Persistence of the Dow Jones Index on Rising Volume

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ABSTRACT

This paper documents a new relation between the persistence of stock returns for a large firm index and trading volume. Previous results on the negative relation between volume and persistence are replicated, but a second effect is discovered. Persistence is directly related to the current rate of change of volume. Also, this effect appears much stronger for postive returns than negative returns. A bootstrapping technique is developed and tested which allows matching many of the known cross dependencies between volume, returns and volatility over time. This is used to test the previous results. Finally, a technical trading rule style specification test is used to test a parametric model designed to capture these effects. The technical trading rules confirm many of the previous results. However, they strongly reject the proposed model.

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I. Introduction

For many years the weak short range correlations in index stock returns has been thought to be well understood. The explanation given in Fisher(1966) which stressed the delayed adjustment of some firms' prices to new information worked very well in explaining observed empirical results. It could account not only for correlations in broad indices, but also the observed cross correlations from small to large stocks. Recently, this explanation for short range correlations has come under some criticism. Several papers have suggested that the magnitude is too large for certain specific models of nontrading and stale prices.[1] Others have noted a changing structure in the correlation pattern.[2] They generally find an inverse relation between correlations and some measure of economic activity, either volatility or trading volume.

One important aspect of these results on changing correlations is that they are all still qualitatively consistent with Fisher's explanation. However, the mechanism must now be defined in a more elaborate framework. To do this we need the idea of changing speeds of economic time put forth in papers by Clark(1973) and Stock(1987), and market micro-structure frictions summarized in Cohen et. al.(1980,1986). These two ideas can be put together to provide explanations which are qualitatively consistent with the observed correlations. During periods when there is very little economic activity and information is moving slowly trading frictions would loom large. There may be a large number of transactions carrying over on specialist books, and transactions costs themselves would be large relative to the magnitude of incoming information. The combination of these effects may cause persistence in observed prices and indices. However, during periods of greater activity economic time is moving faster and the daily obervations are actually spaced farther apart in economic time. Transactions costs and other frictions will be small relative to the magnitude of events. Obseverved persistence in indices and individual stocks during these periods would be small.

[1] For examples of this see Atchison et. al. (1987) and Lo and Mackinlay(1990). Also, Lo and Mackinlay(1990) and Mech(1991) analyze lagged price adjustment issues.

[2] These papers include Campbell et. al.(1991), LeBaron(1992), and Sentana and Wadhwani(1990) for stocks. Bilson(1990), Kim(1989), and LeBaron(1992) for foreign exchange. A very detailed study on individual firms is Wiggins(1991).

Initially it appears that this is a useful explanation, and all that is necessary is to begin exploration into quantifying it and calibrating models. However, there are still several troubling facts that directly contradict some of the previously stated results. First, in an early paper, Morse(1980) demonstrates evidence for increased persistence in individual firms on higher volume. He explains this by appealing to an idea of diverse information. Periods of high volume will be periods when traders' information is more diverse and is in the process of converging. During these periods learning will be taking place and beliefs will be converging. Correlations will be induced by this convergence mechanism. In a more recent paper Antoniewicz(1991) documents the usefulness of conditioning on volume signals in tests based on technical trading for individual NASDAQ firms. These results are consistent with those in Morse(1980), indicating more persistence when trading volume is high. They also agree with a large bulk of technical trading rules which suggest that traders should follow price trends when they occur on generally large volume.[3]

This paper will address problems suggested by these very different results. Evidence for increased persistence for the Dow Jones Index on high volume will be considered. Many of the results stated earlier were applied at the individual firm level to cross sections of firms of varying sizes. Most of the analysis here is done using conditional correlations estimated using volume conditioning information. Significance of the results will be demonstated using bootstrap simulations designed to capture most of the important characteristics of the two series used. Finally, a parametric model will be tested using technical trading based specification tests.

Section II describes the data series used. Section III presents the important empirical message of the paper in some simple plots of conditional correlations. These results are tested more rigorously in section IV. Section V develops and tests bootstrap simulations designed to replicate many of the time series and cross sectional features of volume and returns series. Section VI tests correlations at longer lags and uses an individual firm index to see how much of this phenomenon is coming from correlations across firms and time. Section VII introduces a parametric model and tests it using technical trading rule based tests. Finally, section VIII concludes the paper and connects some of these results to recent theories on trading volume.

[3] Also, one of the tests performed in Wiggins(1991) finds some evidence for increased cross firm correlations when this correlation is conditioned on contemporaneous volume increases.

II. Data Descriptions

This data used in this study come from the Dow Jones index used in Lakonishok and Smidt(1988) and from the Center for Research in Securities Prices (CRSP). The Dow series contains and extensive record of daily prices and trading volume back to 1897. This study will analyze a subset of this daily series from July 1962-December 1987 only. This is done for several reasons. First, it will be useful to align with periods in which the CRSP data is available. Also, in periods before 1953 the existence of half trading days on Saturday causes some difficulty in using the information in the volume series. Finally, this makes these results more comparable to other research. Many of the tests used here will concentrate on the sample ending in September 1987 to avoid the influence of the crash on the nonlinear models.

The CRSP data set will be used for two purposes. First, the value weighted index with dividends will be used for comparison with the Dow. Most results will concentrate on the Dow since it is an index of larger firms and the volume series refers to it. Second, a set individual firms will be selected to closely match up with the Dow series used to study cross effects between individual firms.

The Dow price series is log differenced to give a returns series.[4] Using the volume series requires some extra work to render the series stationary. Campbell et. al. (1991) (hereafter CGW) use several different techniques including a moving average.[5] That technique will be used here. The volume series is first divided by a 100 day moving average,

$$mav_t = (1/100)\sum_{j=0}^{99} v_{t-j}.$$

The series resulting from this procedure is still heavily skewed. The series is then log transformed to give the final volume series used in this study

$$V_t = \log(v_t/mav_t).$$

[4] This series does not include dividend payments.

[5] They actually normalize by a moving average of the logged turnover ratio. It will be shown here that this different volume measure did not greatly affect the results. However, further studies comparing the different techniques of handling volume are clearly necessary.

Summary statistics for some of the series used in this study are given in table 1. For the Dow series and its two subsamples we see the usual amount of large kurtosis present in financial series. The first order correlations show significant correlation at the first lag and no correlation after that. This is typical for a large firm index. The magnitude of these numbers is also crucial since much of this study will be concerned with correlations at 1 lag conditioned on trading volume. The transformed volume series looks closer to normal than the returns series with a kurtosis of 3.7. Also, taking logs has eliminated much of the skewness in the series. Trading volume is highly persistent here as seen in the large autocorrelations. This fact will be important in building volume simulations.

III. Summary Plots

This section presents some pictures examining the movements of conditional autocorrelations in the series. The first piece of conditioning information used will be the normalized trading volume at time t, V_t. The second piece of information attempts to estimate the local rate of change for trading volume. This is difficult for a noisey series such as trading volume. This study will use a local comparison between today's volume and the past 4 days' volume,

$$DV_t = V_t - (1/4)\sum_{j=1}^{4} V_{t-j}.$$

This measure attempts to capture the local growth in trading volume today over the past several days average.

Figure 1 plots estimates of the correlations for the Dow series from July 1962 through September 1987. The estimated correlation from return at time t to $t+1$ is plotted conditional on time t volume information. The series is unconditionally demeaned before the correlations are estimated.[6] Both volume and the change in volume are mapped into their distribution fractiles before the correlations are estimated. Then a nonparametric estimation of the correlation is done using a uniform kernel and a bandwith of 0.3. This can be viewed simply as moving a $0.3x0.3$ square box around on the volume fractile base and plotting the estimated correlation in the vertical direction.

This figure is very informative. Moving along the volume axis on the right the effect of increasing volume can be observed. Moving from low to high (back to front) on this axis the

[6] Similar results were found using means estimated within each volume grouping

general decrease in correlation identified in (CGW) can be seen in the decrease in correlations as volatility increases. Moving from left to right along the front axis a second effect is observed. Conditioning on the local increase in volume there is actually an increase in correlation as we move from the low to high (right to left). This increase appears to flatten out at higher levels of volume. This effect shows some increased persistence in the Dow on a local increase in volume as well as the original decrease in correlation with higher overall volume.

This appears to start to agree with some of the results in Morse(1980) and Antoniewicz(1991) on volume and persistence. Separating the returns into positive and negative returns at time t makes this result more intriguing. Figure 2 plots the relation for positive returns at time t. The increasing delta volume effect is greatly strengthened while the volume effect is greatly reduced. Figure 3 plots the same results for negative returns. Here, we see a reverse picture with an decrease in the delta volume effect and an increase in the volume effect. These results are broadly consistent with some of the asymmetries pointed out by technical analysts. They spend many pages talking about the use of volume confirmation in rising markets, but few pages on what should happen in falling markets.[7]

Also, it is possible that the results for negative returns are related to some of the reversal phenomena documented in Bremer and Sweeney(1991). These authors show that large price decreases tend to be followed by a price increase. Examining figure 3 more closely shows that the delta volume effect appears to be present at lower levels of volume, but disappears at higher levels. This is also consistent with the theory of investor behavior suggested in Brown et. al.(1988) where investors are faced with news shocks for which the uncertainty is resolved over several days. During this resolution period prices will be rising for both positive shocks and negative shocks. This generates persistence for positive shocks and reversals for negative shocks.

