Trading Volume and Cross-Autocorrelations in Stock Returns

Tarun Chordia and Bhaskaran Swaminathan*

* Chordia is from Vanderbilt University and Swaminathan is from Cornell University. We thank Clifford Ball, Doug Foster, Roger Huang, Charles Lee, Craig Lewis, Ron Masulis, Matt Spiegel, Hans Stoll, Avanidhar Subrahmanyam, two anonymous referees, the editor René Stulz, and seminar participants at the American Finance Association meetings, Eastern Finance Association meetings, Southern Finance Association meetings, Southwestern Finance Association meetings, Utah Winter Finance Conference, Chicago Quantitative Alliance, and Vanderbilt University for helpful comments. We are especially indebted to Michael Brennan for stimulating our interest in this area of research. The first author acknowledges support from the Dean's Fund for Research and the Financial Markets Research Center at Vanderbilt University. The authors gratefully acknowledge the contribution of I/B/E/S International Inc. for providing analyst data. All errors are solely ours.

Abstract

Trading Volume and Cross-Autocorrelations in Stock Returns

This paper finds that trading volume is a significant determinant of the lead-lag patterns observed in stock returns. Daily and weekly returns on high volume portfolios lead returns on low volume portfolios, controlling for firm size. Nonsynchronous trading or low volume portfolio autocorrelations cannot explain these findings. These patterns arise because returns on low volume portfolios respond more slowly to information in market returns. The speed of adjustment of individual stocks confirms these findings. Overall, the results indicate that differential speed of adjustment to information is a significant source of the cross-autocorrelation patterns in short-horizon stock returns.

Both academics and practitioners have long been interested in the role played by trading volume in predicting future stock returns.[1] In this paper, we examine the interaction between trading volume and the predictability of short horizon stock returns, specifically that due to lead-lag cross-autocorrelations in stock returns. Our investigation indicates that trading volume is a significant determinant of the cross-autocorrelation patterns in stock returns.[2] We find that daily or weekly returns of stocks with high trading volume lead daily or weekly returns of stocks with low trading volume. Additional tests indicate that this effect is related to the tendency of high volume stocks to respond rapidly and low volume stocks to respond slowly to market-wide information.

This paper is closely related to the literature on cross-autocorrelations initiated by Lo and MacKinlay (1990). Lo and MacKinlay find that positive autocorrelations in portfolio returns are due to positive cross-autocorrelations among individual security returns. Specifically, they find that the correlation between lagged large firm stock returns and current small firm returns is higher than the correlation between lagged small firm returns and current large firm returns. Our results show that trading volume has important information about cross-autocorrelation patterns beyond that contained in firm size.

The explanations that have been proposed for these cross-autocorrelation patterns (see Mech (1993)) can be classified into three groups. The first group of explanations claims that cross-autocorrelations are the result of time varying expected returns (see Conrad and Kaul (1988)). A variant of this explanation suggests that cross-autocorrelations are simply a restatement of portfolio autocorrelations and contemporaneous correlations (see Hameed (1997) and Boudoukh, Richardson, and Whitelaw (1993)). Once account is taken of portfolio autocorrelations, according to this explanation, portfolio cross-autocorrelations should disappear. The second group of explanations (see Boudoukh, Richardson and Whitelaw (1993)) suggests that portfolio autocorrelations and cross-autocorrelations are the result of market microstructure biases such as thin trading.

The final explanation for the lead-lag cross-autocorrelations claims that these lead-lag effects are due to the tendency of some stocks to adjust more slowly (underreact) to economy-wide information than others (see Lo and MacKinlay (1990) and Brennan, Jegadeesh, and Swaminathan (1993)).[3] We refer to this explanation as the speed of adjustment hypothesis. Why do these lead-lag patterns not get arbitraged away? Most likely due to the high transaction costs that any trading strategy designed to exploit these short-horizon patterns would face (see Mech (1993)).

Our empirical tests are designed to take into account the issues raised by the first two explanations. First, we conduct vector auto regressions involving pairs of high and low volume portfolio returns. Holding firm size constant, we examine if lagged high volume portfolio returns can predict current low volume portfolio returns controlling for the predictive power of lagged low volume portfolio returns. We use both daily and weekly returns in our empirical tests and take other precautions to minimize the impact of non-synchronous trading on our results. We find that high volume portfolio returns significantly predict low volume portfolio returns even in the largest size quartile. We also find that these results are robust in the post 1980 time period. These results show that own autocorrelations and non-synchronous trading cannot fully explain the observed lead-lag patterns in stock returns.

Next, in order to examine the source of these cross-autocorrelations, we conduct Dimson market model regressions (see Dimson (1979)) using returns on zero investment portfolios that are long in high volume portfolios and short in low volume portfolios of approximately the same size. The results indicate that the lead-lag effects are related to the tendency of low volume stocks to respond more slowly to market-wide information than high volume stocks. Finally, we use a speed of adjustment measure based on lagged betas from Dimson regressions to examine the *ex-ante* firm characteristics of a subset of stocks that contribute the most (or the least) to portfolio autocorrelations and cross-autocorrelations. The evidence indicates that there are striking differences in trading volume across stocks that contribute the most and the least to portfolio autocorrelations and cross-autocorrelations. Specifically, stocks that contribute the most have 30 percent to 50 percent lower trading volume.

The key conclusions are as follows. Returns of stocks with high trading volume lead returns of stocks with low trading volume primarily because the high volume stocks adjust faster to market-wide information. This is consistent with the speed of adjustment hypothesis. Thus, trading volume plays a significant role in the dissemination of market-wide information. While thin trading can explain some of the lead-lag effects, it cannot explain all of them. The lead-lag effects are also not explainable as due to own autocorrelations.

The rest of the paper is organized as follows. Section I discusses the data and the empirical tests. Section II discusses the empirical results, Section III provides additional evidence using individual stock data and section IV concludes.

I Data and Empirical Tests

A Data

Since Lo and MacKinlay (1990) document that large firm returns lead small firm returns we control for size effects in examining the cross-autocorrelation patterns between high volume and low volume stocks. We do this by forming a set of sixteen portfolios based on size and trading volume, using turnover as our measure of trading volume. Most previous studies (see Jain and Joh (1988) and Campbell, Grossman, and Wang (1993)) have used *turnover*, defined as the ratio of the number of shares traded in a day to the number of shares outstanding at the end of the day, as a measure of the trading volume in a stock. Moreover, using turnover disentangles the effect of firm size from trading volume. Raw trading volume and dollar trading volume are both highly correlated with firm size. In our sample, the cross-sectional correlations between firm size and raw trading volume and firm size and stock price are 0.78 and 0.72 respectively; the correlation between size and turnover is 0.15 and the correlation between turnover and raw volume is 0.60. Thus, turnover is highly correlated with raw volume but more or less uncorrelated with firm size which is exactly what we seek from this variable.[4]

For the period from 1963 to 1996, four size quartiles are formed at the beginning of each year by ranking all firms in the CRSP NYSE/AMEX stock file by their market value of equity as of the December of the previous year, and then dividing them into four equal groups. Only firms with ordinary common shares are included in these portfolios. In addition, all closed-end funds, real estate investment trusts, American Depositary Receipts, and Americus trust components are excluded from these portfolios. Firms in each size quartile are further divided into four equal groups based on their average daily trading volume over the previous year. To be included in one of these sixteen portfolios, a firm must have at least 90 daily observations of trading volume available in the previous year.

Once portfolios are formed in this manner at the beginning of each year, their composition is kept the same for the remainder of the year. Daily and weekly equal-weighted portfolio returns are computed for each portfolio by averaging the non-missing daily or weekly returns of the stocks in the portfolio. Foerster and Keim (1998) report that the likelihood of a NYSE/AMEX stock going without trading for two consecutive days is 2.24 percent and for five consecutive days it is only 0.42 percent. Therefore, in order to minimize the effect of non-synchronous trading on cross-autocorrelations, returns of stocks that did not trade at date t or $t-1$ are excluded from the computation of portfolio returns for date t. This ensures that the daily returns of any stock that did not trade for two days in a row are excluded from the computation of portfolio returns for the days the stock did not trade and for the day following the two days.

