omega^{-1}X)^{-1} \tag{A10}$$

where $\Omega^{-1} = \Sigma^{-1} \otimes I$.

The $(X'\Omega^{-1}X)$ matrix featuring in both (A9) and (A10) can be partitioned into subblocks as

$$\begin{bmatrix} \sigma^{11}X_1'X_1 & \sigma^{21}X_1'X_2 & \cdots & \sigma^{M1}X_1'X_M \\ \sigma^{12}X_2'X_1 & \sigma^{22}X_2'X_2 & \cdots & \sigma^{M2}X_2'X_M \\ \vdots & \vdots & & \vdots \\ \sigma^{1M}X_M'X_1 & \sigma^{2M}X_M'X_2 & \cdots & \sigma^{MM}X_M'X_M \end{bmatrix} \tag{A11}$$

where s^{ij} is the *(i, j)th* element of Σ^{-1}.

Since the off-diagonal subblocks in (A11) are in general nonzero, we no longer have the simplifying structure of the OLS estimation. Consequently, there is no alternative to inverting the stacked matrix design, which is equivalent to inverting a (2720 × 2720) matrix for (2c). We found this task infeasible on our 3090 IBM mainframe. Consequently, we could not obtain GLS estimates and the standard errors of the individual-security regression coefficients. And we also could not *jointly* test the hypothesis that the coefficients of a particular regressor (average trade size or number of transactions) are simultaneously equal to zero for all securities in a particular portfolio.

Although SUR estimation is not feasible, the relative gains in efficiency from this procedure are unlikely to be large because the cross-sectional correlations in the residuals of Regression (2c) are small. Specifically, the average pairwise correlations between the OLS residuals of individual securities range between 0.059 for the smallest portfolio to a high of 0.112 for the largest portfolio. We believe that heteroskedasticity, on the other hand, is a pervasive phenomenon both at the individual-security and portfolio levels [see, for example, Lamoureaux and Lastrapes (1990) and Schwert (1990)]. Consequently, we include 12 lagged $|\hat{\epsilon}_{it}|$'s in Regression (2c) for each security to correct for any persistence in volatility.

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