The results presented in these plots are suggestive of what is going on, but they should not be viewed as statistical tests. There are still many problems that are not being accounted for in these pictures. There is an obvious dependence between the two measures so the box sizes are not uniform. Also, the conditional means are not adjusted for. Finally, the impact of outliers needs to

[7] See Weinstein(1988) page 237. In his section on short selling advice very little emphasis is placed on trading volume.

be accounted for. Some of these issues will be addressed in the next section where the results will be made more precise.

IV. Correlation Regressions

This section begins to quantify what is going on in these plots by estimating nonlinear models designed to capture these effects. In table 2 models where the correlation effect contains a linear and quadratic term are fitted. This is done for comparison with the results in CGW.

The first row of table 2 shows the estimates from fitting an unconditional AR(1) to the returns series. As was evident from table 1, this term is significantly different from zero. The results in CGW showed a negative relation between volume at t and the conditional correlation between returns at time t and t+1. This result is repeated for the Dow in the next two rows of table 2. The linear volume correlation term, β_1 is significantly negative. For the Dow the quadratic term is insignificant. In the bottom section of this table the results are presented for the CRSP value weighted index. The estimated parameters and reported R^2 are very close to those in CGW which is interesting since the volume series is different and is detrended slightly differently.

The row labeled DV in table 1 adds the delta volume effect shown in the first 3 figures. A term is added to the conditional correlation adding the local rate of change for volume for positive returns only. The parameter β_3 is used for this term. Its estimated value is significantly positive as predicted by the earlier pictures. This suggests that there may be two effects connected to trading volume. One related to its overall level, and a second to its local rate of change. This is seen as an increase in persistence when the Dow is rising, and volume is locally rising.

There are two potential weaknesses in this format for estimating conditional correlations. First, the estimate may be sensitive to outliers in the volume series, and second it may be difficult to simulate since the correlation terms are not bounded. This simulation problem would not be bad if the series were independent, but if they are dependent on each other in a complicated way then there may be some problems.

For these reasons the conditional correlations are replaced with a different functional form. The hyperbolic tangent is used to allow a near linear relation for small changes in the series, and bounded response for extreme outliers. An example of the hyperbolic tangent is plotted in figure

4.[8] The function used will normalize the input to the hyperbolic tangent function by the standard deviation of the input series.

The estimated model then takes the form,

$$r_{t+1} = \alpha + (\beta_0 + \beta_1 f(V_t) + \beta_2 S_t f(DV_t))r_t$$

$$f(x) = \tanh(x/\sigma), \qquad \sigma = \mathrm{std}(x)$$

$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Estimated parameters are given in table 3. This table shows very similar results to table 2. The first part of the table replicates the results from table 2. Both the volume effect and the delta volume effect are significant for the full sample estimation. Note that the R^2 did not change greatly from the previous estimates. The remainder of table 3 analyzes the two subperiods and the period including the crash. For each of of these periods the results do not change much. The only major difference seen is a reduction in the volume parameter during the second subperiod.

There are many problems in confirming that the previous results are clearly indicating persistence on a rise in volume. In table 4 several different specifications are tested to try to sort out just what is going on. The first possibility that is considered is related to the fact that volume is a noisey series and the delta volume index may just be a good way for lagged volume to enter into the correlation effect. Since lagged volume is part of the delta volume term and enters negatively this could be the cause for the results seen so far. The first line of table 4 estimates the model putting in a separate term for the sum of 4 lagged volume terms. The estimated parameter for this term, β_3, is not significantly different from zero and the other parameters did not change.[9]

The initial figures show another effect that could be causing these results. There is a very different connection between the level of trading volume and correlations for positive and negative returns. It is possible that the regression results are attempting to fit this effect through the delta volume term. The sign effect is specifically modeled through a term which allows a different

[8] This is a multivariate version of a smooth threshold autoregressive model. See Tong(1990), page 108. The hyperbolic tangent is also used extensively in neural net estimation. For an example see Weigend, Huberman, and Rumelhart(1991).

[9] Also, several lags of volume were added separately to this equation with similar results.

correlation response to volume for positive and negative returns. The parameter for this term is β_4. Estimation of this parameter gives a positive, but insignificant value. The other parameters remain close to their previous values.

To avoid the impact of outliers all of the estimation has been done on a time period which does not include the crash in 1987. However, there are many more large points in this series, and it would be useful to know how sensitive these results are to the presence of these. A first attempt at this is made by replacing the returns series by its distribution fractile and repeating the previous regression. This gives us some idea of how robust the results are. Results of this estimation are given in the third row of table 4. The rank transformation had little impact on the previous results.

It is also possible that the conditional means of the return at time $t+1$ may depend on lagged volume directly.[10] Lagged volume and delta volume are now entered into the regression directly as β_5 and β_6. These terms are insignificant showing that lagged volume was not the cause.

The final test explores another asymmetry present in the initial plots. The delta volume effect had a much bigger impact on the correlations for positive returns than negative. This is directly tested by allowing a delta volume effect for negative returns as well as positive. The parameter β_7 represents this effect. This is not significantly different zero indicating very little impact from a local increase in volume on negative returns.

When working with nonlinear models one can never be completely sure about a specification. But the tests used here support the evidence that there is a positive impact from an increase in volume on the persistence of the index conditioned on a positive return at time t

V. Bootstrap Simulations

Several important facts about trading volume and stock returns involve the connection between volume and volatility. There is strong persistence in both, and a rich set of cross relations.[11] These dependencies may make the standard errors presented under OLS inappropriate. Therefore bootstrap simulations will be necessary. This paper will use two types of bootstraps, parametric and m-dependent. The parametric bootstrap attempts to parameterize the important characteristics of

[10] Antoniewicz(1991) presents results showing that this is the case for a sample of NASDAQ firms.

[11] See Karpov(1986) and Gallant, Rossi and Tauchen(1989).

the series and uses the estimated residuals as actual disturbances in simulation. The m-dependent bootstrap redraws from the actual series in a blocked fashion to recreate the actual dependence. The parametric bootstrap will be described first.

Fitting a model to the joint series will also reveal some of the interesting structure contained in these series. There are several important characteristics to replicate. The value of the simulations will be judged on their ability to match some of these features. The first property is that returns are heteroskedastic, or there are positive correlations in squared returns. Second, volume is very persistent. This has already been seen in table 1. Third, there are strong relations, both contemporaneous and lagged, between volume and returns, and volume and squared returns. This paper will bring together several boostrapping techniques to replicate these effects. To do this a member of the GARCH family, the exponential GARCH,[12] will be used to model returns. In addition a VAR will be used to model volume. Essentially the procedure is attempting to model a bivariate system with a third unobserved state variable, volatility.

This is technique builds off methodologies used in Brock et. al.(1990) and Antoniewicz(1991).[13] The first paper models the univariate properties of the returns series using GARCH and Exponential GARCH models. These are simulated using scrambled residuals to give representative time series for returns. The second paper models returns and volume jointly in a bivariate VAR. Here we merge the two approaches to be able to capture the connections between volume and volatility at all lags.

The procedure models returns as a VAR with Exponential GARCH disturbances.[14] All the models were fit to the Dow volume and returns series from July 1962- Sept 1987. In the identification procedure various lagged variables were added to the exponential GARCH in both the variance and return parts. Three crucial additional variables were insignificant and did not help in terms of the

[12] This model was deleloped by Nelson(1991). Its predecessors are the GARCH model (Bollerslev(1986)) and the ARCH model (Engle(1982)). See Bollerslev et. al. (1990) for a survey of these models.

[13] These papers base much of what they do on Efron(1982) and and Freedman and Peters(1984). See Leger et. al.(1991) for an excellent survey of bootstrap technology.

[14] The exponential GARCH model was used here for two reasons. First, it allows entering many variables into the conditional variance equation without worrying about sign restrictions. Second, it actually generated a better representation of the persistence in squared residuals than the GARCH model for this series.

Schwarz criteria in the exponential GARCH.[15] First, lagged volume was added to the variance equation. Several lags were tried and all turned out to be insignificant. Second, lagged volume was added to the returns equation. This also turned out to be insignificant. Third, volatility was added to the returns equation, a GARCH-m. This also was insignificant for this time period and data set. The only important piece of extra information added was the addition of 1 lagged return to the returns equation, an AR(1). The final identified exponential GARCH is,

$$r_t = a + br_{t-1} + \epsilon_t$$

$$\epsilon_t = e^{\frac{1}{2}h_t} z_t$$

$$h_t = \alpha_0 + g(z_{t-1}) + \beta h_{t-1}$$

$$g(z_t) = \theta z_t + \omega(|z_t| - (2/\pi)^{1/2})$$

$$z_t \sim N(0,1).$$

One interesting fact about the exponential GARCH model is that the sign of past returns is allowed to influence the volatility of future returns.

