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Volume and Autocovariances in Short-Horizon Individual Security Returns

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ABSTRACT

This article tests for the relations between trading volume and subsequent returns patterns in individual securities' short-horizon returns that are suggested by such articles as Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993). Using a variant of Lehmann's (1990) contrarian trading strategy, we find strong evidence of a relation between trading activity and subsequent autocovariances in weekly returns. Specifically, high-transaction securities experience price reversals, while the returns of low-transactions securities are positively autocovarying. Overall, information on trading activity appears to be an important predictor of the returns of individual securities.

IN RECENT YEARS, MANY researchers have presented evidence that short-horizon returns are predictable. Due to the scarcity of short-horizon economic data, the evidence on predictability in short-horizon returns has largely been based on past returns data. For example, Lo and MacKinlay (1988) find that weekly portfolio returns have large positive autocorrelations; Conrad, Kaul, and Nimalendran (1991) and Lehmann (1990) find significant autocorrelations in the returns of individual securities. The evidence suggests that past prices and returns contain important information for forecasting future returns. Typically, these studies also find that the returns of small firms are more predictable.

More recent articles have examined the relation between trading volume and predictable patterns in returns. Blume, Easley, and O'Hara (1994) present a model in which traders can learn valuable information about a security by observing both past price *and* past volume information. In their model, volume provides data on the quality or precision of information in past price movements; this model suggests that there is a significant relation between lagged volume and the current returns on individual securities.

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Traders who include volume measures in their technical analysis perform better in the market than those who do not. Blume, Easley, and O'Hara (1994) also conjecture that the relation between past volume and prices may be more pronounced for smaller, less widely followed firms.

Campbell, Grossman, and Wang (1993) also explore the relations between volume and returns by modeling the interactions between liquidity investors and risk-averse expected utility maximizers, who effectively act as "market makers." In their model, market makers must be compensated for offsetting the fluctuating demands of liquidity traders; thus, if liquidity traders sell on average, the price drops to enable the market makers to earn a higher return. Because the variations in the aggregate demand of the liquidity traders also generate large levels of trade, volume information can help distinguish between price movements that are due to public information and those that reflect changes in expected returns. One implication of this model is that "price changes accompanied by high volume will tend to be reversed; this will be less true of price changes on days with low volume" (p. 906).

This article tests for the relation between lagged volume and prices suggested by these two models. The Blume, Easley, and O'Hara (1994) model does not specify a particular rule of technical analysis, while the Campbell, Grossman, and Wang (1993) article makes specific predictions about the relation between volume and returns autocovariances. We use a variant of the contrarian portfolio strategy proposed by Lehmann (1990) and addressed in Lo and MacKinlay (1990) to measure the strength of the lagged volume/return relation. This method has several important advantages. First, because this technique measures profits, it can provide measures of both the statistical and economic significance of the volume/return relations. Second, the profits from this contrarian strategy are directly related to returns autocovariances, which are particularly important in the Campbell, Grossman, and Wang (1993) article. Third, this strategy works with autocovariances in the volume and returns of individual securities, rather than portfolios. Differences in the number of outstanding shares, in the proportions of liquidity vs. informed traders (or expected utility maximizers in the Campbell, Grossman, and Wang (1993) model), in the number of market makers, etc., across individual securities may make it difficult to detect volume/returns relationships in an aggregate portfolio; in particular, it seems unlikely that the relations described in Blume, Easley, and O'Hara (1994) would be preserved after aggregating stocks into a portfolio.[1] Lastly, the contrarian portfolio strategy, with its predictions of price reversals following sharp price movements, is a particularly vivid example of technical analysis. Indeed, the notion of "overreaction" itself seems to suggest a high volume of trading in the stock as well as a sharp price response.

Using this method, we find a strong relation between lagged changes in trading activity and returns patterns in individual securities. Specifically, returns autocovariances are negative (or securities overreact) only for last

[1] Campbell, Grossman, and Wang (1993) examine the volume and returns of the value-weighted market index as a way of controlling for nontrading. We deal with this potential problem through our sample selection process.

period's heavily traded securities; autocovariances in returns are *positive* if trading declined last week. This result is a striking confirmation of the predictions of Campbell, Grossman, and Wang's (1993) model. We also find that, in low-transactions stocks, trading can reliably predict the next period's returns and that these relations are stronger in smaller firms as Blume, Easley, and O'Hara (1994) suggest.

The remainder of the article proceeds as follows: in Section I we outline the strategy used to detect any relations between lagged volume measures and returns; we present results in Section II and conclude in Section III.

I. Trading and the Autocovariances in Returns

A. Returns Weights

To analyze the relation between autocovariances in returns and trading, we use a variant of the contrarian portfolio weights of Lehmann (1990) and Lo and MacKinlay (1990). These weights involve buying the previous week's losers and selling the previous week's winners. In these articles, the weight given to a security i at time t is:

$$w_{it} = -(1/N)(R_{it-1} - R_{mt-1}), \tag{1}$$

where $R_{mt-1} = \sum_{i=1}^{N} R_{it-1}/N$.[2]

Note that these contrarian weights are constructed so that the resulting portfolio is long the previous week's losers, short the previous week's winners, and has zero net investment. In addition, larger weight is given to extreme winners and losers.

Lo and MacKinlay (1990) show that the use of deviations from a market index as weights implies that a large portion (close to 50 percent) of the measured contrarian "profit" is due to positive autocovariance in the index rather than negative autocovariance in the individual securities. We remove this positive autocovariance as a source of profit by choosing a different return weighting strategy. In this strategy, the weight given to a security i at time t is:

$$w_{\mathrm{pit}} = R_{it-1} / \sum_{i=1}^{N_p} R_{it-1}, \quad p = W, L, \tag{2}$$

where N_p is the number of securities in the winner (W) or loser (L) portfolio. A security is categorized as a winner if $R_{i,t-1}$ is greater than zero and a loser if $R_{i,t-1}$ is less than zero.[3]

[2] These are exactly the weights employed by Lo and MacKinlay (1990). Lehmann's weights are similar, but he employs a factor of proportionality that scales the dollar investment in winner and loser portfolios to be 1. Lehmann (1990) notes that his results are invariant to this factor of proportionality.

[3] Using zero as the benchmark for the selection of "winners" and "losers" is equivalent to assuming that the weekly expected return on individual securities is zero. In fact, the average weekly return on the securities in our sample is 0.004 percent and is not significantly different from zero (t-statistic = 0.02).

Using this strategy, a winner is defined as any security with a positive return, while loser securities are those with negative returns. Because the denominator sums only positive (negative) returns for the winner (loser) securities, note that all weights are positive and that the weights in both the winners' and losers' portfolios sum to one. A combined portfolio with zero net investment can then be formed that consists of buying losers and shorting winners. As in Lehmann's strategy, these weights ensure that larger weight is placed on extreme winners and losers; we provide a more direct comparison of the weights in equation (2) and Lo and MacKinlay's weights in Section II. Most importantly, any measured profits to this strategy must come from (negative) autocovariances in *individual securities*.

B. Transactions Weights

Blume, Easley, and O'Hara (1994) suggest that traders profit from examining the time series of (per capita) volume in an individual security. Campbell, Grossman, and Wang (1993) use a turnover measure in their empirical work. In this article, we use the number of transactions as a measure of trading in the security. Jones, Kaul, and Lipson (1991) test whether number of trades or volume best captures the rate of information arrival in the market. Their empirical evidence suggests that it is the number of orders, rather than their size, that is significant.[4]

To analyze whether the autocovariances in returns are related to trading in the security, we require some measure of "high" or "low" trading. The following measure of abnormal trading in security i at time t is chosen:

$$u_{it} = (T_{it} - T_{it-1})/T_{it-1} \tag{3}$$

where T_{it} is the number of transactions in security i for week t. A positive u_{it-1} implies a positive trading shock or high-transaction security; a negative u_{it-1} is taken to imply a low-transaction security.

