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Volume autocorrelation, information, and investor trading

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Abstract

This study investigates whether the widely documented daily correlated trading volume of stocks is driven by individual investor trading, institutional trading, or both. We find that at least 95% of NYSE and AMEX stocks exhibit statistically significant, positive serial correlation. Volume autocorrelation decreases with the level of institutional ownership of a stock. We also show that the rate of arrivals of new information to the market contributes to the clustering of trades. When there is high information flow to the market, institutional trading generates a more pronounced effect on volume autocorrelation than individual investor trading. Our results are broadly consistent with the predictions of trading volume patterns suggested by most theoretical models of stock trading and by empirical research on investor trading.

JEL classification: G12; G14; G20
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1. Introduction

It is widely documented that the volume of trading in stocks exhibits high serial correlation. Gallant et al. (1992) report that daily trading volume on the S&P

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composite stock index displays strong serial correlation. Subsequent studies such as Campbell et al. (1993) and LeBaron (1992) also obtain similar results. Campbell, Grossman, and Wang use time series of daily volume data on the value-weighted CRSP index and the 30 stocks in the Dow Jones index, while LeBaron looks only at the Dow Jones index. Even though the volume data on individual securities have been extensively employed in numerous recent studies, there is little empirical research that offers reasons why daily trading volume displays such behavior. The goal of this study is to provide an exploratory investigation of this commonly observed volume phenomenon. Specifically, we investigate whether the clustering of daily trading volume arises because of individual investor trading, institutional trading, or both.

Several theoretical and empirical results imply that trading by institutional investors drives daily correlated trading volume. Dynamic trading models such as Admati and Pfleiderer (1988), Foster and Vishwanathan (1990), Kyle (1985), and Wang (1994) show that informed traders tend to strategically split their trade into smaller quantities across time in order to prevent their private information from being revealed too quickly. However, Back et al. (2000) argue that the rate at which information is revealed to the market depends on the number of informed traders and the correlation of their signals. The authors show that aggregate trading is less intense and the information is revealed to the market less quickly when there are multiple (competing) informed traders with diverse information than when there are competing traders with identical information. Such stealth trading with multiple informed traders having diverse information is evident in institutional trades. For example, Chan and Lakonishok (1995) report that more than half the dollar value of institutional trades take at least four days to complete. Keim and Madhavan (1995) find that larger-sized institutional buy orders tend to involve longer durations than equivalent sell orders. These two studies show that stealth trading helps to reduce execution costs. If institutions are more likely to be informed traders, [1] then these results imply that stealth trading by institutions is likely to induce volume autocorrelation in stocks.

Based on a multiperiod trading model, He and Wang (1995) argue that the observed correlated trading-volume pattern reflects the flow and nature of information. Arrivals of new public information generate the clustering of trades when the flow of public information to the market is serially correlated. Conversely, arrivals of new private information, even if the arrivals are independent, generate trading in the current as well as future periods. This is because investors who acquire private information tend to gradually increase or unwind their stock positions to conceal information. It is therefore reasonable to interpret that public information influences the trading behavior of both individual and institutional investors, whereas private information mainly influences the trading behavior of institutional investors, who are more likely to trade strategically in order to hide their large scale informed

[1] Sias et al. (2001) provide evidence that institutions trade because they have superior information.

trades. Thus, we predict that *on average* across both private and public information events, trading by institutional investors will generate stronger autocorrelated trades.

Theoretical results shown in Romer (1993) and Cao et al. (2002) also imply that revelation of information by investors can generate autocorrelated trades. In his model, Romer assumes that an investor must pay a cost to trade immediately based on private information, or to delay and then trade for free. He shows there is little incentive for the investor to trade immediately; as a result, information gets revealed to the market slowly, thereby generating autocorrelated trades. In a model with fixed setup costs of trading, Cao, Coval, and Hirshleifer show that 'sidelined' investors have relevant information about the stock, but may delay trading until price movements confirm the information these investors possess. They assert that such investor trading induces autocorrelation in order flow. But their model does not identify the investor classes that carry the most sidelined information to the market. While individual investors face greater transaction costs, institutional investors seem to be more concerned about transaction costs. We therefore argue that institutional investors are the sidelined investors driving volume autocorrelation. In fact, our argument is in line with our findings below, which indicate a stronger relation between volume and lagged absolute return in stocks with greater institutional ownership.

Finally, studies such as Grinblatt et al. (1995), Lakonishok et al. (1992), and Wermers (1999) also support the prediction that institutional investor herding and positive feedback trading (selling past losers and buying past winners) contribute to volume autocorrelation in individual securities. Also, a recent study by Dennis and Strickland (2002) shows that these trading strategies are more pronounced when there are large market price swings.

In summary, the main empirical implication of these studies is that correlated trading by institutional investors, as a group, may contribute to autocorrelation in the trading volume of individual stocks, and this volume autocorrelation should be positively related to the flow of new (private and public) information. Also, volume autocorrelation may be more pronounced around high market volatility.

On the other hand, recent empirical results obtained by Barber and Odean (2001) suggest that individual investor trading may contribute to correlated volume of trading. They find that individual investors are attention-based buyers of stocks and their buying decisions are based on three factors: abnormal trading volume, news release, and extreme price moves. If individual investors' attention-buying drives volume autocorrelation, then (a) stocks held primarily by individual investors should exhibit greater volume autocorrelation and (b) the relation between volume autocorrelation and lagged absolute returns should be greater for stocks held by individual investors.

