Filter Rules Based on Price and Volume in Individual Security Overreaction

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I present evidence of predictability in a sample constructed to minimize concerns about time-varying risk premia and market-microstructure effects. I use filter rules on lagged return and lagged volume information to uncover weekly overreaction profits on large-capitalization NYSE and AMEX securities. I find that decreasing-volume stocks experience greater reversals. Increasing-volume stocks exhibit weaker reversals and positive autocorrelation. A real-time simulation of the filter strategies suggests that an investor who pursues the filter strategy with relatively low transaction costs will strongly outperform an investor who follows a buy-and-hold strategy.

Recent research suggests that returns on individual stocks and portfolios have a predictable component. These studies find negative autocorrelation in individual security returns and positive autocorrelation in portfolio returns, and that the magnitude of the autocorrelations increases as firm size decreases [e.g., French and Roll (1986) and Conrad and Kaul (1988)]. Whether or not return predictability is attributable to market inefficiencies or time-varying risk premia is the topic of heated debate.

Lehmann (1990) suggests, based on the assumption that expected returns are not likely to change over a week, that this disagreement can be resolved by examining the predictability of short-term (weekly) stock returns.[1] Applying his contrarian strategy to all NYSE and AMEX stocks and controlling for microstructure-induced profit biases, Lehmann finds weekly returns to zero-cost portfolios of approximately 1.2%, with small-capitalization stocks showing the greatest profits.

However, subsequent articles provide alternative explanations for these profits. For example, Lo and MacKinlay (1990b) show that up to 50% of

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[1] Lehmann cites Sims (1984), who hypothesizes that as time intervals shorten, prices should follow a random walk because there should be few systematic changes in valuation over daily and weekly periods if information arrival is unpredictable.

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Lehmann's contrarian profits are due to lagged forecastability across large and small securities rather than to individual security negative autocovariances. Other authors show that using bid-to-bid formation period returns to control for spurious profits attributable to bid-ask bounce [Ball, Kothari, and Wasley (1995) and Conrad, Gultekin, and Kaul (1997)] and including transaction costs [Conrad, Gultekin, and Kaul (1997)] all but eliminate the profit in short-run contrarian strategies.

Given these articles' explanations for contrarian profits, the empirical evidence in support of short-term overreaction is not convincing. Most contrarian studies find the largest level of return predictability in small-capitalization stocks, which are more likely to have larger percentages of their profitability attributable to a lead-lag effect and to experience higher transaction costs. Previous studies' profitability documented in large-capitalization stocks, which are less likely to be influenced by cross-serial covariances of returns and liquidity problems, have their profits disappear at very low transaction cost levels [Conrad, Gultekin, and Kaul (1997)].

In this article I examine whether there is an overreaction phenomenon in the weekly returns of large-capitalization NYSE and AMEX stocks. I develop several modifications to the overreaction portfolio formation methodologies used in past overreaction articles. I design these modifications to boost the "signal-to-noise" ratio of the security selection process used to form contrarian portfolios.

First, I use filters on lagged returns.[2] I define securities as losers and winners if the level of the past-period returns are within specific filter breakpoints. Next, I form equally weighted long (short) portfolios of losers (winners). The filters let me screen on the magnitude of lagged returns in forming loser and winner portfolios. In contrast, the methodology for prior short-term contrarian articles [Lehmann (1990), Lo and MacKinlay (1990b), and Conrad, Gultekin, and Kaul (1997)] emphasizes forming portfolios by investing in all securities in their sample, giving greater weight to securities with larger relative lagged cross-sectional returns. Including stocks regardless of lagged return magnitudes results in inclusion of securities into the overreaction portfolios that may not be subject to "true" investor overreaction.[3] In contrast, my filter portfolio formation method results in an asset being included in a loser (winner) portfolio only if its lagged weekly return moved down (up) by a specified minimum amount.

[2] Other filter articles include Fama and Blume (1966), Sweeney (1986, 1988), Brown and Harlow (1988), Lakonishok and Vermaelen (1990), Bremer and Sweeney (1991), Corrado and Lee (1992), Cox and Peterson (1994), and Fabozzi et al. (1995).

[3] Past short-horizon contrarian articles' inclusion of all securities in their sample may have been an intentional device designed to examine evidence of marketwide security behavior while minimizing the portfolio weights placed on large prior-period winners and losers. I contrast the pros and cons of previous articles' weighting methods with this article's filter weights in Section 2.4.

Second, I incorporate a lagged individual security volume measure into the portfolio formation rules. I use filters on lagged percentage changes in individual security volume with filters on lagged returns to form portfolios. I test for relations between lagged volume and future price changes, as suggested by Campbell, Grossman, and Wang (1993) and Wang (1994). Campbell, Grossman, and Wang present a model in which risk-averse utility maximizers act as market makers for liquidity or noninformational investors in a world of symmetric information. In their model, if liquidity traders sell, causing a drop in stock prices, then risk-averse utility maximizers might act as market makers but would require a higher expected return. Thus their model predicts 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" [Campbell, Grossman, and Wang (1993, p. 906)]. In contrast, Wang (1994) assumes a world with two types of investors: agents with superior information and uninformed investors. In this economy, informed investors trade for informational and noninformational purposes. The heterogeneity among investors may give rise to a different relation between trading volume and returns than the relation hypothesized in Campbell, Grossman, and Wang. Wang (1994) hypothesizes that when informed investors' condition their trades on private information, then high future returns (price continuations) are expected when high returns are accompanied by high trading volume.

I test to see which effect, symmetric information coupled with liquidity trading [Campbell, Grossman, and Wang (1993)] or asymmetric information coupled with informed trading [Wang (1994)], dominates. If the predictions made in Campbell, Grossman, and Wang are correct for my article's dataset, I would expect to observe greater reversals for loser and winner portfolios when I condition on lagged increasing volume. But if the hypothesized relations in Wang are correct, I would expect smaller reversals and/or positive autocorrelation when I condition on lagged increasing volume.

Finally, to mitigate the effects of spurious reversals attributable to a bid-ask bounce effect and other liquidity problems, I use large-capitalization NYSE/AMEX securities as my sample. Conrad, Gultekin, and Kaul (1997) show that evidence of reversals on large-capitalization NYSE/AMEX securities are less affected by bid-ask bounce problems than reversal evidence on small-capitalization securities. Also, Foerster and Keim (1993) document that incidents of nontrading (which may upwardly bias contrarian profits) are considerably less likely on large-capitalization NYSE/AMEX stocks. In addition, the implementation of return reversal trading strategies based on large-capitalization stocks is less likely to be affected by high transactions costs: large-capitalization stocks are more likely to have smaller relative spreads and smaller price pressure effects [Keim and Madhavan (1997)].

Using my filter portfolio formation rules, I find evidence of significant overreaction profits for large-capitalization NYSE and AMEX stocks for the 1962–1993 period. These profits remain after controlling for microstructure problems. I also form portfolios on the same sample of stocks by using weighting rules similar to those developed in earlier short-term overreaction articles. In general, I find lower levels of return reversals. The incorporation of volume substantially improves the predictability of returns: low-volume securities experience greater reversals and high-volume securities have weaker reversals. This finding supports Wang (1994).

The article is organized as follows: In Section 1 I develop the filter methodology and apply it to an overreaction portfolio strategy. In Section 2 I empirically test for reversals, consider potential pitfalls of the filter formation technique, and contrast characteristics of the filter portfolios with prior short-horizon contrarian articles' portfolio formation rules. In Section 3 I conduct a "real-time" simulation of an investor's implementation of the filter investment strategy. The simulation uses an artificial intelligence system that selects sets of optimal in-sample filter rules and recursively tests them in step-ahead trading periods, therefore minimizing the possibility that the results emanate from hindsight. Section 4 concludes.

1. Portfolio Formation Rules

To analyze the relation between lagged weekly returns and lagged weekly volume and subsequent weekly returns, I develop a filter-based portfolio weighting method. The rationale for this methodology is that most previous short-term overreaction articles form portfolios by employing relative cross-sectional portfolio weighting methods. In contrast, I form portfolios by screening on absolute magnitudes of lagged returns, and as a result, my filter method may correspond more closely with the academic evidence on the psychology of overreaction.

Related studies [see DeBondt (1989) for a review] show that individuals tend to overreact to a greater degree when confronted with a larger information shock relative to their prior base-rate expectations. This realization leads DeBondt and Thaler (1985) to postulate an overreaction hypothesis that states: "(1) Extreme movements in stock prices will be followed by extreme movements in the opposite direction. (2) The more extreme the initial movement, the greater will be the subsequent adjustment" (p. 795). DeBondt and Thaler's hypothesized predictable return behavior, manifested in extreme price movements, forms the basis of my filter rules. In these rules I include a security in a portfolio only if its lagged return is within the filter level. Thus, by using filters on lagged returns, I can screen stocks for "large" past price movements that could be investor overreaction, and I can then eliminate securities that experience smaller lagged returns (or those that may be noise to a contrarian strategy).

My portfolio formation rules use filters over two horizons: week $t-1$ (a first-order filter), and from week $t-1$ and week $t-2$ jointly (a second-order filter). I examine eight strategies that illustrate the relation between lagged returns and lagged volume, and subsequent return reversals.

The first four strategies use lagged returns. For example, if a stock's week $t-1$ return is negative, then I define the strategy as "loser-price" and classify it as a first-order filter. If a stock's week $t-1$ and week $t-2$ returns are both positive, then I define the strategy as "winner, winner-price" and classify it as a second-order filter. Hence the four price-only strategies are "loser-price," "loser, loser-price," "winner-price," and "winner, winner-price."

Strategies 5–8 incorporate both price and volume information. For example, if in week $t-1$ the return and weekly percentage changes in volume for a stock are negative, then I define the strategy as "loser-price, low-volume" and classify it as a first-order filter. Thus the four price and volume strategies are "loser-price, low-volume," "loser-price, high-volume," "winner-price, low-volume," and "winner-price, high-volume."

These rules define week $t-1$ and week $t-2$ returns as winners or losers as follows:

First-Order Price Filters:

$$\text{Return states} = \begin{cases} \text{For } k = 0, 1, \ldots, 4: \begin{cases} \text{loser}_{k^*A} & \text{if } -k^*A > R_{i,t-1} \geq -(k+1)^*A \\ \text{winner}_{k^*A} & \text{if } k^*A \leq R_{i,t-1} < (k+1)^*A \end{cases} \\ \text{For } k = 5: \begin{cases} \text{loser}_{k^*A} & \text{if } R_{i,t-1} < -k^*A \\ \text{winner}_{k^*A} & \text{if } R_{i,t-1} \geq k^*A \end{cases} \end{cases} \tag{1}$$

Second-Order Price Filters:

$$\text{Return states} = \begin{cases} \text{For } k = 0, 1, \ldots, 4: \begin{cases} \text{loser}_{k^*A} & \text{if } -k^*A > R_{i,t-1} \geq -(k+1)^*A \\ & \text{and } -k^*A > R_{i,t-2} \geq -(k+1)^*A \\ \text{winner}_{k^*A} & \text{if } k^*A \leq R_{i,t-1} < (k+1)^*A \\ & \text{and } k^*A \leq R_{i,t-2} < (k+1)^*A \end{cases} \\ \text{For } k = 5: \begin{cases} \text{loser}_{k^*A} & \text{if } R_{i,t-1} < -k^*A \\ & \text{and } R_{i,t-2} < -k^*A \\ \text{winner}_{k^*A} & \text{if } R_{i,t-1} \geq k^*A \\ & \text{and } R_{i,t-2} \geq k^*A, \end{cases} \end{cases} \tag{2}$$

where $R_{i,t}$ is the non-market-adjusted return for security i in week t, k is the filter counter that ranges from $0, 1, \ldots, 5$, and A is the lagged return grid width, equal to 2%.