There are some important features of this measure of abnormal trading. First, note that this measure of abnormal trading uses only transactions data from one particular security. Therefore, similar to our returns-based weights, the time-series properties of u_{it} are affected only by the time-series properties of T_{it} and are not contaminated by the time-series properties of the index of aggregate trades. In addition, because this measure looks only at the level of trade in an individual security, it is not affected by aggregation problems, which would occur if we used a portfolio trading measure. This last point is particularly important; in preliminary work, we found substantial differences between the serial cross-correlations of volume and returns in individual

[4] We also reestimated the model using changes in volume, rather than changes in the number of transactions. The results are qualitatively and quantitatively similar: there is a significant difference in the autocovariances of high- and low-transactions groups, although the (negative) profits in the low-transactions securities are not significant. This suggests that, using our methods, volume and number of transactions measure roughly the same thing. The sample correlation between number of transactions and volume in our data set is approximately 0.56.

securities and the same correlations in portfolio volume and returns. Using the weights above, we are testing for relations between trading and returns in individual securities only. In Section II.*D*, we also examine trading profits using two alternative measures of abnormal trade in individual securities.

To determine whether trading provides important information concerning subsequent returns, we combine the returns and transactions weights to form four portfolios. These portfolios are formed by classifying securities each week into winners ($R_{i,t-1} > 0$) or losers ($R_{i,t-1} < 0$) and high or low volume ($u_{i,t-1} > 0$ or $u_{i,t-1} < 0$). The weights in each of the four portfolios are:

$$w_{ipt}^{*} = (R_{it-1}(1 + u_{it-1}))/\sum_{i=1}^{N_p} R_{it-1}(1 + u_{it-1}) \tag{4}$$

where N_p is the number of securities in each particular portfolio. These weights are again all positive and sum to one for each of the four portfolios. The transactions measure employed, u_{it}, also ensures that the weights based on both returns and transactions are always of the same sign as weights based on returns alone (the minimum u_{it} is -1). Therefore, all portfolio strategies considered in this article are "contrarian"; even when transactions weights are used, we are buying losers and shorting winners.

As with the returns-weighted portfolios, zero-weight "arbitrage" portfolios can be formed by buying one portfolio and shorting another and, similar to the returns weights, larger weights are placed on extreme winners and losers. However, the weight placed on an extreme loser or winner security is compounded if the security's price movement is accompanied by an abnormally large level of transactions in the previous week. Thus, if there is a relation between the week t price movements in individual securities and their level of trading in week $t - 1$, the profits from this portfolio strategy should be significantly different from a returns-based strategy alone. In the Blume, Easley, and O'Hara (1994) model, such a profit would be due to an improved ability to detect overreaction in stocks with abnormally high levels of trade.[5] In the Campbell, Grossman, and Wang (1993) model, heavy liquidity trading leads to changes in expected returns, which in turn cause price reversals.

II. Empirical Evidence

To determine whether autocovariances in individual securities' returns are related to trading, we examine a sequence of trading rules. First, as a benchmark, we examine the profits to a portfolio strategy based only on returns, using the portfolio weights described in equation (2). Next, we

[5]The Blume, Easley, and O'Hara (1994) model implies a *nonmonotonic* relation between volume and signal quality, with volume peaking at moderate levels of signal quality. In the context of their model and using the returns/transactions weights above, improved contrarian profits would suggest that overreaction occurs more frequently when signal quality is moderate.

examine the differences in profits of these returns-based strategies in groups of securities with abnormally high and low levels of transactions. Finally, we form new portfolios, using both returns and levels of transactions to calculate weights as in equation (4).

A. Data

The data consist of weekly returns and number of transactions for individual securities in the CRSP National Association of Securities Dealers Automated Quotation (NASDAQ)-National Market System (NMS) file between 1983 and 1990. Neither the Blume, Easley, and O'Hara (1994) nor the Campbell, Grossman, and Wang (1993) model specifies a time interval over which their hypothesized relations hold, although Campbell, Grossman, and Wang (1993) conjecture that low-frequency dependencies in volume data may make the associations difficult to find in long-horizon data. We employ weekly data, since much of the short-horizon contrarian literature focuses on this interval and hence our profits can be easily compared to others.

Securities are included in the sample for week t if they have transactions in each of the previous two weeks and if the most recent Wednesday-to-Wednesday return could be calculated. Because the bid-ask "bounce" leads to negative autocorrelation and therefore spurious overreaction profits if traders cannot buy at bid and sell at ask (see Conrad, Gultekin, and Kaul (1991a, 1991b)), returns are first calculated using the midpoint of the bid-ask spread.

B. Returns-Based Strategies

Panel A of Table I reports the profits to a contrarian portfolio strategy, which is based only on past (spread midpoint) returns (equation (2)). Note that the profit figures for winner and loser portfolios reported in all tables are for a *positive* investment in the portfolio. Hence, price reversals in the winner (loser) portfolio will appear as negative (positive) numbers.

Consistent with the results of Conrad, Gultekin, and Kaul (1991a, 1991b), who also find no profits can be earned from this strategy in NASDAQ-NMS stocks when the bid-ask spread effects are removed, the average "profit" from the combined portfolio (which consists of buying the previous week's losers and selling the previous week's winners) is an insignificant 0.116 percent (t-statistic = 1.60).[6] Looking at previous losers only, there is some marginal evidence of price reversals; last week's loser stocks earn a positive 0.199 percent in the next week (t-statistic = 1.70). However, as Lehmann (1990) and Conrad, Gultekin, and Kaul (1991b) demonstrate, this profit is small compared to reasonable transactions costs. Overall, using these weights there

[6]Throughout the article, we use the convention that statistics must have two-tailed p-values less than 0.05 to be termed significant. For making inferences about returns and profits, standard errors and associated t-statistics are calculated using a Newey-West correction with four lags.

Table I

Contrarian Profits Using Returns-Based Weights on NASDAQ Sample, Weekly Spread Midpoint Returns 1983 to 1990

x is the sample mean return (in percent) of the winner or loser portfolio in week t or the sample mean profit (in percent) to the combined portfolio, and s_x is the sample standard deviation of the portfolio return (W, L) or profit (C) in percentage terms. Newey-West corrections are made using four lags. The sample consists of 407 weeks of returns.

Portfolios consist of winners (W), losers (L), and combined (C). Winners are defined as securities with positive returns in week $t-1$; losers have negative returns in week $t-1$. In the winner and loser portfolios, weights are calculated as: $w_{it} = R_{it-1} / \sum_{i=1}^{N_p} R_{it-1}$, where N_p is the number of securities in each particular portfolio. The combined portfolio is long the loser stocks and short the winner stocks. In Panel B, two variables are used to describe portfolios. The first variable indexes whether the portfolio is winners (W), losers (L), or combined (C). The second variable denotes whether the portfolio is high transactions (H) or low transactions (L). This categorization is made by calculating the percentage change in the number of transactions in the security in week $t-1$; if this number is positive, the stock is high transactions. If the percentage change in transactions is negative, the stock enters the low-transactions group for week t.