As is common in the literature, we measure weekly returns from *Wednesday close to the following Wednesday close*.[5] The use of weekly returns should further alleviate concerns of non-trading. Daily and weekly stock returns, average trading volume, and annual firm size are all obtained from CRSP from January 1963 through December 1996.

Table I presents descriptive statistics on the 16 size-volume portfolios. The mean portfolio returns suggest a negative cross-sectional relationship between trading volume and average stock returns.[6] The daily means for small size stocks are higher than usual since we drop daily returns on days a stock does not trade. The first order autocorrelation in daily portfolio returns, ρ_1, decreases with volume in each size quartile except in the smallest size quartile (ρ_1 is 0.22 for portfolio P11 and 0.30 for portfolio P14).[7] On the other hand, the sum of the first 10 autocorrelations of the daily portfolio returns is positive and declines monotonically with trading volume in each size portfolio.

Table I also reports autocorrelations for weekly portfolio returns with weeks ending on

Wednesday, Tuesday, and Friday. Consistent with the findings of Boudoukh, Richardson, and Whitelaw (1994), we find that autocorrelations based on Tuesday close are too low while autocorrelations based on Friday close are too high. The autocorrelations based on Wednesday close are neither too low nor too high and justify the use of Wednesday close weekly returns. Therefore, all our empirical results from Table II onwards are based on Wednesday close weekly returns. The weekly autocorrelations, both at lag one and the sum of the first four lags, decline monotonically with trading volume in each size portfolio.[8]

Not surprisingly, both daily and weekly autocorrelations also decline with firm size. However, the autocorrelations remain fairly large even in the largest size quartile especially at the daily frequency. The first order autocorrelation for P41 at the daily and the weekly frequency are 0.25 and 0.13 respectively. Predictably, the autocorrelations are lower using weekly returns.

If security prices adjust slowly to information, then price increases (decreases) will be followed by increases (decreases). This would give rise to positive autocorrelation in stock returns.[9] The portfolio autocorrelation evidence in Table I (except for size portfolio 1 involving daily returns) is, therefore, consistent with the hypothesis that returns of stocks with high trading volume adjust faster to common information. On the other hand, positive portfolio autocorrelations are also symptomatic of non-trading problems. However, as Boudoukh, Richardson, and Whitelaw (1994) point out, even heterogeneity in nontrading cannot explain all of the autocorrelations reported in Table I. For instance, Boudoukh, Richardson, and Whitelaw (1994) estimate that with extreme heterogeneity in nontrading and betas, the first order weekly autocorrelation implied by nontrading can be as high as 0.18. This is still less than half of the first order weekly autocorrelation of 0.39 estimated for P11 (see Table I). For larger size portfolios, where non-trading problems are minimal, the nontrading implied autocorrelations are much smaller (see Figure 2, page 559 in Boudoukh, Richardson, and Whitelaw (1994)). This suggests that non-trading issues cannot be the sole explanation for the autocorrelations in Table I and other evidence to be presented in this paper.

Table I also reports the median and average size and the median and average trading volume for each portfolio. These are obtained by averaging the annual cross-sectional statistics. As expected, the median and mean trading volume increase within each size quartile. The median and mean size, however, increase with trading volume only in the first three size quartiles. In the largest size quartile (size quartile 4), the median and mean size decrease with trading volume. This provides an opportunity to test whether trading volume has an independent influence on the cross-autocorrelations patterns. If trading volume has an independent effect then returns on high volume stocks should continue to lead returns on low volume stocks even in the largest size quartile. If, on the other hand, trading volume is simply a proxy of firm size then, in the largest size quartile, low volume portfolio returns should lead high volume portfolio returns. The autocorrelation evidence in Table I suggests that trading volume has an independent effect on portfolio autocorrelations. Additional evidence in support of this is provided later using tests based on cross-autocorrelations.

Finally, Table I reports the average number of firms in each portfolio each day or week during 1963 to 1996. The daily averages are significantly lower for portfolios P11 and P12 (small size, low trading volume portfolios) indicating that many small firms had to be dropped from daily portfolios due to non-trading problems (recall that we drop returns of firms that didn't trade today or yesterday while computing portfolio returns). However, as Table I shows, non-trading problems are minimal in the larger size quartiles. In addition, the weekly averages suggest that at the weekly frequency, non-trading problems are minimal even in the smallest size quartile.

While the autocorrelation evidence is consistent with the hypothesis that the prices of high volume stocks adjust more rapidly to information, it is important to point out that autocorrelations are not likely to provide unambiguous inferences on the differences in speed of adjustment. To see this clearly, consider two stocks A and B. Suppose that the return on stock A responds to both today's market information and yesterday's market information while return on stock B responds only to yesterday's market information. Stock A, which adjusts faster to information, would exhibit *positive* autocorrelation in daily returns. On the other hand, stock B, which adjusts slower to information, would exhibit *zero* autocorrelation. Cross-autocorrelations, on the other hand, do not suffer from this problem. Therefore, in the rest of the paper, we focus our attention on differences in cross-autocorrelations.

B Empirical Tests

B.1 Vector Auto-Regressions

Following Brennan, Jegadeesh, and Swaminathan (1993), we consider two types of time series tests: (1) vector auto-regressions (VAR), and (2) Dimson beta regressions. The VAR tests are designed to address two questions: (a) do cross-autocorrelations have information independent from own autocorrelations? (b) is the ability of returns on high volume stocks to predict returns on low volume stocks better than the ability of returns on low volume stocks to predict returns on high volume stocks?

In order to understand the VAR tests, suppose that we want to test whether returns of portfolio B lead returns of portfolio A. The lead-lag effects between the returns of these two portfolios can be tested using a bivariate vector auto-regression (VAR):[10]

$$r_{A,t} = a_0 + \sum_{k=1}^{K} a_k r_{A,t-k} + \sum_{k=1}^{K} b_k r_{B,t-k} + u_t, \quad (1)$$

$$r_{B,t} = c_0 + \sum_{k=1}^{K} c_k r_{A,t-k} + \sum_{k=1}^{K} d_k r_{B,t-k} + v_t. \quad (2)$$

In regression (1), if lagged returns of portfolio B can predict current returns of portfolio A, controlling for the predictive power of lagged returns of portfolio A, returns of portfolio B are said to *granger cause* returns of portfolio A. In our analysis, we use a modified version of the granger causality test by examining whether the sum of the slope coefficients corresponding to return B in equation (1) is greater than zero.[11] The granger causality test allows us to determine if cross-autocorrelations are independent of portfolio autocorrelations.

Next, we are interested in testing formally whether the ability of lagged returns of B to predict current returns of A is better than the ability of lagged returns of A to predict current returns of B. We test this hypothesis by examining if $\sum_{k=1}^{K} b_k$ in equation (1) is greater than $\sum_{k=1}^{K} c_k$ in equation (2). We refer to this test as the *cross equation test.* This test is crucial to establishing that returns of portfolio B lead returns of portfolio A and is a formal test of any asymmetry in cross-autocorrelations between high trading volume and low trading volume stocks.

B.2 Dimson Beta Regressions

In the VAR tests, we control for size related differences in speed of adjustment by forming four size portfolios and estimating the VAR within each size quartile. We control for other systematic effects in our tests of speed of adjustment by running a market model regression suggested by Dimson (1979) which includes leads and lags of market returns as additional independent variables. The Dimson beta regressions allow us to analyze the pattern of under- or over-reaction of portfolio returns to market returns. They also allow us to measure the speed of adjustment of each stock or portfolio relative to a single common benchmark, which is helpful in comparing the speed of adjustment across individual stocks or portfolios. In contrast, the VAR tests measure speed of adjustment of two portfolios relative to one another. However, both VAR and Dimson beta regressions do capture similar lead-lag effects.