Now that returns are set volume must be modeled. Here a trivariate VAR is identified on lagged volume, lagged returns, and lagged squared residuals, ϵ_t^2 from the GARCH model. Using the Schwarz criterion a model of the following form was identified,

$$v_t = \sum_{j=1}^{10} a_j v_{t-j} + \sum_{j=1}^{3} b_j r_{t-j} + \sum_{j=1}^{3} c_j \epsilon_{t-j}^2 + \mu_t.$$

The model identified a relation from lagged returns and lagged volatility to future volume.[16]

These models hopefully capture much of the lagged dependence in the series. Contemporaneous dependence is captured naturally by the bootstrap procedure in the following way. Both models are estimated and the residuals are stored. These residuals are then scrambled and redrawn simultaneously with replacement. In other words the contemporaneous dependence between μ_t and ϵ_t is maintained while simulating. This should accurately recreate the cross series dependencies.

[15] The Schwarz(1978) criteria will be used as the general identification method here.

[16] This is interesting since there was no connection from lagged volume to volatility in the Exponential GARCH model. This asymmetry should be further tested.

The use of such a complicated model without any diagnostic on how it is doing would be dangerous. Figures 5 through 8 show how well the model is capturing certain features of the series. The figures present correlations and cross correlations for the actual series along with simulated 5-95 percent confidence bands from 500 simulated runs of the estimated model.

Figure 5 shows the correlations of the squared returns from the simulated model. It is clear that the model is doing a good job of replicating the persistence in squared returns. Figure 6 shows the correlations in volume from the data and the simulations. Again the fitted model is doing a good job of matching up with these moments. Both of these effects were modeled directly, so it is not too surprising how well the simulations do at replicating them. Figure 7 presents cross correlations from returns to volume. There is very little correlation from lagged volume to returns. There is a small jump at 1 lag which is accounted for by a boost in the confidence bands. There is a large contemporaneous correlation for both the data and the simulations and then a persistent correlation from return at time t to future volume. The model is clearly able to replicate contemporaneous correlations which were not modeled directly, but were simulated by drawing residuals. Also, the simulations are able to capture some lagged effects that were not directly estimated such as volume from time $t-1$ to return at time t. This is probably a combination of the AR(1) dependence for returns and the joint dependence of contemporaneous returns on volume. The final picture, figure 8, shows the relations between squared residuals and trading volume. The data displays a strong contemporaneous relation and a relation between volatility today and future volume. These results are again well replicated by the simulated model. This model will be referred to as the null model.

Now the null model can be put to use to test the previous results. This is done in table 5. The first row repeats the results for the Dow series. The second line presents the fraction of null model simulations out of 500 which generate values as large large as those in the original data. This clearly shows that the estimated values for β_1 and β_2 were unlikely to have come from a model of this form.

The next row in the table present results from an m-dependent bootstrap.[17] In the first case volume and returns are jointly resampled one point at a time. This replicates the cross correlations, but ignores dependence over time. It again shows the significance of the parameters

[17] See Carlstein(1986) and Kunsch(1989).

against this very restrictive null model. The final two rows attempt to replicate the results with a 10 dependent bootstrap. In this case blocks of points are drawn 10 at a time from both series to recreate the new series. This simulation appears to recreate the original series with the simulated 10 dependent process. This gives us some idea of the reliability of the parameter estimates, but it should still be viewed with some caution. Taking the length of the m-dependence to the length of the sample obviously recreates the original results. A better understanding of the biases in this type of simulation is needed before firm conclusions can be made.

VI. Other correlations: Longer Horizons and Individual Firms

This section explores some other related correlations which are important to completely understanding the phenomenon. Table 6 reruns the earlier regressions which were run at 1 lag for lags 2 and 3. At lag 2 estimating the volume effect on its own gives an insignificant coefficient, but when this is combined with the delta volume term both coefficients are significant. This suggests that the interaction between these effects is crucial for understanding dependence at longer horizons. However, this dependence is short lived since at lag 3 both coefficients are not significant. These results are interesting since the series shows little evidence for unconditional correlation at any lags higher than 1. The merging of these two effects shows a possibility for some further connections.

All the results estimated have used the Dow index. When an index is used a natural question to ask is how much of the correlation is coming from own firm correlations and how much is coming from cross firm correlations. In order to test this a portfolio of 21 large firms sampled to be close to the Dow during this period is constructed from the CSRP data set.[18] The firms used are given in table 7.

Using the individual firms an estimate of the strengths of the own and cross components can be estimated. A model of the following form is estimated for each firm.

$$r_{jt+1} = (\beta_1 + \beta_3 f(V_t) + \beta_5 S_t f(DV_t)) r_{m-jt} + (\beta_2 + \beta_4 f(V_t) + \beta_6 S_t f(DV_t)) r_{jt}$$

$$f(x) = \tanh(x/\sigma), \qquad \sigma = \mathrm{std}(x)$$

$$S_t = 1 \quad r_{mt} \geq 0, \quad S_t = 0 \quad r_{mt} < 0$$

[18] More extensive details on the construction of this series are contained in LeBaron(1991b).

Here, $r_j t$ is the return of firm j at time t, and r_{m-jt} is the return on an equally weighted index of the 21 firms with firm j removed. The average of these parameters estimated over all the firms is given in table 8. The parameter numbering is designed so that each pair refers to the cross and own term for each type of conditioning information, volume and delta volume.

The first two parameters, β_1 and β_2, refer to the parameters without any volume conditioning where β_1 estimates the cross firm effect and β_2 the own firm effect. The numbers in parenthesis are simulated p-values from a simulation done by scrambling the portfolio of firms maintaining the contemporaneous correlations, but detroying time dependence.[19] The two constant terms are both significantly different from zero indicating some amount of own and cross correlation. The next two parameters β_3 and β_4 refer to the volume effect. Again, these parameters represent the cross firm and own firm effects, respectively. From the numbers shown here it is clear that the volume effect is coming mostly from cross firm correlations as opposed to own firm correlations. Looking at β_5 and β_6, the parameters for the delta volume effect, a similar phenomenon is displayed.

These results indicate that most of the changing correlations are coming from cross index effects. This is interesting in that it clearly influences some of our directions in trying to model this.[20] However, it is also possible that this is what should have been expected. The volume series is an aggregate series and we see changes in cross correlations using this series. Very different effects might be seen using individual firm volume.[21]

VI. Testing a Parametric Model Using Trading Rules

This section estimates a parametric model that includes adjustments for heteroskedasticity and the changing correlations. The exponential GARCH model is again used for this purpose. This model will then be simulated and compared to results from the original data generated from technical trading rule style specification tests. The purpose of this exercise is to see whether the

[19] Future work should improve on these simulations which clearly do not well represent the dependencies found in the data. However, this does require modeling the dynamics of the entire index of firms together.

[20] Mech(1991) and LeBaron(1991b) approach this question from a transactions cost direction.

[21] Wiggins(1991) provides an extensive study using individual firm volume. Some evidence is given for increasing amounts of delayed response from the market today to certain individual firms in the future using current volume. These results generally look at smaller firms than are used here.

volume phenomenon documented so far is able to generate the longer range persistence detected by trend following trading rules.

Table 9 presents the estimated parameters for nonlinear model. The crucial terms are b_1 and b_2 which capture the changing correlations on the two volatility effects. The second section of the table shows estimates of these parameters which are both significant and close to their estimated values from the original regressions in table 3. The parameters are also significant in the two subsamples.[22] This model modified model can now be introduced into the return volume simulations. It will be referred to as the alternative model.

The use of technical trading rules in a specification test framework was introduced in Brock et. al. (1990) and extended to volume series in Antoniewicz(1991). In these papers various tests used by technical analysts are applied to simulated stochastic processes to see how well these replicate results in actual financial time series. This section will use these tests on the various volume volatility models that have been estimated. Most importantly they will be used to see if the parametric specification for changing correlations is capable of generating results seen in actual data.

One of the major rules used in Brock et. al.(1990) is the variable length moving average. This rule translates into generating a buy signal when the price is above a moving average of past prices,

$$p_t > (1/N) \sum_{j=0}^{N-1} p_{t-j},$$

and a sell when it is below,

$$p_t < (1/N) \sum_{j=0}^{N-1} p_{t-j}.$$

This divides all days into either buys or sells. Returns over the next day are then calculated and means and standard deviations for returns conditioned on either buy or sell signals are estimated.

Any quick survey of technical trading literature shows the importance of trading volume in the signals used.[23] In an important extension Antoniewicz(1991) uses the rule with a volume signal

[22] One crucial parameter which changed across the subsamples was θ. This indicates some instability in the leverage effect. This may be related to some of the results in Gallant et. al. (1990) which suggest the the leverage effect is related to a few volume outliers.