Portfolio	x	s_x	Min.	Max.	t-Statistic
Panel A: Returns Information Only					
W	0.084	1.919	−9.56	7.10	0.88
L	0.199	2.362	−14.23	12.82	1.70
C	0.116	1.467	−6.47	7.13	1.60
Panel B: Returns-Based Weights for High- and Low-Transactions Stocks					
W, H	0.035	3.382	−18.60	10.87	0.21
W, L	0.171	3.205	−17.88	11.95	1.08
L, H	0.650	3.693	−18.32	17.36	3.55
L, L	−0.374	3.085	−20.78	11.64	−2.45
C, H	0.615	2.750	−9.51	14.43	4.51
C, L	−0.545	2.007	−16.43	7.38	−5.48

is little evidence of price reversals or negative autocovariances in the (spread midpoint) returns of NMS stocks during the 1983 to 1990 period.[7]

C. Transactions and Returns-Based Strategies

If, as both Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993) suggest, the trading activity in a security provides valuable data about the information structure and subsequent price moves in the security,

[7] Using our sample of securities, we compared our returns weights (specifically, the maximum of these returns weights) with those of Lo and MacKinlay (1990). Because the Lo-MacKinlay weights, by design, must sum to zero across the combination of loser and winner securities, whereas our weights sum to one for each of the subsets of loser and winner securities, we would expect some differences in the properties of the weights. Indeed, the maximum weights using our method are larger than the Lo-MacKinlay weights; for example, the average (across the weeks in our sample) maximum weight in the loser portfolio is 1.96 percent using our weights vs. 0.03

then including some measure of trading activity in an autocovariance-based trading rule should alter its profits significantly. Our first transactions- and returns-based strategy uses the same type of portfolio weights as in equation (2), but applies them separately to high- and low-transaction securities, resulting in four, rather than two, groups of securities. Within these groups, we form portfolios using returns-based weights.

Table II presents some descriptive statistics for our measure of abnormal volume u_{it}. Over the 407-week sample period, the average percentage change in the number of transactions of an equally weighted portfolio of the securities in our sample (a representative week) is a significantly positive 25.5 percent. Clearly (and not surprisingly), the number of transactions in NMS securities trends upward from 1983 to 1990. The portfolio abnormal trading measure is also quite volatile, with a standard deviation of 26 percent, a minimum of -35 percent and a maximum of 172 percent. Although this "abnormal trading" measure is one that could easily be incorporated into a portfolio strategy, it is clear that it is not a mean zero measure; in addition, the average (across securities) serial correlation is significantly different from zero at -0.205. In a subsequent section, we explore alternative specifications of abnormal trading.[8]

Panel B in Table II presents the average percentage change in transactions for each of the four groups of securities for week $t-1$ (the portfolio formation period). Consistent with the large dispersion in the u_{it} measure noted above, there are very dramatic differences in the percentage change in the number of transactions across high- and low-transactions stocks in week $t-1$. For winner or loser stocks with an abnormally high level of transactions during week $t-1$, the minimum change in transactions in that week is 26 percent; the maximum is over 200 percent. The average change in transactions for high-transactions winner (loser) stocks is 97 percent (81 percent). In contrast, low-transactions winner (loser) stocks have average changes in transactions of -30 percent (-31 percent).

Examining the changes in transactions for these same securities during week t (Panel C), there is a tendency for high-transactions securities from last week to trade at a higher level this week; the mean percentage change in

percent using the Lo-MacKinlay method. Using either method, the maximum single week, single security weights tend to occur in the early part of the sample, when the number of NMS-listed securities is relatively low. Although our maximum weights tend to be more extreme, they do not seem to preclude holding, on average, a diversified portfolio of winners or losers. When we subdivide securities into 4, rather than 2 portfolios by using volume information, the average number of securities in our four portfolios ranges from approximately 288 (loser, high-transactions) to approximately 380 (loser, low-transactions) across the 407-week sample period.

[8] We also averaged u_{it}s across weeks for each individual security and then formed a grand average of these individual security averages (thus forming a "representative" security). Because each security is weighted equally regardless of the number of weeks it appears in the sample, this second average is more weighted toward the smaller, thinly traded securities in our sample and is therefore relatively volatile. The mean of the distribution of this grand average abnormal volume measure is slightly higher (at 32.8 percent) and the distribution is more skewed than the equally weighted measure above.

Table II

Average Percentage Change (from Previous Week) in Number of Transactions for Overall Sample and for Stocks Grouped by Week $t - 1$ Returns and Trading

In Panel A, x is the average (across weeks) of an equally weighted portfolio of u_{it}s. In Panels B and C, x is the sample mean of the percentage change in number of transactions for that portfolio. s_x is the sample standard deviation of the portfolio percentage change in number of transactions. The sample consists of 407 weeks of data.

Securities are categorized in week t as a) winner if the return in week $t - 1$ is positive, b) loser if the return in week $t - 1$ is negative, c) high-transaction if the percentage change in transactions in week $t - 1$ over trading in week $t - 2$ is positive, and d) low-transaction if the percentage change in transactions in week $t - 1$ over trading in week $t - 2$ is negative. In Panel B, two variables are used to describe portfolios. The first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The combined portfolio (C) is long losers and short winners. The second variable denotes whether the portfolio is high transactions (H) or low transactions (L).

Portfolio	x	s_x	Min.	Max.	t-Statistic
		Panel A: Overall Sample Average			
	25.5	25.9	−35.2	172.1	19.86
		Panel B: Percentage Change in Week $t - 1$ by Portfolio			
W, H	96.86	29.92	37.97	242.83	
W, L	−29.90	4.55	−52.62	−13.56	
L, H	80.77	24.63	25.89	213.33	
L, L	−31.49	4.50	−50.84	−21.30	
		Panel C: Percentage Change in Week t by Portfolio			
W, H	56.44	16.01	18.97	192.81	
W, L	82.13	23.60	20.90	200.70	
L, H	52.68	14.00	3.59	126.67	
L, L	81.42	22.67	31.90	199.24	

the number of transactions from week $t - 1$ for both winners and losers is over 50 percent. Last week's low-transaction securities, both winners and losers, have relatively large changes in the level of trading (over 80 percent), but this primarily reflects the positive change from last week's abnormally low level of activity.

Panel B of Table I presents the profits to the contrarian strategy when stocks are grouped according to last week's trading activity. The results are striking. If one formed an arbitrage portfolio that was long in low-transactions losers and short in low-transactions winners (portfolio (C, L) in the table), one would earn a significantly *negative* profit of -0.545 percent per week (t-statistic $= -5.48$). The negative profit suggests that, instead of price reversals, low-transactions securities have significantly *positive* autocovariances. When we look at low-transactions winners and losers separately, both experience positive autocovariance in week t; the losers portfolio earns a significantly negative -0.374 percent in week t (t-statistic = -2.45), while the winner portfolio's return is 0.171 percent (t-statistic = 1.08).

In contrast to low-transaction winners and losers, the combined portfolio of high-transactions winners and losers earns a significantly positive 0.615 percent per week (t-statistic = 4.51). This profit comes from the high-transactions losers, which earn a significantly positive 0.650 percent return in week t (t-statistic = 3.55). The high-transactions winners are not associated with either positive or negative autocovariance; they earn an insignificant 0.035 percent in week t (t-statistic = 0.21). When these returns are contrasted with those of the low-transactions stocks, the evidence seems clear that price reversals appear to occur more frequently in (loser) stocks that have simultaneously experienced a sharp price change and an abnormally high level of trade.[9]

Table I presents clear evidence of a difference in the *sign* of the returns autocovariance across high- and low-transactions stocks. Thus, there appears to be a significant relation between the autocovariances in returns and last period's trading activity; specifically, in our contrarian strategy, the use of trading information can lead to significant differences in profits. These results support the implications of the Campbell, Grossman, and Wang (1993) model.

C.1. Transactions Weights

Finally, for the low- and high-transactions securities, we form portfolios using the weights in equation (4). This strategy assigns greater weight to securities that experienced *both* sharp price movements and abnormally high trading. Profits from a portfolio constructed with these weights come from two sources: autocovariance in returns and significant relations between trading and returns autocovariances. To see this, it is helpful to use Lehmann's (1990) and Lo and MacKinlay's (1990) method of decomposing week t contrarian profits to the combined portfolio. For simplicity, we suppress the denominator in equation (4). The total profits to the combined portfolio (long losers and short winners) in week t are:

$$\pi_t = \sum_{i=1}^{n} w_{it} R_{it} \tag{5}$$

$$= \sum_{i=1}^{n} (-(1 + u_{it-1}) R_{it-1}) R_{it} \tag{6}$$

$$= -\sum_{i=1}^{n} R_{it-1} R_{it} - \sum_{i=1}^{n} u_{it-1} R_{it-1} R_{it} \tag{7}$$

[9]Although the difference in magnitude of winner and loser profits in Table III (and, to a lesser extent, in Table I) is consistent with much previous work on contrarian strategies (see, e.g., DeBondt and Thaler (1985) or Lehmann (1990)), there is nothing in Campbell, Grossman, and Wang's (1993) model that suggests that we should see different patterns in winners' and losers' price reversals. In fact, there are few explanations for this phenomenon in the contrarian literature (for one possibility, see Brown, Harlow, and Tinic (1987)); we provide little further insight into it, and a more complete explanation or analysis is outside the scope of this article.