To analyze whether return reversals are related to trading volume, as suggested by Campbell, Grossman, and Wang (1993) and Wang (1994), I define individual security weekly percentage changes in volume (henceforth described as "growth in volume"), adjusted for the number of outstanding shares of a security, as

$$\%\Delta v_{i,t} = \left[\frac{V_{i,t}}{S_{i,t}} - \frac{V_{i,t-1}}{S_{i,t-1}}\right] \Big/ \left[\frac{V_{i,t-1}}{S_{i,t-1}}\right], \tag{3}$$

where $S_{i,t}$ is the number of outstanding shares for security i in week t and $V_{i,t}$ is the weekly volume for security i in week t. Next, my rules define week $t-1$ growth in volume, $\%\Delta v_{i,t-1}$, as being low or high, as follows:

Volume Filters:

$$\text{Growth in volume states} = \begin{cases} \text{For } k = 0, 1, \ldots, 4: \begin{cases} \text{low}_{k^*B} \ \text{ if } -k^*B > \%\Delta v_{i,t-1} \\ \qquad\qquad \geq -(k+1)^*B \\ \text{high}_{k^*C} \ \text{ if } k^*C \leq \%\Delta v_{i,t-1} \\ \qquad\qquad < (k+1)^*C \end{cases} \\ \text{For } k = 5: \qquad \begin{cases} \text{low}_{k^*B} \ \text{ if } \%\Delta v_{i,t-1} < -k^*B \\ \text{high}_{k^*C} \ \text{ if } \%\Delta v_{i,t-1} \geq k^*C, \end{cases} \end{cases} \tag{4}$$

where k is the filter counter that ranges from $0, 1, \ldots, 5$, B is the grid width for low growth in volume (i.e., $\%\Delta v_{i,t-1} < 0$) and is equal to 15%, C is the grid width for high growth in volume (i.e., $\%\Delta v_{i,t-1} > 0$) and is equal to 50%.

The asymmetry in the high- and low-volume filters is due to skewness in the growth-in-volume distribution. For each of the eight strategies, whether price-only or price plus volume, I form portfolios in week t by including stocks that meet the appropriate lagged filter-level constraints. For the price-only strategies, the constraints result in six sets of portfolios for each category of loser or winner and first- or second-order horizon. For the price-plus-volume strategies, the constraints result in 36 portfolios for each category of loser or winner and high or low growth in volume.

For example, consider a "winner-price, high-volume" strategy. Setting the minimum level of the first-order price filter at 4% (equation 1 for winners with $k = 2$ and $A = 2$) and the minimum level of the high growth-in-volume filter at 100% [Equation (4) for high with $k = 2$ and $C = 50$] results in forming an equally weighted portfolio of securities that have an increase in price of greater than or equal to 4% and less than 6% and whose growth in volume is greater than or equal to 100% and less than 150%. The filter breakpoints for weekly returns, low growth in volume, and high growth in volume (k^*A, k^*B, and k^*C, respectively) are determined by each variable's overall sample distribution (approximately the 1, 2.5, 5, 10, 25, 50, 75, 90, 95, 97.5, and 99 percentile points) from the annually ranked top 300 largest market capitalization NYSE and AMEX stocks.

For each combination of filter values, I form into equally weighted portfolios the securities whose lagged weekly returns meet the filter constraints during week t. All portfolios are held for a period of one week and then liquidated. I calculate the resulting mean returns for weeks in which the portfolios hold equity positions. If the portfolios' mean returns are significantly different from zero, I take this as evidence in favor of return predictability. Thus the null hypothesis of no predictability is that the mean return of a portfolio equals zero. I follow the practice of other short-horizon contrarian articles and report mean-equal-to-zero t-statistics. I also calculate t-statistics (not reported in the article) by subtracting the unconditional weekly mean return of the sample from the return of each filter portfolio and find that this measure of excess returns produces little variation in the reported t-statistics. To compute the mean and standard errors of the time series of trades for each portfolio and to perform comparisons between the means of different strategies, I estimate moment conditions by using generalized method of moments (GMM) [Hansen (1982)] and use Newey and West (1987) weights on the variance/covariance matrix.[4] Comparing the mean returns in a GMM framework has the advantage of controlling for contemporaneous and time-series correlations in the portfolios' time series of returns.

2. Empirical Results

2.1 Data

To determine the effects of the filter rules on contrarian profits, I examine a sample consisting of Wednesday-close to Wednesday-close weekly returns and weekly volume for the top 300 largest market capitalization (henceforth described as the "top 300 large-cap") NYSE and AMEX individual securities in the CRSP file between July 2, 1962, and December 31, 1993. I annually perform the market capitalization ranking at the beginning (January 1) of each year, except for the ranking performed on July 2 for the 1962 data (since CRSP does not include daily data prior to July 2, 1962). I include a security in the sample for week t if it has daily nonmissing volume for each of the previous 10 trading days. Since I base the weights placed

[4] The mean return and associated "t" statistic for each portfolio is estimated in GMM with the following moment condition: $\varepsilon_1 = R_p - \mu_p * 1$, where R_p is a $t \times 1$ time series of trades from a given filter rule's portfolio; μ_p, a scalar, is the mean return parameter to be estimated; and 1 is a column vector of ones. I compare mean returns (for example, comparing the returns of a first-order filter rule to a second-order filter rule) using the moment conditions: $\begin{Bmatrix} \varepsilon_1 = R_{p1} - \mu * 1 \\ \varepsilon_2 = R_{p2} - \mu * 1 \end{Bmatrix}$, where R_{p1} is the time series of trades from the first filter rule and R_{p2} is the time series of trades from the second filter rule. μ is the mean return parameter to be estimated. The system of moment conditions is overidentified, with two moment conditions and only one parameter to estimate. Thus the resulting χ^2_1 statistic tests the null hypothesis of $\bar{R}_{p1} = \bar{R}_{p2}$, where $\bar{R}_{p1}$ and $\bar{R}_{p2}$ are the mean returns of portfolios 1 and 2, respectively. Using the filter rules results in frequent entry and exit of individual securities into the time series of portfolio returns used in the above moment conditions. Frequent entry and exit may produce heterogeneity in the portfolio's time series of returns. However, since the GMM estimates are invariant to heteroscedasticity, then heterogeneity in the time series of returns should not be a concern. For further discussion, see Gallant (1987, Theorem 3, p. 534).

on individual securities to form portfolios on non-market-adjusted returns, the profits to the filter-based strategies should not result from positive index autocorrelation.[5]

2.1.1 Overview of the data. Table 1 reports sample statistics for the dataset. Across the entire sample period, the average security size has a mean market capitalization of \$3.31 billion and a mean security price of approximately \$46 a share. The cross-sectional average of individual security weekly autocorrelation coefficients is -4.34% at the first lag and -1.63% at the second lag. The negative autocorrelation is either consistent with a reversal effect for individual stocks or it may indicate the existence of a bid-ask spread effect. However, the four-day return's (a "skip-day" weekly return measure that I use as a precaution against bid-ask bounce problems) first-order autocorrelation of -3.57% indicates that spurious negative autocorrelation induced by the bid-ask spread is probably not driving the negative autocorrelations in the five-day weekly returns.

2.2 Price strategies

Panel A of Table 2 illustrates the average weekly returns for the four price-only strategies: (1) loser-price, a strategy of buying last week's losers based on five-day week $t-1$ returns; (2) skip-day loser-price, a strategy of buying last week's losers based on four-day week $t - 1$ returns; (3) loser, loser-price, a strategy of investing in stocks that incurred two consecutive weeks of losses, based on five-day returns in both weeks $t - 1$ and $t - 2$; and (4) skip-day loser, loser-price, a strategy of investing in stocks that incurred two consecutive weeks of losses, based on four-day week $t - 1$ returns and five-day week $t - 2$ returns. Panel B of Table 2 documents the same four strategies for winner stocks. The profit figures reported throughout the article are for a positive investment. Hence reversals in the loser (winner) portfolios appear as positive (negative) returns.

2.2.1 Filter levels and portfolio returns. Perhaps the most striking feature of Table 2 is the magnitude of the portfolios' weekly returns, especially at the higher filter levels. Across both the loser and winner portfolio strategies, the degree of reversals increase as the absolute value of the filter levels increases. The losers' average weekly returns (panel A, Table 2) start out at 0.315% ($t = 5.61$) for the loser-price strategy at a lagged return filter level of between 0% and -2%, and increase monotonically to a 1.601% ($t = 8.32$) weekly return at the less than -10% filter.

[5] Conrad, Gultekin, and Kaul (1997) and Lo and MacKinlay (1990b), using a profit decomposition originally derived in Lehmann (1990), show that contrarian strategies that base their weights on a security's deviation from an equally weighted index typically result in a large percentage of profits attributable to positive autocovariances of the returns of an equally weighted portfolio of the component assets.

Table 1
Sample statistics for the annually ranked top 300 large-cap stocks for the period July 7, 1962–December 31, 1993

	Mean	Median	Std. Dev.	Min.	25th percentile	75th percentile	Max.	$\bar{\rho}_1$ (SD)	$\bar{\rho}_2$ (SD)
Five-day return (%)	0.221	0.000	4.051	−44.531	−1.961	2.272	99.079	−4.339 (11.485)	−1.626 (10.057)
Four-day return (%)	0.167	0.000	3.622	−44.136	−1.761	1.961	99.079	−3.573 (11.244)	−1.468 (9.701)
$\%\Delta v_{i,t}$ (%)	19.243	−0.834	154.060	−100.0	−28.491	38.883	5700.428	−24.102 (9.376)	−5.188 (9.810)
$\%\Delta v_{it,4}$ (%)	0.558	−4.382	37.810	−100.0	−24.804	19.912	300.0	9.115 (10.780)	−14.897 (9.694)
$\%\Delta v_{it,20}$ (%)	1.898	−9.876	58.431	−100.0	−32.858	21.222	1900.0	30.675 (15.218)	16.251 (13.077)
Capitalization (billions)	3.318	1.481	6.127	0.0009	0.724	3.401	1046.0		
Price	46.164	39.375	33.25	2.0	28	55	687		

Five-day return is a Wednesday-to-Wednesday close weekly holding period return. Four-day return is a "skip-day" Wednesday-to-Tuesday close four-day holding period return. $\%\Delta v_{i,t}$ is the weekly percentage change in volume for security i from week $t-1$ to week t. $\%\Delta v_{it,4}$ and $\%\Delta v_{it,20}$ employ an average of the last 4 and 20 weeks of volume, respectively, to form longer-term volume measures. The sample statistics for capitalization and price are calculated across time and across securities. The capitalization ranking is done annually, at the beginning (January 1) of each year, with the exception of the capitalization ranking being performed on July 2 for the 1962 data (since CRSP does not include daily data prior to July 2, 1962). The statistic $\bar{\rho}_j$ is the average jth-order autocorrelation coefficient. The numbers in parentheses are the population standard deviation (SD). Since the autocorrelation coefficients are not cross-sectionally independent, the reported standard deviations cannot be used to draw the usual inferences; they are presented as a measure of cross-sectional variation in the autocorrelation coefficients.

