Price Momentum and Trading Volume

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Comments Welcome

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Abstract

Past trading volume predicts both the magnitude and persistence of future price momentum. In the intermediate-term, a strategy of buying past high-volume winners and selling past high-volume losers outperforms a similar strategy based on price momentum alone by 2% to 7% per year. In the long-term, a strategy of buying low-volume winners and selling high-volume losers exhibits return continuation up to three years, while a strategy of buying high-volume winners and selling low-volume losers exhibits return reversals in years two and three. Differences in firm size and stock price or the Fama-French (1993) three-factor model cannot explain these results. Several possible explanations are discussed, but the evidence is most consistent with past trading volume providing information about the level of investor interest in a stock and, indirectly, about the imminence of price reversals. In particular, high-volume stocks behave like *glamour* stocks while low-volume stocks behave like *neglected* stocks.

I. Introduction

This paper examines the interaction between price momentum and past trading volume. Financial academics and practitioners have long recognized that past trading volume may provide valuable information about a security. However, there is little agreement on how past volume information should be handled and interpreted. Even less is known about how past trading volume interacts with past price movement in the prediction of cross-sectional stock returns. In this study, we present new evidence on how price movements and trading volume jointly predict cross-sectional returns over intermediate to longer time horizons. We also evaluate alternative explanations for these documented empirical facts.

Our investigation is closely aligned with the price momentum literature [see Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), and Rouwenhorst (1998)]. Prior research in this area shows that portfolios of stocks formed on the basis of returns over the past 3 to 12 months exhibit a pattern of return continuation over the next 3 to 12 months, i.e., past winners continue to outperform past losers, even after controlling for known determinants of cross-sectional risk. These studies do not, however, examine the role of past trading volume.

We contribute to this literature by demonstrating that past trading volume predicts both the magnitude and persistence of future price momentum.[1] In the intermediate-term (up to one year), the return differential between past winners and past losers is wider for high-volume firms, due mainly to the tendency of low-volume losers to rebound. Specifically, a strategy of buying high-volume winners and selling high-volume losers outperforms the traditional price momentum strategy of buying winners and selling losers by 2% to 7% per year. In the long-term, a strategy of buying low-volume winners and selling high-volume losers continues to earn positive returns beyond the first year while a strategy of buying high-volume winners and selling low-volume losers earns negative returns after the first year. Firm size, stock price, or the Fama-French (1993) three-factor model cannot explain these results.

[1] We use average daily turnover as a measure of trading volume. Turnover is defined as the ratio of the number of shares traded to the number of shares outstanding. Any unqualified reference to trading volume henceforth refers to this definition.

Our study is also related to two other studies that investigate the relation between trading volume and subsequent returns. Conrad, Hameed, and Niden (1994) use weekly data to show that past trading volume is useful in explaining the short-term return reversal pattern documented by Lehmann (1990) and Jegadeesh (1990). Specifically, they report that short-term return reversal is driven mainly by high-volume securities. High-volume stocks experience short-run return reversals in the following week, while low-volume firms experience return continuations.

Our study is distinct from the Conrad et al. in both motivation and content. Conrad et al. are interested in short-term price movements associated with market microstructure issues discussed in Campbell, Grossman, and Wang (1993). Therefore, they examine future weekly returns conditional on past price and volume changes. In contrast, our interest lies in the prediction of cross-sectional returns over longer (3 month or more) time horizons. In the intermediate time horizon, the primary empirical puzzle is not return reversal, but return continuation. Given the longer time horizon, these price continuations are unlikely to be due to the liquidity effects discussed in Campbell, Grossman, and Wang (1993).

In another related study, Datar, Naik, and Radcliffe (1998) show that low-volume stocks generally earn higher returns than high-volume stocks.[2] They interpret this result as providing support for the liquidity risk hypothesis. According to the liquidity hypothesis, firms with relatively low trading volume are less liquid, and therefore command a higher expected return. We build on the finding of Datar et al (1998) by examining the interaction between past price momentum and trading volume in predicting cross-sectional returns. We find evidence consistent with their results, but also present additional evidence, which is difficult to reconcile with the liquidity hypothesis. Our results show that the intermediate-horizon return continuation first documented by Jegadeesh and Titman (1993) is a joint function of past prices and past trading volume. Specifically, we find that the spread in subsequent returns between past winners and past losers (the "momentum premium") is much larger for the high-volume portfolio. Between 1965 and 1995, a strategy of buying high-volume winners and selling high-volume losers outperforms a similar momentum strategy based on price alone by 1.8% to 7.2% per year, across various holding periods.

[2] Datar, Naik, and Radcliffe (1998) also use turnover as a measure of trading volume.

The fact that a portfolio of high-volume (and presumably more liquid) stocks can earn a higher average return than a portfolio of low-volume stocks presents a challenge to the liquidity explanation for the momentum puzzle. On further investigation, we find that the larger momentum premium on high-volume portfolios is driven primarily by the exclusion of low-volume losers; low-volume losers exhibit a strong tendency to rebound, while high-volume losers continue to lose in the next 12 months. The high-volume price momentum strategy outperforms a momentum strategy based on price alone primarily because the former avoids selling low-volume losers.

What can account for these results? The standard explanation that volume is a proxy for liquidity fails to explain why a zero-investment portfolio of high-volume stocks outperforms a similar portfolio of low-volume stocks. We find no significant difference in firm size or stock price across the volume-based price momentum portfolios, so the effect is not likely due to firm size or differences in stock price. The conventional wisdom on Wall Street that "volume is the fuel for stock prices" also does not explain our results.[3] According to this hypothesis, higher volume serves to "sustain" past price movements. Therefore, high-volume winners should keep winning and high-volume losers should keep losing. While this prediction holds true for losers, we find the opposite effect among past winners.

We suggest an alternative explanation, which we dub the *Expectation Life Cycle Hypothesis*.[4] According to this hypothesis, trading volume (turnover) serves as a useful indicator of the level of investor interest in a stock. When a stock falls into disfavor or neglect, the number of sellers tends to exceed the number of buyers. Generally, this leads to falling share prices and dwindling trading activity. Conversely, when a stock is popular or glamorous, the number of buyers exceed the number of sellers, so prices tend to rise and trading activity increases. As a result, a firm's turnover ratio is a proxy for investor interest -- relatively low turnover is an indication of a firm near the bottom of its expectation cycle, while relatively high turnover is an indication of a firm close to the top of this cycle.