In order to understand the Dimson beta regressions, consider a zero net investment portfolio O that is long in portfolio B and short in portfolio A. Now consider a regression of the return on the zero net investment portfolio on leads and lags of the return on the market portfolio:

$$r_{O,t} = \alpha_O + \sum_{k=-K}^{K} \beta_{O,k} r_{m,t-k} + u_{O,t}, \tag{3}$$

where $\beta_{O,k} = \beta_{B,k} - \beta_{A,k}$. It is easy to show that portfolio B adjusts more rapidly to common information than portfolio A if and only if the contemporaneous beta of portfolio B, $\beta_{B,0}$, is greater than the contemporaneous beta of portfolio A, $\beta_{A,0}$, and the sum of the lagged betas of portfolio B, $\sum_{k=1}^{K} \beta_{B,k}$, is less than the sum of the lagged betas of portfolio A, $\sum_{k=1}^{K} \beta_{A,k}$. In terms of the regression in equation (3), this translates into examining whether $\beta_{O,0} > 0$ and $\sum_{k=1}^{K} \beta_{O,k} < 0$. The basic intuition behind this result is that if portfolio B responds more rapidly to market-wide information than portfolio A, its sensitivity to today's common information (market return) should be greater than that of portfolio A. In the same vein, since portfolio A responds sluggishly to contemporaneous information, it should respond more to past common information (lagged market returns). The important thing to note here is that the speed of adjustment (relative to the market portfolio) is a function of both the contemporaneous beta and the lagged betas.

B.3 Hypothesis Testing

Note that all the hypothesis tests discussed above are *one sided* tests involving one sided alternate hypotheses. In tests involving a single restriction, this can be easily handled using a traditional one sided Z-test. However, in tests involving more than one restriction (as in the case of joint tests involving a system of equations), the regressions have to be estimated under the constrained alternate hypothesis.[12] This is what we do in this paper. The resulting Wald test statistic, however, is not distributed as the traditional χ^2 with the appropriate number of degrees of freedom but as a mixture of chi-square distributions (See Gourieroux, Holly, and Monfort (1982)). Specifically, a one sided test with m restrictions has the following distribution:

$$W_m \sim \sum_{j=0}^{m} w_j \chi_j^2, \tag{4}$$

where $0 < w_j < 1$. The complication is that w_j is a complex, non-linear function of the data and depends on the particular alternate hypothesis. Therefore, there are no general closed form solutions for the weight function. However, as pointed out by Gourieroux, Holly, and Monfort (1982), a one sided test that takes into account the constrained alternate hypothesis ought to have better power characteristics than a two sided test. This suggests that hypothesis tests that use the distribution in equation (4) should be able to reject the null hypothesis more often than those that use the traditional chi-square distribution. This in turn suggests that if we are able to reject the null hypothesis against the one sided alternate hypothesis using the traditional chi-square distribution, then we should most likely be able to reject the null hypothesis using the mixture of chi-square distributions.[13] This is the approach we adopt for the purpose of hypothesis testing.

In the next section, we discuss three pieces of evidence: (a) own autocorrelations and cross-autocorrelations, (b) results from VAR regressions and granger causality tests, and

(c) results from Dimson beta regressions.

II Empirical Results

A Cross-Autocorrelations and Own Autocorrelations

Table II presents cross-autocorrelations for size-volume portfolio returns. Panel A presents cross-autocorrelations for daily portfolio returns and Panel B presents cross-autocorrelations for weekly portfolio returns with weeks ending on a Wednesday. The correlations are computed using only the extreme trading volume portfolios within each size quartile. The results show that, in every size quartile, the correlation between lagged high volume portfolio returns, $r_{i4,t-1}$, and current low volume portfolio returns, $r_{i1,t}$, is always larger than the correlation between lagged low volume portfolio returns, $r_{i1,t-1}$, and current high volume portfolio returns, $r_{i4,t}$. For instance, in the largest size quartile, using daily returns (see Panel A), the correlation between lagged high volume portfolio returns, $r_{44,t-1}$, and the contemporaneous low volume portfolio returns, $r_{41,t}$, is 0.30 while the correlation between lagged low volume portfolio returns, $r_{41,t-1}$, and the contemporaneous high volume portfolio returns, $r_{44,t}$, is only 0.12. Similarly, using weekly returns (see Panel B), the correlation between $r_{44,t-1}$ and $r_{41,t}$ is 0.15 while the correlation between $r_{41,t-1}$, and $r_{44,t}$ is only 0.06. The fact that we observe these lead-lag patterns in the largest size quartile using both daily and weekly returns suggests that non-synchronous trading cannot be the only source of these lead-lag patterns.

Based on a simple AR(1) model of portfolio returns suggested by Boudoukh, Richardson, and Whitelaw (1994), we examine whether cross-autocorrelations are simply an inefficient way of describing the high autocorrelations of low volume portfolios.[14] In the context of the size-volume portfolios, the AR(1) model would predict that the correlation between the lagged returns of the high volume portfolio, $r_{i4,t-1}$, and the current returns of the low volume portfolio, $r_{i1,t}$, should be less than or equal to the autocorrelation in the returns of the low volume portfolio, $r_{i1,t}$, i.e., $\mathrm{corr}(r_{i1,t}, r_{i4,t-1}) \leq \mathrm{corr}(r_{i1,t}, r_{i1,t-1})$. In other words, the model predicts that the low volume portfolio returns' autocorrelations should be larger than their cross-autocorrelations with lagged high volume returns.

The results in Table II show that in every size quartile, for low volume portfolios Pi1, cross-autocorrelations with lagged high volume portfolio returns exceed own autocorrelations, i.e., corr($r_{i1,t}$, $r_{i4,t-1}$) > corr($r_{i1,t}$, $r_{i1,t-1}$). For instance, in Panel B, in size quartile 1, corr($r_{11,t}$, $r_{14,t-1}$) is 0.43 and corr($r_{11,t}$, $r_{11,t-1}$) is 0.39. The same pattern is seen in every size quartile regardless of whether we use daily or weekly returns. These results clearly indicate that cross-autocorrelations contain independent information about differences in speed of adjustment. We establish this more formally in the next section using vector auto-regression tests.

Contrast the above result with cross-autocorrelations related only to size differences as seen in Panel B of Table II. Consider portfolios P11 and P41, which are extreme size quartile portfolios. In examining the lead-lag patterns between the returns of these two portfolios, we find that the autocorrelation in the returns of P11, corr($r_{11,t}, r_{11,t-1}$) = 0.39, exceeds the correlation between lagged returns of P41 and current returns of P11, corr($r_{41,t-1}, r_{11,t}$) = 0.30. This is what Boudoukh, Richardson, and Whitelaw (1994) report in their paper and why they conclude that cross-autocorrelations are not as important as own autocorrelations in size sorted portfolios.

B Vector Auto Regressions

We estimate the VAR using daily or weekly returns of the two extreme volume portfolios in each size quartile: (P11, P14), (P21, P24), (P31, P34), and (P41, P44). With daily returns, the VAR is estimated using five lags, i.e., $K = 5$.[15] With weekly returns, the VAR is estimated with one lag (K=1) since additional lags only add noise. All regressions are estimated with the White heteroskedasticity correction for standard errors. The White correction and the use of lagged dependent variables as regressors result in the use of asymptotic statistics for making statistical inferences. Table III summarizes the results from the four VAR regressions. *Low* and *High* represent the sum of the slope coefficients of the lagged returns on the low volume portfolio and the lagged returns on the high volume portfolio, respectively. *L1* and *H1* represent the slope coefficients of the one lag returns of the low volume portfolio and the high volume portfolio (a_1 and b_1 or c_1 and d_1), respectively. Panel A presents VAR results using daily returns and Panel B presents VAR results using weekly returns.

B.1 Daily Returns

We first focus on the daily results in Panel A of Table III. The evidence indicates that lagged returns on the high volume portfolio strongly predict current returns on both the low volume and the high volume portfolio in each size quartile. The sum of the slope coefficients corresponding to lagged returns of the high volume portfolio is positive and significant at the one percent level in every regression. While the individual coefficients show that most of the impact occurs at lag one, there is also significant predictability beyond lag one. In addition, the results in Panel A indicate that the ability of $r_{i4,t-1}$ to predict $r_{i1,t}$ is better than the ability of $r_{i1,t-1}$ to predict $r_{i1,t}$. These results suggest that portfolio cross-autocorrelations are more important than own autocorrelations in determining differences in the speed of adjustment of security prices to economy-wide information.