For the loser, loser-price portfolios, the same pattern is evident. Returns increase as the filter levels decrease, with the greatest weekly returns (3.667%, $t = 3.22$) emanating from the portfolio formed by conditioning on stocks that incurred two consecutive weekly losses of less than −10%.

In panel B, the winners also exhibit greater reversals as the filter levels are raised. For example, the average weekly returns for the winner-price strategy start out at approximately 0.313% ($t = 5.94$) for the winner-price strategy at a filter of between 0% and 2%, and decrease to −0.088% ($t = -0.59$) for the greater than 10% filter. The t statistics of the winner strategies are smaller than the loser strategies and generally do not indicate significant reversals.

There is a clear asymmetry between the magnitude and statistical significance of reversals for losers and winners. This difference is consistent with findings in other short-term overreaction articles, such as those of Lehmann (1990), Lo and MacKinlay (1990b), and Conrad, Gultekin, and Kaul (1997). This finding is also consistent with much of the filter literature results that show that short positions for various holding periods are generally not as profitable as long positions [Brown and Harlow (1988), Sweeney (1988), Bremer and Sweeney (1991), and Cox and Peterson (1994)].

Table 2
Weekly portfolio returns to price-only strategies

A: Loser strategies

Strategy		Lagged weekly return filter (%)					
		< 0 and ≥ -2	< -2 and ≥ -4	< -4 and ≥ -6	< -6 and ≥ -8	< -8 and ≥ -10	< -10
(1) Loser-price	Mean (%)	0.315	0.470	0.747	0.913	1.525	1.601
	Std. dev.	2.007	2.296	2.785	3.497	4.346	5.384
	N	1642	1641	1604	1428	994	833
	t-statistic	5.605	7.445	9.899	9.456	10.314	8.316
(2) Skip-day loser-price	Mean (%)	0.351	0.560	0.799	0.985	1.085	1.390
	Std. dev.	1.978	2.345	2.780	3.634	4.638	5.785
	N	1641	1640	1593	1329	871	697
	t-statistic	6.425	8.407	11.038	9.954	7.036	6.698
(3) Loser, loser-price	Mean (%)	0.294	0.639	0.979	1.562	0.788	3.667
	Std. dev.	2.087	3.112	4.133	5.830	8.411	11.350
	N	1629	1440	729	260	70	76
	t-statistic	4.991	7.385	6.364	4.302	0.946	3.222
(4) Skip-day loser, loser-price	Mean (%)	0.377	0.673	1.054	1.595	2.215	3.203
	Std. dev.	2.110	3.018	4.253	5.999	7.421	11.268
	N	1636	1437	716	244	64	74
	t-statistic	6.286	7.983	6.641	3.933	2.823	2.436
Comparisons of portfolio means[a]							
(1) vs. (2)	χ_1^2	9.062*	13.631*	1.102	0.916	5.308**	2.295
(3) vs. (4)	χ_1^2	9.97*	1.414	0.034	0.320	0.043	2.337
(1) vs. (3)	χ_1^2	0.022	10.290*	7.783*	3.057*	1.545	0.712
(2) vs. (4)	χ_1^2	1.007	10.865*	3.618***	1.375	0.008	0.204

B: Winner strategies

Strategy		Lagged weekly return filter (%)					
		≥ 0 and < 2	≥ 2 and < 4	≥ 4 and < 6	≥ 6 and < 8	≥ 8 and < 10	≥ 10
(1) Winner-price	Mean (%)	0.313	0.300	0.238	0.032	−0.065	−0.088
	Std. dev.	1.925	2.124	2.438	3.082	3.823	4.209
	N	1642	1641	1618	1533	1325	1198
	t-statistic	5.942	5.428	3.747	0.392	−0.596	−0.597
(2) Skip-day winner-price	Mean (%)	0.300	0.228	0.181	−0.082	−0.011	0.051
	Std. dev.	1.917	2.187	2.669	3.225	3.754	4.647
	N	1641	1638	1604	1463	1176	1045
	t-statistic	5.760	3.996	2.657	−0.963	−0.069	0.371
(3) Winner, winner-price	Mean (%)	0.280	0.330	0.168	−0.225	−0.051	−0.086
	Std. dev.	1.987	2.994	3.375	4.481	5.879	7.772
	N	1635	1473	955	400	160	201
	t-statistic	5.041	4.299	1.576	−0.925	−0.117	−0.169
(4) Skip-day winner, winner-price	Mean (%)	0.286	0.092	0.091	−0.133	−0.452	−0.565
	Std. dev.	1.995	2.676	3.547	4.287	5.359	7.501
	N	1630	1472	907	364	121	173
	t-statistic	5.348	1.242	0.714	−0.614	−0.747	−0.961
Comparisons of portfolio means[a]							
(1) vs. (2)	χ_1^2	2.334	7.581*	2.624	0.954	0.002	9.448*
(3) vs. (4)	χ_1^2	0.214	7.163*	7.754*	0.002	0.084	1.46
(1) vs. (3)	χ_1^2	1.714	0.154	2.473	2.123	0.227	0.175
(2) vs. (4)	χ_1^2	0.385	8.484*	0.207	0.288	0.444	2.214

Table 2
(continued)

C: Mean return and percent of positive returns for 1-, 4-, 13- and 52-week horizons

			Lagged weekly return filter (%)					
	Portfolio horizon (weeks)	Loser filters	< 0 and ≥ -2	< -2 and ≥ -4	< -4 and ≥ -6	< -6 and ≥ -8	< -8 and ≥ -10	< -10
Loser-price	1	Mean (%)	0.315	0.470	0.747	0.913	1.525	1.601
		Percent pos.	57.92	59.42	62.22	60.78	63.68	63.14
		$N(1)$	1642	1641	1604	1428	994	833
	4	Mean (%)	1.294	1.923	2.977	3.232	4.055	3.822
		Percent pos.	64.63	66.82	70.48	67.48	69.89	71.42
		$N(4)$	410	410	410	409	382	357
	13	Mean (%)	4.283	6.429	10.076	10.953	12.999	11.906
		Percent pos.	73.01	78.57	82.54	77.77	84.00	81.14
		$N(13)$	126	126	126	126	125	122
	52	Mean (%)	18.346	28.493	46.802	52.521	62.65	54.462
		Percent pos.	83.87	90.32	90.32	100.00	96.77	87.09
		$N(52)$	31	31	31	31	31	31
	Portfolio horizon (weeks)	Winner filters	≥ 0 and < 2	≥ 2 and < 4	≥ 4 and < 6	≥ 6 and < 8	≥ 8 and < 10	≥ 10
Winner-price	1	Mean (%)	0.313	0.300	0.238	0.032	−0.065	−0.088
		Percent pos.	58.95	57.28	55.44	50.62	47.62	47.33
		$N(1)$	1642	1641	1618	1533	1325	1198
	4	Mean (%)	1.281	1.229	0.960	0.127	−0.211	−0.244
		Percent pos.	66.09	63.17	59.02	49.02	45.56	45.88
		$N(4)$	410	410	410	410	406	401
	13	Mean (%)	4.231	4.049	3.174	0.490	−0.634	−0.529
		Percent pos.	73.61	68.25	65.87	46.03	41.27	42.85
		$N(13)$	126	126	126	126	126	126
	52	Mean (%)	18.098	17.276	13.63	1.740	−0.814	−2.310
		Percent pos.	80.645	87.09	74.19	38.71	45.16	41.93
		$N(52)$	31	31	31	31	31	31

Panel A shows the average weekly returns to the four price-only strategies: (1) loser-price, a strategy of buying last week's losers based on five-day week $t-1$ returns; (2) skip-day loser-price, a strategy of buying last week's losers based on four-day week $t-1$ returns; (3) loser, loser-price, a strategy of investing in stocks that incurred two consecutive weeks of losses based on five-day returns in both weeks $t-1$ and $t-2$; and (4) skip-day loser, loser-price, a strategy of investing in stocks that incurred two consecutive weeks of losses based on four-day week $t-1$ returns and five-day week $t-2$ returns. Panel B documents the same four strategies for winner stocks. For a stock to be included in a winner or loser portfolio, its lagged weekly return must be within the given filter ranges. The sample is the annually ranked top 300 large-cap NYSE and AMEX stocks for the July 1962–December 1993 period. Included are the corresponding portfolios' means, standard deviations, and t-statistics for a mean $= 0$ null hypothesis for weeks in which equity positions are held. In panels A and B, N is the number of portfolio weeks the strategy traded at the respective price filter level out of a possible 1,642 weeks. The t- and χ_1^2-statistics are robust to heteroscedasticity and autocorrelation. Panel C presents mean return and percent of positive return weeks for 1-, 4-, 13-, and 52-week nonoverlapping horizons for loser and winner portfolios, respectively. $N(1)$, $N(4)$, $N(13)$, and $N(52)$ are the number of periods that portfolios were formed for the 1-, 4-, 13-, and 52-week horizon returns, respectively. The longer horizon portfolios are only formed in periods in which there is at least one weekly return to form the longer horizon return.

[a] The comparison of portfolio means uses a χ_1^2-statistic to test the null hypothesis of equality of average weekly returns between various pairs of strategies.

*, **, *** The null hypothesis of equality of average weekly portfolio returns is rejected at the 1%, 5%, and 10% levels, respectively.

2.2.2 One-week versus two consecutive one-week returns. I examine whether stocks that have declined or increased in value for a longer period of time are more likely to experience greater return reversals. Alternatively, I wish to see if information contained in a longer sequence of security price changes provides a trader with extra information in predicting subsequent price changes, as suggested by Brown and Jennings (1989) and Grundy and McNichols (1989). To do this, I use the results in Table 2, and examine the returns to the second-order filters.