This explanation is consistent with the empirical facts. First, it explains why low-volume firms generally outperform high-volume firms. Specifically, low-volume firms are more

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[3] For an example of this view see Freeman (1993), as quoted in Stickel and Verrecchia (1994).

[4] As we explain in more detail later, this explanation closely parallels the "Earnings Expectation Life Cycle" proposed by Bernstein (1993, 1995).

likely to be firms that have fallen out of investor favor and therefore have greater upside potential on average, regardless of their past price performance. Our results suggest that in the 12-month horizon, the *expectation life cycle effect* is more pronounced among past losers. For these firms, low-volume is a signal that the stock has "bottomed out," and that a price reversal is imminent. High-volume losers, on the other hand, still have plenty of negative price momentum.

The same story applies to winners. Low-volume winners have a greater upside potential than high-volume winners because stocks that earn positive returns on high-volume tend to be nearer to the top of their expectation life cycle. However, unlike low-volume losers, low-volume winners do not realize their relatively higher returns primarily in the next 12-months. Instead, we show that these gains are realized gradually over the next three years, so that low-volume winners outperform high-volume winners even two or three years after portfolio formation. This is why a dollar-neutral portfolio of buying low-volume winners and selling high-volume losers earns positive returns up to three years, while a similar strategy of buying high-volume winners and selling low-volume losers earns negative returns in years 2 and 3.

Our results also suggest an interesting link between the momentum strategies of Jegadeesh and Titman (1993) and the contrarian strategies of De Bondt and Thaler (1985). The reality of momentum investing is that winners cannot continue to be winners and losers cannot continue to be losers forever. The results of De Bondt and Thaler (1985) suggest that, ultimately, some past winners have to start under-performing past losers. Chan, Jegadeesh, and Lakonishok (1996), however, find that price momentum winners do not underperform losers even in the third year after the portfolio formation date.

We show trading volume information can offer some resolution to this apparent contradiction. Specifically, trading volume allows us to determine whether a winner or a loser stock is early in the expectation cycle or late in the expectation cycle. In the long run, early-stage winners outperform early-stage losers, and late-stage winners underperform late-stage losers. By combining early-stage stocks with later-stage stocks, simple price momentum strategies obscure the price reversal would have been observed had we focused solely on late-stage winners and losers. Thus, past trading volume, in conjunction with past price movements, helps us to better understand the link between the momentum results of Jegadeesh and Titman (1993) and De Bondt and Thaler (1985).

We provide a test of this hypothesis by examining the time-series relation between *ex post* monthly returns on various volume-based price momentum portfolios and the Fama and French (1993) "risk" factors: excess return on the market, a small firm factor (SMB), and a book-to-market factor (HML). Consistent with the investor interest hypothesis, the returns on high-volume and low-volume portfolios have significantly different loadings on the book-to-market (HML) factor. Specifically, we find that low-volume portfolios behave like *value stocks* in that they have high positive loadings on the HML factor. Conversely, high-volume portfolios behave like *growth stocks* in that they have much lower, and sometimes negative, HML loadings. The same regression also shows that the price momentum-volume portfolios earn high abnormal returns (in excess of 14% per year) even after controlling for the three Fama and French (1993) factors.

To further distinguish the *expectation life cycle* effects from the *liquidity risk* effects, we investigate the pattern of changes in the operational performance of stocks in various price-and-volume portfolios. Specifically, we examine changes in accounting rates of return -- that is, returns-on-book-equity, or ROE -- for firms in the extreme volume portfolios. We find that low-volume losers exhibit significant ROE increases over the next three years, while high-volume losers exhibit significant ROE decreases. The pattern is similar among winners: future changes in ROEs are much more positive for low-volume winners than for high-volume winners.

This evidence shows that, conditional on past price momentum, past volume is a leading indicator of superior future operating performance. Consistent with the expectation life cycle explanation, low-volume firms tend to outperform high-volume firms, after controlling for past price momentum. The link between changes in accounting ROE and the level of liquidity risk is far more dubious. Hence these results cast further doubt on the liquidity risk explanation.

The remainder of the paper is organized as follows. In the next section, we discuss in greater detail the relation of our work to other related research. In section III we describe our sample and methodology. In Section IV we present our empirical results, and in Section V we conclude with a summary and discussion of the implications of our findings.

II. Related Research

In recent years, a number of researchers have presented evidence that cross-sectional stock returns are predictable based on past returns. For example, DeBondt and Thaler (1985, 1987) document long-term price reversals, such that long-term past losers outperform long-term past winners over the subsequent three to five years. Similarly, Lehmann (1990) and Jegadeesh (1990) report price reversal at weekly intervals, whereby firms with higher returns one week continue to outperform firms with firms with low past returns over the next week.

But perhaps the most puzzling phenomenon occurs in the intermediate time horizon, where Jegadeesh and Titman (1993) report a strong pattern of return continuation. Forming portfolios over three to twelve month periods, they show that past winners on average continue to outperform past losers over the next three to twelve months. While many competing explanations have been suggested for the price reversal patterns, [5] far fewer explanations have been advanced to explain the intermediate horizon "price momentum" effect.

For example, Fama and French (1996) show that long-term price reversals can be consistent with a multifactor model of returns, but their model fails to explain intermediate horizon price momentum. Chan, Jegadeesh and Lakonishok (1996) show that intermediate-horizon return continuation can be partially explained by underreaction to earnings news, but price momentum is not subsumed by earnings momentum. More recently, Rouwenhorst (1998) finds a similar pattern of intermediate horizon price momentum in twelve other countries, suggesting that the effect is not likely due to a data snooping bias. None of these studies examine the interaction between past trading volume and past price movements in the forecasting of cross-sectional returns.