[23] See Weinstein(1988) or Colby et. al.(1988). Many of the results in this paper were actually inspired from some of the more casual comments of technical traders.

and applies this to a subset of NASDAQ individual firms. The rule is extended by requiring that both price and volume be above a moving average for a buy signal. Volume is required to exceed the lagged moving average by a multiple γ,

$$V_t > \gamma(1/N)\sum_{j=1}^{N} V_{t-j}$$

Sell signals are not considered.[24]

This paper uses a slightly different version of volume in the trading signal. Volume is used simply as a trend confirmation signal. A day is classified as a buy if either one of the following conditions holds: 1.) the price on day t is above the moving average and volume is above γ times its moving average, 2.) the price on day t is above the moving average and the signal on day t-1 was a buy. This generates signals that capture the idea that high volume signals the start of a trend, but high volume is not required to maintain buy signals during the trend.

This rule will be used with a 4 day volume moving average. This means that $N = 4$ in the above equation. Little difference was seen in modifying this short range moving average. Also, this moving average is used since it aligns exactly with the volume change term used in the nonlinear model. This gives that model its best chance of being detected.

Some initial tests of this rule are shown for varying confirmation strengths, γ, in figure 9 for a 50 day price moving average. The returns numbers given are simply the mean over periods classified as buy or sell. Volume confirmation is implemented in exactly the same way for sells as it is for buys. The figure shows dramatically that volume confirmation has a very different impact for buys and sells. For the buy signals the conditional returns are steadily rising, almost doubling by $\gamma = 1.8$. The sell returns which start negative actually start to increase as volume confirmation is added. Obviously this is not useful for a trader using this rule who would like to observe large conditional negative returns for the sells. This general asymmetry appears broadly consistent with the results in the early plots and estimated models, and with the general feeling of technical traders toward volume confirmation on the sell side.

Table 10 presents simulation results using the volume confirmation rule. The null model used in section 5 which has a constant correlation in returns from an AR(1) is now simulated and run

[24] The use of volume confirmation on the sell side is not a very agreed upon issue by technical traders.

through the volume trading rules. This will be compared to the model which allows this correlation to change over time.

The first part of the table present results for the 50 day price moving average rule. The results are given for no volume confirmation, and $\gamma = 1$, $\gamma = 1.5$, $\gamma = 1.75$ respectively. In each case volume confirmation is added to the buys only. The sells use the same rule throughout. The first row, labeled Dow, gives the values for the original Dow Jones series. The table reports several pieces of information. The number of signals are labeled Nbuys and Nsells. The mean one day buy return during buy periods is labeled Buy, and the 1 day standard deviation is labeled σ_b. For sells these are Sell and σ_s respectively. The final column shows the difference between the buys and the sells. The table then gives a detailed report on the outcome of 500 simulations of the null model with constant correlations. Fraction > Dow is the fraction of simulation runs greater than the Dow for each statistic. Mean and Std are the mean and standard deviation from the simulations.

From the table it can be seen that without volume confirmation there is little evidence against the simulated null model using the 50 day moving average. The mean buy return of 0.046 percent was not significantly different from returns generated by the simulated null model. As γ is increased the number of mean buy returns increased, as the number of signals falls. At $\gamma = 1.75$ the mean buy return was 0.095 percent with only 2.6 percent of the simulations generating returns as large as the actual series. The number of actual buy signals has reduced dramatically to only 612. This obviously questions the actual profitability of such a real when it is really used.

Similar results are displayed for the 150 price moving average rule. As γ is increased the returns for the buys increases, while the number of buy signals decreases. The fraction of buy returns from the simulations which are larger than the actual series generally falls from 7.4 percent with no volume confirmations to 0.8 percent for $\gamma = 2$. Also, note that for both the 50 and 150 MA rules there is little difference between the number of buy and sell signals generated for the simulations and the actual series.

This table shows the general impact of volume confirmation on both buy and sell returns and their significance in comparison to the simulated null model for volume and returns. The important point is that volume confirmation adds to the persistence detected by the moving average rules. For the 50 day moving average it actual moves the trading rule specification test from being insignificant to significant. These are interesting facts, but the important question here is whether the estimated nonlinear model can replicate this increased persistence on high trading volume.

In table 11 the alternative model which allows correlations to change over time as a function of volume is not simulated and compared with the technical trading rule results. For both the 50 and 150 day rules used the performance of this model does not do a very good job of replicating the trading rule results. Results are shown for $\gamma = 1.75$ for the 50 day rule and $\gamma = 1.75$ and $\gamma = 2$ for the 150 day rule. The results clearly show that this model is unable to capture what the rules are picking up. For example, for the 150 day rule using $\gamma = 2$ the mean buy return is 0.10 percent and the fraction of simulations that generates a value of this magnitude is 0.8 percent.

The results in this section show that the tradings rules detected patterns that were consistent with other results in the paper. These patterns, indicating persistence on high volume for positive returns agree with what has been found in all of the earlier sections of the paper. A nonlinear model that captured most of these effects was estimated and simulated, but was unable to replicate the trading rule results. The nonlinear correlation terms are not able to generate the kind of persistence seen by the rules. This questions this simple specification as a good picture of what is going on in the data. Also, it questions the implicit measures of total persistence that it's parameters imply.

VIII. Conclusions

This paper has demonstrated that there is evidence for increased persistence in the Dow Jones Index on rising volume. The volume effect is actually more complicated than previously thought with an inverse relation between the level of trading volume and correlations, and a positive relation between correlation and the local rate of change of volume. This second effect appears to be asymmetric across positive and negative returns, showing up much stronger for positive returns. These results are justified through the use of bootstrap techniques replicating the connections between volume, returns, and volatility. The changing correlation patterns for both volume effects are shown to be coming primarily from index cross correlations as opposed to own firm correlations. Finally, a parametric model displaying this characteristic is rejected by technical trading rule tests tuned to use volume conditioning information.

While the empirical results here appear strong and consistent across the subperiods they should still be viewed with some caution. In the nonlinear modeling world it is difficult to test for all possible specifications. Table 4 makes some first attempts at this, but further tests on just how lagged volume should enter into the relation are necessary to sharply demonstrate that it is coming in through the rate of change of volume mechanism. Finally, the fact that the estimated model can not generate the level of persistence seen by the technical trading rules is troubling for this exact specification.

These results, showing that the relation between volume and correlations may be quite complex, are related to recent theoretical work on trading volume. Wang(1991) shows that large volume may be associated with more negative or positive autocorrelations depending on whether there is informational asymmetry. Without informational asymmetry large volume indicates a large amount of buying or selling for liquidity reasons and the price should rebound quickly to its previous levels. In the presence of informational asymmetries large volume may be connected with persistence in price movements since the price does not fully reflect the private information of informed traders.

Another interesting theoretical paper which is related to some of the results seen here is Blume, Easley, and O'Hara(1991). This paper introduces trading volume into heterogeneous rational expectations model. Volume can be used by traders to indicate the quality of information signals coming in. This quality is changing over time in the model. Part of this model outlines the connection between the informativeness of the signal and trading volume. For very uninformative signals volume is low since traders place very little confidence in there signals. As the precision of the signal increases, trading volume increases at first. However, when the informativeness of the signal gets very large trading volume starts to fall do to the fact that people are actually receiving very precise and highly correlated signals. This model also shows how the value of technical analysis depends critically on how informative new signals are for traders relative to prior information. These results again stress a rather complex relation between price movements and trading volume.

The theoretical possibilities are further complicated by results such as those in Kim and Verrecchia(1991) which emphasize the impact of new information arrival, diversity of opinions, and market liquidity. This model suggests that when new information arrives traders diverse interpretations of this information cause more heterogeneity of beliefs in the market, and therefore bid-ask spreads widen and the overall liquidity of the market falls. However, this may be accompanied by increases in trading volume as the informed traders have more diverse beliefs. Uninformed traders stay out of the market at this time. This also suggests several different ways in which volume may interact with price movements depending on what type of volume it is (liquidity or information). It also suggests that the volume volatility connection might be very complicated.

These papers show the complexity possible in volume price relationships, but they do not help much in explaining the asymmetry observed here between positive and negative returns. This could be related to the model of Brown et. al.(1988) in which it takes time to resolve the uncertainty connected with new information shocks. Both good and bad shocks have a negative uncertainty impact on prices along with their good or bad impact. For a good shock there is an initial jump and the upward persistence after that as uncertainty is resolved. For a bad shock there is an initial downward jump and then a reversal as uncertainty is resolved. This model is consistent with the asymmetries observed here.

Clearly more theoretical and empirical work is needed in this interesting area. It still is unknown whether we will be able to use volume data for both aggregate and individual stocks to sort out between various competing theoretical models for heterogeneity and learning dynamics. However, the challenge is certainly an exciting one.