In panel A of Table 2, across the filter values, the returns to loser portfolios that condition on two consecutive weeks of losses (loser, loser-price) are generally larger than the returns to their one-week counterparts. For example, securities that experience two consecutive weeks of losses of between -2% and -4% each week (in weeks $t-1$ and $t-2$) experience trade-week profits of 0.639% versus a 0.470% return for securities that experience a similar one-week drop in returns. The difference in means is statistically significant ($\chi_1^2 = 10.29$, $p < .01$). As the loser filters become more extreme, I observe a similar pattern of greater profits for the two-week strategies relative to the one-week strategies. However, the chi-square statistics that test for significance in mean returns across the first- and second-order filters are significant in only three of the six loser versus loser, loser comparisons in panel A and never significant in the winner versus winner, winner comparisons in panel B.[6]

These results imply that loser stocks are somewhat more likely to experience greater reversals if they have incurred two consecutive weeks of losses relative to securities that have experienced one week of losses. This suggests second-order filters provide more information than do first-order filters. This finding is consistent with McQueen and Thorley (1991), who show that it is possible to obtain more accurate directional forecasts of weekly equally weighted and value-weighted index returns by conditioning on the information contained in two consecutive one-week lagged returns rather than a single one-week lagged return. If reversals are interpreted as evidence of overreaction, then markets may overreact to a greater degree for stocks that have experienced relatively longer periods of losses or gains. For longer horizon returns, DeBondt and Thaler (1985) report similar re-

[6] I use GMM to estimate moment conditions to perform these comparisons. Because the second-order filter portfolios are a subset of the first-order portfolios, the GMM comparisons examine the difference in returns for weeks in which there exists both a first- and second-order portfolio (since GMM will not use observations in which one variable has missing data). An alternative comparison would be to test the differences in returns for the cases that are not examined in the GMM tests. I use a "classical" paired means t-test to compare the difference between the returns of the second-order portfolios to the first-order portfolios, where the first-order portfolio returns are obtained from weeks in which the second-order portfolios did not trade. Using this method, the difference in mean returns between first- and second-order loser filters at the more extreme filter values are marginally statistically significant. For example, the paired t statistic for the difference in means between the first- and second-order portfolios at a less than -10% filter is 1.68.

sults. They find that the degree of reversals is smaller for shorter formation periods.

In both this and the previous section, which provide evidence of filter-based contrarian predictability based upon one-week and two-week price filters, respectively, I find greater profits than do prior filter articles, such as Fama and Blume (1966) and Sweeney (1988). The differences in results could be attributable to differences in the exact manner in which the filters are defined and implemented. Prior filter articles, for example, Fama and Blume, usually use rules of the form "buy when the stock's price rises Y% above its past local low and sell when it falls Z% below its past local high." A typical value of Y and Z is one-half of 1%. Thus, previous articles examine relatively smaller filters and do not use a fixed-time horizon in which the filter condition must be met. In contrast, I require that the return movement imposed by a filter must be met in a one- or two-week horizon, and I examine a broader range of filters, including some that are much more extreme than Fama and Blume or Sweeney.

2.2.3 Consistency of profits. Another benchmark I want to consider is how consistently profitable the filter portfolios are over longer time horizons. For example, Lehmann (1990) examines longer horizon J-period returns, where J ranges from 4 to 52 weeks. The results to 1-, 4-, 13-, and 52-week nonoverlapping holding period returns for the first-order loser and winner strategies are reported in panel C of Table 2.[7] As we move to more extreme winner and loser filters and longer horizons, the basic pattern that emerges indicates a greater degree of consistency in profitability. For example, at a one-week horizon, returns are positive to the loser-price strategy using a filter between 0% and −2% during approximately 58% of the one-week periods. At the less than −10% loser filter, returns are positive approximately 63% of the trade weeks for the one-week horizon. At the 52-week horizon, the degree of consistent profitability for the more extreme loser filters attains levels of 90% to 100% with annual holding period returns of between 50% and 60%.

This can be compared to annual holding period returns of the component assets (the annually ranked top 300 large-cap stocks). Those securities experienced positive returns in 77% of the years and had an average return of 12.319% per year (not reported in the table). The winners exhibit similar trends of increasing consistency (that is, a lower percent positive) from lower to higher magnitude filters within each horizon.

Overall the longer horizon results are striking. The more extreme loser filters consistently earn positive profits in upwards of 90% of the 52-week

[7] I calculate the average J-week nonoverlapping holding period return to portfolio p as $R_p^J = [\prod_{t=1}^{J}(1 + R_{p,t})] - 1$. I calculate the J-week return for periods in which there is at least one weekly return available and compute the J-week return by assigning a value of zero to any missing return weeks in the period.

periods, and experience annual returns of approximately 40% to 50% in excess of the unconditional top 300 large-cap stocks' annual average returns.

2.2.4 Skip-day results and volume in the trade week: Are bid-ask bounce and unusual market conditions driving the results? Since the reported profits for many of the filter strategies appear to be relatively large, I want to determine the extent to which the results might be attributable to bid-ask bounce and other possible microstructure problems. Although it is true that average bid-ask spreads on the top 300 large-cap stocks are probably quite small, the *conditional* bid-ask spreads might be large. To guard against related spurious reversal profits from a "bid-ask bounce" effect [Roll (1984)] due to a lack of closing bid-ask spread data in CRSP, I use Lehmann's (1990) "skip-day" return methodology. The skip-day returns are employed in the portfolio formation period (week $t-1$) and are formed from four-day Wednesday-close to Tuesday-close returns.

The results of the skip-day returns appear in Table 2, rows 2 and 4. In both panels A and B, there is not a large decrease in profits over the strategies that use a five-day conditioning period return. Except for the two most extreme loser filter portfolios (between -8% and -10% and less than -10%) and the winner portfolio of greater than or equal to 10%, the skip-day portfolios actually earn greater weekly profits compared to the five-day portfolios. For example, the between -2% and -4% filter results in portfolios that earn 0.47% when conditioning on five-day lagged returns compared to portfolios that earn 0.56% when conditioning on four-day lagged returns. The test for a difference in means is significant ($\chi_1^2 = 13.63$, $p < .01$).

I also observe the same pattern of slightly greater reversals at lower-magnitude filters and slightly smaller reversals at the higher-magnitude filters for the second-order loser-loser and winner-winner skip-day strategies relative to their non-skip-day counterparts (rows 3 and 4 of Table 2, panels A and B). Overall the level of reversals attributable to the skip-day portfolios suggests that after controlling for possible spurious negative autocorrelations emanating from bid-ask bounce, significant profits exist.

I also examine trade-week relative volume measures as a further heuristic in determining if the securities chosen by the filters experience unusual conditions that might affect the profitability of the portfolios. For example, Lee, Mucklow, and Ready (1993) and Michaely and Vila (1996) show that effective spreads can increase in periods of high or low volume depending on whether a period's price movement is based on an information or a non-infomation event. Therefore, as a further safety check, I divide the volume in week $t-1$, week t, and opening trade-day volume (the first day of week t) by their previous 40-week average to give three relative volume measures. My hypothesis is that extremely large or small relative volume in the trade week might result in greater microstructure problems and lead to either lower profitability or greater impediments to implementing the filter portfolios.

The pattern that emerges for relative volume (not reported in the tables) is one of increasing opening day, week $t-1$, and week t volume as I raise the filters for both losers and winners. For example, loser portfolios formed at the filter level of between 0% and −2% experience weekly volume for all three measures close to their trailing 40-week mean (1.003, 0.97, and 1.019 for opening day, week $t-1$ and week t, respectively). In contrast, the portfolio formed from the extreme loser filter of less than −10% experiences increases in volume of approximately twice the normal opening day volume (2.163, 2.28, and 1.624 for opening day, week $t-1$ and week t, respectively). However, it is still within approximately one standard deviation of the unconditional opening day relative volume, which has a mean of 1.068 and a standard deviation of 1.321.

Overall the trade-week volume measures show that many of the intermediate filter strategies, and even some of the more extreme filter strategies, do not experience trade-week volume that deviates much more than one standard deviation away from their unconditional means. These results could imply a liquid market in which a trader executes a majority of the filter strategy trades at relatively favorable bid-ask and price pressure conditions, especially since the trader probably helps to supply liquidity on the opposite side of the majority of orders.[8]

2.3 Price and volume strategies

In this section I examine if return reversals are related to lagged volume, as hypothesized by Campbell, Grossman, and Wang (1993) and Wang (1994). Table 1 shows statistics for the growth-in-volume measure, $\%\Delta v_{i,t}$ (see Equation 3), the average percentage change in individual security weekly volume. Over the 1,642-week sample period, $\%\Delta v_{i,t}$ averages 19.243%.

Figure 1 illustrates the general pattern in weekly portfolio returns as I condition on different values of lagged return and lagged growth in volume. The increase in forecasting value from lagged volume is dramatic. Conditioning on negative growth in volume results in increased negative return autocorrelations and conditioning on positive increases in growth in volume results in decreased negative return autocorrelations.

[8] As a further robustness check, I calculate average weekly returns for the loser-price and winner-price skip-day portfolios in Table 2 by screening on low/low and high/high relative volume measures for the first and last day of the trade week, on the assumption that greater profits in the low/low division could indicate liquidity problems in implementing these portfolios. I use the overall sample averages of open- and close-day relative volume as the cutoff points for "low" and "high." The profits do decrease between the low/low and high/high divisions, consistent with a potential liquidity problem. For example, for the portfolios formed from stocks with lagged weekly skip-day returns less than −10%, the average weekly return to the low/low portfolio is 1.53% and the return to the high/high portfolio is 1.23%. However, the relatively large profits for the high/high portfolio indicate that significant reversals do exist in a group of stocks for which an investor who implements the filter strategies would most likely not experience significant liquidity problems.

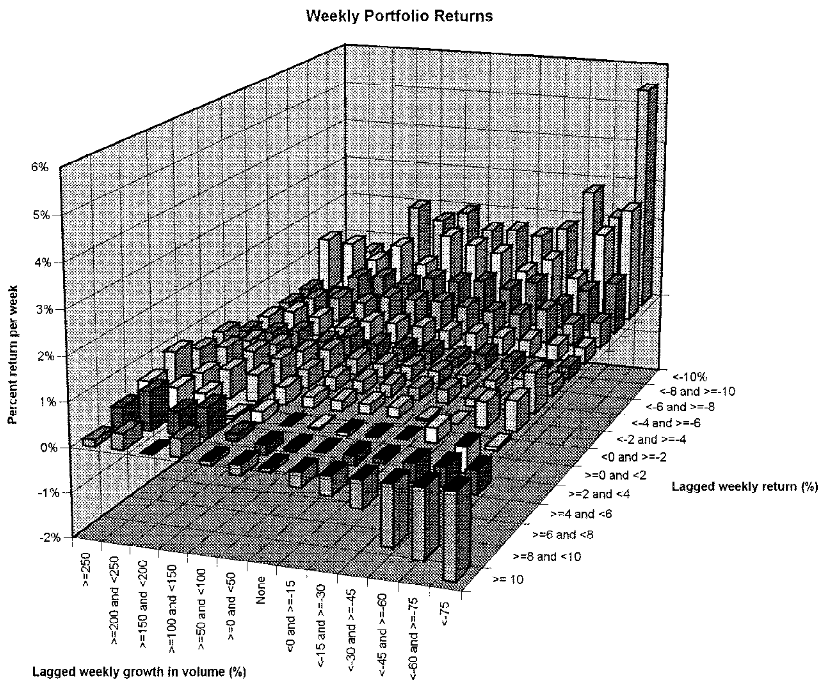

Figure 1
Weekly portfolio returns to the price-volume strategies

Table 3 presents results for the graphical relations in Figure 1. In Table 3, panel A, the loser-price, low-volume strategy, which jointly conditions on lagged price and growth in volume, results in large percentage increases in weekly portfolio profits relative to the price-only strategies. The same effect is evident in panel C of Table 3 for the winner-price, low-volume strategy, where a -0.088% ($t = -0.60$) weekly return at a filter level of less than -10% for the price-only strategy monotonically decreases to -1.918% ($t = -2.14$) with the inclusion of decreasing-volume information. For both losers and winners, the increased return reversals found in portfolios that condition on low growth in volume are more evident at the extreme price filters.