At least two analytical papers suggest that past trading volume may provide valuable information about a security. Campbell, Grossman, and Wang (1993) present a model in which trading volume proxies for the aggregate demand of liquidity traders. However,

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[5] For example DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok, and Ritter (1992) attribute long-term price reversals to investor overreaction. In contrast, Ball, Kothari, and Shanken (1995), Conrad and Kaul (1993) and Ball and Kothari (1989) point to market microstructure biases or time-varying returns as the most likely causes. Similarly, short-horizon price reversals have been attributed to return cross-correlations [Lo and MacKinlay (1990)] and transaction costs [Lehmann (1990), Conrad, Gultekin, and Kaul (1991)].

their model focuses on short-run liquidity imbalances (or volume shocks) of a daily or weekly duration, and makes no predictions about the relation between longer-term returns and trading volume. Blume, Easley and O'Hara (1994) present a model in which traders can learn valuable information about a security by observing both past price and past volume information. However, their model does not specify the nature of the information that might be derived from past volume. We provide empirical evidence on the nature of this information.

Another related study is Conrad, Hameed, and Niden (1994). Conrad et al. study the effect of trading volume on return autocovariances in the short horizon. Specifically, they examine the effect of trading volume on the weekly return reversal phenomenon reported by Jegadeesh (1990), and Lehmann (1990). Conrad et al. show that, at weekly intervals, the price reversal pattern is observed only for heavily traded stocks. In contrast, less traded stocks exhibit return continuation. These results are consistent with the predictions of Campbell, Grossman, and Wang (1993).

Our study is distinct from Conrad et al. (1994) in several respects. Conrad et al. are interested in short-term price movements associated with market microstructure issues discussed in Campbell, Grossman, and Wang (1993). Therefore, they attempt to predict weekly returns conditional on past price and volume changes. In contrast, our interest lies in the prediction of cross-sectional returns over longer (3 month and longer) horizons. In the intermediate time horizon, the primary empirical puzzle is not return reversal, but return continuation. Accordingly, our research is more aligned with the price momentum results in Jegadeesh and Titman (1993), and Chan, Jegadeesh, and Lakonishok (1996). Given the longer time horizons, these price continuations are unlikely to be due to the liquidity effects discussed in Campbell, Grossman, and Wang (1993).

Our research design and data also differ sharply from Conrad et al. While they focus on weekly returns, we deliberately form our portfolios with a one-week lag to minimize the effect of bid-ask bounce. In addition, while Conrad et al. use NASDAQ firms, we use only NYSE and AMEX firms. We exclude NASDAQ firms from our analysis for two reasons. First, NASDAQ firms tend to be smaller and more difficult to trade in momentum-based strategies. Second, trading volume for NASDAQ stocks are inflated relative to NYSE and AMEX stocks due to the double counting of dealer trades [Gould and Kleidon (1994)]. Because we rank our firms by turnover (trading volume divided by the number of shares outstanding), mixing NASDAQ and NYSE firms will result in inconsistent treatment of firms across these different markets.

In sum, several prior studies have documented a striking pattern of price momentum in the intermediate horizon. Other studies have examined the relation between trading volume and future returns without conditioning on past price movements. We integrate these two lines of research and demonstrate a strong interaction effect between past trading volume and past returns in the prediction of future returns. Our results shed light on both the price momentum phenomenon and the literature on the relation between trading volume and future returns.

II. Sample and Methodology

Our sample consists of all firms listed on the New York (NYSE) and American (AMEX) Stock Exchange during the period January 1965 through December 1995 with at least two years of data prior to the portfolio formation date. We eliminate any firm that was a prime, a closed-end fund, a real estate investment trust (REIT), an American Depository Receipt (ADR), or a foreign company. We also eliminate firms that were delisted within five days of the portfolio formation date and firms whose stock prices as of the portfolio formation date was less than a dollar. Finally, to be included in our sample a stock must also have available information on past returns, trading volume, market capitalization, and stock price.

At the beginning of each month, from January 1965 to January 1995, we rank all eligible stocks *independently* on the basis of past returns and trading volume. The stocks are assigned to one of ten portfolios based on returns over the previous J months and one of three portfolios based on the trading volume over the same time period. The intersections resulting from the two independent rankings give rise to 30 price momentum-volume portfolios. We focus our attention on the monthly returns of extreme winner and loser deciles over the next K months where $K=3,6,9, or\ 12$.

Trading volume (*Volume*) is defined as the average daily turnover in percent during the portfolio formation period where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day.[6]

Similar to Jegadeesh and Titman (1993), the monthly return for a *K*-month holding period is based on an equal-weighted average of portfolio returns from strategies implemented in the current month and the previous *K-1* months. For example, the monthly return for a 3-month holding period is based on an equal-weighted average of portfolio returns from this month's strategy, last month's strategy, and the strategy from two months ago. This is equivalent to revising (approximately) the weights of 1/3rd of the portfolio each month and carrying over the rest from the previous month. To avoid potential microstructure biases, a one-week lag is imposed between the portfolio formation period (J) and the beginning of the portfolio performance measurement period (K).

III. Results

In this section, we present empirical results from our tests. In Subsection A, we confirm the price momentum strategy for our sample of firms. We also ensure that our results are consistent with the stylized facts from prior volume studies. In Subsection B, we introduce volume-based price momentum portfolios and examine their predictive power for cross-sectional returns. In Subsection C, we discuss the difficulty of existing theories to accommodate these facts, and introduce the "Expectation Life Cycle" hypothesis as a plausible alternative explanation. Finally, in Subsection D, we provide additional evidence consistent with this hypothesis.

III-A. Price Momentum

Table 1 summarizes results from several price momentum portfolio strategies. Each January, stocks are ranked and grouped into decile portfolios on the basis of their returns over the previous 3, 6, 9, and 12 month. We report results for the bottom decile portfolio of extreme losers (R1), the top decile of extreme winners (R10), and one intermediate portfolio (R5). The other intermediate portfolio results are consistent with findings in prior

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[6] Most previous studies have used turnover as a measure of the trading volume in a stock [see Campbell, Grossman, and Wang (1993)]. Note also that raw trading volume is unscaled and, therefore, is likely to be highly correlated with firm size.

papers [Jegadeesh and Titman (1993)] and are omitted for simplicity of presentation. For each portfolio, Table 1 reports the mean return, and volume during the portfolio formation period, as well as the equally-weighted average monthly return over the next K months (K= *3, 6, 9, 12*). In addition, for each portfolio formation period (J) and holding period (K), we report the mean monthly return from a dollar-neutral strategy of buying the extreme winners and selling the extreme losers (R10-R1). The numbers in parentheses represent t-statistics.