The negative sign in equation (6) denotes the fact that we are buying losers and selling winners.

Using standard contrarian weights, positive profits are earned if the autocovariance in individual securities (the first term in equation (7)) is negative.[10] Including the level of abnormal trading in the calculation of portfolio weights affects profit if the magnitude of the autocovariances of returns in individual securities are related to the magnitude of abnormal trading in the security last week (u_{it-1}). In particular, if the autocovariances in high-transactions (positive u_{it-1}) stocks are more negative while the autocovariances in low-transactions stocks (negative u_{it-1}) are closer to zero or positive (as Campbell, Grossman, and Wang (1993) and Panel B of Table I suggest), profits will increase by including transactions measures in the construction of portfolio weights. Empirically, this happens because we are increasing the relative weight on high-transactions securities that experience price reversals, while decreasing the weight on low-transactions stocks that appear to experience price trending.

Table III presents the profits of a portfolio strategy using these weights. When securities with high levels of abnormal trading are given greater weight, profits to the combined or arbitrage portfolio of high-transactions securities increase over 42 percent, from 0.615 percent in Panel B of Table I, to 0.875 percent per week in Table III (t-statistic = 4.09). The additional weighting of abnormal trading levels in individual securities does appear to increase the profits from the contrarian strategy. In contrast, if only low-transactions securities are included in the portfolio, the "arbitrage" portfolio of buying low-transactions losers and shorting low-transactions winners earns a significantly negative -0.546 percent in week t (t-statistic = -5.04). As before, we see evidence of *positive* autocovariance in low-transactions stocks. Note that the profit using returns/transactions weights in low-transactions securities is virtually identical to the profit of -0.545 percent earned in the low-transaction group in Panel B of Table I; this similarity arises due to low dispersion in the measures of abnormal trading, u_{it-1}, across the securities in the low-transactions group. The low cross-sectional volatility of u_{it-1} results in very little difference in the returns and returns/transactions weights for this group of securities.

As the last term in equation (7) makes clear, increased profits using transaction-based weights could potentially result either from a relation between lagged trading and lagged returns or from a relation between lagged trading and current returns. In both Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993), there may be contemporaneous relations between the volume of trade and the absolute magnitude of returns. Therefore, we further explore the source of the higher profits in the returns/transactions strategy of equation (4) by examining the relation

[10] For this interpretation, we are assuming that the expected return on each security is zero. In our sample, this hypothesis cannot be rejected (see footnote 3).

Table III

Contrarian Profits Using Returns/Transactions Weights on NASDAQ Sample, Weekly Spread Midpoint Returns 1983 to 1990

x is the sample mean return (in percent) of the winner or loser portfolio in week t or the sample mean profit (in percent) to the combined portfolio. s_x is the sample standard deviation of the portfolio return (W, L) or profit (C) in percentage terms. Newey-West corrections are made using four lags. y is the sample mean cross-product (deflated by the factor of proportionality in equation (4) of the article) in percent, and s_y is the sample standard deviation of the cross-product in percent. The sample consists of 407 weeks of returns.

Four portfolios are formed using last week's percentage changes in both price (R_{it-1}) and number of transactions (u_{it-1}). Securities are categorized in week t as a) winner if the return in week $t-1$ is positive, b) loser if the return in week $t-1$ is negative, c) high-transaction if the percentage change in transactions in week $t-1$ over week $t-2$ (u_{it-1}) is positive, and d) low-transaction if the percentage change in transactions in week $t-1$ over trading in week $t-2$ is negative. In each of these four portfolios, weights are given by: $w_{it}^* = R_{it-1}(1 + u_{it-1})/\sum_{i=1}^{N_p} R_{it-1}(1 + u_{it-1})$, where N_p is the number of securities in each of the portfolios. Combined portfolios are formed for both high- and low-transactions stocks by going long the previous week's losers and short the previous week's winners. Two variables are used to describe the portfolio. The first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The second variable denotes whether the portfolio is high transactions (H) or low transactions (L).

Panel A: Week t Returns of Returns/Transactions Portfolio Strategy

Portfolio	x	s_x	Min.	Max.	t-Statistic
W, H	−0.174	4.483	−28.74	17.10	−0.78
W, L	0.210	3.219	−17.67	12.58	1.32
L, H	0.701	3.952	−17.52	18.97	3.58
L, L	−0.336	3.128	−20.72	12.06	−2.17
C, H	0.875	4.320	−11.42	31.66	4.09
C, L	−0.546	2.184	−19.20	6.52	−5.04

Panel B: Cross-Products of Lagged Percentage Changes in Transaction and Current Returns ($u_{it-1}R_{it}$)

Portfolio	y	s_y	t-Statistic	Median	p-Value
W, H	0.025	0.150	3.35	0.034	0.0001
W, L	−0.028	0.272	−2.08	−0.051	0.0001
L, H	0.004	0.177	0.46	0.011	0.1974
L, L	0.062	0.274	4.54	0.051	0.0005

Panel C: Cross-Products of Lagged Percentage Changes in Transaction and Lagged Returns ($u_{it-1}R_{it-1}$)

Portfolio	y	s_y	Median
W, H	0.572	0.107	0.583
W, L	−0.386	0.091	−0.378
L, H	−0.489	0.081	−0.496
L, L	0.439	0.089	0.432

between returns and our abnormal trading measure. We analyze the relation between $u_{i,t-1}$ and both $R_{i,t-1}$ and R_{it} by comparing the signs and magnitudes of their cross-products in our sample. Panel B presents the cross-product of the percentage change in transactions in week $t-1$ and returns in week t. These cross-products are deflated by the (absolute value of the) factor of proportionality used in equation (4).[11]

If the inclusion of the level of abnormal trades in a security last week can help one to earn returns from price reversals this week, then the cross-product of lagged changes in transactions and current returns should be negative for high-transactions winners and positive for high-transactions loser stocks. We do observe a positive cross-product for high-transactions loser stocks, but the estimate is insignificant (t-statistic = 0.46). For high-transactions winners, the cross-product is significantly *positive* (t-statistic = 3.35). Thus, once we subdivide securities into high- and low-transactions groups, the additional profit obtained from the high-transactions strategy does not appear to result from a relation between our measure of last week's abnormal trading and this week's price reversal.

For low-transactions stocks, price reversals would result in positive cross-products of $u_{i,t-1}$ and R_{it} for winner stocks and negative cross-products for loser stocks. In fact, just the reverse is observed in the data for low-transactions stocks (Panel B). The cross-product for winners is significantly negative (t-statistic = -2.08) while the cross-product is significantly positive (t-statistic = 4.54) for loser stocks. As before, we find evidence of positive autocovariances in both winner and loser low-transactions stocks. More importantly, these cross-products suggest that the price response in week t for last week's low-transactions stocks is related to the level of abnormal trading in these securities in week $t-1$; however, this price response is not a reversal, but rather a continuation of last week's price movement.