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Table 1
Summary Statistics

Description	Dow 62-87	Dow 62-74	Dow 75-87(Sept)	Volume/MA(62-87)
N	6346	3124	3222	6346
Mean*100	0.024	0.003	0.045	0.689
Std.*100	0.855	0.798	0.906	23.4
Skewness	0.247	0.234	0.239	0.163
Kurtosis	5.317	6.311	4.602	3.753
ρ_1	0.131	0.202	0.074	0.665
ρ_2	0.000	-0.008	0.007	0.489
ρ_3	-0.001	0.006	-0.007	0.448
ρ_4	-0.011	0.007	-0.027	0.446
ρ_5	-0.014	-0.023	-0.010	0.437
Bartlett Std.	0.0125	0.0178	0.0176	0.0125

Table 2
Comparison Regressions

$$r_{t+1} = \alpha + (\beta_0 + \beta_1 V_t + \beta_2 V_t^2 + \beta_3 S_t DV_t) r_t$$
$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Series	β_0	β_1	β_2	β_3	R^2
Dow 62-87 (Sept)					
AR(1)	0.131				0.017
	(0.012)				
Vol(1)	0.147	-0.166			0.019
	(0.013)	(0.047)			
Vol2(1)	0.148	-0.158	-0.027		0.019
	(0.015)	(0.058)	(0.122)		
DV	0.137	-0.274	-0.139	0.374	0.022
	(0.015)	(0.064)	(0.124)	(0.081)	
VW 62-87 (Sept)					
AR(1)	0.218				0.048
	(0.012)				
Vol(1)	0.249	-0.290			0.053
	(0.013)	(0.047)			
Vol2(1)	0.245	-0.311	0.069		0.053
	(0.014)	(0.060)	(0.123)		
DV	0.238	-0.393	-0.013	0.276	0.055
	(0.014)	(0.064)	(0.125)	(0.078)	

These regressions are presented for comparisons with Campbell et. al.(1991). Numbers in parenthesis are OLS standard errors. VW is the CRSP value weighted index with dividends included.

Table 3
Modified Conditional Regressions

$$r_{t+1} = \alpha + (\beta_0 + \beta_1 f(V_t) + \beta_2 S_t f(DV_t))r_t$$
$$f(x) = \tanh(x/\sigma), \qquad \sigma = \mathrm{std}(x)$$
$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Series	β_0	β_1	β_2	R^2
Dow 62-87 (Sept)	0.147	-0.077		0.019
	(0.013)	(0.020)		
	0.124	-0.130	0.154	0.023
	(0.014)	(0.023)	(0.030)	
Dow 62-74	0.234	-0.161		0.051
	(0.018)	(0.028)		
	0.214	-0.205	0.140	0.055
	(0.019)	(0.031)	(0.043)	
Dow 75-87 (Sept)	0.076	-0.015		0.005
	(0.019)	(0.028)		
	0.056	-0.070	0.149	0.009
	(0.019)	(0.032)	(0.042)	
Dow 62-87 (Dec)	0.137	-0.097		0.015
	(0.014)	(0.020)		
	0.117	-0.139	0.196	0.022
	(0.014)	(0.020)	(0.029)	

Numbers in parenthesis are OLS standard errors.

Table 4
Modified Conditional Regressions: Further Specification Tests

$$r_{t+1} = \alpha + (\beta_0 + \beta_1 f(V_t) + \beta_2 S_t f(DV_t) + \beta_3 f((1/4)\Sigma_{j=1}^{4} V_{t-j}) + \beta_4 S_t f(V_t) + \beta_7 (S_t)(DV_t))r_t$$

$$+\beta_5 V_t + \beta_6 DV_t$$

$$f(x) = \tanh(x/\sigma), \qquad \sigma = \mathrm{std}(x)$$

$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Series	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	R^2
Lagged Volume	0.125	-0.129	0.154	-0.001					0.024
	(0.014)	(0.032)	(0.036)	(0.031)					
Sign Effect	0.123	-0.151	0.139		0.047				0.023
	(0.014)	(0.031)	(0.034)		(0.045)				
Rank Transform	0.133	-0.106	0.122						0.024
	(0.013)	(0.022)	(0.031)						
Means	0.124	-0.138	0.181			5.65e-4	-12.7e-4		0.024
	(0.013)	(0.023)	(0.036)			(5.7e-4)	(8.2e-4)		
Sign on DV	0.125	-0.133	0.156					0.011	0.023
	(0.014)	(0.024)	(0.013)					(0.032)	

Numbers in parenthesis are OLS standard errors.

Table 5
Regression Bootstraps

$$r_{t+1} = \alpha + (\beta_0 + \beta_1 f(V_t) + \beta_2 S_t f(DV_t))r_t$$
$$f(x) = \tanh(x/\sigma), \qquad \sigma = std(x)$$
$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Series	β_0	β_1	β_2
Dow 62-87 Sept	0.124	-0.130	0.154
Parametric	(0.156)	(0.008)	(0.000)
MDEP1	(0.000)	(0.000)	(0.000)
MDEP10 Mean	0.119	-0.115	0.116
MDEP10 std	[0.018]	[0.031]	[0.038]

Numbers in parenthesis are simulated p-values from various models. Parametric is a parametric bootstrap and MDEP1 and MDEP10 are m-dependent bootstraps. Numbers in brackets are the simulation standard errors.

Table 6
Persistance at Longer Lags

$$r_{t+j} = \alpha + (\beta_0 + \beta_1 f(V_t) + \beta_2 S_t f(DV_t))r_t$$
$$f(x) = \tanh(x/\sigma), \qquad \sigma = std(x)$$
$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Series	β_0	β_1	β_2	R^2
$j = 2$	0.004	-0.027		0.0003
	(0.013)	(0.020)		
	-0.006	-0.054	0.078	0.0013
	(0.014)	(0.023)	(0.030)	
$j = 3$	-0.002	0.005		0.0000
	(0.013)	(0.020)		
	-0.007	-0.009	0.040	0.0003
	(0.014)	(0.023)	(0.030)	

Numbers in parenthesis are OLS standard errors.

Table 7
Firms: Sorted By Percentage Spread

Percentage Spread	Name	Ticker
0.001194	INTERNATIONAL BUSINESS MACHS	IBM
0.001810	GENERAL ELEC CO	GE
0.001843	INTERNATIONAL PAPER CO	IP
0.001907	MERCK & CO INC	MRK
0.002829	MINNESOTA MNG & MFG CO	MMM
0.002985	PROCTER & GAMBLE CO	PG
0.003328	AMERICAN TEL & TELEG CO	T
0.003431	GENERAL MTRS CORP	GM
0.003899	INCO LTD	N
0.003968	TEXACO INC	TX
0.004228	EXXON CORP	XON
0.004415	WOOLWORTH F W CO	Z
0.005231	CHEVRON CORPORATION	CHV
0.005348	UNITED TECHNOLOGIES CORP	UTX
0.005495	DU PONT	DD
0.005602	ALUMINUM CO AMER	AA
0.005634	WESTINGHOUSE ELEC CORP	WX
0.005666	AMERICAN BRANDS INC	AMB
0.005900	EASTMAN KODAK CO	EK
0.005917	GOODYEAR TIRE & RUBR CO	GT
0.006270	SEARS ROEBUCK & CO	S

Spread data is $2(a-b)/(b+a)$ for each firm sampled at 9:45 ET on September 9th, 1991.

Table 8
Individual Cross Correlations

$$r_{jt+1} = (\beta_1 + \beta_3 f(V_t) + \beta_5 S_t f(DV_t) r_{m-jt} + (\beta_2 + \beta_4 f(V_t) + \beta_6 S_t f(DV_t)) r_{jt}$$

$$f(x) = \tanh(x/\sigma), \qquad \sigma = \mathrm{std}(x)$$

$$S_t = 1 \quad r_{mt} \geq 0, \quad S_t = 0 \quad r_{mt} < 0$$

Description	β_1	β_2	β_3	β_4	β_5	β_6
Dow 62-87 (Sept)	0.081	0.037	-0.169	-0.002	0.152	0.007
	(0.002)	(0.000)	(0.000)	(0.650)	(0.000)	(0.164)

Numbers are the average of the individual firm regressions over the 21 large firms. r_{jt} is the return on firm j at time t, and r_{m-jt} is the return on the equally weighted index of the 21 firms with firm j removed.