Table 1 shows the effect of price momentum in our sample. For example, with a 9-month portfolio formation period (J=9), past winners gain an average of 1.65% per month over the next 9-months (K=9). Past losers gain an average of only 0.55% per month over the same time period. The difference between R10 and R1 is 1.15% per month. This difference in average monthly returns between R10 and R1 is significantly positive in all (J,K) combinations. The magnitude of these return differences is similar to those reported in Jegadeesh and Titman (1993).

The results in Table 1 also confirm the stylized facts about price movements and trading volume observed in prior studies. As expected, trading volume is positively correlated with absolute returns, so that the extreme price momentum portfolios exhibit higher trading activities. For example, the average daily turnover for the R10 and R1 portfolios in the 9-month formation period are 0.17% and 0.23% respectively, compared to 0.12% for the intermediate (R5) portfolio. In addition, we find that the positive relation between absolute returns and trading volume is asymmetric, in that extreme winners have a higher trading volume than extreme losers [see Lakonishok and Smidt (1986)].

Table 2 reports additional portfolio characteristics and long-term returns for price momentum portfolios. Column 2 shows the time-series average of the median market capitalization for the firms in each portfolio on portfolio formation date in millions of dollars (*Size*). Column 3 reports the time-series average of the decile size ranking for the median firm in each portfolio at the end of the calendar year prior to the calendar year in which the portfolio was formed (*SzRnk*). Column 4 reports the stock price of the median firm in the portfolio on the portfolio formation date. The last three columns report the annual returns of each portfolio in the three 12-month periods following the portfolio formation month, with t-statistics based on the Hansen-Hodrick correction for autocorrelation up to lag 11.

Results for the dollar-neutral portfolio (R10-R1) show that significant positive returns to the price momentum strategy are obtained only in the first year after portfolio formation. In Year 1, the R10-R1 portfolio yields a statistically significant return of between 10.42% and 12.86%. However, returns in Years 2 and 3 are negative and insignificant. Consistent with Jegadeesh and Titman (1993), we observe a modest reversal to momentum profits. However, the reversal is not of a sufficient magnitude to explain the initial gains.

III-B. Volume-based Price Momentum

Table 3 reports returns to portfolios formed on the basis of the two-way sort based on price momentum and past trading volume. To create this table, we sort all sample firms at the beginning of each month based on their returns over the past *J* months, and divide them into ten portfolios (R1 to R10). We then independently sort these same firms based on their average daily turnover rate over the past *J* months, and divide them into three volume portfolios (V1 to V3). V1 represents the lowest trading volume portfolio and V3 represent the highest trading volume portfolio. Table values represent the average monthly return over the next *K* months (K=3, 6, 9, 12).

Several key results emerge from Table 3. First, conditional on past returns, low-volume stocks generally do better than high-volume stocks over the next 12 months. This is seen in the consistently negative returns to the V3-V1 portfolio across most (J,K) combinations. For example, with a nine-month estimation period and six month holding period (J=9, K=6), low-volume losers outperform high-volume losers by 1.02% per month while the low-volume winners outperform high-volume winners by 0.26% per month. We find similar results in almost every (J, K) cell. Apparently firms that experience low trading volume in the recent past tend to outperform firms that experience high trading volume.

The finding that low-volume firms earn higher expected returns is consistent with the results in Datar, Naik, and Radcliffe (1998, forthcoming). In that paper, this finding is interpreted as evidence that low-volume firms face greater liquidity risk. However, Table 3 also contains evidence that is difficult to explain by liquidity risk. The bottom row of each cell in this table shows the return to a dollar-neutral, price momentum strategy (R10-R1). Focusing on this row, it is clear that R10-R1 returns are higher for high-volume (V3) firms than for low-volume (V1) firms. For example, for J=3 and K=3, the price momentum spread is 1.26% for high-volume firms and only 0.02% for low-volume firms. The difference of 1.24% is both economically and statistically significant. The other cells illustrate qualitatively the same effect. The price momentum premium is clearly higher in high-volume (presumably more liquid) firms.

According to the liquidity hypothesis, the portfolio with the higher expected returns should be less liquid. It is difficult to understand why a dollar-neutral portfolio of high-turnover stocks should be less liquid than a dollar-neutral portfolio of low-turnover stocks. Moreover, the magnitude of the difference is too large to be explained by illiquidity. For example, for J=6, K=6, the difference in momentum premium between V3 and V1 is 0.91% per month or approximately 11% annualized. For the liquidity hypothesis to hold, high-volume winners would have to be so illiquid as to be worth 11% less in expected returns than are high-volume losers.

Table 3 shows that this counter-intuitive result is driven primarily by the return differential in the loser portfolio (R1). Low-volume losers (R1V1) rebound strongly in the next 12 months, averaging more than 1% per month in virtually all (J, K) combinations. In contrast, losers in the high-volume portfolio (R1V3) earn an average return of between -0.21% and +0.41% per month. The difference in returns between high and low-volume losers (V3-V1 for R1) is 0.69 to 1.53 percent per month -- highly significant in both economic and statistical terms. Apparently past trading volume provides information useful in distinguishing between past losers that will rebound, and past losers that will continue to lose.

The return differential between high and low-volume winners is not nearly as large. In fact, in most cells the difference in returns between low-volume winners and high-volume winners is small and statistically insignificant. Nevertheless, high-volume winners generally *underperform* low-volume winners, so buying high-volume winners does not enhance the performance of the price momentum strategy. On the contrary, Table 3 results suggest that an even more profitable strategy would be to buy low-volume winners and sell high-volume losers.

Table 4 confirms these patterns for three sub-periods. The first subperiod spans 1965 to 1975, the second subperiod covers 1976 to 1985, and the last subperiod covers 1986 to 1995. We report results for the six-month formation period (J=6), but results are similar for other formation periods. In all three subperiods, winners outperform losers. In fact, the result is strongest in the more recent subperiod. Similarly, in all three subperiods, low-volume losers rebound while high-volume losers continue to lose. Finally, in all three subperiods, the spread between winners and losers is more pronounced among high-volume stocks.