An examination of adjusted R^2s in Panel A reveals that, in each size quartile, low volume portfolio returns are more predictable than high volume portfolio returns. The adjusted R^2 in regressions involving low volume portfolio returns as the dependent variable (returns of portfolios P11, P21, P31 and P41) is in the range of 0.09 to 0.22. Each adjusted R^2s is higher than the square of the first order autocorrelation of the corresponding low volume portfolio return, which provides further evidence that cross-autocorrelation patterns are not driven (solely) by own autocorrelations.

The results in Panel A indicate that lagged returns on the low volume portfolio can also predict future returns on the high volume portfolio (see columns titled *L1 or Low* for P14, P24, P34, and P44). Therefore, as discussed earlier, we test formally whether the ability of lagged high volume portfolio returns, $r_{i4,t-1}$, to predict current low volume portfolio returns, $r_{i1,t}$, is better than the ability of lagged low volume portfolio returns, $r_{i1,t-1}$, to predict current high volume portfolio returns, $r_{i4,t}$. In other words, is $\sum_{k=1}^{5} b_k > \sum_{k=1}^{5} c_k$? In each size quartile, the asymptotic Z-statistic, $Z(A)$, tests the null hypothesis that the sum of the slope coefficients across equations are equal; i.e., $\sum_{k=1}^{5} b_k = \sum_{k=1}^{5} c_k$. The null is rejected in each size quartile at the one percent level indicating that returns on the high volume portfolio lead returns on the low volume portfolio.[16] In a joint test of the cross-equation null hypothesis, since the inequality constraints under the alternate hypothesis, $\sum_{k=1}^{5} b_k > \sum_{k=1}^{5} c_k$, are satisfied in all four pairs of regressions, the unconstrained Wald test statistic and the constrained Wald test statistic are the same, i.e, $W_{A,U} = W_{A,C} = 75.15$. The Wald test statistics reject the joint null hypothesis at the one percent level. Overall, the results provide strong evidence that returns on high volume portfolios lead returns on low volume portfolios.

A brief discussion of the economic significance of the results in Panel A is in order here. Focusing on the P41 regression in the largest size quartile (because these are the most liquid stocks), on average, a one percent increase in today's return of high volume stocks, P44, all else equal, leads to a 0.1706 percent increase in tomorrow's return of low volume stocks, P41. The daily standard deviation of the high volume portfolio return is 1.10 percent. Therefore, a one percent increase is within one standard deviation. The 0.1706 percent increase in the returns of the low volume portfolio is approximately three times above its daily mean of 0.05 percent. This suggests that these lead-lag cross-autocorrelations effects could be economically significant. Similarly a one percent increase in the low volume portfolio return, P41, leads to a 0.2160 percent decrease (conditionally) in the high volume portfolio return, P44, which is again economically significant given its daily mean of 0.05 percent.

B.2 Weekly Returns

Foerster and Keim (1998) report that since 1963 less than one percent of the stocks in the three largest size deciles in NYSE and AMEX did not trade on a given day. The results in Panel A show that the lead-lag cross-autocorrelations between high volume and low volume portfolio returns are as strong in the largest size quartile as they are in the smallest size quartile. This makes it unlikely that these results could be due to non-synchronous trading.

However, in order to allay any remaining concerns about non-synchronous trading, we repeat the VAR tests using weekly portfolio returns. The results involving weekly portfolio returns are presented in Panel B of Table III. The VAR is estimated with one lag since additional lags only add noise. The results in Panel B show that high volume portfolio returns lead low volume portfolio returns even at the weekly frequency. In every size quartile, lagged returns on the high volume portfolio exhibit statistically and economically significant predictive power for future returns on the low volume portfolio. In contrast, lagged returns on the low volume portfolio exhibit little or no ability to predict future returns on the high volume portfolio and only weak ability to predict returns on the low volume portfolio. Once again the joint test statistic for the cross-equation null hypothesis A is significant at the one percent level. Overall, the weekly results closely parallel the daily results and make it unlikely that non-synchronous trading could be the primary explanation for the lead-lag cross-autocorrelations reported in this paper.

B.3 Additional Robustness Checks

As a final check to see if non-trading influences our results, we estimate the VAR both at the daily and the weekly frequency using only post 1980 data. The results (not reported in the paper) are similar to those in Table III and strongly support the hypothesis that returns on the high volume portfolio lead returns on the low volume portfolio.

One potential criticism of these results, given the positive correlation between firm size and volume (a correlation of 0.15 in our sample), is that trading volume simply proxies for firm size. We address this issue in two ways. First recall that, in size quartile 4, volume and size are negatively correlated (see Table I). Therefore, if the cross-autocorrelation results with respect to volume are being driven by firm size, we should see returns on portfolio P41 lead returns on portfolio P44. Yet, the cross-autocorrelations in Table II, indicate that the correlation between lagged returns of P44 and current returns of P41 is higher than the correlation between lagged returns of P41 and current returns of P44. Moreover, the VAR results in Table III confirm that returns on P44 lead returns on P41.

Next, we choose high and low volume portfolios from adjacent size quartiles to ensure that portfolio size and volume are negatively correlated. Consider the following three pairs of portfolios: (P21, P14), (P31, P24), and (P41, P34). In each of these pairs, firm size and volume are negatively correlated. For instance, the average size of P21 is about four times that of P14 (See Table I), but, the average volume of P21 is only about one fifth that of P14. The negative correlation between size and volume allows us to see whether the volume effect is independent of the size effect in determining lead-lag cross-autocorrelations. Now, let us return to the cross-autocorrelation evidence in Table II. In both Panel A and Panel B, the correlation between lagged returns of the high volume portfolio (P14, P24, or P34) and current returns of the low volume portfolio (P21, P31, or P41) is higher than the correlation between lagged returns of the low volume portfolio (P21, P31, or P41) and current returns of the high volume portfolio (P14, P24, or P34). This suggests that the volume effect is independent of the size effect. We also perform VAR tests involving the three pairs of low and high volume portfolios from adjacent size quartiles. The regression results (not reported) are similar to those in Table III.

C Dimson Beta Regressions

As discussed in subsection B.2, we use zero investment portfolios in the Dimson beta regressions. The zero investment portfolios are constructed by subtracting low volume portfolio returns from high volume portfolio returns. Since we expect high volume portfolio returns to adjust to common factor information faster than low volume portfolio returns, the contemporaneous betas from these regressions, $b_{O,0}$, should be positive and the sum of lagged betas, $\sum_{k=1}^{K} b_{O,k}$ should be negative. The intuition behind these restrictions is as follows. If the return on the high volume portfolio responds more rapidly to common information than the return on the low volume portfolio then its sensitivity to today's common information (market return) should be greater than that of the low volume portfolio. Therefore, the contemporaneous beta of the zero investment portfolio should be positive. In addition, since the low volume portfolio responds sluggishly to contemporaneous factor information (current market returns), it should respond more to past common factor information (lagged market returns). Therefore, the lagged betas of the zero investment portfolio should be negative.

We estimate the Dimson beta regressions in equation (3) using the NYSE/AMEX equal weighted portfolio return as a proxy for the common factor.[17] All standard errors are corrected for generalized heteroskedasticity using the White correction. Table IV presents results from Dimson beta regressions. Panel A reports results using daily returns and Panel B reports results using weekly returns. We use five leads and lags of market returns in daily Dimson beta regressions and two leads and lags of market returns in weekly Dimson beta regressions.[18]

First, we focus on the daily results in Panel A. The contemporaneous betas of the zero investment portfolio, $b_{O,0}$, are positive and significant at the one percent level in each size quartile. Also, the sum of the lagged betas is significantly negative in each size quartile. These results indicate that, in each size quartile, the returns on the low volume portfolio adjust more slowly to market-wide information than the returns on the high volume portfolio. Not surprisingly, both the constrained and the unconstrained Wald test statistics strongly reject the joint null hypothesis that the sum of the lagged betas is zero in each size quartile, at the one percent level. The sum of leading betas indicates that current returns on the zero investment portfolios in size quartiles 2, 3, and 4 are able to predict future returns of the equal weighted market index. This suggests that returns on high volume portfolios in the larger size quartiles lead returns on the equal weighted market index. The weekly results in Panel B are similar to the daily results and reveal significant differences in speed of adjustment related to trading volume. Overall, the results indicate that the lead-lag cross-autocorrelations observed between high volume and low volume stocks are driven by differences in the speed of adjustment to common factor information.