Table 9
Exponential GARCH Parameter Estimates

$$r_t = a + (b_1 + b_2(f(V_t) + b_3 S_t f(DV_t))r_{t-1} + \epsilon_t$$
$$\epsilon_t = e^{\frac{1}{2}h_t} z_t$$
$$h_t = \alpha_0 + g(z_{t-1}) + \beta h_{t-1}$$
$$g(z_t) = \theta z_t + \omega(|z_t| - (2/\pi)^{1/2})$$
$$z_t \sim N(0,1)$$
$$f(x) = \tanh(x/\sigma), \qquad \sigma = \mathrm{std}(x)$$
$$S_t = 1 \quad r_t \geq 0, \quad S_t = 0 \quad r_t < 0$$

Period	α_0	β	θ	ω	b_1	b_2	b_3
62-87 (Sept)	-0.078	0.992	-0.044	0.115	0.142		
	(0.015)	(0.002)	(0.004)	(0.006)	(0.012)		
62-87 (Sept)	-0.078	0.992	-0.043	0.114	0.134	-0.106	0.136
	(0.015)	(0.002)	(0.004)	(0.007)	(0.012)	(0.020)	(0.027)
62-74	-0.138	0.986	-0.091	0.106	0.205	-0.130	0.106
	(0.023)	(0.002)	(0.007)	(0.011)	(0.019)	(0.028)	(0.039)
75-87 (Sept)	-0.128	0.986	0.029	0.080	0.061	-0.061	0.141
	(0.036)	(0.004)	(0.005)	(0.010)	(0.018)	(0.032)	(0.042)

Estimation is by maximum likelihood. Numbers in parenthesis are asymptotic standard errors.

Table 10
Technical Trading Rule Specification Tests: Null Simmulations

Rule		Nbuys	NSells	Buy %	σ_b %	Sell %	σ_s %	Buy-Sell %
50 MA No Volume	Dow	3623	2673	0.046	0.788	-0.009	0.939	0.055
	Fraction > Dow	(0.464)	(0.526)	(0.268)	(0.670)	(0.530)	(0.750)	(0.356)
	Mean	3603	2680	0.038	0.814	-0.009	0.998	0.047
	Std	[264]	[241]	[0.014]	[0.073]	[0.021]	[0.098]	[0.025]
50 MA $\gamma = 1$	Dow	3525	2673	0.046	0.787	-0.009	0.939	0.054
	Fraction > Dow	(0.452)	(0.502)	(0.256)	(0.614)	(0.540)	(0.718)	(0.338)
	Mean	3505	2661	0.036	0.808	-0.007	0.999	0.043
	Std	[266]	[243]	[0.015]	[0.073]	[0.021]	[0.102]	[0.026]
50 MA $\gamma = 1.5$	Dow	1503	2673	0.053	0.897	-0.009	0.939	0.062
	Fraction > Dow	(0.480)	(0.480)	(0.142)	(0.126)	(0.490)	(0.726)	(0.208)
	Mean	1495	2659	0.030	0.802	-0.010	0.993	0.039
	Std	[229]	[239]	[0.022]	[0.087]	[0.020]	[0.100]	[0.030]
50 MA $\gamma = 1.75$	Dow	612	2673	0.095	1.033	-0.009	0.939	0.104
	Fraction > Dow	(0.428)	(0.476)	(0.026)	(0.078)	(0.522)	(0.740)	(0.058)
	Mean	580	2656	0.023	0.850	-0.008	0.998	0.031
	Std	[179]	[241]	[0.042]	[0.126]	[0.020]	[0.101]	[0.048]
150 MA No Volume	Dow	3771	2424	0.047	0.782	-0.018	0.956	0.065
	Fraction > Dow	(0.556)	(0.442)	(0.074)	(0.576)	(0.828)	(0.810)	(0.046)
	Mean	3806	2376	0.028	0.792	0.002	1.039	0.026
	Std	[412]	[390]	[0.013]	[0.068]	[0.022]	[0.108]	[0.024]
150 MA $\gamma = 1$	Dow	3729	2424	0.045	0.782	-0.018	0.956	0.063
	Fraction > Dow	(0.550)	(0.418)	(0.080)	(0.504)	(0.808)	(0.820)	(0.082)
	Mean	3767	2352	0.028	0.785	0.002	1.042	0.025
	Std	[387]	[362]	[0.013]	[0.070]	[0.022]	[0.108]	[0.026]
150 MA $\gamma = 1.5$	Dow	2597	2424	0.055	0.818	-0.018	0.956	0.073
	Fraction > Dow	(0.314)	(0.424)	(0.014)	(0.260)	(0.830)	.770)	(0.030)
	Mean	2398	2373	0.021	0.774	0.002	1.033	0.019
	Std	[395]	[363]	[0.018]	[0.078]	[0.023]	[0.108]	[0.028]
150 MA $\gamma = 1.75$	Dow	1422	2424	0.059	0.969	-0.018	0.956	0.077
	Fraction > Dow	(0.300)	(0.436)	(0.036)	(0.050)	(0.840)	(0.796)	(0.022)
	Mean	1206	2343	0.018	0.785	0.003	1.040	0.015
	Std	[393]	[371]	[0.028]	[0.110]	[0.021]	[0.118]	[0.034]
150 MA $\gamma = 2$	Dow	616	2424	0.099	1.093	-0.018	0.956	0.117
	Fraction > Dow	(0.303)	(0.409)	(0.008)	(0.064)	(0.830)	(0.818)	(0.006)
	Mean	501	2340	0.001	0.823	0.003	1.042	-0.002
	Std	[286]	[368]	[0.072]	[0.179]	[0.023]	[0.111]	[0.075]

Results of 500 simulated volume-volatility models. Numbers in parenthesis show the fraction of simulations for a given statistic larger than the value in the data. Numbers in brackets are the standard deviation of the simulations. Also given are the values from the series, Dow, and the mean from the simulations, Mean. Nbuys and Nsells are the number of buys and sells. Buy and Sell are the mean 1 day returns during buy and sell periods. σ_b and σ_s are the standard deviations. Buy-Sell is the difference between the buy and sell means.

Table 11
Technical Trading Rule Specification Tests: Alternative Simulations

Rule		Nbuys	NSells	Buy %	σ_b %	Sell %	σ_s %	Buy-Sell
50 MA $\gamma = 1.75$	Dow	612	2672	0.095	1.033	-0.009	0.939	0.104
	Fraction > Dow	(0.396)	(0.436)	(0.026)	(0.060)	(0.504)	(0.662)	(0.036)
	Mean	579	2637	0.024	0.833	-0.008	0.976	0.032
	Std	[175]	[252]	[0.040]	[0.126]	[0.020]	[0.100]	[0.043]
150 MA $\gamma = 1.75$	Dow	1422	2424	0.059	0.969	-0.018	0.956	0.077
	Fraction > Dow	(0.282)	(0.386)	(0.038)	(0.046)	(0.838)	(0.728)	(0.018)
	Mean	1197	2316	0.017	0.771	0.004	1.025	0.013
	Std	[400]	[370]	[0.026]	[0.105]	[0.022]	[0.114]	[0.033]
150 MA $\gamma = 2$	Dow	616	2424	0.099	1.093	-0.018	0.956	0.117
	Fraction > Dow	(0.301)	(0.371)	(0.008)	(0.056)	(0.823)	(0.717)	(0.006)
	Mean	483	2324	0.000	0.795	0.003	1.012	-0.003
	Std	[277]	[360]	[0.064]	[0.184]	[0.022]	[0.107]	[0.067]

Results of 500 simulated volume-volatility models. Numbers in parenthesis show the fraction of simulations for a given statistic larger than the value in the data. Numbers in brackets are the standard deviation of the simulations. Also given are the values from the series, Dow, and the mean from the simulations, Mean. Nbuys and Nsells are the number of buys and sells. Buy and Sell are the mean 1 day returns during buy and sell periods. σ_b and σ_s are the standard deviations. Buy-Sell is the difference between the buy and sell means.