Table 5 compares the average monthly return from three different trading strategies. The first strategy is the simple price momentum strategy (R10-R1). The second strategy is a price momentum strategy implemented only with high-volume firms (R10V3-R1V3). The third strategy involves buying the low-volume winners and selling the high-volume losers (R10V1-R1V3). The results show that all three dollar-neutral strategies yield significant positive returns in the 3, 6, 9 and 12-month holding periods. The highest return achieved is 2.15% per month in the third strategy for J=12 and K=3. The lowest return achieved is 0.66% per month in the first strategy for J=3, K=3.

Table 5 also presents the difference in returns between the three strategies. Diff1=(R10V3-R1V3) - (R10-R1) is the incremental return from a high-volume price momentum strategy relative to a simple price momentum strategy. Similarly, Diff2=(R10V1-R1V3)-(R10-R1) is the difference between the third and the first strategy, and Diff3=(R10V1-R1V3)-(R10V3-R1V3) is the difference between the third and the second strategy. These results show that both the second and the third strategy significantly outperform the simple price momentum strategy.

Prop1 (Prop2) represents the proportion of total months when the second (third) strategy outperforms the first strategy. The results show that most volume-based strategies outperform simple price momentum strategies between 56% and 64% of the time. A non-parametric Z-statistic shows that this superior performance is statistically significant in all but one cell. As mentioned earlier, the key to this superior performance is the omission of low-volume losers from the short portfolio of R10-R1.

Prop3 represents the proportion of total months in which the third strategy outperforms the second strategy. We see that for shorter holding periods (3 and 6 months), the two strategies perform about as well. However, for longer holding periods (9 and 12 months), the third strategy earns 30 to 40 basis points per month more than the second strategy. This result shows that buying low-volume winners, rather than high-volume winners, also provide a modest improvement in expected returns over the next 9 to 12 months.

Table 6 reports long-term (event time) returns for various portfolios based on past returns and trading volume (same portfolios as in Table 4). In this table, *J* represents the portfolio formation period (*J* =3, 6, 9, or 12 months). As in earlier tables, V1 represents the portfolio of firms with the lowest third trading volume and V3 represents the portfolio of firms with the highest third trading volume. R1 (R10) represents the decile portfolio with the lowest (highest) returns over the past *J* months. *Year1, Year2,* and *Year3* represent the annual returns to each portfolio in the three 12-month periods following the portfolio formation month. Since these are event time returns, i.e., returns for the same portfolio over the next three years, we face the problem of induced autocorrelation from overlapping observations. To correct for this, we compute t-statistics using the Hansen-Hodrick correction for autocorrelation up to lag 11.

Focusing on *Year1* results for R10-R1, we see that the price momentum effect reported by Jegadeesh and Titman is robust across all volume portfolios. In the first year after portfolio formation, returns to the R10-R1 portfolio is reliably positive, ranging from 6.76% (V1, J=3) to 15.42% (V3, J=6). The V3-V1 column shows that the price momentum effect is generally larger for high-volume portfolios. For example, for J=3, returns to the price momentum strategy is 5.86% greater in the high-volume stocks than in the low-volume stocks (see J=3; R10-R1; V3-V1). However, the price momentum effect dissipates after 12 months in each volume portfolio.

Table 6 shows that while price momentum dissipates in 12 months, the volume effect is more persistent. Focusing on *Year2* and *Year3* results, we see that R10-R1 portfolios generally do not earn statistically significant returns in years 2 and 3. However, from the V3-V1 column, we see that low-volume stocks tend to outperform high-volume stocks in all three years for portfolios R1, R5, and R10. In the first year, the effect is most pronounced among the losers -- for example, for J=3, low-volume losers outperform high-volume losers by 8.99% while low-volume winners outperform high-volume winners by only 1.93%. In years 2 and 3, however, the effect is equally strong in both winner and loser portfolios -- for example, low-volume winners outperform the high-volume winners by 4.32% to 8.24% per year in *Year2* and *Year3*. In other words, while low-volume losers start outperforming high-volume losers immediately, it takes a while for low-volume winners to start outperforming high-volume winners.

It is useful to summarize the empirical facts at this point. Thus far we have seen that, without conditioning on past price movements, low-volume stocks generally earn higher returns. This fact is consistent with the liquidity effect. However, we have also seen that the price momentum effect is stronger in high-volume stocks than in low-volume stocks. This suggests that the price momentum effect is unlikely to be due to differences in liquidity risk.

From Table 3, we see that low-volume losers experience a strong rebound in performance over the next 12-months while high-volume losers continue to lose. From Table 6, we see that low-volume stocks, both winners and losers, generally outperform high-volume stocks in the second and third year after price formation. The magnitude of the difference in long-term (years 2 and 3) returns between high- and low-volume portfolios is around 5 to 6 percent per year. Prior literature has interpreted this difference as evidence that low-volume stocks face greater liquidity risk. In the next section, we discuss an alternative, perhaps complementary, explanation.

III-C. The Expectation Life Cycle Hypothesis

What can account for these results? In this subsection, we suggest an alternative explanation that fits the empirical facts. This explanation closely parallels the "Earnings Expectation Life Cycle" proposed by Bernstein (1993, 1995). Bernstein provides a graphic representation of how investor expectation for a stock changes over time (see Figure 1a). In this graph, he depicts a stock as traveling through a cycle of negative and positive earnings surprises. A stock with positive price and/or earning momentum (past winner) would be on the left half of the cycle while a stock with negative price and/or earning momentum (past loser) would be on the right half of the cycle.

Growth stocks are stocks that have generally experienced positive earnings-per-share (EPS) momentum and are identified by positive surprise models. Eventually, these stocks experience an earnings disappointment and are "torpedoed." Stocks with disappointing earnings fall to the bottom of earnings surprise models. These stocks are labeled "Dogs" and experience general neglect. If they fall far enough in price, they may become attractive to contrarian investors. Eventually, some of these stocks may experience positive surprises again, and the cycle continues. He argues that most stocks probably travel such a path.