Thus, a priori, it is difficult to predict the source of the observed correlated volume phenomenon. Both predictions (whether institutional trading or individual investor trading drives the volume phenomenon) seem equally probable. We, therefore, let the data bear out the prediction.

For this study, we use the institutional holdings data from CDA Investment Technologies, Inc. to determine the level of institutional ownership in each stock. We then classify stocks with no or low institutional ownership as stocks that are mainly owned by individual investors and those with high institutional ownership as stocks that are primarily held by institutional investors. Our results provide substantial evidence of positive serial correlation in daily trading volume of all individual stocks, traded on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). About 95% of the volume autocorrelation coefficients are statistically significant at conventional levels. We find that when there is no arrival of new information, stocks that are predominantly held by individual investors induce a higher correlated volume than those that are primarily owned by institutions. In contrast, however, during periods of high information flow, institutional trading produces greater clustering of trades than individual investor trading. These results are also found to be robust to variations of the time-series dynamic model that we suggest. In summary, our evidence that correlated trading by institutional investors contributes to daily volume autocorrelation is consistent with the trading volume patterns suggested by most theoretical models of stock trading and by empirical research on institutional trading behavior.

The rest of the paper is organized as follows. In Section 2, we describe the data that we employ in this study. Section 3 presents a simple dynamic model of trading volume. In the same section, we empirically analyze whether the type of investor trading drives autocorrelation in stock trading volume. In Section 4 we perform various robustness checks of the results. Section 5 concludes the paper.

2. Data description

This study employs two data sets: institutional holdings data from CDA Investment Technologies, Inc., a service company engaged by the SEC to process and maintain 13(f) filings, and daily stock data from the Center for Research in Security Prices (CRSP). Since we only have institutional holdings data from March 1986 to June 1998, we use the CRSP stock data for the same sample period. The description of the information that we use from the data sets is detailed below.

2.1. Institutional equity holdings

Large institutional investment managers are required under Section 13(f) of the Securities Exchange Act of 1934 to file information about the equity holdings under their investment discretion to the SEC. In 1979, the revised 13(f) rule requires that institutional managers who exercise investment discretion over $100 million in equity securities file the information prescribed by form 13F with the SEC, quarterly. The originally proposed rule required the form to be filed annually, but since 1979 the final version of the rule has required quarterly filings. The reporting threshold encompasses various types of institutional managers such as banks, investment companies, pension funds, insurance companies, and brokerage houses. The reports contain information about equity holdings of reporting managers and the type of investment discretion they and their other investment managers exercise with respect to those securities.

Our study uses institutional holdings of common stocks traded on the NYSE and AMEX. We therefore exclude stocks traded on NASDAQ, ADRs, foreign stocks, closed-end funds and REITs from the sample. As required by the SECs form 13F, all common stock positions of these institutions greater than \$200,000 or 10,000 shares must be reported quarterly. To implement the tests in this study, we need to calculate the fraction of shares of a stock owned by all institutions relative to the total number of outstanding shares. We assume that stocks with no or low institutional holdings would capture the trading patterns of individual investors, while stocks with high institutional holdings would capture those of institutions.

2.2. Trading volume of individual stocks

We avoid the averaging effect of using portfolios of securities or indexes by focusing on daily data of individual stocks. To ensure stability of stock-specific characteristics throughout the testing period, we split the entire sample period into four equal subperiods: (i) July 1986 to June 1989, (ii) July 1989 to June 1992, (iii) July 1992 to June 1995, and (iv) July 1995 to June 1998. Using a 3-year period helps not only to maintain stability in the stock parameters, but also to reduce variation in the market capitalization and the level of institutional ownership of each stock within the period. We also experimented with a longer sample period of 6 years. The results, while less pronounced, did not differ substantially from those reported here. But it is worthwhile to point out that the market capitalization and ownership distribution of the stocks did change quite significantly between the two sample periods. For example, we observed that many of the stocks moved from the smaller (larger) to the larger (smaller) size portfolios. [2] In their study, Chan and Chen (1991) show that 66% of the NYSE firms have fallen from the higher quintiles and about 20% of the firms in the top quintile have moved up from the lower quintiles. This makes it difficult for one to control for the size of the stocks if a longer sample period were used.

For each 3-year period, we exclude only stocks that have at least a month of continuous missing observations. As a result, each 3-year sample period has an average of about 2080 stocks. We compute daily turnover, market capitalization of the stock (market price multiplied by the number of shares outstanding as of the end of June), and institutional holdings for all individual stocks across the four sample periods. As in existing studies such as Campbell et al. (1993) and Llorente et al. (2002), our analysis uses turnover as a proxy for trading volume of individual stocks. [3] The turnover of a stock is measured by the number of shares traded at a given day relative to the number of shares outstanding. Following the two studies, we detrend the log of turnover. Thus, the daily volume series v_{it} of each stock is given by [4]

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[2] We examined the variation in the market capitalization of stocks by examining the movement of a stock's membership across five size-ranked portfolios.

[3] We also employed alternative measures of volume such as log of dollar volume and average number of shares traded daily, and our results were virtually the same as those reported in this paper.

[4] We performed the augmented Dickey–Fuller test on the detrended series and found the series to be stationary.

$$v_{i,t} = \text{logturnover}_{i,t} - \frac{1}{200}\sum_{s=1}^{200}\text{logturnover}_{i,t-s}$$

where

$$\text{logturnover}_{i,t} = \log(100 \cdot \text{turnover}_{i,t} + 0.000255).$$

Notice that the measure of detrended series includes a small constant (0.000255). The reason is that since stocks often have zero daily trading volume, the constant term is added to the series before taking logs. [5] Therefore, throughout this analysis, the detrended turnover is employed as a proxy for trading volume, unless otherwise stated.