Figure 1
Return Correlation (t,t+1)
Conditioned on Volume
and Delta Volume

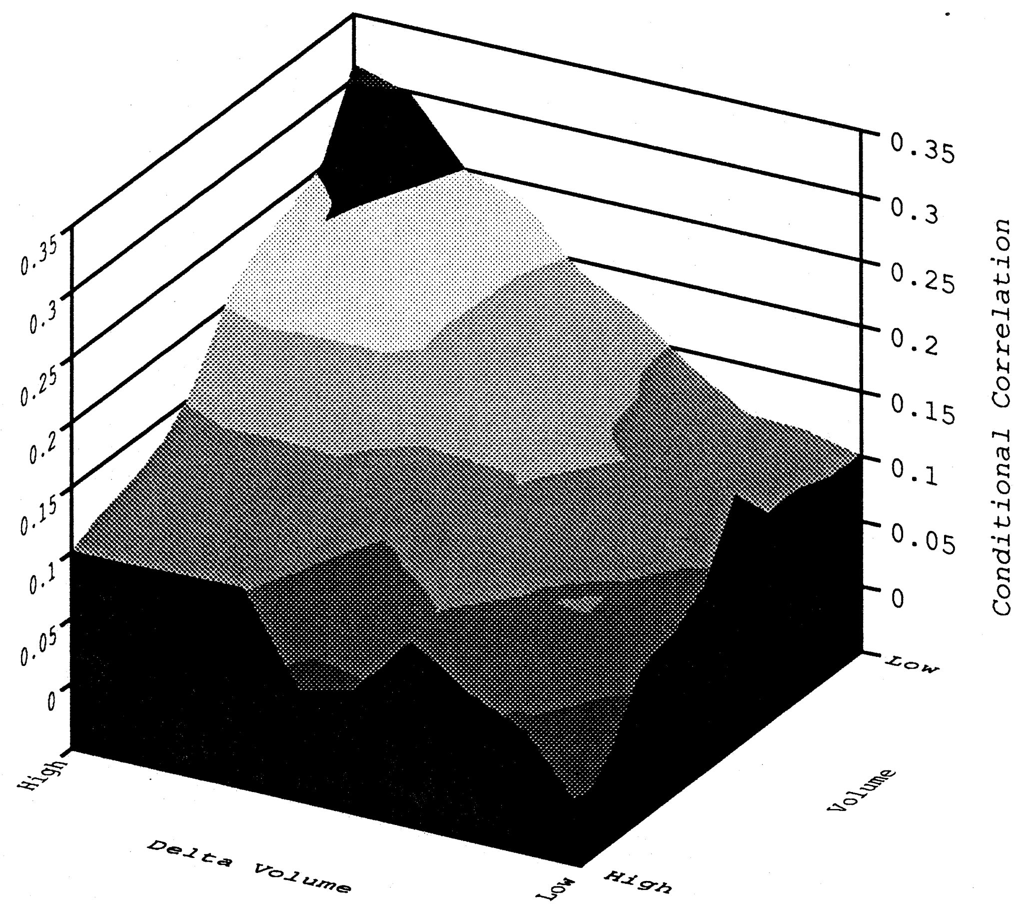


Figure 2
Return Correlation (t,t+1)
Conditioned on Volume
and Delta Volume
(Return(t)>0)

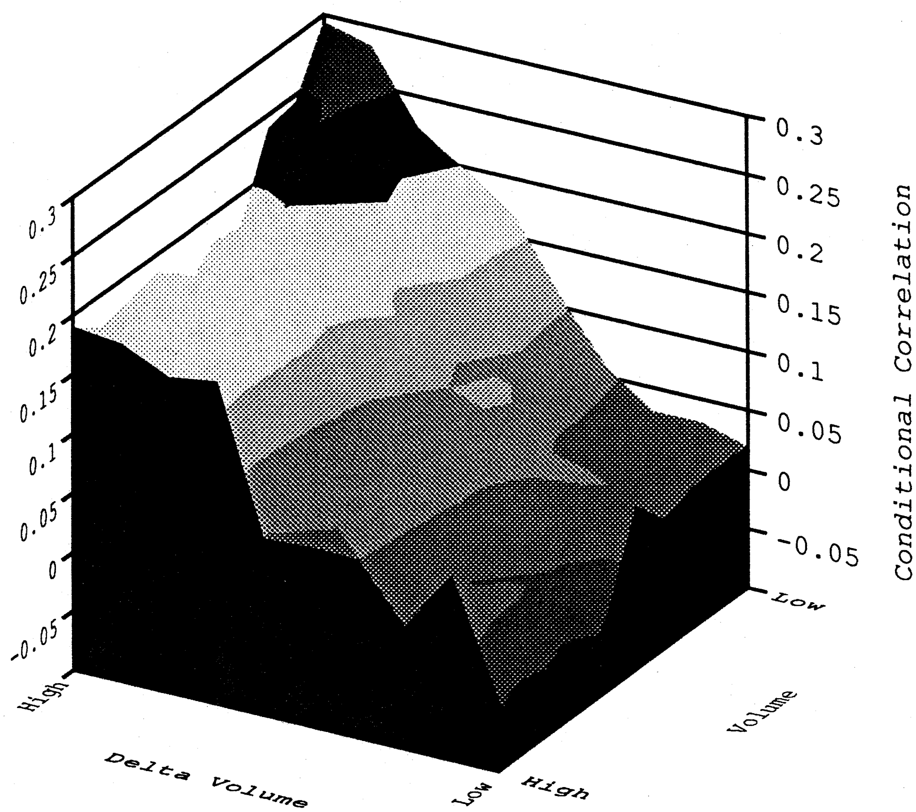


Figure 3
Return Correlation (t,t+1)
Conditioned on Volume
and Delta Volume
(Return(t)<0)