Bernstein uses this graph to distinguish between various style investors. Value managers, he notes, typically operate on the bottom half of the cycle, while growth managers operate on the upper half. However, style alone does not determine one's success. This is because good value managers tend to operate between 6 and 9 o'clock while bad value managers operate between 3 and 6 o'clock. Similarly, good growth managers operate between 9 and 12 o'clock while bad growth managers operate between 12 and 3 o'clock. Successful managers, Bernstein argues, can follow either a value or growth strategy.

While the Bernstein analysis offers a useful framework for thinking about momentum and style investing, it does not provide specifics on how to identify where a firm currently belongs in this cycle. The key issue in momentum investing is not how long the stock has been winning (or losing), it is how much longer it will continue to win (or lose) -- i.e., how much "leg" is left in the run. When buying a past winner or shorting a past loser, the pertinent issue is whether we are closer to 6 o'clock or 12 o'clock.

Figure 1b suggests how trading volume in conjunction with past returns may serve as a useful indicator of where a given firm is in its expectation cycle. As illustrated, when a stock falls into disfavor, the number of sellers tends to exceed the number of buyers. Generally, this results in falling prices and dwindling trading activity. Conversely, when a stock is popular, the number of buyers exceed the number of sellers, so prices tend to rise and trading activity increases. As a result, a firm's turnover ratio is a proxy for investor expectation and investor interest -- relatively low turnover is an indication of a firm near the bottom of its expectation cycle, while relatively high turnover is an indication of a firm close to the top of this cycle.

This explanation is consistent with the facts that we have presented thus far. First, it explains why low-volume firms generally outperform high-volume firms. Specifically, low-volume firms are more likely to be firms that have fallen out of investor favor and therefore have greater upside potential, regardless of their past price performance. Our results suggest this effect is most pronounced among past losers in the 12 months after portfolio formation. For these firms, low-volume is a signal that the stock has "bottomed out," and that a price reversal is imminent. High-volume losers, on the other hand, still have plenty of negative price momentum.[7]

The same story applies to winners (the left-side of Figure 1). Low-volume winners have greater upside potential than high-volume winners because stocks that earn positive returns on high-volume tend to be nearer to the top of their expectation life cycle. However, unlike

[7] Merton (1987) suggests investors trade only in stocks they "know" about. Because recent extreme winners and extreme losers are more likely to be in the news, investors are more likely to trade them. This could explain the higher turnover in these stocks.

low-volume losers, low-volume winners appear to take longer to realize their relatively higher returns. Table 6 shows these gains are realized gradually over the next three years, so that low-volume winners outperform high-volume winners even two or three years after portfolio formation.

The expectation life cycle hypothesis suggests a strategy of buying low-volume winners (winners at the bottom of an up-cycle) and selling high-volume losers (losers at the top of a down-cycle). According to the theory, this strategy will capture early-stage winners and short late-stage losers. Figure 2 compares the annual returns from a simple price momentum strategy (R10-R1) to the returns from a strategy of buying low-volume winners and selling high-volume losers (R10V1-R1V3). This figure shows that the volume-based strategy outperforms a pure price strategy in each of the next three years and over all four portfolio formation periods (J=3, 6, 9, 12 months). The return differential ranges from 3.91% (Year1, J=6) to 8.70% (Year2, J=9).

It is interesting to compare Figure 2 results to the abnormal returns for a price momentum strategy based on high-volume stocks alone (R10V3-R1V3). Table 6 shows that the high-volume price momentum strategy yields abnormal returns only in the first 12 months. In contrast, the R10V1-R1V3 strategy yields abnormal returns in each of the next three years. This comparison shows that substituting low-volume winners for high-volume winners in the long portfolio results in greater persistence in long-term abnormal returns.

Now consider a volume-based price momentum strategy in which we buy high-volume winners and sell low-volume losers. Figure 3 compares the three-year event time returns of this strategy to that based on past prices alone. This volume-based strategy still qualifies as a price momentum play, in that we are buying past winners and selling past losers. However, Figure 3 shows that this strategy significantly underperforms the simple price momentum strategy each year over the next three years.

More interestingly, this alternate volume-based momentum strategy earns significantly negative returns in years 2 and 3. In other words, the high-volume winners from our formation period have significantly underperformed the low-volume losers in years 2 and 3. This is consistent with the contrarian results of De Bondt and Thaler (1985), and contrasts sharply with the long-term return continuation exhibited in Figure 2.

The expectation life cycle hypothesis offers a simple explanation for these results. Specifically, low-volume winners and high-volume losers are, early winners and early losers, respectively. In contrast, high-volume winners and low-volume losers are late winners and late losers, respectively. Figure 2 shows that buying early winners and selling late losers outperforms a simple price strategy over each of the next 3 years. Conversely, Figure 3 shows that buying late winners and selling early losers results in lower returns than the price strategy in year 1, and significant losses in years 2 and 3.

III-D. Further Evidence on Volume-based Momentum Strategies

In this subsection, we provide further evidence on portfolio and return characteristics for the volume-based price momentum portfolios. Our objective is to better understand the nature of these positive future returns, and perhaps distinguish between the investor expectation hypothesis and other risk-based explanations.

Table 7 presents portfolio characteristics for portfolios based on price momentum and trading volume. In this table, *Return* refers to the average monthly return in percent during the previous J months and *Volume* refers to the average daily turnover in percent over the same time period. *Size* is the time-series average of median market capitalization of each portfolio on the portfolio formation date in millions of dollars. One concern with this variable is that it is a function of price movements during the portfolio formation period. As an alternative, *SzRnk* measures the time-series average of the median size decile of the portfolio at the end of the calendar year prior to the calendar year in which the portfolio was formed. *Price* represents the time-series average of the median stock price of the portfolio in dollars on the portfolio formation date. Finally, *N* represents the average number of firms in each portfolio.

Table 7 shows that our results are unlikely to be due to firm size or stock price effects. The median firm in the long portfolio (R10) is larger and higher priced than the median firm in the short portfolio (R1) in all three volume categories and across all four portfolio formation periods (J=3, 6, 9, 12 months). Comparing firms in the volume-based price strategy (R10V1 - R1V3), we also find little difference in terms of firm size and stock price. For example, with a nine-month formation period (J=9), the long portfolio firms (R10V1) are generally larger (*Size* = 99.8 versus 71.8) and higher priced (*Price* = 18.55 versus 9.90) than the short portfolio firms (R1V3). *SzRnk* shows that the median firms from these two portfolios are less than two deciles apart in market capitalization before the portfolio formation period. These results suggest that the large difference in future returns between the winner and loser portfolios is not due to dramatic differences in firm size or stock price.