Finally, Panel C of Table III reports the cross-products of contemporaneous abnormal trading measures and returns ($u_{i,t-1}$ and $R_{i,t-1}$). Obviously, the signs of the cross-products in Panel C are determined by our method of portfolio construction. However, the magnitudes of these cross-products are much larger than those in Panel B. Comparing the signs and particularly the magnitudes of the lagged and contemporaneous cross-products, a substantial portion of the extra contrarian profit earned by using trading information appears to come from the high contemporaneous correlation between trading and return last week. That is, after grouping stocks on the basis of trading, any further contrarian profits in the high-transactions securities seem to be the result of increasing the weight on last week's most extreme winners and

[11] This constructed variable is unlikely to be normally distributed, therefore, we also report median numbers and p-values from testing the hypothesis that the median is equal to zero in the table.

losers, rather than using more specific information about last week's trading to select stocks that will experience price reversals this week.[12]

As further evidence of this, we use an alternative nonlinear weighting scheme, similar to that in equation (4), which does not use trades data but does put higher weights on the more extreme winners and losers. These weights are:

$$w'_{ipt} = (R_{it-1}(1 + |R_{it-1}|)) / \sum_{i=1}^{N_p} R_{it-1}(1 + |R_{it-1}|). \tag{8}$$

We use these weights for two sets of portfolios. The first set consists of the two portfolios (winners and losers) formed using only the sign of the previous period's returns and the weights in equation (8). The second set consists of four portfolios. To form these portfolios, we use the sign of last period's volume measure, u_{it}, only as a signal to group securities into portfolios (similar to the portfolios in Panel B of Table I); the nonlinear returns-based weights in equation (8) are then applied to these securities. The results from these two strategies are presented in Table IV.

When returns data only are used to group stocks into winner/loser portfolios, using the weights in equation (8) puts higher weights on more extreme winners and losers. Not surprisingly, the profits to the combined portfolio increase from 0.116 percent in Panel A of Table I to 0.380 percent in Panel A of Table IV. However, these profits are substantially smaller than those obtained when trading data are first used to group winner and loser securities into high and low transactions stocks and the *simple* returns-weights of equation (2) are used (Panel B of Table I). Thus, while more extreme weights, such as the nonlinear weights in equation (8), do provide additional profits, they do not provide as much profit as grouping the stocks on the basis of high or low volume.

Once stocks have been grouped on the basis of volume, however, using volume data in the weights does not appear to provide any additional source of profits. After grouping into four categories on the basis of past volume and returns, the nonlinear returns-based weights in equation (8) actually give slightly higher profits (shown in Panel B of Table IV) than the returns/transactions weights in equation (4) (for the combined high-transactions portfolio, 0.959 percent vs. 0.875 percent). The low-transactions stocks in Panel B still

[12] The well-known correlation between volume and magnitude of returns may cause a feedback effect in our returns/transactions weights, increasing the weight given to a few securities in our sample. When we examine the largest weights given to securities, the most extreme weights do increase relative to returns-based weights; some of this, of course, is due to the fact that we are now dividing our sample into four, rather than two, portfolios. On average, the largest weights given to a single security during the 407 weeks in our sample for our four portfolios are: (W, H) = 10.8 percent, (W, L) = 5.1 percent, (L, H) = 7.6 percent, and (L, L) = 3.0 percent. The weight given to individual securities declines fairly sharply in each portfolio; for example, the average weight given to the fifth most heavily weighted security in the winner, high-transactions portfolio is 2.6 percent. The highest *single week*, single security weight is 79 percent and occurs, not surprisingly, in the early part of the sample when there are few NMS listings.

Table IV

Contrarian Profits Using Nonlinear Returns-Based Weights on NASDAQ Sample, Weekly Spread Midpoint Returns, 1983 to 1990

In the table below, x is the sample mean return (in percent) of the winner or loser portfolio in week t or the sample mean profit (in percent) to the combined portfolio. s_x is the sample standard deviation of the portfolio return (W, L) or profit (C) in percentage terms. Newey-West corrections are made using four lags. The sample consists of 407 weeks of returns.

Portfolios consist of winners (W), losers (L), and combined (C). Winners are defined as securities with positive returns in week $t-1$; losers have negative returns in week $t-1$. In the winner and loser portfolio, weights are defined as: $w'_{it} = R_{i,t-1}(1 + |R_{i,t-1}|)/\sum_{i=1}^{N_p} R_{i,t-1}(1 + |R_{i,t-1}|)$, where N_p is the number of securities in each particular portfolio. The combined portfolio is long the loser stocks and short the winner stocks. In Panel B, two variables are used to describe the portfolio. The first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The second variable denotes whether the portfolio is high transactions (H) or low transactions (L). This categorization is made by calculating the percentage change in the number of transactions in the security in week $t-1$; if this number is positive, the stock is high transactions. If the percentage change in transactions is negative, the stock enters the low-transactions group for week t.

Portfolio	x	s_x	Min.	Max.	t-Statistic
Panel A: Returns Information Only					
W	−0.055	3.480	−18.61	15.60	−0.32
L	0.326	3.360	−19.06	14.60	1.96
C	0.380	2.515	−15.74	13.40	3.05
Panel B: Nonlinear Returns-Based Weights for High- and Low-Transactions Stocks					
W, H	−0.152	3.670	−18.88	13.98	−0.83
W, L	0.117	3.407	−18.01	15.88	0.69
L, H	0.807	3.972	−18.45	20.69	4.10
L, L	−0.338	3.028	−20.81	12.09	−2.25
C, H	0.959	3.428	−9.70	18.47	5.64
C, L	−0.455	2.325	−16.93	12.24	−3.95

show evidence of positive autocovariance in returns, although the (negative) profits are slightly smaller in magnitude than the (negative) profits for the low-trade combined group in Table III (0.455 percent vs. 0.545 percent). This confirms that, *after grouping*, additional contrarian profits using the returns/transactions weights in equation (4) come from larger weights on more extreme winners and losers. Thus, simply grouping securities on the basis of high or low trade appears to reliably distinguish between price reversals or price trends; using our weights, it is the sign and not the magnitude of abnormal trading that provides information about which particular stocks reverse.

Overall, we find evidence that a naive measure of "high" or "low" trading in a security last week is related to the price movement this week. First, in combined portfolios that are long loser and short winner securities, the sign of the autocovariance appears to reverse across high- and low-transactions stocks; in both groups, loser securities drive much of this effect. Specifically, last week's high-transactions securities tend to experience price reversals, while last week's low-transactions stocks experience smaller price changes which are, on average, of the same sign as last week's price change. This result is consistent with the general predictions of the Campbell, Grossman, and Wang (1993) model. Second, and perhaps equally intriguing, there is a significant relation between last week's percentage change in transactions and this week's return, but only in low-transactions stocks. That is, the observation of low transactions last week appears to reliably signal a price trend in an individual security. This relation between lagged trading and current returns is consistent with the implications of the Blume, Easley, and O'Hara (1994) model.

D. Alternative Volume Measures

We calculate profits to a returns/transactions-based contrarian strategy using two other measures of abnormal trading. Rather than the previous week's number of transactions, both measures use a simple average of previous weeks' number of transactions as the "expected" level of trading. The measures differ in how many previous weeks of trade information are used to calculate the mean or expected level of trade. That is, our measure of abnormal trading becomes:

$$z_{m,it} = \frac{T_{it} - (1/m)\sum_{j=1}^{m} T_{i,t-j}}{(1/m)\sum_{j=1}^{m} T_{i,t-j}}. \tag{9}$$

The values of m we examine, corresponding to the number of previous weeks' trade information, are 4 and 26.

Panel A of Table V presents some descriptive statistics for these measures of abnormal volume. The average (across weeks) of an equally weighted portfolio of $z_{m,it}$s for both $m = 4$ and $m = 26$ is much smaller than the average u_{it} of 25.5 percent reported in Table II. Adjusting by the adverage of the previous 4 weeks of transactions information produces an average abnormal trading measure which is still significantly positive (mean = 9.46 percent, t-statistic = 9.58). Using the previous 26 weeks of transactions information produces an average abnormal trading measure that is not significantly different from zero (mean = 0.14 percent, t-statistic = 0.12). In contrast to the average negative serial correlation in individual securities' u_{it} measures, the average serial correlation of both mean-adjusted measures is significantly positive and is equal to 0.158 and 0.420, respectively, for the 4- and 26-week measures.