III Speed of Adjustment of Individual Stocks

Up to this point, our empirical tests use portfolio returns to examine the relationship between cross-sectional differences in trading volume and speed of adjustment to common information. We find that returns of high volume portfolios adjust to market-wide information faster than do those of low volume portfolios. In this section, we use data on individual stocks to examine the relation between trading volume and the speed of adjustment. Specifically, we identify stocks that contribute the most or the least to portfolio autocorrelations and cross-autocorrelations and examine their ex-ante firm chracteristics. We want to determine if trading volume emerges as an important characteristic in explaining the differences in the speed of adjustment across the two groups of stocks.

The sample of stocks used in this section contains all stocks available at the intersection of CRSP NYSE/AMEX files and annual IBES files from 1976 to 1996. We use the IBES files in order to obtain the number of analysts making annual earnings forecasts. The sample contains a total of 24,704 firm years or an average of around 1,200 firms per year.

In order to identify stocks that contribute the most (or least) to portfolio autocorrelations and cross-autocorrelations we use a measure of speed of adjustment based on contemporaneous and lagged betas from Dimson beta regressions. Each year, from 1977 to 1996, the following Dimson beta regression is estimated for each stock in the sample:

$$r_{i,t} = \alpha_i + \sum_{k=-5}^{5} \beta_{i,k} r_{m,t-k} + u_{i,t} \tag{5}$$

where $r_{i,t}$ is the daily return on the stock and $r_{m,t}$ is the daily return on the market index, and $\beta_{i,k}$ is the beta with respect to the market return at lag k. We use NYSE/AMEX equal-weighted market index as a proxy of the market portfolio. Tests involving NYSE/ AMEX/ NASDAQ value-weighted market index provide similar results.

Recall our discussion in section B.2 that the speed of adjustment (relative to the market portfolio) is a function of both contemporaneous and lagged betas. For simplicity consider a Dimson beta regression with just one lag and one lead. In comparing the speed of adjustment of two stocks A and B, returns of stock B are said to adjust more rapidly to common information than do returns of stock A if and only if stock B's contemporaneous beta, $\beta_{B,0}$, is greater than stock A's contemporaneous beta, $\beta_{A,0}$, and stock B's lagged beta, $\beta_{B,1}$, is less than stock A's lagged $\beta_{A,1}$. We can state this result in a more parsimonious way as follows. Returns of stock B adjust more rapidly to common information than do returns on stock A if and only if $\beta_{B,1}/\beta_{B,0}$, is less than $\beta_{A,1}/\beta_{A,0}$.

For a Dimson beta regression with five leads and five lags, the speed of adjustment ratio is defined to be $\sum_{k=1}^{5} \beta_{j,i,k}/\beta_{j,i,0}$. We use a logit transformation of this ratio as our measure of speed of adjustment:

$$\text{DELAY}_i = \frac{1}{1+e^{-x}}, \tag{6}$$

where

$$x = \frac{\sum_{k=1}^{5} \beta_{i,k}}{\beta_{i,0}},$$

Our measure is a modification of a measure proposed by McQueen, Pinegar, and Thorley (1996). If x is the ratio of lagged beta to contemporaneous beta then the measure proposed by McQueen, Pinegar, and Thorley (1996) is equal to the logit transformation of $x/(1+x)$. While this measure is monotonic in x for $x > 1$, it is non-monotonic in x for $x < 1$. x is often less than one when measuring the speed of adjustment of large stocks relative to the equal-weighted market index. This is because large stocks adjust faster to common information than the equal-weighted market index. As a result, for a large stock, the contemporaneous beta tends to be greater than one while the lagged beta tends to be negative and less than one. This creates a problem in comparing a positive value of x to a negative value of x or in comparing two negative values of x. For $x > 0$, our DELAY measure provides values greater than 0.5 and for $x < 0$, our measure provides values less than 0.5.

The logit transformation has several appealing properties. First, it is monotonic in x. Secondly, the transformation moderates the influence of outliers and yields values between zero and one. Values closer to zero imply a faster speed of adjustment and values closer to one imply a slower speed of adjustment. Therefore, stocks with high (low) DELAY are likely to contribute most (least) to portfolio autocorrelations and cross-autocorrelations. We use this measure to examine the cross-sectional relation between trading volume and the speed of adjustment of individual stocks.

Next, for each firm in the sample, we match the DELAY measure computed in year t with firm characteristics as of year $t-1$. The firm characteristics are *Volume* defined as the average number of shares traded per day during year $t-1$, *Turnover* defined as the average daily turnover in percent during year $t-1$, *Size*, which is the market capitalization in millions of dollars as of the December of year $t-1$, *Price*, which is the stock price as of December of year $t-1$, *Stdret*, defined as the standard deviation of daily returns in percent during year $t-1$, *Nana*, which is the number of security analysts making annual forecasts as of the September of year $t-1$, and *Spread* defined as the average of the beginning and end-of-year relative spread in percent.[19] The data on relative spread is the same as that used in Eleswarapu and Reinganum (1993) and is available only for the 1980 to 1989 time period and covers only NYSE stocks.

Finally, each year, we form four size quartiles and then divide each size quartile into four quartiles based on DELAY. We focus our attention on the extreme DELAY quartiles *High* and *Low* within each size quartile. *High* represents 25 percent of stocks within each size quartile that are likely to contribute the most to delayed reaction to common factor information and *Low* represents 25 percent of stocks that are likely to contribute the least to delayed reaction to common factor information. For each portfolio, each year, we compute the median *ex-ante* firm characteristic and then average the annual medians over time.

The results are reported in Table V. In general, in each size quartile, both raw trading volume, *Volume*, and relative trading volume, *Turnover*, differ significantly across the two DELAY portfolios *High* and the *Low*. On average, the raw trading volume for the high DELAY portfolio, *High* is 25 percent to 45 percent lower than the raw trading volume for the low DELAY portfolio, *Low*. Similarly, the turnover for the high DELAY portfolio is, on average, 20 percent to 35 percent lower than the turnover for the high DELAY portfolio. An exception is size quartile 4, in which there is not much difference in turnover across the two DELAY portfolios. This is probably due to the fact that in size quartile 4, turnover and size tend to be negatively correlated (see in Table 1). In addition, Dimson beta estimators are likely to be very noisy for individual stocks. This can be seen from the results in Table IV where using portfolio returns, we find significant differences in the speed of adjustment between high turnover and low turnover portfolios.

In order to allay any remaining concerns that our results are driven by the small-illiquid stocks, we focus our attention on the results for the smallest size quartile-highest DELAY portfolio. The time-series average of the median daily trading volume for the smallest size quartile-highest DELAY portfolio is 6,422 shares. The time-series average of the 25th percentile (on average there are less than 20 stocks below this cut-off) daily trading volume of the above portfolio is 3,244 shares. The time-series average of the fifth percentile (less than four out of 77 stocks are below this cut-off) daily trading volume is 1,103 shares. For comparison, the fifth percentile daily trading volume for size quartiles 2, 3, and 4 (larger size portfolios) are 3,764 shares, 8,705 shares, and 30,593 shares respectively. All these show that our results are not driven by extremely illiquid stocks.

Stocks with high DELAY also tend to be smaller, have fewer analysts, are higher priced, and have lower volatility. Differences in relative spread across *High* and *Low* DELAY stocks do not seem economically significant. In sum, the univariate statistics based on the speed of adjustment of individual stocks confirm our earlier findings and strongly support the hypothesis that trading volume is a significant determinant of how slowly or rapidly stock prices adjust to new information.