To gauge the cross-sectional stock characteristics, we sort all the stocks into five quintiles based on institutional ownership, with each quintile having the same distribution of market capitalization. The construction of the five portfolios that we use throughout our analysis is as follows. As of June of each 3-year estimation period, we assign all stocks into five quintiles according to their market capitalization. Within each size-ranked quintile, we further divide the stocks into five equal groups based on the institutional ownership of the stock as of June of each 3-year period. For instance, we use June of 1986 as the sorting month for the testing period of July 1986 to June 1989. We deliberately avoid using December as the month for sorting stocks so as to ensure that our results are not driven by the January effect or the turn-of-the-year effect. Then we stratify the resulting 25 portfolios into five quintiles based on the fraction of institutional ownership, with each quintile having the same distribution of market capitalization. For ease of discussion, we label them institutional holding-ranked quintiles. The bottom quintile consists mainly of stocks with lowest institutional holdings; such stocks are primarily owned by individual investors. In contrast, the top quintile consists of stocks with largest institutional ownerships and these stocks are predominantly held by institutional investors.

Table 1 contains the time-series cross-sectional daily mean, median, and standard deviation of stock turnover (in percent), detrended log turnover, market capitalization, and institutional ownership (in fraction) for all of the stocks within each institutional holding-ranked quintile. Average daily turnover increases monotonically across holding-ranked quintiles, ranging from 0.22% (the bottom quintile of stocks that are predominantly held by individual investors) to 0.29% (the top quintile of stocks that are predominantly held by institutional investors). This observation is not surprising, given the increasingly growing dominance of institutions in US markets over the past decade, [6] and their trading accounts for at least 70% of the daily trading volume on the NYSE. [7] Note that with the same distribution of market

[5] As noted in Llorente et al., the value of the constant is chosen to maximize the normality of the distribution of daily trading volume.

[6] See Gompers and Metrick (2001).

[7] See Schwartz and Shapiro (1992).

Table 1
Descriptive statistics on daily volume, market capitalization, and institutional ownership of individual stocks across institutional holding-ranked quintiles

Ranked by institutional holdings	Percentage of shares traded	Detrended log turnover (in %)	Market capitalization ($million)	Institutional ownership (fraction)
Individuals				
Mean	0.218	−0.001	971.97	0.003
Median	0.187	−0.002	184.32	0.000
Standard deviation	0.175	0.084	2308.16	0.013
Quintile 2				
Mean	0.235	−0.001	1337.23	0.139
Median	0.214	−0.002	183.58	0.128
Standard deviation	0.184	0.085	4479.33	0.111
Quintile 3				
Mean	0.259	−0.001	1628.95	0.277
Median	0.238	−0.001	181.24	0.280
Standard deviation	0.188	0.076	5595.71	0.149
Quintile 4				
Mean	0.271	0.002	1261.39	0.386
Median	0.254	0.001	194.44	0.419
Standard deviation	0.194	0.073	3342.31	0.165
Institutions				
Mean	0.286	0.002	962.32	0.540
Median	0.261	0.001	235.55	0.586
Standard deviation	0.191	0.068	1904.30	0.173

This table summarizes the mean, median, and standard deviation of daily volume, market capitalization, and institutional ownership for individual stocks, which are ranked by institutional holdings. At the end of each 3-year period, starting from June 1986, all stocks traded on the NYSE and AMEX are assigned to five quintiles based on institutional ownership of the stock, with each quintile having the same distribution of market capitalization. 'Percentage of shares traded' is the percentage of daily average number of shares traded relative to the total number of outstanding shares. In the 'Detrended log of turnover', turnover is defined as the ratio of the daily number of shares traded to the number of outstanding shares during the sample period. 'Market capitalization' is computed by multiplying the number of shares outstanding by the market price as of the beginning of the 3-year period. 'Institutional ownership' is defined as the fraction of shares owned by 13f institutional investors at the end of each quarter. The entire sample period is from July 1986 to June 1998.

capitalization, the five holding-ranked quintiles display no systematic pattern in the mean and median values of their size. [8]

Finally, the table indicates that the average fraction of institutional ownership varies from 0.3% in the bottom quintile to 54% in the top quintile. Thus, the results suggest that individual investors on average hold about 99.7% of the stocks in the smallest holding-ranked quintile, whereas institutional investors on average own about 54.0% of the largest holding-ranked quintile. Using these two extreme

[8] For verification, we performed tests for equality of market capitalization across the five quintiles and we could not reject the null that they are equal.

quintiles will certainly help to delineate the difference, if any, in the trading behavior of individual versus institutional investors.

3. Correlated volume and investor trading

In this section, we propose a simple parsimonious model to capture the dynamics of trading volume in individual stocks. We show how the model is modified in a manner that will allow us to conduct tests of whether trading by individual investors, or trading by institutions, contributes to the observed correlated trading volume. We then proceed to discuss the estimation results.

3.1. A simple dynamic model

To start, we consider a first-order autoregressive process for daily trading volume: [9]

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + \epsilon_{i,t+1}, \tag{1}$$

where $v_{i,t+1}$ represents the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies used to capture differences in mean trading volume (see, for example, Gallant et al., 1992), and $\epsilon_{i,t+1}$ is the error term. The coefficient $a_{1,i}$ measures the degree of autocorrelation in trading volume for each stock.