Table 8 provides additional evidence on the source of the abnormal return from the various volume-based price momentum strategies. In this table, we report the results of a series of time-series regressions based on the Fama-French (1993) three-factor model. Specifically, we run the following time-series regression using monthly portfolio returns:

$$(r_i - r_f) = a_i + b_i (r_m - r_f) + s_i \, SMB + h_i \, HML + e_i \,, \qquad (1)$$

where r_i is the monthly return for portfolio i, r_f is the monthly return on one-month T-bill obtained from the Ibbotson Associates' Stocks, Bonds, Bills, Inflation (SBBI) series, r_m is the value-weighted return on the NYSE/AMEX/ NASDAQ market index, SMB is the Fama-French small firm factor, HML is the Fama-French value (book-to-price) factor and a_I is the intercept or the *alpha* of the portfolio.[8] For parsimony, we report results for symmetrical combinations of portfolio formation and holding periods (J and K= 3, 6, 9, and 12 months). The first cell on the left in each panel reports the estimated intercept coefficient, the subsequent cells report estimated coefficients for b_i, s_i, and h_i, respectively. The last cell of each panel reports the adjusted R^2.

The estimated intercept coefficients from these regressions (a_i) are interpretable as the risk-adjusted return of the portfolio relative to the three-factor model. Focusing on these intercepts, it is clear that our earlier results are not explained by the Fama-French factors. The intercepts corresponding to R10-R1 are positive across all three volume categories. The return differential between winners and losers remains much higher for V3 firms than for V1 firms. Finally, a strategy of buying low-volume winners and shorting high-volume losers yields average abnormal returns of between 1% and 1.5% per month across all four panels.

Even more revealing are the estimated factor loadings on the SMB and HML factors. First focus on the estimated coefficients for the HML factor (h_i) in the 6-month horizon. Here

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[8] SMB is small firm return minus large firm return and HML is high book-to-market portfolio return minus low book-to-market portfolio return. For details on portfolio construction, see Fama and French (1993).

we see that low-volume stocks (V1 portfolios) have a much more positive loading on the HML factor. This applies to winners (R10), losers (R1), and even the intermediate portfolio (R5). Apparently low-volume stocks behave more like value stocks, i.e., stocks with high book-to-market ratios. High-volume stocks, on the other hand, behave more like growth stocks, i.e., stocks with low book-to-market ratios. In fact, high-volume winners (R10V3) have a negative loading on the HML factor. The magnitude of this HML loading corresponds to those obtained for the growth stocks (lowest 40% by book-to-market ratio) in Fama and French (1993). The difference in estimated HML loadings for our low- and high-volume winner portfolios is -0.51. This is comparable to the spread Fama and French obtains when they separate firms on the basis of high versus low book-to-price ratios.[9] Consistent with the investor expectation hypothesis, future returns on the low-volume portfolios are more highly correlated with HML. In short, they behave more like value stocks.

The factor loadings on the SMB factor also provide interesting information in support of the investor expectation hypothesis. Table 8 shows that our high- and low-volume portfolios exhibit virtually no difference in their sensitivity to the SMB factor. In the winner and loser portfolios (R10 and R1), differences in trading volume has no explanatory power for a stock's sensitivity to firm size. In the intermediate price portfolio (R5), there is some evidence that high-volume firms actually behave more like small stocks than do low-volume firms. Since small stocks are generally more illiquid, this evidence runs counter to the liquidity explanation for the volume effect.

To sum up, Table 8 results show that the abnormal returns from the volume-based price momentum strategies are not sensitive to the Fama-French risk factors. Moreover, we find that low-volume firms are significantly more positively correlated with HML, suggesting that the reason these firms do better is because they behave more like value stocks. Finally, high-volume firms and low-volume firms are not significantly different in their sensitivity to SMB, suggesting that the volume-based results are not due to firm size.

To further distinguish between the *expectation life cycle hypothesis* and the *liquidity risk hypothesis*, we examine the average book-to-market ratio and operation performance

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[9]See Fama and French (1993), page 25, Table 6. Combining the estimated h_i coefficient for the top two and bottom two book-to-market quintiles, the Fama-French HML factor differential between low book-to-market and high book-to-market firms is around -0.7.

for firms in various price momentum-volume portfolios. Table 9 report these results for two portfolio formation periods (J=6 and J=12). The results for J=3 and J=9 are similar and are not reported. In this table, B/M is the book-to-market ratio, where B is the book value of equity just before the portfolio formation date (from Annual Compustat), and M is the market value of equity as of the portfolio formation date. ROE represents the accounting return-on-average-equity, defined as ROE(t)= NI(t) / [0.5*[B(t)+B(t+1)]], where NI is net income before extraordinary items.[10]

Table 9 reports the current ROE, ROE(0), as well as the ROE three years before and after the portfolio formation date -- ROE(-3) and ROE(3), respectively. The last two columns report the change in ROE over the three years just *before* the portfolio formation date, DROE(-), and the change in ROE over the three years immediately *after* the portfolio formation date, DROE(+). To help put these numbers in economic context, the average ROE over the sample period for all firms is around 12.5 percent.

Table 9 shows that low-volume losers (R1V1) have the highest B/M ratio and the lowest current ROE. The average ROE for these firms is between 3 and 6 percent, suggesting that their accounting rate of return is much lower than their cost-of-capital. Not surprisingly, the market has assigned a much higher B/M ratio to these firms. Consistent with the Fama-French regression results from Table 8, we see that low-volume firms tend to have higher B/M ratios than high-volume firms even after controlling for past price momentum. Results for DROE(-) show that over the past three years, losers (R1 firms) experience ROE declines of 4 to 8 percent while winners (R10 firms) generally experienced ROE increases.