Panel B of Table V shows that, despite these differences in transactions weights, the portfolio profits using returns and the new transactions weights, with $m = 4$ and $m = 26$, are very similar to those in Table III. That is, for both $m = 4$ and $m = 26$, the profits to the high-transactions, combined

Table V

Characteristics of Mean-Adjusted Abnormal Volume Measures and Contrarian Strategy Profits Using Returns/Mean-Adjusted Transactions Weights on NASDAQ Sample, Weekly Spread Midpoint Returns, 1983 to 1990

y is the sample mean (in percent) of the trading variable in week t. The average $z_{m,it}$ in Panel A is an average (across weeks) of an equally weighted portfolio of securities' abnormal volume measures. s_y is the sample standard deviation of the trading variable in percentage terms. N is the number of weeks of abnormal volume measures. x is the sample mean return (in percent) of the winner or loser portfolio in week t or the sample mean profit (in percent) to the combined portfolio. s_x is the sample standard deviation of the portfolio return (W, L) or profit (C) in percentage terms. Newey-West corrections are made using four lags. The sample consists of 407 weeks less the number of weeks used to construct $z_{m,it-1}$.

Four portfolios are indexed by returns (winners and losers) and trading (high or low). Winners are defined as securities with positive returns in week $t-1$; losers have negative returns in week $t-1$. High and low trading is indexed by positive and negative values of $z_{m,it-1}$, where $z_{m,it-1}$ is the realized number of transactions in week $t-1$ less the average of the last m weeks of transactions and is defined as: $z_{m,it-1} = (T_{it} - (1/m)\sum_{j=1}^{m} T_{i,t-j})/((1/m)\sum_{j=1}^{m} T_{i,t-j})$. The weights in winner and loser portfolios are then defined as: $w''_{it} = R_{it-1}(1 + z_{m,it-1})/\sum_{i=1}^{N_p} R_{it-1}(1 + z_{m,it-1})$, $p = 1, \ldots, 4$, where N_p is the number of securities in each particular portfolio. In Panel B, two variables are used to describe portfolios. The first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The combined portfolio (C) is long losers and short winners. The second variable denotes whether the portfolio is high-transactions (H) or low-transactions (L).

Panel A: Overall Sample Average of the Abnormal Volume Measure $z_{m,it-1}$ for $m = 4$ and $m = 26$

m	y	s_y	Min.	Max.	N	t-Statistic
4	9.46	19.86	−44.35	137.35	405	9.58
26	0.14	22.83	−44.48	107.87	383	0.12

Panel B: Contrarian Strategy Profits

$m = 4$				$m = 26$			
Portfolio	x	s_x	t-Statistic	Portfolio	x	s_x	t-Statistic
W, H	−0.264	4.394	−1.21	W, H	−0.473	4.560	−2.03
W, L	0.129	3.366	0.77	W, L	0.156	3.397	0.90
L, H	0.888	3.933	4.55	L, H	0.982	4.139	4.64
L, L	−0.326	3.210	−2.04	L, L	−0.358	3.262	−2.15
C, H	1.152	4.144	5.60	C, H	1.455	4.566	6.24
C, L	−0.454	1.974	−4.63	C, L	−0.514	1.834	−5.48

portfolio are significantly positive (means = 1.15 percent and 1.45 percent, respectively), while the low-transactions, combined portfolio profits are significantly negative (means = −0.45 percent and −0.51 percent, respectively). Thus, the use of longer-horizon trade information generates significant "profits" for both high- and low-transactions stocks, and these profits demonstrate similar patterns to those using one week of trade information. We continue to find that stocks with relatively high levels of trade in week $t-1$ experience price reversals in week t, while stocks with relatively low levels of trade in week $t-1$ experience price trending.[13]

Although our results are robust to these particular alternative measures of abnormal trading, it is important to emphasize that we have not attempted to optimize the contrarian portfolio trading rule. Certainly, there may be other, better measures of high or low trading in a stock; indeed, given the relation between volume and the absolute value of price changes in both the Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993) models, it may be possible empirically to develop a returns-only measure, which reliably distinguishes between stocks whose prices reverse and those which have price trends. However, our results suggest that even relatively naive measures of abnormal trading can readily provide valuable information about subsequent returns in individual securities, as implied by both Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993). Moreover, using this simple measure of abnormal trading, the pattern of the relation between volume and returns appears to support the predictions of Campbell, Grossman, and Wang (1993).

E. Size, Trading, and Contrarian Portfolio Returns

Blume, Easley, and O'Hara (1994) conjecture that the use of volume information may be particularly useful for small, less widely followed stocks since there tends to be more uncertainty about these firms. We test for significant size-based differences in the relations between lagged trading and returns by grouping stocks into one of three portfolios based on size at the end of every calendar year. For each of these three size-ranked portfolios, we conduct the analysis of contrarian profits based on the returns/transactions-based weighting scheme of equation (4). Table VI summarizes these results.

For all three size-ranked portfolios, an arbitrage contrarian portfolio formed from high-transactions winners and losers earns significant profits. By far the largest price reversals and profits comes from the portfolio of small firms with a profit of 0.975 percent in week t (t-statistic = 2.86); however, even the portfolio of large firms earns a statistically significant 0.634 percent (t-statistic = 3.72).

For low-transactions stocks, all three portfolios present clear evidence of negative profits and, therefore, of positive autocovariances in individual

[13] We also attempted to construct a measure of abnormal trading by regressing percentage change in individual security trades on the percentage change in trades for an equally weighted index of securities in our sample (similar to a transactions "market model" regression). The residuals from this regression would then be another "abnormal trading" measure. However, we found that the residuals from such a regression invariably had minimums (maximums) that were much smaller than -1 (much larger than $+1$). Since the use of these weights would have made our results much more sensitive to outliers as well as destroying the "contrarian" nature of our strategy, we chose to use a mean-adjusted measure of abnormal trading instead.

Table VI

Profits From Returns/Transactions-Based Contrarian Strategies for Three Size-Ranked Portfolios, NASDAQ Sample, Weekly Spread Midpoint Returns, 1983 to 1990

x is the sample mean return (in percent) of the winner or loser portfolio in week t or the sample mean profit (in percent) to the combined portfolio. y is the sample mean cross-product (deflated by the factor of proportionality in equation (4) in the article) in percent. Standard errors are calculated using Newey-West corrections with four lags. The sample consists of 407 weeks of returns.

Portfolios are formed using both last week's percentage changes in price (R_{it-1}) and number of transactions (u_{it-1}). Securities are categorized in week t as a) winner if the return in week $t - 1$ is positive, b) loser if the return in week $t - 1$ is negative, c) high-transaction if the percentage change in transactions in week $t - 1$ over week $t - 2$ (u_{it-1}) is positive, and d) low-transaction if the percentage change in transactions in week $t - 1$ over trading in week $t - 2$ is negative. The weights in the winner and loser portfolios are: $w_{it}^* = R_{it-1}(1 + u_{it-1})/ \sum_{i=1}^{N_p} R_{it-1}(1 + u_{it-1})$, where N_p is the number of securities in each particular portfolio. Combined portfolios are formed for both high- and low-transactions stocks by going long the previous week's losers and short the previous week's winners. In addition to this categorization, firms are ranked into one of three portfolios on the basis of beginning of the year market value of equity. The portfolios are described by two variables: the first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The second variable denotes whether the portfolio is high-transactions (H) or low-transactions (L).