To test whether the arrival of information contributes to the clustering of trades, we expand (1) to take the form

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} f_{i,t} + \epsilon_{i,t+1}, \tag{2}$$

where $f_{i,t}$ is the rate of information flow. If the flow of new public and private information induces the clustering of trading volume, then the coefficient of $a_{2,i}$ in (2) will be statistically significant. In contrast to $a_{1,i}$ that captures the constant component of volume autocorrelation, $a_{2,i}$ measures the effect on volume autocorrelation that varies with the level of information flow.

To implement the test, we need to define a measure for information flow. Extant studies have shown that the variance of asset returns reflects the arrival of information and the extent to which the market evaluates and assimilates new information. Ross (1989) shows that in a no-arbitrage economy the variance of returns is directly related to the rate of flow of information to the market. Engle et al. (1990) attribute

[9] In our preliminary analysis, we also estimated an autoregressive model with five lags in order to capture the day-of-the-week effect. We found consistently strong evidence of first-order autocorrelation in trading volume, while the significance of the coefficients on the other four lags was, however, sporadic across individual stocks. Thus we chose to focus and report only results from the first-order autoregressive model.

movements in variance to the time needed for market participants to process new information or in policy coordination. Other studies such as Clark (1973), Lamoureux and Lastrapes (1990), and Laux and Ng (1993) also establish a linkage between price volatility and the rate of information arrivals to the market. Drawn from the substantial empirical evidence in the literature, this study employs the absolute value of daily return as a proxy for the flow of new information to the market. To incorporate this measure of information flow, we re-express (2) as

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + \epsilon_{i,t+1}, \tag{3}$$

where $|r_{i,t}|$ denotes the absolute value of the stock return at time t. Given that this measure does not allow us to distinguish between private and public information, or between new and existing private information, our test shall only look at the effects of general information shocks on correlated trading volume.

3.2. Empirical evidence

3.2.1. Effects of investor trading

Table 2 presents estimates of regression (1) across the five institutional holding-ranked quintiles. Specifically, it contains the time-series cross-sectional distribution of coefficient estimates of the lagged trading volume for all individual securities within each quintile during the four estimation periods. It reports mean values of $\hat{a}_{1,i}$ together with their average standard deviations and the numbers of significant and non-significant positive and negative $\hat{a}_{1,i}$ coefficients. All statistics are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. [10] The average $\bar{R}^2$ value ranges from 11% to 13% across the five quintiles.

The most notable observation in Table 2 is that all of the individual stocks across quintiles exhibit positive serial correlation in trading volume. About 95% of the stocks within each quintile portfolio display statistically significant serial correlation in their detrended turnover. The average coefficient of $\hat{a}_{1,i}$ decreases monotonically from 0.34 for stocks in the bottom holding-ranked quintile to 0.30 for stocks in the top holding-ranked quintile. Our strong evidence of volume autocorrelation exhibited in individual stocks is in accord with the existing findings that are mainly based on aggregate stock indexes.

More importantly, the table reports a 0.04 (t-statistic = 9.7) difference in the mean $\hat{a}_{1,i}$ coefficients between the top and bottom quintiles of stocks, and this difference is statistically significant at the 5% level. The result therefore suggests that the average volume autocorrelation coefficient for stocks predominantly held by individual investors is greater than that for stocks predominantly owned by institutional managers. We interpret this finding to be consistent with the "attention-based" trading behavior of individual investors. Our results therefore imply that stocks with abnormally high volume of trading will continue to have high volume, and those with

[10] Throughout this study, we employ the Newey–West autocorrelation test with five lags.

Table 2
Serial correlation patterns in daily trading volume of individual stocks across institutional holding-ranked quintiles

	Mean	SD	N^{S}	N^{NS}	# of obs.	$\bar{R}^2$
Distribution of $\hat{a}_{1,i}$						
Individuals	0.336	0.128	1623(0)	37	1660	0.13
Quintile 2	0.323	0.134	1582(0)	78	1660	0.12
Quintile 3	0.313	0.119	1569(0)	91	1660	0.11
Quintile 4	0.311	0.119	1586(0)	74	1660	0.11
Institutions	0.295	0.110	1574(0)	86	1660	0.11
(Individuals – Institutions)	0.041					
	(9.72)					

The table shows the distribution of the first-order autocorrelation coefficients estimated from the following regression:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + \epsilon_{i,t+1},$$

where $v_{i,t+1}$ is the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies used to capture differences in mean trading volume, and $\epsilon_{i,t+1}$ is the error term. The regression estimates are obtained, separately, for four 3-year sample periods: 86:07–89:06; 89:07–92:06; 92:07–95:06; and 95:07–98:06. The construction of institutional holding-ranked quintiles is given in Table 1. The table shows the distribution of $\hat{a}_{1,i}$ across the four time-series cross-sectional regressions and also the difference in the means of $a_{1,i}$ between the smallest- and largest-institutional holding quintiles, with the t-statistic in parentheses. All statistics are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. N^{S} denotes the number of significant positive coefficients at the 5% level, while those in parentheses indicate the significant negative ones. N^{NS} is the number of insignificant coefficients. $\bar{R}^2$ represents the average adjusted R-squared value.

abnormally low volume of trading will persist to have low volume. Given that individual investors, on average, own about 99.7% of the stocks in the bottom quintile, it is not surprising to find more clustering of trades in this quintile than in the top quintile.