In contrast, conditioning on high growth in volume results in decreased return reversals, and in some cases, positive autocorrelation. In panel B of Table 3, the loser-price, high-volume portfolios, the general pattern shows decreasing return reversals across the price filters for increasing levels of the volume filter. For example, portfolios formed from using no volume filter and price declines of 10% in week $t - 1$, generate weekly profits of 1.601% ($t = 8.32$). At the same price filter, but requiring that securities

Table 3
Weekly portfolio returns to price and volume strategies

A: Loser-price, low-volume

Lagged weekly growth in volume filter (%)		Lagged weekly return filter (%): < 0 and ≥ -2	< -2 and ≥ -4	< -4 and ≥ -6	< -6 and ≥ -8	< -8 and ≥ -10	< -10
No volume filter	Mean (%)	0.315	0.470	0.747	0.913	1.525	1.601
	Std. dev.	2.007	2.296	2.785	3.497	4.346	5.384
	N	1642	1641	1604	1428	994	833
	t-statistic	5.605	7.445	9.899	9.456	10.314	8.316
< 0 and ≥ -15	Mean (%)	0.315	0.432	0.682	0.987	1.378	1.661
	Std. dev.	2.280	3.005	3.733	4.546	5.256	6.202
	N	1624	1498	1128	607	301	181
	t-statistic	5.026	5.055	6.266	5.453	5.247	4.347
< -15 and ≥ -30	Mean (%)	0.230	0.444	0.626	0.853	0.971	1.574
	Std. dev.	2.386	2.891	3.614	4.396	5.919	7.886
	N	1621	1507	1117	643	279	152
	t-statistic	3.483	5.869	5.412	4.929	2.648	2.725
< -30 and ≥ -45	Mean (%)	0.368	0.414	0.627	1.075	1.333	1.815
	Std. dev.	2.507	3.024	3.800	4.660	5.320	7.169
	N	1593	1436	1036	539	249	143
	t-statistic	5.421	5.046	5.270	5.321	4.266	3.518
< -45 and ≥ -60	Mean (%)	0.268	0.411	0.800	0.599	0.906	2.817
	Std. dev.	2.595	3.099	4.185	4.387	5.991	8.346
	N	1534	1315	908	415	171	98
	t-statistic	3.949	4.432	5.753	2.824	1.713	3.612
< -60 and ≥ -75	Mean (%)	0.131	0.360	0.510	0.998	2.082	2.222
	Std. dev.	3.432	3.295	4.001	4.735	5.047	6.790
	N	1309	979	543	235	78	46
	t-statistic	1.226	3.290	2.795	3.440	3.111	1.711
< -75	Mean (%)	0.279	0.362	0.606	1.245	2.747	5.506
	Std. dev.	3.123	3.715	5.190	5.996	6.023	23.256
	N	828	421	216	71	30	19
	t-statistic	2.377	2.055	1.793	1.289	2.400	1.314

must also have weekly growth in volume of greater than 250%, results in weekly returns of 0.723% ($t = 1.94$).

The same pattern of decreased reversals, and even positive autocorrelation, in subsequent weekly portfolio returns appears in panel D of Table 3, the winner-price, high-volume portfolios. I perform a Pearson correlation test to determine the relation between weekly portfolio returns and lagged volume. The correlation between the absolute value of weekly portfolio returns and the lagged volume return filters is negative and significant (-0.294 with a p-value of .0003), suggesting increased profits to a contrarian strategy with the inclusion of lagged volume information.[9]

As with the price-only strategies, I also examine the trade-week relative volume (not reported in the tables) for securities included in portfolios

[9] I also examine returns to strategies that condition on longer-horizon volume measures. I consider two other volume measures that employ an average of the last 4 and 20 weeks of volume to form longer-term

Table 3
(continued)

B: Loser-price, high-volume

Lagged weekly growth in volume filter (%)		Lagged weekly return filter (%): <0 and ≥ -2	<-2 and ≥ -4	<-4 and ≥ -6	<-6 and ≥ -8	<-8 and ≥ -10	<-10
No volume filter	Mean (%)	0.315	0.470	0.747	0.913	1.525	1.601
	Std. dev.	2.007	2.296	2.785	3.497	4.346	5.384
	N	1642	1641	1604	1428	994	833
	t-statistic	5.605	7.445	9.899	9.456	10.314	8.316
≥ 0 and < 50	Mean (%)	0.350	0.491	0.732	0.936	1.707	2.004
	Std. dev.	2.191	2.757	3.362	4.104	4.913	6.406
	N	1638	1611	1394	1008	551	350
	t-statistic	5.688	6.258	7.806	7.066	7.335	6.059
≥ 50 and < 100	Mean (%)	0.455	0.470	0.740	0.735	0.906	1.752
	Std. dev.	2.950	3.062	3.563	4.367	4.928	5.953
	N	1586	1450	1153	767	429	329
	t-statistic	5.670	5.687	6.643	4.435	3.907	5.032
≥ 100 and < 150	Mean (%)	0.271	0.252	0.520	0.851	1.327	2.037
	Std. dev.	2.855	3.181	3.786	4.268	6.561	5.698
	N	1323	1072	764	482	297	243
	t-statistic	3.100	2.422	3.360	4.403	3.904	5.555
≥ 150 and < 200	Mean (%)	0.455	0.454	0.588	0.782	0.903	0.749
	Std. dev.	3.170	3.547	3.980	4.728	4.688	6.697
	N	869	670	482	317	170	168
	t-statistic	4.056	3.253	3.219	3.026	2.685	1.563
≥ 200 and < 250	Mean (%)	0.356	0.527	0.514	0.232	1.275	0.746
	Std. dev.	3.264	3.592	4.047	4.283	4.390	7.642
	N	564	400	272	163	110	130
	t-statistic	2.536	2.898	2.139	0.546	3.092	1.691
≥ 250	Mean (%)	0.333	0.341	0.335	0.350	1.330	0.723
	Std. dev.	3.137	3.576	3.944	4.557	5.244	6.193
	N	847	647	412	279	179	291
	t-statistic	2.927	2.323	1.878	1.212	3.628	1.940

formed from the more extreme volume filters. I want to determine if those securities are experiencing unusual conditions that might affect their profitability. For portfolios formed from the two lowest-growth-in-volume filters (less than -60% to greater than or equal -75%, and less than -75%), the pattern that emerges is one of slightly increasing opening day, week $t-1$, and week t volume relative to their trailing 40-week mean as the filters

shocks to volume expectations:

$$\Delta v_{it,m} = \frac{V_{it} - (1/m)\sum_{j=1}^{m} V_{i,t-j}}{(1/m)\sum_{j=1}^{m} V_{i,t-j}},$$

where $m = 4$ or 20, the number of weeks used to form the volume average for security i in week t. The Pearson correlation coefficients between weekly portfolio returns and the lagged 4- and 20-week volume measures are -0.336 ($p = .0001$) and -0.525 ($p = 0.0001$), respectively, which supports the negative relation documented earlier between reversals and weekly percentage changes in volume. Overall the alternate volume measures support the conclusion that contrarian profits can be increased by conditioning on decreasing changes in individual security volume.

Table 3
(continued)

C: Winner-price, low-volume

Lagged weekly growth in volume filter (%)		Lagged weekly return filter (%) ≥ 0 and < 2	≥ 2 and < 4	≥ 4 and < 6	≥ 6 and < 8	≥ 8 and < 10	≥ 10
No volume filter	Mean (%)	0.313	0.300	0.238	0.032	−0.065	−0.088
	Std. dev.	1.925	2.124	2.438	3.082	3.823	4.209
	N	1642	1641	1618	1533	1325	1198
	t-statistic	5.942	5.428	3.747	0.392	−0.596	−0.597
< 0 and ≥ −15	Mean (%)	0.328	0.287	0.229	−0.078	−0.016	−0.332
	Std. dev.	2.268	2.814	3.401	3.758	4.666	5.215
	N	1612	1544	1256	799	495	327
	t-statistic	5.426	3.860	2.342	−0.553	−0.208	−1.206
< −15 and ≥ −30	Mean (%)	0.276	0.276	0.222	−0.044	−0.215	−0.436
	Std. dev.	2.255	2.731	3.432	3.850	4.676	5.992
	N	1621	1540	1213	782	433	304
	t-statistic	4.478	4.020	2.067	−0.382	−0.971	−1.150
< −30 and ≥ −45	Mean (%)	0.264	0.309	0.039	−0.011	−0.095	−0.623
	Std. dev.	2.712	2.759	3.302	3.939	4.402	4.744
	N	1605	1460	1083	683	303	230
	t-statistic	3.562	4.274	0.312	−0.021	−0.364	−1.974
< −45 and ≥ −60	Mean (%)	0.205	0.178	0.016	0.339	−0.435	−1.369
	Std. dev.	2.535	3.163	3.525	4.969	4.295	5.809
	N	1518	1268	844	462	186	138
	t-statistic	3.069	1.978	0.074	1.511	−1.439	−2.524
< −60 and ≥ −75	Mean (%)	0.319	0.125	0.579	−0.584	−0.446	−1.567
	Std. dev.	2.878	3.141	3.734	4.986	6.462	6.279
	N	1291	870	480	234	103	60
	t-statistic	4.190	1.114	3.458	−1.874	−1.675	−2.431
< −75	Mean (%)	0.281	0.925	0.687	0.075	−0.519	−1.918
	Std. dev.	2.924	3.667	5.158	4.339	5.918	4.957
	N	761	386	151	65	20	21
	t-statistic	2.684	4.995	1.810	−0.185	−0.872	−2.136

are raised for both losers and winners. Most of these portfolios experience opening day and week t average volume close to the average of their trailing 40-week means. As expected, portfolios formed from the most extreme price filters (greater than 10% and less than −10%) and the most extreme low-volume filter (less than −75%) experience the lowest opening day relative volume of 0.719% and 0.898%, for losers and winners, respectively.

Overall the level of relative volume in week t does not appear to be especially low for the majority of portfolios formed by conditioning on low growth in volume in week $t-1$. Thus many of the more profitable positions in the price-volume filters are probably not suffering from unusual market conditions attributable to low levels of volume in the trade week.