Panel A: Week t Returns to Returns/Transactions Portfolio Strategy

	Small Firms		Moderate Firms		Large Firms	
Portfolio	x	t-Statistic	x	t-Statistic	x	t-Statistic
W, H	0.039	0.13	−0.205	−1.13	−0.295	−1.55
W, L	0.661	2.45	0.023	0.13	0.152	0.97
L, H	1.014	3.43	0.332	1.62	0.339	1.84
L, L	−0.646	−3.78	−0.412	−2.37	−0.060	−0.34
C, H	0.975	2.86	0.536	2.60	0.634	3.72
C, L	−1.307	−4.05	−0.434	−2.90	−0.211	−2.21

Panel B: Cross-Products of Lagged Percentage Changes in Transaction and Current Returns ($u_{it-1}R_{it}$)

	Small Firms		Moderate Firms		Large Firms	
Portfolio	y	t-Statistics	x	t-Statistic	x	t-Statistic
W, H	0.032	4.04	0.020	2.17	0.013	1.45
W, L	−0.071	−2.04	−0.021	−1.50	−0.028	−1.86
L, H	0.004	0.34	−0.005	−0.58	0.014	1.64
L, L	0.092	7.35	0.098	3.96	0.025	1.51

security returns. There is a monotonic decline in the magnitude of this profit, with the smallest portfolio having a profit of -1.307 percent in week t (t-statistic = -4.05) and the largest portfolio having a profit of -0.211 percent (t-statistic = -2.21). Consistent with the evidence of Lehmann (1990), Lo and MacKinlay (1990), and Conrad, Kaul, and Nimalendran

(1991), there appears to be more evidence of significant autocovariances in portfolios of small firms.[14]

Panel B of Table VI reports the cross-product of the percentage change in the number of transactions in week $t - 1$ and the returns in week t. For low-transactions stocks, the same pattern emerges in size-based portfolios as in the overall sample: there is a significant relation between the level of last week's abnormal trading and this week's price trending. This relation appears to be stronger and generally more significant for the smallest firms, as Blume, Easley, and O'Hara (1994) conjecture. This provides evidence of a stronger relation between lagged trading and current returns in small, low-transactions firms.

F. Other Issues

F.1. Profitability and Risk

Our results so far suggest that information concerning lagged trading activity in individual securities is important in predicting price movements in week t. The Campbell, Grossman, and Wang (1993) model suggests that these price movements reflect changes in expected returns; the Blume, Easley, and O'Hara (1994) model, with its emphasis on technical analysis, suggests that the returns movements may reflect profit opportunities. If one is inclined to the latter view, one obvious question is whether these returns are true arbitrage profits. In particular, the returns measured here may overstate profits because they ignore any increases in risk associated with such a portfolio strategy and the transactions costs of this strategy.

In measuring his contrarian profits, Lehmann (1990) cites work that argues that a week is too short a period for substantial changes in expected returns and that the risk of such a strategy is also minimal over a week. However, Conrad, Gultekin, and Kaul (1991a), using a multivariate general autoregressive conditional heteroskedasticity model, measure changes in both

[14] We also examined the contrarian profits of securities sorted into price-ranked portfolios. Each year, we grouped securities into one of two portfolios depending on whether they were "high-priced" (beginning-of-year price greater than 5.00) or "low-priced" (beginning-of-year price less than or equal to 5.00). Since transactions costs and measurement biases are typically related to price (as one example, see Conrad and Kaul (1993)), this analysis should tell us whether the patterns in profits we observe are primarily driven by such market frictions.

In general, we find a similar pattern of profits across high- and low-transactions securities for both pricing groups. Specifically, profits in the combined high-transactions portfolio of low-priced stocks are a significantly positive 1.44 percent per week; the profits in the combined low-transactions portfolio of low-priced stocks are negative and significant at -0.684 percent per week. For the high-priced securities, the combined high-transactions portfolio earns 0.240 percent per week, which is not significant at the 5 percent level (p-value = 0.14), and the low-transactions portfolio earns a significantly negative profit of -0.557 percent per week. Although the high-transactions portfolio in high-priced securities doesn't earn a significant profit, note that we continue to find a significant difference between low- and high-transactions portfolio profits in high-priced securities. Moreover, the direction of this difference is consistent with Campbell, Grossman, and Wang (1993).

the systematic and unsystematic risk of weekly returns after the formation of a contrarian portfolio and find small but significant increases in both risk components. The estimation of risk in this article is complicated, as in the Conrad, Gultekin, and Kaul (1991a) article, by frequent portfolio rebalancings and contemporaneous correlations between trading and risk. However, we can provide some heuristic measures of the risk of our portfolio strategy.

Table VII reports comparisons of the sample variances of the four portfolios' returns in week $t - 3$ (the base week) and week t (the evaluation week). For the high-transactions winners and losers, the sample standard deviation of returns in week t is significantly higher than in week $t - 3$. The sample variance of high-transactions losers, which is the single largest source of profits to our portfolio strategy, is two and one-half times higher in week t than in week $t - 3$. In addition, high-transactions stocks, particularly winners, have continued high levels of trade in week t when compared to the level of trade in week $t - 3$, which is consistent with continuing high volatility in these securities; many researchers have documented strong positive relationships between volatility and trading (see, e.g., Lamoureaux and Lastrapes (1990)).

For low-transactions stocks, the pattern is reversed. The volatility in week t is less than that observed in the base week $t - 3$. Relatively high levels of volatility in week $t - 3$ are also associated with high levels of trade in week $t - 3$ for low-transactions winners and losers. Therefore, low-transactions

Table VII

Comparisons of Sample Variances and Trading Level of Contrarian Portfolios Across Base Week $t - 3$ and Performance Week t

Portfolios are formed using both last week's percentage changes in price (R_{it-1}) and number of transactions (u_{it-1}). Securities are categorized in week t as a) winner if the return in week $t - 1$ is positive, b) loser if the return in week $t - 1$ is negative, c) high-transaction if the percentage change in transactions in week $t - 1$ over week $t - 2$ (u_{it-1}) is positive, and d) low-transaction if the percentage change in transactions in week $t - 1$ over trading in week $t - 2$ is negative. Two variables are used to describe the portfolios. The first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The second variable denotes whether the portfolio is high transactions (H) or low transactions (L).

The sample variance is calculated as the variance of 407-week t returns and 406-week $t - 3$ returns. Both variances are multiplied by 100. An asterisk denotes a significant (at the 1 percent level) difference in sample variances across week $t - 3$ and week t, using an F-test statistic. Trading is the average number of transactions for that portfolio for week $t - 3$ or week t.

	Sample Variances		Trading	
Portfolio	Week ($t - 3$)	Week (t)	Week ($t - 3$)	Week (t)
W, H	0.062*	0.131	111.76	138.19
W, L	0.116*	0.073	133.69	113.69
L, H	0.057*	0.132	101.55	116.22
L, L	0.103	0.081	132.39	110.33

stocks experience both lower trading and volatility in week t when compared to three weeks earlier. These results suggest that the risk associated with price reversals (contrarian profits) in week t is higher than average, while the negative contrarian profits from the low-transactions stocks have lower variances relative to the base week.

In addition to changes in risk, there can also be substantial transactions costs associated with a strategy that involves trading large numbers of securities each week. Lehmann (1990) and Conrad, Gultekin, and Kaul (1991b) find that profits smaller than approximately 1.0 percent per week would be eliminated by one-way transactions costs of 0.20 percent. Few of the returns to the portfolio strategies in this analysis exceed this number; those that do tend to occur in smaller securities, where one might expect transactions costs to be higher. Therefore, these profits, while statistically significant, may not be true profit measures for an individual trader.[15]

While these results may give some comfort to those who believe that "easy" arbitrage opportunities should not persist in well-functioning markets, the larger point should not be overlooked. Our results suggest that, consistent with the model of Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993), *any* arbitrage strategy (pricing model) that attempts to profit from (explain) the time-series patterns in short-horizon returns should incorporate (also explain) the dramatically different price movements taken by high- and low-transactions securities.

[15]Note that if the group of "market makers" or liquidity providers in the Campbell, Grossman, and Wang (1993) model (or a subset of them) can, like registered market makers, buy at the bid quote and sell at the ask quote, then the use of spread midpoint returns may understate profits for this group (we are grateful to Rob Stambaugh for this comment). In addition, Lehmann (1990) suggests several reasons why the actual transaction prices of a contrarian strategy may be either higher or lower than the observed transaction price, depending on the specialist's inventory problem, price pressures, etc. To explore the magnitude of this effect, we also calculated profits to the returns/transactions portfolio strategy using transactions, rather than spread midpoint, returns. To break out the bid-ask spread effect specifically, we also split the sample into high- and low-spread stocks.