3.2.2. Investor trading and flow of information

Table 3 (Panels A and B) report the time-series cross-sectional distribution of coefficient estimates of the lagged trading volume ($\hat{a}_{1,i}$) and of the interaction between the lagged trading volume and absolute value of lagged return ($\hat{a}_{2,i}$), respectively. [11] As in Table 2, they report mean values of the coefficients together with their average standard deviations, and the numbers of significant and non-significant positive and negative $\hat{a}_{1,i}$ and $\hat{a}_{2,i}$ coefficients. The two panels also present the test statistics for the mean difference of the coefficients on $\hat{a}_{1,i}$ and on $\hat{a}_{2,i}$ between the top and bottom quintiles.

[11] We also re-estimated the results in Table 3, together with the subsequent tables reported in this study, by standardizing the variables, and the results were qualitatively similar to the ones reported in the paper.

Table 3
The effect of information flow on correlated trading of individuals versus institutions

	Mean	SD	N^{S}	N^{NS}	% of Obs.	$\bar{R}^2$
Panel A: Distribution of $\hat{a}_{1,i}$						
Individuals	0.270	0.127	1592(0)	68	1660	0.14
Quintile 2	0.256	0.133	1562(0)	98	1660	0.13
Quintile 3	0.246	0.120	1564(0)	96	1660	0.13
Quintile 4	0.244	0.119	1556(0)	104	1660	0.12
Institutions	0.236	0.111	1569(0)	91	1660	0.11
(Individuals – Institutions)	0.033					
	(8.11)					
Panel B: Distribution of $\hat{a}_{2,i}$						
Individuals	2.939	2.820	1229(10)	421	1660	
Quintile 2	3.358	2.971	1153(7)	500	1660	
Quintile 3	3.826	2.763	1130(6)	524	1660	
Quintile 4	3.913	2.573	1178(8)	474	1660	
Institutions	4.113	2.538	1127(9)	524	1660	
(Individuals – Institutions)	−1.174					
	(−12.61)					

The table shows the distribution of the slope coefficients from the following regression:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + \epsilon_{i,t+1},$$

where $v_{i,t+1}$ is the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies used to capture differences in mean trading volume, $|r_{i,t}|$ denotes the absolute return on the stock at time t, and $\epsilon_{i,t+1}$ is the error term. The regression estimates are obtained, separately, for four 3-year sample periods: 86:07–89:06; 89:07–92:06; 92:07–95:06; and 95:07–98:06. The construction of institutional holding-ranked quintiles is given in Table 1. The table shows the distribution of the estimates across the four time-series cross-sectional regressions. All statistics are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. N^{S} denotes the number of significant positive coefficients at the 5% level, while those in parentheses indicate the significant negative ones. N^{NS} is the number of insignificant coefficients. $\bar{R}^2$ represents the average adjusted R-squared value.

The results in Panel A are broadly consistent with those reported in Table 2 with one exception. The magnitude of the autocorrelation coefficients $\hat{a}_{1,i}$'s has reduced, on average, by about 20% across the five quintiles. For example, the mean values of $\hat{a}_{1,i}$ are 0.24 (the top quintile) and 0.27 (the bottom quintile), as compared to 0.30 and 0.34 in Table 2, respectively. However, similar to the evidence presented in Table 2, the mean difference in $\hat{a}_{1,i}$ of 0.03 (t-statistic = 8.1) between the top and bottom quintiles remains statistically significant. The number of significant positive volume autocorrelation coefficients within each quintile, on average, has fallen only marginally by about 1%. The adjusted R-squared values are slightly greater than those reported in Table 2, varying between 11% and 14%. Thus, introducing the proxy for information arrivals in regression (1) mitigates the magnitude of $\hat{a}_{1,i}$ coefficient, but only marginally affects its level of statistical significance.

In contrast to Panel A, Panel B of Table 3 shows a lower percentage of significant positive coefficients on $\hat{a}_{2,i}$. About 71% of the $\hat{a}_{2,i}$ estimates are statistically significant at the 5% level. The time-series cross-sectional mean coefficient of $\hat{a}_{2,i}$ increases, while $\hat{a}_{1,i}$ decreases, monotonically from the bottom to the top quintile. The mean values of $\hat{a}_{2,i}$ are 2.94 for stocks that are predominantly held by individuals and 4.11 for those that are mainly owned by institutions. Their difference of -1.17 (t-statistic $= -12.6$) is found to be statistically significant at conventional levels. As those on $\hat{a}_{1,i}$'s, the significant coefficients obtained on $\hat{a}_{2,i}$'s are mostly positive, with less than 1% being significantly negative; the number of significant negative coefficients is reflected in parentheses. It is evident that the flow of new information has a significantly positive effect on autocorrelated trades: the greater the rate of new informational arrivals, the more persistent is volume autocorrelation. Furthermore, the effect is stronger on volume of trades generated by institutional investors than by individual investors. The result is generally consistent with the "stealth trading" argument that institutions tend to split their trades into smaller quantities to conceal their private information.

Overall, the positive relation between volume autocorrelation and the absolute lagged stock return supports the prediction that arrivals of new information cause clustering in trading. During periods of no arrivals of new information, stocks with low institutional ownership display a higher serial correlation in daily volume, whereas during periods of high information flow, stocks with high institutional ownership produces a stronger volume autocorrelation.

4. Robustness checks

It can be argued that the preceding results could be driven by the correlation between volume and other independent variables that are not incorporated into our dynamic daily trading-volume model. For example, previous research has found evidence of significant relations between volume and the contemporaneous absolute stock return, and between volume and the lagged stock return. In this section, we subject our model to some robustness tests by examining the possible factors that may affect trading volume of stocks as well.