The results in this section support the implications of the Wang (1994) model: winners and losers that experience high growth in volume in week $t-1$ tend to experience reduced reversals, and even positive autocorrelation, in week t for winners. In light of Wang's model, this suggests that periods

Table 3
(continued)

D: Winner-price, high-volume

Lagged weekly growth in volume filter (%)		Lagged weekly return filter (%) ≥ 0 and < 2	≥ 2 and < 4	≥ 4 and < 6	≥ 6 and < 8	≥ 8 and < 10	≥ 10
No volume filter	Mean (%)	0.313	0.300	0.238	0.032	−0.065	−0.088
	Std. dev.	1.925	2.124	2.438	3.082	3.823	4.209
	N	1642	1641	1618	1533	1325	1198
	t-statistic	5.942	5.428	3.747	0.392	−0.596	−0.597
≥ 0 and < 50	Mean (%)	0.371	0.313	0.246	−0.005	−0.223	−0.233
	Std. Dev.	2.064	2.533	3.016	3.729	4.078	4.539
	N	1638	1607	1510	1226	867	689
	t-statistic	6.858	4.634	3.059	−0.026	−1.500	−1.359
≥ 50 and < 100	Mean (%)	0.513	0.419	0.401	0.249	0.155	−0.097
	Std. Dev.	2.620	2.651	3.098	3.648	4.481	4.815
	N	1578	1473	1286	1002	710	618
	t-statistic	7.045	5.641	4.481	2.148	0.926	−0.375
≥ 100 and < 150	Mean (%)	0.417	0.619	0.612	0.059	0.677	0.404
	Std. Dev.	3.138	3.152	3.441	3.686	4.481	5.743
	N	1326	1136	892	705	489	490
	t-statistic	4.544	6.087	5.513	0.383	3.687	1.514
≥ 150 and < 200	Mean (%)	0.509	0.722	0.669	0.505	0.502	−0.016
	Std. dev.	3.359	3.654	3.948	3.997	4.265	5.450
	N	861	726	567	431	308	341
	t-statistic	4.158	5.477	4.151	2.691	2.104	0.072
≥ 200 and < 250	Mean (%)	0.531	0.747	0.516	0.576	0.877	0.361
	Std. dev.	3.331	3.551	3.802	4.180	5.707	6.855
	N	564	427	328	247	202	247
	t-statistic	3.847	4.463	2.540	2.447	2.396	0.905
≥ 250	Mean (%)	0.670	0.641	0.947	0.655	0.457	0.146
	Std. dev.	3.127	3.525	4.109	3.771	4.625	5.024
	N	812	598	429	374	275	481
	t-statistic	6.122	4.582	5.211	3.036	1.923	0.743

Panels A, B, C, and D give the corresponding portfolios' means, standard deviations, and t-statistics for a mean $= 0$ null hypothesis for the four joint price and volume strategies for weeks in which equity positions are held. I include securities in a given portfolio if the stock's lagged weekly return and lagged growth in volume are within the filter ranges for both lagged return and lagged volume. I examine four price-volume strategies, "loser-price, low-volume," "loser-price, high-volume," "winner-price, low-volume," and "winner-price, high-volume," in panels A, B, C, and D, respectively. A "no volume filter" corresponds to a price-only strategy and is included for comparison purposes with the volume strategies. The sample is the annually ranked top 300 large-cap NYSE and AMEX stocks for the July 1962–December 1993 period. N is the number of portfolio weeks the strategy traded at the respective price and volume filter levels out of a possible 1,642 weeks. The t-statistics are robust to heteroscedasticity and autocorrelation.

of high growth in volume reflect an environment in which informed traders use private information. In contrast, the evidence of increased reversals for the filter portfolios formed from low growth in volume can be interpreted to represent periods of portfolio rebalancing for both informed and uninformed investors. Thus the price-volume results suggest that in large-capitalization stocks, the Wang model of asymmetric information coupled with informed trading tends to govern the behavior of return reversals more so than does the

Campbell, Grossman, and Wang (1993) model of symmetric information coupled with liquidity trading.

Other articles [LeBaron (1992), Antoniewicz (1992), and Fabozzi et al. (1995)] that have examined the lagged return, lagged volume, and subsequent return relation across various return horizons (other than weekly), lagged-volume measures, and individual securities and indexes have documented results similar to mine.

In contrast, Conrad, Hameed, and Niden (1994) examine weekly return reversals on relatively smaller Nasdaq National Market securities and find opposite results. They agree with Campbell, Grossman, and Wang (1993) that high-transaction securities tend to experience larger negative autocovariances. Thus there could be a systematic difference in the relation between volume and subsequent return autocorrelations across large and small securities. This idea is supported to some degree by Conrad, Hameed, and Niden's finding that the relation between return reversals and volume is weaker for larger stocks within their sample. This finding supports predictions made by Blume, Easley, and O'Hara (1994). Thus in the context of Wang's (1994) model, it may be that in periods of large price movements, high volume for smaller (larger) stocks represents a higher percentage of liquidity (informed) traders, resulting in greater subsequent reversals (continuations).

2.4 Contrasts with previous short-term overreaction weighting methodologies

I want to consider the various pros and cons of the filter-based portfolio weighting methodology versus previous short-term overreaction portfolio formation techniques that are based on relative cross-sectional rankings of lagged returns.

First, to directly compare my results with those of past short-term overreaction articles, I form portfolios by using my data sample and contrarian portfolio weights similar to Lehmann (1990), Lo and MacKinlay (1990b), and Conrad, Hameed, and Niden (1994). I test two weighting schemes. The first incorporates market-adjusted returns to construct portfolio weights. In this case, the weight given to security i during week t for a winner or loser portfolio is:

$$w_{pit} = -\frac{\lfloor R_{it-1} - \bar{R}_{t-1} \rfloor}{\sum_{i=1}^{Np} \left[R_{it-1} - \bar{R}_{t-1} \right]}, \tag{5}$$

where p equals a loser or winner portfolio, R_{it-1} is the lagged weekly return for security i, and $\bar{R}_{t-1}$ is the average weekly return at time $t-1$ for the universe of the top 300 large-cap stocks.

The second method uses non-market-adjusted returns to construct the weights:

$$w_{pit} = -\frac{\lfloor R_{it-1} \rfloor}{\sum_{i=1}^{Np} R_{it-1}}. \tag{6}$$

The portfolios are formed so that the weights of both the winner and loser portfolios sum to one.

The average weekly profits for weighting method 1 using five-day week $t-1$ returns are 0.285% ($t = 17.93$) for losers and -0.223% ($t = -12.59$) for winners. The results using skip-day week $t-1$ returns are 0.302% ($t = 18.88$) for losers and -0.236% ($t = -13.22$) for winners.

The results for the second weighting method, which does not use market-adjusted returns, are 0.705% per week for losers and 0.235% per week for winners for five-day week $t-1$ returns and 0.681% per week for losers and 0.157% per week for winners using skip-day week $t-1$ returns. In this article, for both five-day and skip-day returns, all of the middle to high loser filter portfolios' returns are statistically greater than the returns to the loser portfolios from both alternative-weighting methods. However, the results are mixed for the winners. Most of my extreme winner filter portfolios perform significantly better (i.e., more negative returns) than does the winner portfolio from the second weighting method. In contrast, most of my winner filter portfolios experience statistically significantly worse results (i.e., more positive returns) than weighting method 1's winner portfolio.

Thus, when I use prior articles' weighting methods to form portfolios using my data, the levels of average weekly profits are generally lower than the more extreme filter portfolios' profits, especially for loser portfolios. This suggests that although prior contrarian articles give somewhat greater weight to larger lagged return movements, the variation in weights is not sufficient to compensate for the fact that their methodologies invest in all stocks. Essentially, previous studies' weighting schemes may obscure the search for overreaction by not asking simply (i.e., with equally weighted portfolios) which securities overreact. In contrast, by investing in securities that meet filter constraints on the level of last week's price movement and then forming equally weighted portfolios, I am able to directly analyze which securities overreact and eliminate those securities whose lagged weekly returns may be noise.

The previous articles' weights result in portfolios that are invested every week and contain all securities in the sample. This has some possible advantages, one of which is that past articles' portfolio selection methods are less likely to place extreme weights on securities that experience unusual conditions.[10]

[10] For example, in the first alternate portfolio method, which uses market adjusted returns to form portfolios, the average weight placed on each stock in the loser (winner) portfolio over the entire sample period is

Thus their results are less likely to be influenced by microstructure problems that might overstate profits.

In contrast, the filter strategy varies widely in the number of securities per portfolio per week. For example, panel A of Table 2 reports the number of portfolio weeks (N) that loser strategies traded out of a possible 1,642 weeks. At a price filter of less than 0% to greater than or equal to -2%, the one- and two-week strategies traded very frequently, missing 0 and 13 weeks, with an average of 71.9 and 19 stocks per portfolio per week, respectively (the number of stocks per portfolio per week is not reported in the tables). At the largest magnitude loser filter of less than -10%, the one- and two-week strategies traded 833 and 76 weeks, respectively, with an average of 4.9 and 3.5 stocks per portfolio per week. Thus the more extreme filters could select securities that are experiencing greater microstructure problems. I try to mitigate this problem by using a sample of extremely large, liquid stocks and documenting, via skip-day portfolios and an examination of trade week relative volume, that the profits are probably not being overly affected from spurious profitability attributable to microstructure issues.

A second advantage of previous articles' portfolios being invested every week is that their results may have greater longer-horizon returns, even though in most cases they have lower weekly average profits. For example, the second weighting method, defined in Equation (6), which forms portfolios from investing in all securities in the universe in an amount proportional to the level of lagged raw returns, has an average 52-week loser return of 43.8% (42.3% using skip-day returns) and experiences positive returns in 30 of 31 years (30 of 31 using skip-day returns; not reported in the tables). In contrast, many of the middle- to extreme-value filter portfolios experience as great or greater 52-week returns (Table 2, panel C). Thus even though the cross-sectional weighting methods are invested every week, they do not outperform many of the moderate to extreme filter strategies at longer return horizons.

Third, transaction costs might seriously affect the profitability of other weighting schemes and the filter portfolios. For example, many of the intermediate to more extreme filter portfolios earn weekly profits of between 1% and 2% per week invested. If I assume that the portfolios turn over every week, then the implied transaction costs to equate the filter returns to the unconditional top 300 large-cap stocks' weekly mean return of 0.221% is between approximately 0.8% and 1.8% round-trip.[11] In contrast, the im-

0.64% with a standard deviation of 0.54% (0.69% with a standard deviation of 0.66%). However, the portfolios do experience periods in which there are relatively large weights placed on both winners and losers. For example, the loser (winner) portfolio weights have a 95th percentile of 1.65% and a maximum weight of 10.7% (95th percentile of 1.91% and a maximum weight of 18.39%).

[11] The extreme filter portfolios may experience relatively smaller transaction costs than the more moderate filter portfolios. Lehmann (1990) hypothesizes that a security that is a big winner (loser) may have a

plied transaction costs to equate the previous articles' returns, as obtained from applying their portfolio weights to my sample, to the unconditional top 300 large-cap stocks' weekly mean return is between approximately 0.1% and 0.5% round-trip. Thus, to the extent that the marginal investor can limit transaction costs to under 0.5% round-trip, then both the cross-sectional and filter strategies will be profitable.[12] Obviously, as the investor faces greater transaction costs, the cross-sectional method appears to become unprofitable at smaller transaction levels than does the filter method.

Finally, another potential advantage of previous articles is the relative simplicity of their portfolio formation rules. They typically form just one loser and one winner portfolio, using all securities in their sample. In contrast, my use of multiple independent cells to form portfolios means that I test a large number of strategies. Thus previous articles are less likely to fall prey to data mining concerns.