As expected, contrarian profits increase when transactions returns are used for both the high- and low-transactions subsamples. This difference appears to be largely due to the negative autocovariance induced by the bid-ask "bounce." For low-spread securities, there is still significant evidence of negative autocovariances in high-transactions stocks.

The portfolio of low-transactions, low-spread securities also shows evidence of increased negative autocovariance, since profits for this group are not significantly different from zero. For high-spread securities, however, the transactions returns profits are positive and virtually identical across the high- and low-transactions groups. Since the spread midpoint profits in the low-transactions, high-spread securities are significantly *negative* while the high-transactions group are positive, this suggests that there is an additional source of negative autocorrelation in the transactions returns of low-transactions, high-spread securities. We explored the possibility that week $t - 1$ spreads might be larger in the low-transactions group, or that nontrading might be more of a problem, but we could not find evidence of either one. Currently, this additional evidence of negative autocorrelation in the most thinly traded (in week $t - 1$), highest spread securities is the focus of future work.

F.2. Longer Horizon Results

In the results above, we have observed entirely different patterns in returns and variances in week t for high- and low-transactions securities. If abnormal trading signals changes in expected returns as in Campbell, Grossman, and Wang (1993), then it would be useful to know how long such changes persist.[16] In contrast, a Blume, Easley, and O'Hara (1994) trader may simply find it difficult to detect overreaction in low-transactions winners and losers, since thin trading can imply low precision of information in the past price movements. Trading subsequent to week t may provide additional information about possible overreaction in large price movements and lead to price reversals in low-transactions securities in the weeks following week t.[17] We examine the price behavior of high- and low-transactions winners and losers during the four-week period subsequent to portfolio formation.

Table VIII reports the returns earned for all four portfolios and the profits for the arbitrage portfolios formed for both high- and low-transactions groups during the four weeks after portfolio formation. We analyze nonoverlapping four-week periods. An interesting pattern emerges: the combined portfolio of low-transactions stocks, after experiencing an average price movement of the same sign in week t as week $t - 1$, experiences price reversals in the subsequent three weeks. These price reversals are significant in weeks $t + 2$ and $t + 3$ (t-statistics of 2.62 and 2.17, respectively). In addition, while price reversals in these securities occur later and tend to persist longer, they are not more variable: the sample standard deviation of these profits is quite low. One way to interpret these results favors the overreaction hypothesis: for low-transactions stocks, a larger price movement (in week $t - 1$ and week t) is needed to determine whether overreaction has occurred. If these returns patterns instead represent changes in expected returns, then the long-horizon results suggest that variation in expected returns for some securities is more complex than that proposed in models such as Conrad and Kaul (1988) or Campbell, Grossman, and Wang (1993). However, these results must be interpreted with caution; we are not controlling for the level of trading in the portfolios in weeks $t + 1$ through $t + 3$.

We also estimate four-week returns for size-based portfolios; for brevity, these results are not shown. Consistent with our other results, the first week's profits are largest for the small, high-transactions contrarian strategy. Low-transactions stocks, as before, experience positive autocovariances in returns in week t, which are larger for the smallest firms. In addition, price reversals occur at longer horizons for low-transactions stocks in all three size-based portfolios. Interestingly, these reversals occur later for smaller stocks; contrarian profits for low-transactions securities are significantly

[16] In daily index returns, Campbell, Grossman, and Wang (1993) find that volume effects on autocorrelations persist only up to 2 days.

[17] The overreaction hypothesis itself gives little guidance concerning when price reversals occur. Empirical tests have looked for reversals over horizons ranging from 1 week (Lehmann (1990)) to three years (DeBondt and Thaler (1985)).

Table VIII

Four-Week Returns to Contrarian Portfolio Strategy, Returns / Transactions Weights NASDAQ Sample, Spread Midpoint Returns, 1983 to 1990

x is the sample mean return (in percent) of the winner or loser portfolio in week t or the sample mean profit (in percent) to the combined portfolio. Standard errors are calculated using Newey-West corrections with one lag. The sample consists of 407 weeks of returns. Nonoverlapping four-week performance intervals are used. For each interval, weights are based on returns and trading in week $t-1$, then the portfolio is held from week t to week $t+3$.

Portfolios are formed using both last week's percentage changes in price (R_{it-1}) and number of transactions (u_{it-1}). Securities are categorized in week t as a) winner if the return in week $t-1$ is positive, b) loser if the return in week $t-1$ is negative, c) high-transaction if the percentage change in transactions in week $t-1$ over week $t-2$ (u_{it-1}) is positive, and d) low-transaction if the percentage change in transactions in week $t-1$ over trading in week $t-2$ is negative. In the winner and loser portfolios, weights are defined as: $w_{it}^{*} = R_{it-1}(1 + u_{it-1}) / \sum_{\iota=1}^{N_p} R_{it-1}(1 + u_{it-1})$, where N_p is the number of securities in each particular portfolio. Combined portfolios are formed for both high- and low-transactions stocks by going long the previous week's losers and short the previous week's winners. Two variables are used to describe the portfolios. The first variable indexes whether the portfolio is winner (W), loser (L), or combined (C). The second variable denotes whether the portfolio is high transactions (H) or low transactions (L).

	Week t		Week $t+1$		Week $t+2$		Week $t+3$	
Portfolio	x	t-Statistic	x	t-Statistic	x	t-Statistic	x	t-Statistic
W, H	−0.490	−1.12	0.100	0.39	0.112	0.25	−0.074	−0.24
W, L	0.189	0.79	−0.296	−1.22	−0.440	−1.80	−0.171	−0.58
L, H	0.225	0.60	−0.043	−0.26	0.153	0.64	0.098	0.29
L, L	−0.526	−2.11	−0.065	−0.30	−0.074	−0.38	0.202	0.57
C, H	0.715	1.62	−0.143	−0.56	0.041	0.10	0.172	0.91
C, L	−0.715	−2.91	0.231	1.72	0.366	2.62	0.373	2.17

positive in weeks $t+2$ and $t+3$ for the smallest firms, in week $t+2$ for moderate-sized firms, and in week $t+1$ for the largest firms.

III. Conclusion

We test for the existence of relations between lagged trading measures and current price responses suggested by Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993). Using a variant of the contrarian portfolio strategy of Lehmann (1990), we test whether trading information is important in predicting the price movements of securities. Our results are striking: the autocovariances of high- and low-transactions securities differ in sign and magnitude, with high-transactions stocks experiencing price reversals or negative autocovariance in returns and low-transactions stocks experiencing positive autocovariances in returns. This result is strongly consistent with the Campbell, Grossman, and Wang (1993) model. There is also evidence that the price movement in low-transactions stocks is directly related to last week's trading. These relations are stronger for smaller firms, as Blume, Easley, and O'Hara (1994) suggest.

One important feature of our results is that the autocovariances detected, both positive and negative, are found in the returns of *individual securities*. In contrast, Conrad, Kaul, and Nimalendran (1991) must use portfolio measures to extract reliable autocovariances in individual securities' returns. Our results suggest that at least part of this difficulty may be attributable to the fact that returns patterns differ sharply across securities with different levels of trading. Note also that the evidence for positive autocovariances in "own" returns found here cannot be due to cross-security effects, such as those documented in Lo and MacKinlay (1990). It is possible that our evidence of price trending in low-transaction securities, followed by delayed price reversals, is consistent with lagged price adjustment in *individual securities*.

Although the returns from our contrarian "strategy" may not be true arbitrage profits when one allows for transactions costs and changes in risk, it seems clear that any method of technical analysis, or any model of short-horizon time-varying returns processes, can profitably include trading activity as a valuable source of information about future price responses.

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