4.1. The endogeneity problem

One might argue that trading volume and the absolute return are endogenously related, and such a relationship can distort the contribution of the absolute stock return. To circumvent this problem, we first employ a principal component analysis to extract the common factor that affects both the trading volume and absolute return, and this common factor is employed as an instrumental variable in a two-stage least-square method. In the first stage, we regress volume on the common factor and then extract the resulting residuals, which measure the volume-specific information. In the second stage, we regress return on the resulting residuals from the first stage and derive the second-stage forecast error, which captures the proportion of the change in return that is not explained by the volume-specific information. We employ the absolute value of this second-stage forecast error as an alternative proxy for the flow of

Table 4
Alternative information flow proxy and correlated trading

	Mean	SD	N^{S}	N^{NS}	% of obs.	$\bar{R}^2$
Panel A: Distribution of $\hat{a}_{1,i}$						
Individuals	0.280	0.135	1570(0)	90	1660	0.14
Quintile 2	0.264	0.131	1552(0)	108	1660	0.13
Quintile 3	0.249	0.122	1560(0)	100	1660	0.13
Quintile 4	0.245	0.116	1543(0)	117	1660	0.12
Institutions	0.231	0.110	1555(0)	105	1660	0.11
(Individuals – Institutions)	0.049					
	(11.44)					
Panel B: Distribution of $\hat{a}_{2,i}$						
Individuals	2.979	2.870	1033(13)	614	1660	
Quintile 2	3.287	2.812	1019(9)	583	1660	
Quintile 3	3.647	2.566	1068(10)	582	1660	
Quintile 4	3.856	2.491	1064(8)	588	1660	
Institutions	4.023	2.422	1052(7)	601	1660	
(Individuals – Institutions)	−1.044					
	(−11.33)					

The table shows the distribution of the slope coefficients from the following regression:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r^{*}_{i,t}| + \epsilon_{i,t+1},$$

where $v_{i,t+1}$ is the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies used to capture differences in mean trading volume, $|r^{*}_{i,t}|$ is an information proxy estimated using a two-stage least square approach, and $\epsilon_{i,t+1}$ is the error term. The regression estimates are obtained, separately, for four 3-year sample periods: 86:07–89:06; 89:07–92:06; 92:07–95:06; and 95:07–98:06. The construction of institutional holding-ranked quintiles is given in Table 1. The table shows the distribution of the estimates across the four time-series cross-sectional regressions. All statistics are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. N^{S} denotes the number of significant positive coefficients at the 5% level, while those in parentheses indicate the significant negative ones. N^{NS} is the number of insignificant coefficients. $\bar{R}^2$ represents the average adjusted R-squared value.

new information, and using this proxy we re-estimate regression (3). Table 4 contains the results.

To summarize, using the alternative information proxy improves the number of statistically significant $\hat{a}_{1,i}$ by about 1% and the number of statistically significant $\hat{a}_{2,i}$ by about 6%. The size and order of magnitude of the two coefficients are generally consistent with those shown in Table 3.

4.2. The effect of absolute stock returns

Previous studies have provided strong evidence of a significant relation between volume and absolute stock returns. It is plausible that the statistically-significant interaction between volume autocorrelation and the lagged absolute stock return shown in the preceding section merely captures the relation between volume and the absolute return. To examine this possible effect, we incorporate a lagged absolute stock return in our earlier regression model (3), as follows:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + a_{3,i} |r_{i,t}| + \epsilon_{i,t+1}. \tag{4}$$

We also consider an alternative specification that expands Eq. (4) by incorporating a contemporaneous absolute stock return as well. [12] The model is given by

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + a_{3,i} |r_{i,t}| + a_{4,i} |r_{i,t+1}| + \epsilon_{i,t+1}. \tag{5}$$

Tables 5 and 6 contain the distributions of the slope coefficients in regressions (4) and (5), respectively. A few notable observations emerge from these two tables. The absolute lagged stock return plays very little role in the model. The adjusted R-squared values (see Table 5) are the same as those in Table 3, and on average, less than 15% of its coefficients, $\hat{a}_{3,i}$, are statistically significant across the five quintiles. In contrast, the coefficients on the contemporaneous absolute stock return, $\hat{a}_{4,i}$, are not only positive, but are strongly significant across almost all stocks.

Interestingly, adding contemporaneous and lagged absolute stock returns to the model has virtually no impact on the significance of volume autocorrelation, but has some impact on the effect of the interaction variable. In Table 6, we observe that the numbers of significant positive $\hat{a}_{2,i}$ coefficients reduce, on average, to about 40% across all quintiles, as compared to those reported in Table 3. The results show that on average stocks held mainly by individuals have the lowest $\hat{a}_{2,i}$ coefficient of 2.42 and those primarily owned by institutions have the highest of 3.22.

In summary, even in the presence of contemporaneous and lagged absolute stock returns, the relation between volume autocorrelation and lagged absolute stock return remains substantially significant. Thus, the results reinforce our earlier finding that information contributes to volume autocorrelation in stocks.

4.3. The role of small stocks

One might ask whether the results presented thus far are due largely to the role of small stocks. We take a simple approach to address this issue by regressing estimates of the coefficients, $a_{1,i}$ and $a_{2,i}$, from individual stocks against the level of their institutional ownership and the log of their stock market capitalization. [13] Table 7 contains the cross-sectional regression estimates for each 3-year period, with the t-statistics shown in parentheses.

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[12] We thank the referees for this suggestion.