IV Conclusion

In this paper, we find that trading volume is a significant determinant of lead-lag cross-autocorrelations in stock returns. Specifically, returns of portfolios containing high trading volume lead returns of portfolios comprised of low trading volume stocks. Additional tests establish that the source of these lead-lag cross-autocorrelations is the tendency of low volume stock prices to react sluggishly to new information. While non-trading may be a part of the story, the magnitude of the autocorrelations and cross-autocorrelations indicate that non-trading cannot be the sole explanation of our results.

While at first glance, these results may suggest some market inefficiency, it is not clear that investors could profitably trade on these patterns since transaction costs are likely to overwhelm any potential profits. This might explain why these patterns do not get arbitraged away. Nevertheless, the results are interesting since they indicate a market in which trading volume plays a major role in the speed with which prices adjust to information, yielding insights into how stock prices become more informationally efficient.

References

Badrinath, Swaminathan G., Jayant R. Kale, and Thomas H. Noe, 1995, Of shepherds, sheep and the cross-autocorrelations in equity returns, *Review of Financial Studies* 8, 401-430.

Bessembinder, Hendrik, and Michael G. Hertzel, 1993, Return autocorrelations around nontrading days, *Review of Financial Studies* 6, 155-190.

Boudoukh, Jacob, Matthew P. Richardson, and Robert F. Whitelaw, 1994, A tale of three schools: Insights on autocorrelations of short-horizon stock returns, *Review of Financial Studies* 7, 539-573.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345-374.

Brennan, Michael J., Narasimhan Jegadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, *Review of Financial Studies* 6, 799-824.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 107, 907-939.

Connolly, Robert A., and Chris T. Stivers, 1997, Time-varying lead-lag of equity returns in a world of incomplete information, Working paper, University of North Carolina at Chapel Hill.

Conrad, Jennifer, and Gautam Kaul, 1988, Time varying expected returns, *Journal of Business* 61, 409-425.

Datar, Vinay, Narayan Naik, and Robert Radcliffe, 1998, Liquidity and asset returns: An alternative test, forthcoming, *Journal of Financial Markets*.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197-226.

Eleswarapu, Venkat R., and Marc R. Reinganum, 1993, The seasonal behaviour of the liquidity premium in asset pricing, *Journal of Financial Economics* 34, 373-386.

Foerster, Stephen R., and Donald B. Keim, 1998, Direct evidence of non-trading of NYSE and AMEX stocks, forthcoming, in Ziemba, W., and D. B. Keim, eds: *Security Market Imperfections in Worldwide Equity Markets* (Cambridge University Press).

Gallant, Ronald A., Peter E. Rossi, and George Tauchen, 1992, Stock prices and volume, *Review of Financial Studies* 5, 199-242.

Gourieroux, Christian B., Alberto Holly, and Alain Monfort, 1982, Likelihood ratio test, Wald test and Kuhn-Tucker test in linear models with inequality constraints on the regression parameters, *Econometrica* 50, 63-80.

Hameed, Allaudeen, 1997, Time varying factors and cross-autocorrelations in short-horizon stock returns, *Journal of Financial Research* 20, 435-458.

Jain, Prem C., and Gun-Ho Joh, 1988, The dependence between hourly prices and trading volume, *Journal of Financial and Quantitative Analysis* 23, 269-283.

Karpoff, Jonathan, 1987, The relation between price changes and trading volume: A survey, *Journal of Financial and Quantitative Analysis* 22, 109-126.

Keim, Donald B., and Robert F. Stambaugh, 1984, A further investigation of the weekend effect in stock returns, *Journal of Finance* 39, 819-834.

Lo, Andrew, and Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175-205.

McQueen, Grant, Michael Pinegar, and Steven Thorley, 1996, Delayed reaction to good news and cross-autocorrelation of portfolio returns, *Journal of Finance* 51, 889-920.

Mech, Timothy S., 1993, Portfolio return autocorrelation, *Journal of Financial Economics* 34, 307-344.

Footnotes

1. For the literature on volume and volatility see Karpoff (1987) and Gallant, Rossi, and Tauchen (1992).

2. To be specific, we use the average daily stock turnover as a proxy of trading volume.

3. Others who have provided similar explanations include Badrinath, Kale, and Noe (1995), McQueen, Pinegar, and Thorley (1996), and Connolly and Stivers (1997).

4. Henceforth, unless otherwise stated, trading volume refers to this specific definition of trading volume.

5. Seasonal patterns in weekly autocorrelations have been examined in detail by Keim and Stambaugh (1984), Bessembinder and Hertzel (1993), and Boudoukh, Richardson, and Whitelaw (1994). For instance, Bessembinder and Hertzel (1993) find that the patterns in autocorrelations across weekdays are related to the importance of weekend returns versus non-weekend returns in autocorrelation patterns and are robust to alternative market microstructures. While this is an interesting issue, as far as our paper is concerned, we simply want to show that our results are robust to these patterns. In order to check the robustness of the weekly results, we repeat all our analysis using weekly returns computed from Friday close to the following Friday close and Tuesday close to the following Tuesday close. The results are similar.

6. See Brennan, Chordia, and Subrahmanyam (1998) and Datar, Naik, and Radcliffe (1998).

7. One reason this happens is because of the way we compute portfolio returns. Note that we drop firms that do not trade at day t or $t-1$ from the portfolio at day t. This throws away valuable information about delayed reaction to private information and reduces the autocorrelations for the low turnover portfolio.

8. For P11, P12, and P13, the first-order daily autocorrelations are somewhat lower than first-order weekly autocorrelations. This is the result of persistence in daily

autocorrelations. The sum of first 10 daily autocorrelations are, however, uniformly higher than the sum of first four weekly autocorrelations.

9. Contrary to this hypothesis, most individual stocks exhibit a small negative autocorrelation in daily and weekly returns (see Lo and MacKinlay (1990) while portfolio returns exhibit positive autocorrelations.

10. Since the regressors are the same for both regressions, the VAR can be efficiently estimated by running ordinary least squares (OLS) on each equation individually.

11. The usual version is to jointly test whether the slope coefficients corresponding to the lagged returns of the portfolio B are equal to zero. Our version, tests not only for predictability but also for the sign of the predictability. Therefore, it is a more stringent test.

12. We thank the referee for pointing this out.

13. Gourieroux, Holly, and Monfort (1982) provide results on the power characteristics of the constrained test only for the case of the single constraint. They also provide critical statistics only for the two constraint case and that too for limited parameter values. Computing the critical statistics or examining the power characteristics for tests involving more than two constraints is beyond the scope of this paper.

14. Specifically, Boudoukh, Richardson, and Whitelaw (1994) specify an AR(1) model for the return generating process for each size portfolio where the AR(1) parameter is positive and declines monotonically with size. The shocks to the AR(1) process are assumed to be white noise but are contemporaneously correlated across size portfolios. It is important to point out that the AR(1) model, by assumption, rules out independent cross-autocorrelations between portfolio returns.

15. The results for 10 lags are similar.

16. Notice that in size quartiles 2, 3 and 4, low volume portfolio returns predict high volume portfolio returns with a negative sign. This is simply a result of the fact that

we are measuring relative speed of adjustment between two portfolios. Brennan, Jegadeesh, and Swaminathan (1993) show that if returns on the low volume portfolio adjust more slowly to common information than returns on the high volume portfolio then in regressions involving the high volume portfolio return as the dependent variable, the slope coefficient corresponding to the lagged return on the low volume portfolio could be negative.

17. We also perform all regressions reported in Table IV using the CRSP value-weighted market index and the results are similar.

18. For daily returns, the results with 10 leads and lags are similar. For weekly returns, the use of additional lags only adds more noise to statistical inference.