Obviously, data snooping [Lo and MacKinlay (1990a)] should always be a serious concern in any empirical study of predictability.[13] One method to directly address data snooping is to employ a recursive forecasting methodology such as that of Fama and Schwert (1977), Breen, Glosten, and Jagannathan (1989), Pesaran and Timmerman (1995), Bossaerts and Hillion (1998), and others. For example, Bossaerts and Hillion illustrate the pitfalls of relying on in-sample evidence of predictability. They document large degrees of in-sample predictability on international stock returns, but find that the evidence of predictability vanishes out of sample. Not finding out-of-sample forecasting ability is all the more striking because they use an in-sample model selection methodology designed to select models that will generalize to the out-of-sample periods. Bossaerts and Hillion suggest

majority of buy (sell) orders being executed at the ask (bid). Thus a contrarian trader who wants to sell short (go long) the winners (losers) might actually be able to open a position closer to the ask (bid) than would normally be possible. This effect could be stronger for bigger winners and losers, resulting in smaller than normal effective bid-ask spreads at more extreme filter levels.

[12] Although transaction costs have undoubtedly varied across the sample, Jones and Lipson (1995), using the 1990–1991 period, report conditional effective spreads of approximately 0.69% for securities that experience intraday continuations and reversals on the largest quintile of NYSE/AMEX. Keim and Madhavan (1997) report round-trip total execution costs ranging from 45% to 63% (price impact, bid-ask spreads, and commission costs), depending on the size of the trade, calculated from actual trades placed by 21 institutional investors on the largest quintile of NYSE securities over the 1991–1993 period. To the extent that floor traders can obtain lower total execution costs, then they may be the more likely marginal investor.

[13] One method to control for a false rejection of the null hypothesis of no predictability is to perform a Bonferroni adjustment on the t-statistics. If I consider each filter level for winners and losers, whether the filter is first order or second order, the use of five-day and four-day portfolio formation returns, the number of experiments performed in the volume section, the out-of-sample section, and prior drafts of the article, then I examine approximately 600 strategies. Using the Bonferroni inequality, which provides a bound for the probability of observing a t-statistic of a certain magnitude with N tests that are not necessarily independent, I find that there is a less than 1.56×10^{-24} probability of obtaining a t-statistic of 11.03 for the skip-day loser-price strategy at between the -4 and -6% filter. In addition, many of the t-statistics that I report greatly exceed the magnitude of the Bonferroni t-statistic critical value of 3.96. Thus the Bonferroni adjustments suggest that the results do not appear to be attributable to a type I error (false rejection of the null hypothesis).

the lack of out-of-sample forecasting ability could be attributed to model nonstationarity in excess stock returns. Their work, and the work of others, suggests that it is critically important to validate evidence of predictability via an out-of-sample methodology.

3. A Real-Time Simulation of the Filter Strategies

All of the filter rules in the previous sections are ex ante trading rules. However, the knowledge of the "best" strategies is obtained ex post. Therefore there is as yet no solid evidence on the trading strategies that an investor, operating without the benefit of hindsight, would have actually chosen at various times across the sample period.

To address this issue, I perform an out-of-sample forecasting experiment that simulates an investor's portfolio decisions in "real time." Real-time forecasts arise because of the algorithm's method of endogenously determining within the in-sample period the critical security selection parameters (such as filter grid widths, predictor variable selection, and selection of each predictor's optimal filter rules). The important point is that my simulation uses information before time t (prior to the out-of-sample period) to determine the security selection parameters used in the out-of-sample period (after time t). Thus the algorithm minimizes the possibility that the out-of-sample results might depend in part on look-ahead biases in the trading rule parameter selection. I test the optimal rules out of sample and judge their performance in comparison to a buy-and-hold strategy and other measures.

I use the 1978–1993 period for the simulation. Consistent with the sample used in Section 2, I use the top 300 large-cap NYSE and AMEX securities. I use skip-day lagged weekly returns as a precaution against bid-ask bounce problems. I follow the steps, similar to those of Allen and Karjalainen (1996) and Pesaran and Timmerman (1995), to obtain out-of-sample forecasts:

1. The investor's first decision period is December 31, 1977. On that date, the top 300 large-cap stocks are ranked and a 15-year in-sample period, from January 1, 1963 to December 31, 1977, is defined. I use the in-sample period to calculate weekly returns to portfolios formed from all combinations of the three predictors of skip-day weekly returns (lagged one week), weekly returns (lagged two weeks), and weekly growth in volume (lagged one week). The algorithm determines 10 filter cutoff points for each security, for each predictor, by calculating deciles of each stock's three predictors' historical distributions from the in-sample period. Thus there is no look-ahead bias from filter cutoff levels during the out-of-sample periods. In addition, similar to methods in Pesaran and Timmerman (1995), I minimize look-ahead bias in predictor variable selection by examining in-sample all n-way combinations of the three predictors. I examine all one-way, two-way, and three-way combinations of the three predictors in sample for a

total of 1,330 trading rules.[14] Thus the algorithm is indifferent to the choice of predictors once I select the n predictors (for this simulation, $n = 3$). The algorithm chooses the predictors that perform best according to an in-sample goodness-of-fit criteria (defined in the next step). Thus it may be the case that certain variables or combinations of variables that predict weekly returns over the entire out-of-sample period (which we know as a benefit of hindsight from the results in Section 2) are not chosen as optimal in-sample rules.

2. I select the optimal rules from an in-sample rule validation method. I design the validation procedures to screen out rules that could result from overfitting or noise, and to select rules that are more likely to generalize (based on in-sample persistence) to the out-of-sample period. The rule validation criterion selects long (short) rules by choosing the top (bottom) 10% of the rules (based on the average weekly return of each rule) from the first 7.5-year subperiod of the in-sample period and then retains only those rules with average weekly returns in the top (bottom) 10% of all rules in the second 7.5-year subperiod. Thus I select two sets of optimal rules: one to form long portfolios and one to form short portfolios in the out-of-sample period.

3. I use the optimal in-sample rules to form “active” long, short, and combined portfolios in the out-of-sample period, from January 1978 to December 1978. I form a combined portfolio by subtracting the return of the short portfolio from the long portfolio. I form combined portfolios during weeks in which there is at least a long or short portfolio available. I maintain a long (short) position in a security in the out-of-sample period when a buy (sell) signal is generated from the optimal long (short) rules. If no securities meet the criteria to form a long, short, or combined portfolio, then the respective portfolio invests in a risk-free asset.

4. The investor’s decision period rolls forward to December 31 of the next year (1978 for the second time through the steps) and steps 1–3 are repeated. I repeat step 4 fourteen more times, resulting in a total of 16 nonoverlapping out-of-sample forecasts spanning January 1, 1978, through December 31, 1993.

To show in more detail how the optimal in-sample filter rules chose stocks in the out-of-sample period, Table 4 illustrates the composition of subsets (the top 15 rules as ranked on in-sample weekly mean return) of optimal long (panel A) and short (panel B) rules for a typical in-sample

[14] For the three sets of one-variable rules, that is, rules based on each of (A) skip-day weekly returns (lagged one week), (B) weekly returns (lagged two weeks), or (C) percentage change in volume (lagged one week), there are 10 filter rules for each predictor, for a total of 30 rules. For the two-way rules (i.e., rules formed from all two-way combinations of the three predictors) there are 100 (10 times 10) rules for each two-way combination and three two-way combinations (A with B, A with C, and C with B), for a total of 300 rules. Finally, the three-way rules (A with B with C) form 1,000 (10 times 10 times 10) rules. In total, I examine 1,330 rules in each in-sample period.

Table 4
An example of optimal in-sample rules

A: Long rules

Rule	N	In-sample mean return in Week t	Decile filter values for the lagged predictors: Week $t-1$ skip-day return	Week $t-2$ weekly return	Week $t-1$ growth in volume
1	132	1.698	1	9	1
2	151	1.520	1	10	5
3	93	1.339	1	6	2
4	100	1.336	1	5	3
5	133	1.297	1	1	6
6	148	1.272	1	1	9
7	144	1.250	5	2	9
8	428	1.248	1	NA	1
9	164	1.244	1	7	9
10	138	1.219	7	1	8
11	137	1.210	8	3	10
12	100	1.202	1	7	1
13	92	1.201	1	1	3
14	110	1.191	1	8	1
15	174	1.172	1	4	8
Average	149.600	1.293			

B: Short rules

Rule	N	In-sample mean return in Week t	Week $t-1$ skip-day return	Week $t-2$ weekly return	Week $t-1$ growth in volume
1	92	−1.050	10	3	2
2	157	−0.838	10	10	8
3	156	−0.819	10	9	6
4	87	−0.796	2	10	9
5	135	−0.777	10	6	6
6	200	−0.744	10	10	9
7	448	−0.662	10	10	NA
8	121	−0.655	10	2	3
9	227	−0.634	3	9	2
10	174	−0.617	2	8	1
11	90	−0.617	10	8	3
12	185	−0.567	4	8	7
13	197	−0.544	3	5	4
14	110	−0.529	10	9	3
15	154	−0.527	10	10	6
Average	168.867	−0.692			

Panel A (B) contains an example of the optimal in-sample long (short) rule sets, sorted on the basis of average in-sample weekly return, obtained from the in-sample rule validation procedure. I use these rules to select securities in the out-of-sample period. Each row shows individual rules. I select securities from each row by using an AND operator across the three predictor variables. The rules from each row in panel A (B) are then combined, using an OR operator to create long (short) portfolios. For example, rule 1 in panel A invests in securities that have week $t-1$ skip-day returns within the first decile (where $1 =$ smallest and $10 =$ largest) and week $t-2$ weekly returns within the ninth decile and week $t-1$ growth in volume within the first decile. Equally weighted out-of-sample long portfolios are then formed from securities that meet rule 1's requirements or rule 2's conditions, and so on. NA in columns 4–6 implies that the predictor was not used in that row's rule. N is the number of portfolio weeks each rule traded out of a possible 780 weeks in the in-sample periods.

15-year period. These rules are representative of the other years' optimal rules. Individual rules appear in each row.

The rules select stocks by using Boolean logical functions of "AND" and "OR." Securities are selected from each row's rules using an AND operator across the three predictor variables. The rules from each row are then combined using an OR operator to create long and short portfolios. For example, rule 1 in panel A signals an investment in securities that have week $t-1$ skip-day weekly returns within the first decile (where $1 =$ smallest and $10 =$ largest) and week $t-2$ weekly returns within the ninth decile and week $t-1$ growth in volume within the first decile. Thus I form equally weighted out-of-sample long portfolios by including securities that meet rule 1 or rule 2, and so on.

Table 5 reports the profitability of the out-of-sample forecasts. The active long strategy earns an average of 0.722% per week over the 1978–1993 period, while the benchmark portfolio (a "buy-and-hold" portfolio formed from buying the top 300 large-cap securities each year) earns an average weekly return of 0.317%. The difference in means is statistically significant ($\chi^2 = 17.59$, $p < .01$). Similarly, the active short portfolio earns average weekly returns of -0.245%. The difference in means from the benchmark portfolio is also statistically significant ($\chi^2 = 30.52$, $p < .01$).

The long, short, and combined portfolios also perform well over longer horizons relative to the benchmark. For example, column 5 of Table 5 shows that the long portfolio earns an average 52-week return of 44.95% and experiences positive returns in 100% of the sixteen 52-week out-of-sample periods. In contrast, the benchmark portfolio earns an average 52-week return of 17.91% and has positive returns in 81% of the sixteen 52-week out-of-sample periods.