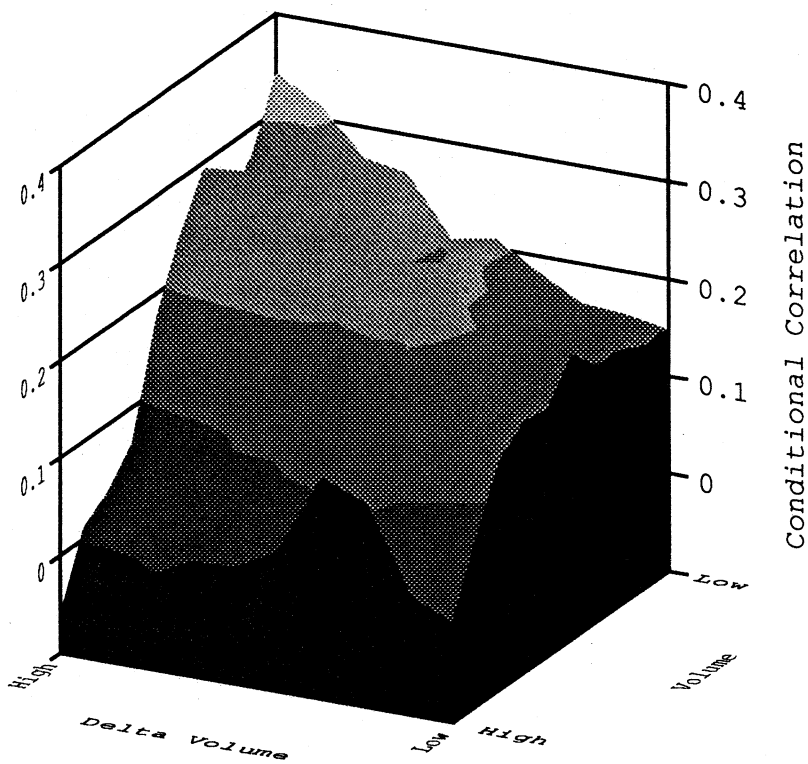


Figure 4
Hyperbolic Tangent

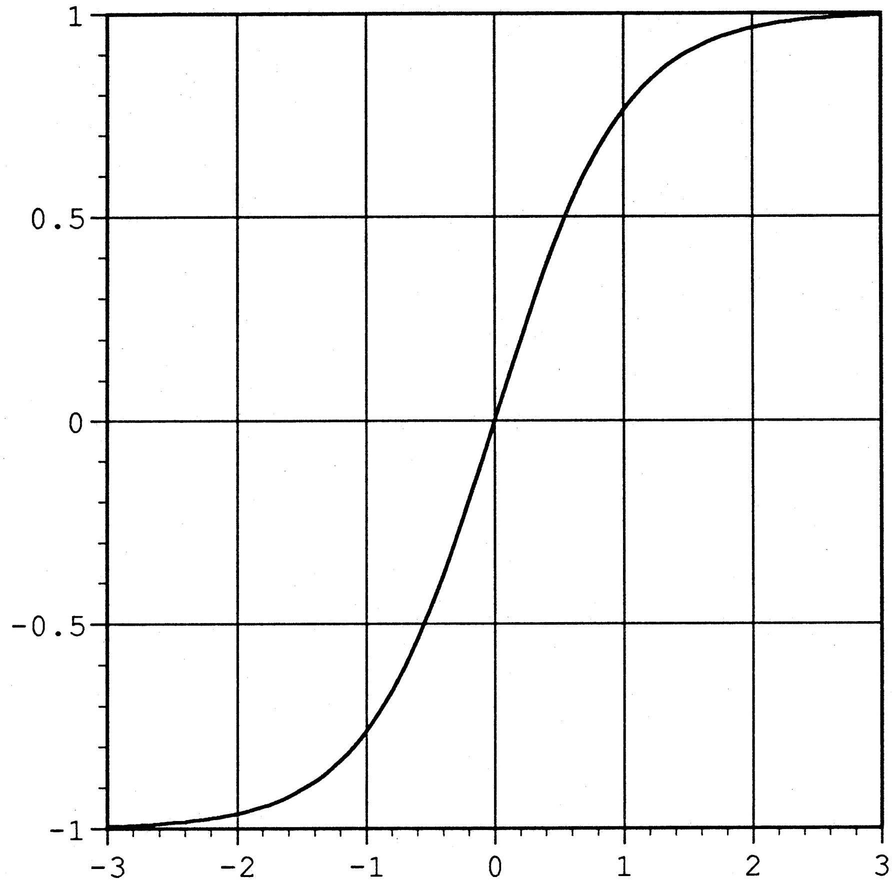
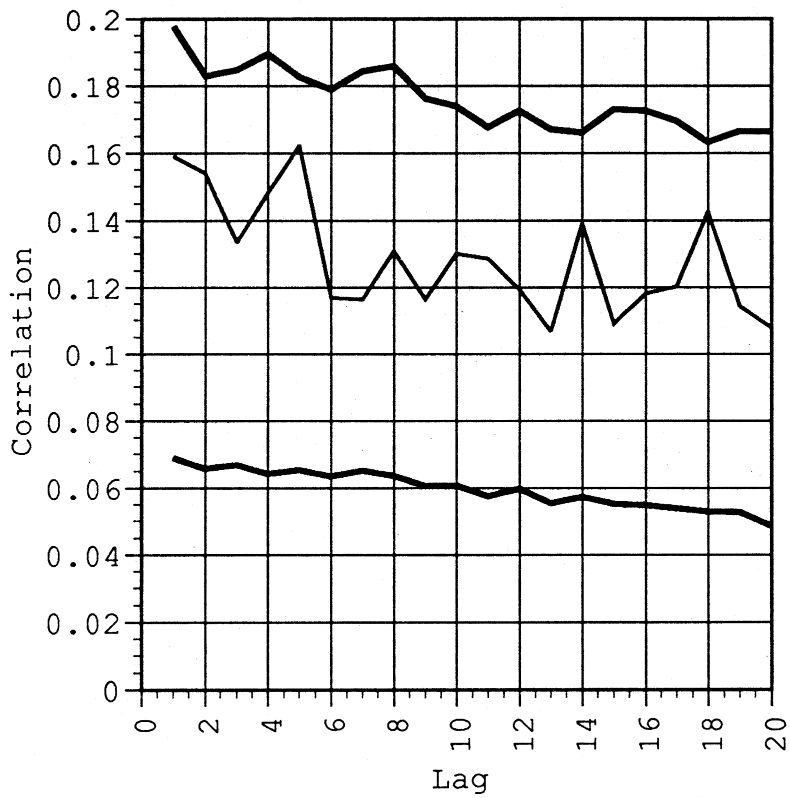
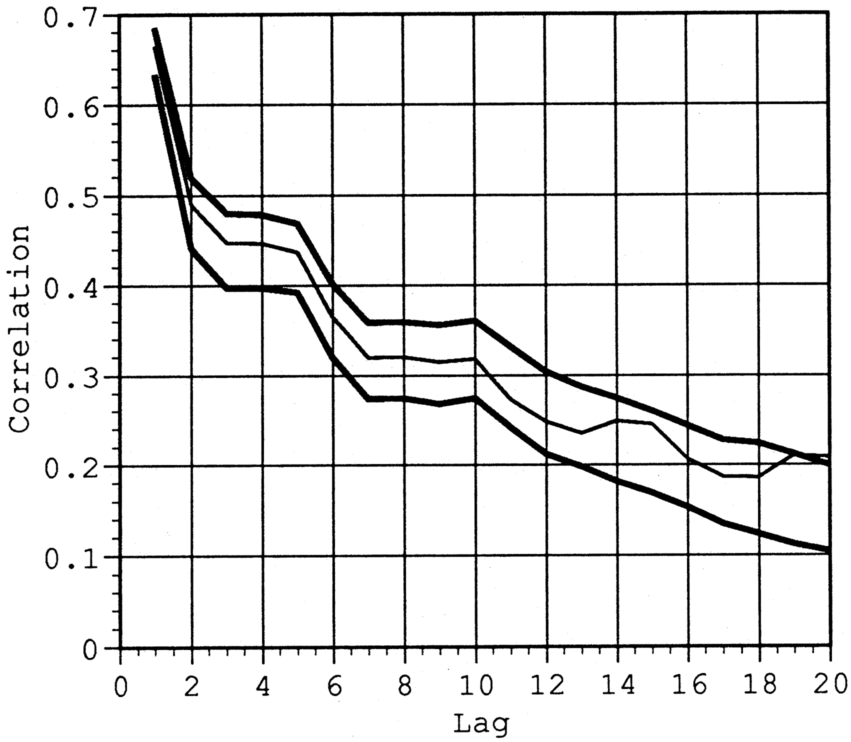


Figure 5
Correlations:
Squared Residuals(t,t+j)



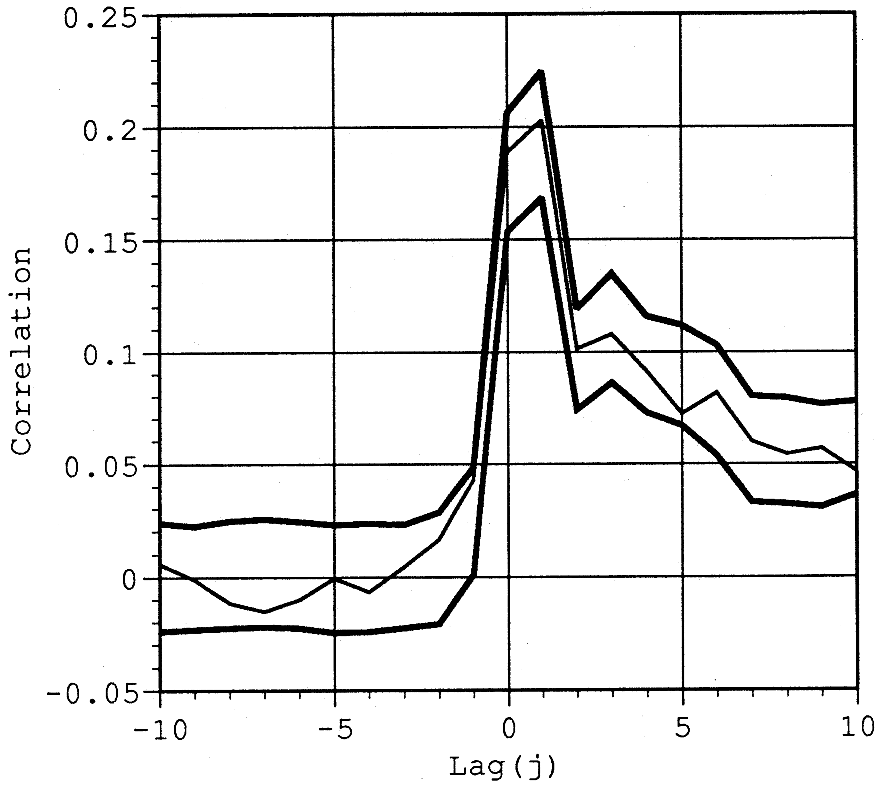
Dark lines are 5-95 percent confidence bands from 500 simulations of the parametric model for volume and volatility.

Figure 6
Correlations:
Volume(t,t+j)



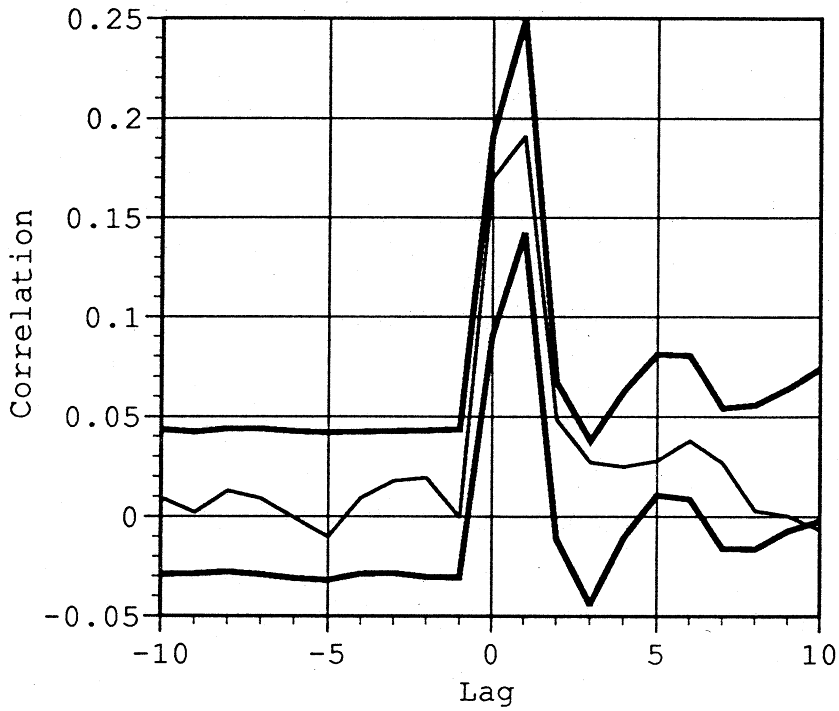
Dark lines are 5-95 percent confidence bands from 500 simulations of the parametric model for volume and volatility.

Figure 7
Cross Correlations:
Return(t) - Volume(t+j)



Dark lines are 5-95 percent confidence bands from 500 simulations of the parametric model for volume and volatility.

Figure 8
Cross Correlations:
Squared Residuals)(t) -
Volume(t+j)



Dark lines are 5-95 percent confidence
bands from 500 simulations of the
parametric model for volume and volatility.

Figure 9
Trading Rule Returns
50 Day MA