19. Relative spread is defined as the ratio of the dollar bid-ask spread to the average of the bid and ask prices.

Table I
Summary Statistics for Size-Volume Portfolios

Summary statistics for size-volume portfolios are computed over 1963-1996. *Pij* refers to a portfolio of size i and volume j. $i = 1$ refers to the smallest size portfolio and $i = 4$ refers to the largest size portfolio. Similarly $j = 1$ refers to the lowest volume and $j = 4$ refers to the highest volume portfolio. *EW* refers to an equal-weighted market index of NYSE/AMEX firms. Summary statistics for returns are computed using both daily returns and non-overlapping weekly returns. *Each week ends on a Wednesday.* For comparison, we also report autocorrelations computed using weekly returns with weeks ending on Tuesday and Friday. The columns titled Wednesday, Tuesday, and Friday refer to weeks defined with those ending days. Statistics of portfolio size and volume are obtained as follows: First, the cross-sectional statistics (median and mean) of size and volume are computed for each portfolio for each year. Then the yearly cross-sectional statistics of each portfolio are averaged over time and reported below. N refers to the average number of firms in each portfolio each day or each week over 1963-1996. The number of daily returns for all portfolios from 1963 to 1996 is 8,560. The number of non-overlapping weekly returns over the same time period is 1,774. ρ_k refers to the k^{th} order auto-correlation. S_k refers to the sum of first k autocorrelations. The size figures are in billions of dollars. The volume numbers represent average daily percentage turnover.

	Statistics for daily returns					Statistics for weekly returns									Size		Volume	
	%	%				%	%	Wednesday		Tuesday		Friday					%	%
	Mean	Sdev	ρ_1	S_{10}	N	Mean	Sdev	ρ_1	S_4	ρ_1	S_4	ρ_1	S_4	N	Med.	Mean	Med.	Mean
P11	0.32	1.09	0.22	1.37	72	0.58	2.33	0.39	0.95	0.36	0.87	0.46	1.06	123	0.010	0.011	0.045	0.043
P12	0.24	1.03	0.28	1.29	95	0.54	2.56	0.37	0.88	0.33	0.77	0.41	0.97	130	0.010	0.012	0.088	0.089
P13	0.19	1.06	0.28	1.08	107	0.45	2.74	0.34	0.75	0.27	0.60	0.39	0.84	131	0.012	0.013	0.146	0.149
P14	0.13	1.15	0.30	0.99	116	0.30	3.15	0.29	0.62	0.24	0.53	0.34	0.71	129	0.014	0.014	0.275	0.343
P21	0.11	0.64	0.36	1.27	104	0.34	1.72	0.33	0.67	0.29	0.59	0.37	0.77	132	0.055	0.060	0.051	0.049
P22	0.09	0.80	0.34	1.00	124	0.35	2.25	0.28	0.56	0.23	0.46	0.33	0.67	133	0.056	0.061	0.111	0.113
P23	0.07	0.96	0.31	0.79	129	0.30	2.66	0.23	0.46	0.18	0.35	0.28	0.54	133	0.058	0.063	0.192	0.195
P24	0.05	1.19	0.26	0.61	130	0.23	3.14	0.22	0.40	0.15	0.29	0.24	0.47	131	0.063	0.066	0.366	0.433
P31	0.07	0.56	0.37	1.03	122	0.31	1.59	0.27	0.49	0.23	0.40	0.31	0.59	134	0.229	0.252	0.057	0.052
P32	0.07	0.70	0.35	0.81	133	0.32	1.99	0.23	0.40	0.17	0.30	0.26	0.47	136	0.246	0.266	0.116	0.117
P33	0.06	0.90	0.32	0.63	134	0.29	2.47	0.19	0.34	0.13	0.24	0.22	0.41	135	0.235	0.258	0.196	0.200
P34	0.05	1.20	0.22	0.42	131	0.24	3.09	0.17	0.28	0.10	0.19	0.18	0.32	131	0.239	0.259	0.379	0.449
P41	0.05	0.65	0.25	0.36	134	0.24	1.66	0.13	0.19	0.07	0.10	0.11	0.22	138	1.321	3.516	0.074	0.067
P42	0.05	0.73	0.25	0.28	138	0.26	1.88	0.10	0.14	0.05	0.08	0.08	0.17	138	1.420	2.632	0.120	0.120
P43	0.06	0.83	0.24	0.27	137	0.28	2.12	0.09	0.13	0.05	0.06	0.08	0.16	138	1.312	2.185	0.172	0.174
P44	0.05	1.10	0.19	0.25	135	0.23	2.75	0.10	0.14	0.06	0.08	0.11	0.18	135	1.076	1.595	0.294	0.363
EW	0.09	0.80	0.34	0.85	—	0.33	2.19	0.26	0.51	0.20	0.40	0.29	0.59	—	—	—	—	—

Table II
Size-Volume Portfolio Cross-Autocorrelations

$r_{ij,t}$ refers to time t return of a portfolio corresponding to the i^{th} size quartile and the j^{th} volume quartile within the i^{th} size quartile. The number of daily observations between 1963 and 1996 is 8,560. The number of non-overlapping weekly observations between 1963 and 1996 is 1,774. Each week ends on a Wednesday. Panels A and B report cross-autocorrelations at the first lag.

Panel A: Daily Returns

	$r_{11,t}$	$r_{14,t}$	$r_{21,t}$	$r_{24,t}$	$r_{31,t}$	$r_{34,t}$	$r_{41,t}$	$r_{44,t}$
$r_{11,t-1}$	0.22	0.24	0.29	0.14	0.25	0.10	0.12	0.06
$r_{14,t-1}$	0.35	0.30	0.39	0.21	0.35	0.14	0.17	0.09
$r_{21,t-1}$	0.31	0.27	0.36	0.17	0.34	0.11	0.16	0.06
$r_{24,t-1}$	0.34	0.36	0.44	0.26	0.41	0.19	0.23	0.13
$r_{31,t-1}$	0.30	0.28	0.39	0.19	0.37	0.13	0.19	0.08
$r_{34,t-1}$	0.33	0.36	0.45	0.29	0.44	0.22	0.26	0.16
$r_{41,t-1}$	0.27	0.27	0.39	0.22	0.42	0.17	0.25	0.12
$r_{44,t-1}$	0.31	0.35	0.45	0.30	0.46	0.25	0.30	0.19

Panel B: Weekly Returns

	$r_{11,t}$	$r_{14,t}$	$r_{21,t}$	$r_{24,t}$	$r_{31,t}$	$r_{34,t}$	$r_{41,t}$	$r_{44,t}$
$r_{11,t-1}$	0.39	0.25	0.28	0.15	0.20	0.11	0.05	0.04
$r_{14,t-1}$	0.43	0.29	0.32	0.19	0.24	0.12	0.08	0.05
$r_{21,t-1}$	0.40	0.28	0.33	0.19	0.27	0.13	0.10	0.06
$r_{24,t-1}$	0.40	0.32	0.35	0.22	0.28	0.15	0.12	0.08
$r_{31,t-1}$	0.37	0.26	0.33	0.19	0.27	0.13	0.12	0.07
$r_{34,t-1}$	0.38	0.32	0.36	0.24	0.31	0.17	0.14	0.10
$r_{41,t-1}$	0.30	0.22	0.30	0.17	0.27	0.12	0.13	0.06
$r_{44,t-1}$	0.34	0.29	0.34	0.23	0.30	0.16	0.15	0.10

Table III
Vector-Auto Regressions for the Size-Volume Portfolios

The following VAR is estimated using daily or weekly data from 1963 to 1996:

$$\begin{aligned} r_{A,t} &= a_0 + \sum_{k=1}^{K} a_k r_{A,t-k} + \sum_{k=1}^{K} b_k r_{B,t-k} + u_t, \\ r_{B,t} &= c_0 + \sum_{k=1}^{K} c_k r_{A,t-k} + \sum_{k=1}^{K} d_k r_{B,t-k} + v_t. \end{aligned}$$

The LHS variable is the return on the lowest ($r_{A,t}$) or the highest ($r_{B,t}$) volume portfolio within each size quartile. The portfolios P_{ij} are defined in Table 1. Low refers to $\sum_{k=1}^{K} a_k$ or $\sum_{k=1}^{K} c_k$ and High refers $\sum_{k=1}^{K} b_k$ or $\sum_{k=1}^{K} d_k$ as per the dependent variable. Similarly, L1 denotes a_1 or c_1 and H1 denotes b_1 or d_1. $\bar{R}^2$ is the adjusted coefficient of determination. $Z(A)$ is the Z-statistic corresponding to the cross-equation null hypothesis $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$ in each bi-variate VAR. The alternate hypothesis is $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k$. $K = 5$ ($K = 1$) for regressions involving daily (weekly) returns. The significance levels for $Z(A)$ are based on upper-tail tests. $W^U_{A,m}$ ($W^C_{A,m}$) is the *Wald* test statistic corresponding to the joint-test of null hypothesis across all equations against an *unconstrained* (*inequality constrained*) alternate hypothesis. m is the number of constraints (degrees of freedom) of the test. All statistics are computed based on White heteroskedasticity corrected standard errors.