Columns 7, 8, and 9 of Table 5 present the terminal wealths of the various portfolios and the effects of transaction costs. With low transaction costs (0.25% round-trip), the terminal wealths (defined as the final value in 1993 of investing $1 in 1978) of the long, short, combined, and benchmark portfolios are $61.31, $1.68, $72.58, and $11.59, respectively. At a higher transaction cost level (0.5% round-trip), the terminal wealths of the long, short, combined, and benchmark portfolios drop to $15.19, $0.46, $5.03, and $11.48, respectively. Clearly the profitability of the active strategies is very dependent on transaction costs. To the extent that a trader could have implemented the active strategies for less than 0.25% in round-trip transaction costs, then the filter rule portfolios would have been extremely profitable. In contrast, if the trader had faced higher costs, say greater than 0.5% round-trip, then probably none of the active strategies would have outperformed the benchmark portfolio.

Columns 10, 11, and 12 present the results of various risk and performance measures. Jensen's alphas for the winner, loser, and combined portfolios are 0.443 ($t = 4.29$), -0.495 ($t = -5.46$), and 0.673 ($t = 4.78$), respectively, suggesting significant excess returns attributable to all three portfolios. In addition, the long, short, and combined portfolios all have market betas of less than one, which suggests that they are less risky than the benchmark portfolio, at least with respect to their exposure to the value-

Table 5
Out-of-sample forecasts

	Weekly results					Terminal Wealth Under Various Transaction Costs			Various Risk Measures		
1	2	3	4	5	6	7	8	9	10	11	12
Portfolio	Average weekly mean return (%) over all weeks (t-statistic)	Standard dev. (%)	Average weekly mean return (%) for weeks invested (t-statistic)	Average 52-week returns (%) (percent positive)	χ_1^2-statistic for a comparison of means: active vs. passive	Terminal wealth ($) with zero transaction costs	Terminal wealth ($) with low transaction costs	Terminal wealth ($) with high transaction costs	Market model beta (t-statistic)	Weekly Jensen's alpha (t-statistic)	Weekly Sharpe ratio
Active long	0.722 (6.08)	3.487	0.917 (5.63) $N = 616$	44.95 (100%)	17.59*	247.65	61.31	15.19	0.935 (19.04)	0.443 (4.29)	0.147
Active short	-0.248 (-2.57)	2.771	-0.290 (-1.96) $N = 541$	-12.60 (12.5%)	30.52*	5.768	1.681	0.465	0.576 (13.45)	-0.495 (-5.46)	-0.156
Active combined	0.914 (6.84)	3.965	0.964 (6.60) $N = 783$	62.68 (93.75%)	18.31*	1042.85	72.58	5.03	0.367 (5.863)	0.673 (4.78)	0.174
Passive benchmark	0.317 (4.17)	2.145	N.A.	17.91 (81.25%)	N.A.	11.732	11.59	11.48	1.027 (214.07)	0.019 (1.85)	0.051

*,**,*** The null hypothesis of equality of average weekly portfolio returns between the active and passive portfolio is rejected at the 1%, 5%, and 10% levels, respectively. A comparison of active trading strategies derived from out-of-sample forecasts of the annually ranked top 300 large-cap NYSE and AMEX securities' weekly returns to the mean return of a passive, equally weighted buy-and-hold strategy. The active portfolio is based on weekly return forecasts derived from three lagged predictors and is estimated recursively over the period of January 1978–December 1993 using data starting in 1963. The three individual security predictors are weekly "skip-day" returns (lagged 1 week), weekly returns (lagged 2 weeks), and weekly percentage changes in volume (lagged 1 week. The passive benchmark strategy is to buy and hold the securities each year that are included in the annually ranked top 300 large-cap stocks. The terminal wealth represents the final value in 1993 of investing $1 at the beginning of 1978. N in column 4 is the number of weeks that the active strategies traded out of a total 837 weeks in the out-of-sample period. Low (high) transaction costs are 0.25% (0.50%) round-trip. In column 6 I use a χ_1^2-statistic to test the null hypothesis of equality of average weekly returns between the passive strategy and the out-of-sample strategy. The t-statistics (in parenthesis) and χ_1^2-statistics are robust to heteroscedasticity and autocorrelation.

weighted market index. All three portfolios have absolute weekly Sharpe ratios of approximately 0.15, whereas the Sharpe ratio from a buy-and-hold strategy of the top 300 large-cap stocks is 0.051. To the extent that a market model and mean-variance criteria correctly adjust for risk, the performance measures suggest there is genuine out-of-sample predictability from the filter rules.

To better understand the out-of-sample forecasts, I examine which types of rules emerge as the optimal in-sample rules. In general, the rules that survive the in-sample validation (Table 4) tend to be three-way rules. For example, for the long (short) rules, only rule 8 (7) is a two-way rule. Thus it appears that the three-way rules tend to produce higher mean returns and tend to be more stable within subperiods of the in-sample periods relative to one-way or two-way rules.

The individual rules appear to profit from both negative and positive autocorrelation in lagged returns. For example, most of the rules in panels A and B of Table 4 profit from negative correlations that result from conditioning on lower deciles of lagged weekly returns and lower deciles of growth in volume. However, long rules 7, 10, and 11 appear to profit from positive autocorrelation by conditioning on higher-decile lagged returns and higher-decile growth in volume.

Therefore the optimal rules that emerge from the artificial intelligence algorithm are similar to the in-sample price-volume results presented in Table 3. Conditioning on low growth in volume tends to result in subsequent negative autocorrelations of returns, but conditioning on high growth in volume results in positive autocorrelation. Thus this section's results provide out-of-sample support for Wang (1994).

Although the optimal in-sample rules appear to be sufficiently stationary to generate significant out-of-sample profits, there is a nontrivial decrease in profits between the rules' in-sample and out-of-sample returns. For example, the average return across all long (short) in-sample optimal rules (not reported in the tables), as weighted by the number of weeks invested, is 1.235% (−0.520%). In contrast, the out-of-sample long and short portfolios earn 0.917% and −0.290%, respectively, for weeks in which they were invested (Table 5, column 4). Thus the out-of-sample profits are approximately 25 to 45% less than the returns of the in-sample rules used to generate them. The degradation in performance between the in-sample and out-of-sample periods might imply that the significance of some of the in-sample optimal rules are partly based on spurious relations, or that some of the optimal in-sample rules are not sufficiently stationary over the out-of-sample periods. Nevertheless, the decrease in profits highlights the importance of running real-time simulations to validate return anomalies. Thus the out-of-sample forecasting algorithm endogenizes, as much as is practically possible, the choice of predictors and rules used to forecast returns in step-ahead periods, and rolls through many in-sample/out-of-sample forecasting periods to avoid the possibility of data mining a single holdout period.[15] Overall the out-of-sample findings support the in-sample conclusions that the use of filter-based trading rules on lagged returns and volume result in profitable trading strategies for large-capitalization securities.

4. Conclusion

This article examines the overreaction hypothesis for large-capitalization securities. I use a portfolio weighting methodology designed to mirror the psychology of investor overreaction. This is accomplished through the use of filters that only invest in securities that have experienced movements in lagged returns and growth in volume of at least as large a magnitude as the filter value. I examine large-capitalization securities to minimize biases due to bid-ask spreads and other microstructure problems.

In support of overreaction, I document large and consistent profits for portfolios formed from the filter rules. I attribute the success of the filter rules to their ability to increase the signal-to-noise ratio of the security selection process by screening on lagged return magnitudes instead of using cross-sectional lagged return rankings.

Incorporating volume improves the predictability of returns, in a manner which supports Wang (1994). High-growth-in-volume stocks tend to exhibit weaker reversals and even positive autocorrelation, and low-growth-in-volume securities experience greater reversals. In addition, a security is more likely to have greater reversals if it has incurred two, rather than just one, consecutive weeks of losses or gains.

Last, to more directly assess the investor's rather than the ex post econometrician's problem, I develop a real-time simulation of the filter rules. This real-time forecasting methodology includes an artificial intelligence component that performs an investor's portfolio allocation decision via in-sample selection of optimal rules. I use these rules to form portfolios in step-ahead out-of-sample periods. The optimal rules selected by the algorithm are based on negative and positive autocorrelations of individual security returns.

The forecasts provide out-of-sample support for Wang (1994) and suggest that when volume information is incorporated into a contrarian portfolio strategy, the relation between lagged returns and subsequent weekly returns is more complex than would be implied by a simple linear negative autocorrelation relation.

The results of the real-time simulation show that an investor with relatively low transaction costs would strongly outperform an investor who

[15] For example, Markowitz and Xu (1994), in a study of data-mining corrections, reject the use of a single holdout period because they claim that it is likely that an investigator will examine many methods in the base period until one is found that predicts effectively in the holdout period. By using many recursive periods, as in this article, that type of forward fitting can be avoided.

follows a buy-and-hold strategy. The success of the out-of-sample forecasts suggests there is genuine predictability attributable to filters on lagged return and volume information.

My results provide strong evidence of predictability emanating from short-horizon, filter-based strategies. Short-horizon predictability can be attributed to a microstructure, to an expected return phenomena, to an abnormal return phenomena, or to some combination of all three. In my sample, I minimize false evidence of predictability due to microstructure-based spurious profitability by using large-capitalization stocks and skip-day returns. The models of time-varying expected returns considered could not explain the documented predictability. This suggests that the results can be attributed to market inefficiency. Nonetheless, it is possible that future asset-pricing models that allow for short-horizon variations in risk premia may explain the results. However, because of the filter portfolios' large and consistent profits, it is difficult to interpret them as having emanated from time-varying risk premia. Moreover, it appears that the exercise of examining return reversals with filters on lagged returns and volume provides a new approach to examining and understanding short-horizon predictability.

For future research, it might be useful to explain the differences in the volume-subsequent return relation across large- and small-capitalization stocks. Although I find that low-volume, large-capitalization stocks experience greater reversals and high-volume stocks tend to exhibit weaker reversals, Conrad, Hameed, and Niden (1994) find that low-volume, small-capitalization stocks show positive autocorrelation and high-volume securities experience greater reversals. Thus, in the context of Wang's (1994) model, which posits a link among return reversals, lagged volume, and the trading activity of informed versus uninformed traders, future return-autocorrelation work that incorporates methods of estimating the probability of informed trade, using techniques such as Easley et al. (1996), might explain the different reversal effects across large- and small-cap stocks.

Another extension would be to apply return and volume filters to the intermediate [Jegadeesh and Titman (1993)] and long-term [DeBondt and Thaler (1985)] return horizon literature. This literature has typically used portfolio formation techniques that are based on relative cross-sectional rankings of lagged returns. Conrad and Kaul (1998) find that the primary determinant of the profitability of these trading strategies is the cross-sectional dispersion in the mean returns of individual securities, not individual security positive or negative autocorrelation. Thus Conrad and Kaul's results suggest that irrational time-series patterns in returns do not explain profitability in momentum and long-term overreaction strategies. However, similar to my results in this article at the weekly horizon, the use of filters on returns and volume might provide a higher signal-to-noise ratio in the longer-horizon strategies, as compared to using relative cross-sectional return portfolio methods. Therefore the filters might contribute to further discoveries on the sources of profitability in such strategies.

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