[13] We computed the correlation coefficient between the level of institutional ownership and market capitalization to be about 0.4. The degree of correlation between these two variables did not seem high enough to cause any multicollinearity problem, and it is indicated in Table 7 as well.

Table 5
Information flow and correlated trading of individuals versus institutions, in the presence of lagged absolute stock return

	Mean	SD	N^{S}	N^{NS}	% of Obs.	$\bar{R}^2$
Panel A: Distribution of $\hat{a}_{1,i}$						
Individuals	0.278	0.130	1565(0)	95	1660	0.14
Quintile 2	0.269	0.134	1532(0)	128	1660	0.13
Quintile 3	0.256	0.123	1553(0)	107	1660	0.13
Quintile 4	0.252	0.121	1547(0)	113	1660	0.12
Institutions	0.245	0.113	1542(0)	118	1660	0.11
(Individuals – Institutions)	0.033					
	(7.78)					
Panel B: Distribution of $\hat{a}_{2,i}$						
Individuals	2.428	2.997	838(9)	813	1660	
Quintile 2	2.883	3.250	822(4)	834	1660	
Quintile 3	3.068	2.931	908(11)	741	1660	
Quintile 4	3.134	2.793	834(5)	821	1660	
Institutions	3.251	2.961	818(4)	838	1660	
(Individuals – Institutions)	−0.823					
	(−7.96)					
Panel C: Distribution of $\hat{a}_{3,i}$						
Individuals	1.218	3.653	209(36)	1415	1660	
Quintile 2	1.416	5.338	183(47)	1430	1660	
Quintile 3	1.121	4.605	180(38)	1442	1660	
Quintile 4	1.358	5.086	212(31)	1417	1660	
Institutions	1.412	5.257	267(23)	1370	1660	
(Individuals – Institutions)	−0.194					
	(−1.24)					

The table shows the distribution of the slope coefficients from the following regression:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + a_{3,i} |r_{i,t}| + \epsilon_{i,t+1},$$

where $v_{i,t+1}$ is the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies used to capture differences in mean trading volume, $|r_{i,t}|$ denotes the absolute return on the stock at time t, and $\epsilon_{i,t+1}$ is the error term. The regression estimates are obtained, separately, for four 3-year sample periods: 86:07–89:06; 89:07–92:06; 92:07–95:06; and 95:07–98:06. The construction of institutional holding-ranked quintiles is given in Table 1. The table shows the distribution of the estimates across the four time-series cross-sectional regressions. All statistics are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. N^{S} denotes the number of significant positive coefficients at the 5% level, while those in parentheses indicate the significant negative ones. N^{NS} is the number of insignificant coefficients. $\bar{R}^2$ represents the average adjusted R-squared value.

The cross-sectional regression results corroborate those reported in Section 3. In Table 7 (Panel A), the constant component of the volume autocorrelation coefficient, $\hat{a}_{1,i}$, is positively related to the market capitalization of the firm, but is inversely related to the level of institutional holdings. In the latter, the evidence suggests that stocks primarily owned by individual investors have a larger autocorrelation coefficient $\hat{a}_{1,i}$ than those stocks mainly held by institutions. Moreover, the coefficients of

Table 6
Information flow and correlated trading of individuals versus institutions, in the presence of contemporaneous and lagged absolute returns

	Mean	SD	N^{S}	N^{NS}	# of observations	$\bar{R}^2$
Panel A: Distribution of $\hat{a}_{1,i}$						
Individuals	0.268	0.129	1565(17)	78	1660	0.18
Quintile 2	0.250	0.135	1526(13)	121	1660	0.18
Quintile 3	0.250	0.124	1557(2)	101	1660	0.18
Quintile 4	0.239	0.121	1560(3)	97	1660	0.17
Institutions	0.237	0.114	1559(2)	99	1660	0.16
(Individuals – Institutions)	0.031					
	(7.36)					
Panel B: Distribution of $\hat{a}_{2,i}$						
Individuals	2.418	3.103	628(15)	1017	1660	
Quintile 2	2.779	3.230	647(21)	992	1660	
Quintile 3	3.175	3.117	720(16)	924	1660	
Quintile 4	3.174	2.977	669(9)	982	1660	
Institutions	3.223	2.874	690(11)	959	1660	
(Individuals – Institutions)	−0.805					
	(−7.75)					
Panel C: Distribution of $\hat{a}_{3,i}$						
Individuals	−1.474	4.810	54(181)	1425	1660	
Quintile 2	−1.852	5.344	37(146)	1477	1660	
Quintile 3	−2.313	5.786	41(226)	1393	1660	
Quintile 4	−2.300	7.080	60(225)	1375	1660	
Institutions	−2.416	7.106	75(206)	1379	1660	
(Individuals – Institutions)	0.943					
	(4.48)					
Panel D: Distribution of $\hat{a}_{4,i}$						
Individuals	15.240	14.476	1630(0)	30	1660	
Quintile 2	18.606	18.050	1621(0)	39	1660	
Quintile 3	18.622	23.454	1643(0)	17	1660	
Quintile 4	19.548	23.357	1645(0)	15	1660	
Institutions	20.574	26.240	1651(0)	9	1660	
(Individuals – Institutions)	−5.333					
	(−7.25)					

The table shows the distribution of the slope coefficients from the following regression:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + a_{3,i} |r_{i,t}| + a_{4,i} |r_{i,t+1}| + \epsilon_{i,t+1},$$

where $v_{i,t+1}$ is the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies used to capture differences in mean trading volume, $|r_{i,t}|$ denotes the absolute return on the stock at time t, and $\epsilon_{i,t+1}$ is the error term. The regression estimates are obtained, separately, for four 3-year sample periods: 86:07–89:06; 89:07–92:06; 92:07–95:06; and 95:07–98:06. The construction of institutional holding-ranked quintiles is given in Table 1. The table shows the distribution of the estimates across the four time-series cross-sectional regressions. All statistics are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. N^{S} denotes the number of significant positive coefficients at the 5% level, while those in parentheses indicate the significant negative ones. N^{NS} is the number of insignificant coefficients. $\bar{R}^2$ represents the average adjusted R-squared value.