Panel A: Daily Returns, NOBS=8,555

LHS	L1	Low	H1	High	$\bar{R}^2$	$Z(A)$
P11	-0.0308‡	0.1524*	0.3053*	0.4511*	0.16	5.05*
P14	0.0767*	0.1565*	0.2466*	0.3289*	0.11	
P21	-0.0343	0.1942*	0.2429*	0.2507*	0.22	3.05*
P24	-0.1798†	-0.0912	0.3310*	0.4067*	0.08	
P31	0.0240	0.1633‡	0.1943*	0.2129*	0.21	3.18*
P34	-0.2645*	-0.3154†	0.3157*	0.4541*	0.06	
P41	0.0161	0.0111	0.1706*	0.1993*	0.09	3.97*
P44	-0.2160*	-0.3758*	0.3032*	0.4371*	0.05	

Joint Test : $W^U_{A,4} = W^C_{A,4} = 75.15^*$

Panel B: Weekly Returns, NOBS=1,773

LHS	L1	H1	$\bar{R}^2$	$Z(A)$
P11	0.1195†	0.2423*	0.19	1.92†
P14	0.0512	0.2610*	0.08	
P21	0.0867	0.1506*	0.12	1.18
P24	-0.0563	0.2477*	0.05	
P31	0.0477	0.1374*	0.09	1.37‡
P34	-0.0889	0.2045*	0.03	
P41	0.0088	0.0836*	0.02	1.66†
P44	-0.1413	0.1704*	0.01	

Joint Test : $W^U_{A,4} = W^C_{A,4} = 24.21^*$

$*$ - significant at 1 percent level; † - significant at 5 percent level; ‡ - significant at 10 percent level.

Table IV
Dimson Beta Regressions for Size-Volume Portfolio Returns

The following regression is estimated using daily or weekly data from 1963 to 1996:

$$r_{O,t} = \alpha_O + \sum_{k=-K}^{K} \beta_{O,k} r_{m,t-k} + u_{O,t},$$

where $r_{O,t}$ is the difference between returns on the highest volume and the lowest volume portfolios within each size quartile and $r_{m,t-k}$ refers to CRSP (NYAM) equal-weighted market returns. $\sum_{k=1}^{K} b_{O,k}$ refers to the sum of lagged betas, and $\sum_{k=-1}^{-K} b_{O,k}$ refers to the sum of leading betas. $b_{O,0}$ refers to the contemporaneous beta. $\bar{R}^2$ is the adjusted coefficient of determination. NOBS refers to the number of daily or weekly returns used in the regressions. The individual equation statistical tests corresponding to $\sum_{k=1}^{K} b_{O,k}$ are lower tail (one-sided) tests. W_m^U is the *Wald* test statistic corresponding to the joint null hypothesis (across all equations) that $\sum_{k=1}^{K} b_{O,k} = 0$ against an *unconstrained* (two-sided) alternate hypothesis. W_m^C is the *Wald* test statistic corresponding to the joint null hypothesis (across all equations) $\sum_{k=1}^{K} b_{O,k} = 0$ against an *inequality constrained* (one-sided) alternate hypothesis that $\sum_{k=1}^{K} b_{O,k} \leq 0$. m is the number of constraints (degrees of freedom). All statistics are computed based on White heteroskedasticity corrected standard errors. The significance levels for both the constrained and the unconstrained Wald test statistics are based on standard χ^2 distribution (see text for details).

Panel A: Daily Returns, NOBS=8,549

Size	LHS	$\sum_{k=-1}^{-5} b_{O,k}$	$b_{O,0}$	$\sum_{k=1}^{5} b_{O,k}$	$\bar{R}^2$
1	P14-P11	-0.0252	0.4832*	-0.2688*	0.13
2	P24-P21	0.0489*	0.7941*	-0.3652*	0.60
3	P34-P31	0.1122*	0.8584*	-0.4239*	0.65
4	P44-P41	0.1286*	0.5600*	-0.2752*	0.50

Joint Test: $W_4^U = W_4^C = 493.31^*$

Panel B: Weekly Returns, NOBS=1,769

Size	LHS	$\sum_{k=-1}^{-2} b_{O,k}$	$b_{O,0}$	$\sum_{k=1}^{2} b_{O,k}$	$\bar{R}^2$
1	P14-P11	0.0067	0.5114*	-0.1929*	0.35
2	P24-P21	0.0301	0.6848*	-0.1858*	0.63
3	P34-P31	0.0391‡	0.6871*	-0.1971*	0.60
4	P44-P41	0.0372‡	0.4872*	-0.1311*	0.46

Joint Test: $W_4^U = W_4^C = 101.94^*$

$*$ - significant at 1 percent level; † - significant at 5 percent level; ‡ - significant at 10 percent level.

Table V
Speed of Adjustment and Ex-Ante Firm Characteristics

This table provides time-series averages of the annual portfolio medians of the speed of adjustment measure *DELAY* and other *ex-ante* firm characteristics. The sample period is 1976-1996 and the sample size is 24,704 firm-years. The speed of adjustment measure *DELAY*, defined in equation (6), is computed by running the Dimson beta regression in equation (5) for each stock each year. *DELAY* is constructed to be between zero and one where higher values represent stocks contributing most to portfolio cross-autocorrelations (slower speed of adjustment) and lower values represent stocks contributing the least to portfolio cross-autocorrelations (faster speed of adjustment). The NYSE/AMEX equal-weighted market index is used as the proxy of the market index. At the beginning of each year all stocks available at the intersection of NYSE/AMEX and annual IBES files are divided first into four quartile portfolios based on firm size as of the December of previous year. Size 1 represents the smallest size quartile and size 4 represents the largest size quartile. Each size quartile is further divided into four quartile portfolios based on *DELAY* computed from daily returns for that year. In each size quartile we focus our attention on the extreme *DELAY* quartiles. *High* represents 25 percent of stocks with the highest *DELAY* measure and *Low* represents 25 percent of stocks with the smallest *DELAY* measure within each size quartile. Each *DELAY* portfolio contains, on average, 77 stocks. The *ex-ante* portfolio characteristics for these portfolios are reported below. *Size* is the market capitalization as of the December of the previous year in millions of dollars, *Volume* is the average number of shares traded per day over the previous year, *Turnover* is the average daily turnover in percent over the previous year, *Nana* is the number of security analysts making annual earnings forecasts as of the September of the previous year, *Price* is the stock price as of the December of the previous year, *Stdret* is the standard deviation of daily returns over the previous year in percent, and *Spread* is the average relative spread for the stock in the previous year also in percent.

Size	Delay	DELAY	Volume	Turnover	Size	Price	Stdret	Nana	Spread
1 (Small)	Low	0.35	11777	0.193	64.22	9.64	2.83	1.93	2.36
	High	0.70	6422	0.132	54.11	12.02	2.39	1.85	2.08
2	Low	0.34	27342	0.217	243.43	18.59	2.30	5.18	1.43
	High	0.65	15663	0.146	223.76	22.16	1.83	4.38	1.34
3	Low	0.33	61394	0.206	742.95	25.58	1.85	11.15	1.04
	High	0.58	46238	0.169	664.29	29.31	1.71	8.93	0.98
4 (Large)	Low	0.30	209481	0.187	3662.73	39.11	1.56	21.48	0.63
	High	0.50	128966	0.194	2214.57	39.30	1.62	16.95	0.71