Table 7
Results from cross-sectional regressions

Sample period	Intercept	Log of market capitalization	Log of ownership	$\bar{R}^2$
Panel A: Dependent variable: $\hat{a}_{1,i}$				
86:07–89:06	−0.389	0.034	−0.056	0.22
	(−14.16)	(22.82)	(−4.49)	
89:07–92:06	−0.254	0.027	−0.046	0.17
	(−10.22)	(19.83)	(−4.06)	
92:07–95:06	−0.273	0.028	−0.036	0.17
	(−10.75)	(19.93)	(−3.23)	
95:07–98:06	−0.411	0.035	−0.070	0.28
	(−17.27)	(27.69)	(−3.93)	
Panel B: Dependent variable: $\hat{a}_{2,i}$				
86:07–89:06	1.920	0.074	1.079	0.02
	(3.11)	(1.18)	(3.81)	
89:07–92:06	−4.224	0.381	1.804	0.12
	(−6.59)	(10.86)	(6.13)	
92:07–95:06	−3.368	0.364	0.867	0.08
	(−4.86)	(9.49)	(3.01)	
95:07–98:06	2.930	0.028	0.421	0.01
	(2.83)	(0.61)	(2.37)	

The table shows regression estimates of the model

$$\hat{a}_{x,i} = \text{intercept} + \alpha \log(\text{market capitalization}) + \delta \log(\text{ownership}) + u_i,$$

where $x = 1$ and 2, market capitalization is defined as the number of outstanding stocks times the market price, ownership represents the level of institutional ownership, and $\hat{a}_{x,i}$'s are estimated from

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_{2,i} v_{i,t} |r_{i,t}| + \epsilon_{i,t+1}.$$

In the second equation, $v_{i,t+1}$ is the trading volume of stock i at time $t+1$, $D_{k,t+1}$'s are the five day-of-week dummies, $|r_{i,t}|$ represents the absolute return, and u_i is the error term. The regression estimates are obtained, separately, for four 3-year sample periods: 86:07–89:06; 89:07–92:06; 92:07–95:06; and 95:07–98:06. All t-statistics, reported in parentheses, are calculated based on the Newey and West (1987) autocorrelation and heteroskedasticity-consistent standard errors. $\bar{R}^2$ represents the average adjusted R-squared value.

both the variables, the log of market capitalization and the level of institutional ownership, are consistently significant across the four sample periods with an average adjusted R-squared value of about 21%.

Table 7 (Panel B) reports the cross-sectional regressions of $\hat{a}_{2,i}$ against firm size and the fraction of shares of stocks owned by institutions. The sign and the level of statistical significance of the coefficients on firm size seem sporadic; only two estimates are significant. On the other hand, the coefficients on institutional ownership are consistently positive and statistically significant across the subperiods. This therefore suggests that the greater the flow of new information, the more persistent is volume autocorrelation in stocks held by institutions.

Thus, this subsection shows that our earlier results are not driven by smaller market-capitalization stocks. Instead, it indicates that the type of stock ownership indeed plays an important role in the dynamics of trading volume.

4.4. The market factor

All the above regression models we have estimated did not control for the market factor. It can be argued that the previous results are not specific to individual stocks, but perhaps they merely capture the market factor. In light of this, we reestimate (1) by incorporating the aggregate trading volume variable as follows:

$$v_{i,t+1} = \sum_{k=1}^{5} a_{0,ik} D_{k,t+1} + a_{1,i} v_{i,t} + a_m v_{m,t+1} + \epsilon_{i,t+1}, \tag{6}$$

where $v_{m,t+1}$ is measured by using the daily volume of shares of stocks traded divided by the total number of shares outstanding for all the stocks in the sample. Similarly, we also add $v_{m,t+1}$ to the regression models (2) and (3). We re-run all the regression models and find the results, not reported, to be substantially similar to those presented in Tables 2 and 3. The evidence therefore reinforces our preceding results that they are not attributable to the market factor.

5. Conclusion

This paper presents an exploratory investigation of whether the type of investor trading induces the widely documented phenomenon that daily trading volume exhibits high serial correlation. Many theoretical models on dynamic stock trading and empirical studies on investor trading behavior have implied that the trading volume phenomenon can be attributed to correlated trading patterns of institutional investors, whereas other studies have suggested that the phenomenon can be due to the attention-based buying behavior of individual investors. In our study, we let the data determine the prediction of whether individual investor trading or institutional trading drives daily correlated volume.

Using a simple dynamic trading-volume model, we establish that at least 95% of NYSE and AMEX securities exhibit positive serial correlation in their daily stock turnover, and the degree of volume autocorrelation decreases monotonically with the level of institutional ownership of a stock. The results show that arrivals of new information to the market on average generate more clustering of trading by institutions than by individual investors. These findings are consistent with the correlated trading behavior of institutional investors, as argued by many theoretical models and empirical studies on institutional dynamic trading.

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