Perhaps the most interesting result pertains to changes in future ROEs, reported in the last column of Table 9. Here we see that, controlling for price momentum, low-volume stocks have greater increases in future ROEs than high-volume stocks. For example, for J=6, low-volume losers (R1V1) increased their average ROE by 1.61 percent over the next three years. High-volume losers (R1V3), on the other hand, experienced a further decline in their average ROE by 2.81 percent over the next three years. The difference of 4.42 percent is strongly significant at the one-percent level. We see a similar pattern among the winners: low-volume winners have ROE improvements that exceed those of high-volume winners by 1.78 percent, again statistically significant at the one-percent level.

[10]Using returns-on-asset (ROAs) rather than ROEs yield similar results.

The evidence in Table 9 shows that conditional on past price momentum, past volume is a leading indicator of future operating performance. Consistent with the expectation life cycle hypothesis, conditional on past price momentum, low-volume firms outperform high-volume firms in the future. However, we know of no theory or empirical evidence linking changes in accounting ROE to the level of liquidity risk. Hence Table 9 results cast further doubt on the liquidity risk explanation.

As a final test, Table 10 presents evidence on the correlation in volume ranks across years. For the expectation life cycle hypothesis to hold, firms' volume ranking should exhibit mean reversion over time. In other words, firms with high turnover should drift downward in ranking over time, while low-turnover firms should drift upward. In the absence of significant changes in volume ranking over time, our measure of past volume is more likely to be a proxy for liquidity risk.

Table 10 reports the Spearman rank correlation between turnover in the 12-months before the formation date and the turnover in each of the following five years. This table shows that the correlation in volume ranks decays over time. The rank correlation between year t-1 and t trading volume is 0.82. This implies current year turnover rankings explain around 65 percent of next year's rankings. However, the rank correlation between year t-1 and year t+4 is only 0.54, suggesting that current year rankings explain only around 26 percent of volume rankings in five years. The fact that the correlations do not go to zero suggests cross-sectional volume rankings have some persistence over time. However, Table 10 also shows significant shifts in volume rankings over the next few years. High- (low-) volume firms do not remain so indefinitely, rather, they tend to mean revert.

V. Conclusion

In this study, we have extended the literature on the prediction of intermediate horizon cross-sectional returns by examining the interaction between price momentum and past trading volume. We show that the momentum effect is a function of both past prices and past trading volume. From 1965 to 1995, New York (NYSE) and American (AMEX) Stock Exchange firms with low-volume (low turnover ratios) over the past 3 to 12 months generally outperform high-volume firms in the future. We observe this effect for both past winners and past losers, but find that it is most pronounced for recent losers over the next 12 months; low-volume losers exhibit a strong tendency to rebound, while high-volume losers continue to lose in the next 12 months.

Our findings show trading volume provides valuable information not only about the magnitude of the price momentum effect, but also its persistence. While abnormal returns on pure price momentum strategies persist for only 12 months, trading strategies based on both price and volume yield significant abnormal returns over the next 36 months. In fact, a simple strategy of buying low-volume losers and selling high-volume winners outperforms a similar momentum strategy based on price alone by more than 4% to 8.5% over each of the next three years. This result is robust across 3, 6, 9, and 12-month estimation and holding periods, and is not explained by traditional risk proxies such as firm size, stock price, or the Fama-French (1993) three-factor model.

These findings have implications for the price momentum puzzle as well as the current debate on market efficiency. First, our results show that past volume information is not fully impounded in current prices. Consistent with the predictions of Blume, Easley, and O'Hara (1994), judicious use of past returns and trading volume information can generate surprisingly large abnormal returns. The magnitude of these returns will decrease substantially with transaction costs. However, given the number of investors already trading on very similar price momentum strategies, the relative improvement gained by conditioning on past trading volume information appears to be economically significant even after transaction costs.

What may account for these results? Most of the standard explanations do not reconcile with the facts. As an alternative, we suggest an "investor expectation hypothesis," in which past trading volume is a proxy for the level of investor interest in (or expectation for) a stock. Low-volume stocks are "neglected" by investors and are therefore more likely to experience upward price movements. High-volume stocks, on the other hand, are experiencing high investor interest and are more likely to experience downward price movements. Therefore, by revealing something about the level of investor interest in a stock, trading volume provides a useful signal for distinguishing between stocks at the top of their expectation cycle and stocks at the bottom.

The evidence we have to date is consistent with this hypothesis. Low-volume firms generally outperform high-volume firms. Low-volume losers, in particular, exhibit a strong tendency to rebound. In addition, we find that low-volume firms load much more positively on the Fama-French HML factor than do high-volume firms. This evidence suggests low-volume firms behave like value stocks -- they earn positive excess returns when value stocks in general do well.

We also document a significant relation between firms' past trading volume and their future operating performance relative to other firms in the same price momentum category. Consistent with the expectation life cycle hypothesis, we find that low-volume firms exhibit much greater ROE gains than high-volume firms in the same price momentum portfolio. Since accounting profitability is unlikely to be related to market liquidity, this evidence casts further doubt on the liquidity risk explanation.

If the investor expectation hypothesis is correct, then our results imply stock prices are a function of investor interest, and not just fundamentals. Specifically, our results suggest that, given the same price momentum, high (low) trading volume is an indication of relative over (under) pricing. This mispricing is corrected in the future when subsequent accounting profits are realized. Interpreted in terms of the expectation life cycle hypothesis, our results suggest that neglected stocks are underpriced while glamour stocks that receive more investor attention tend to be overpriced.

Our work also suggests a possible link between intermediate-horizon price continuation and long-horizon price reversal. One of the paradoxes of momentum investing is that winners cannot keep winning forever, nor could losers always continue to lose. Yet in the empirical literature to date, the mid-horizon momentum effect has not been reconciled to the long-horizon reversal effect. Chan, Jegadeesh, and Lakonishok (1996), for example, show very little price reversal in their price momentum strategies in years 2 and 3. By demonstrating that the duration of price continuation is a function of trading volume, our results begin to establish a link between the two empirical phenomena.

Finally, we find it remarkable that measures so readily available as past returns and past trading volume should have such strong predictive powers for subsequent returns. Why the information contained in these measures is not fully reflected in current prices is a puzzle we leave for future research. In the mean time, we remain agnostic as to the prediction that this phenomenon will yield positive abnormal returns in future periods.

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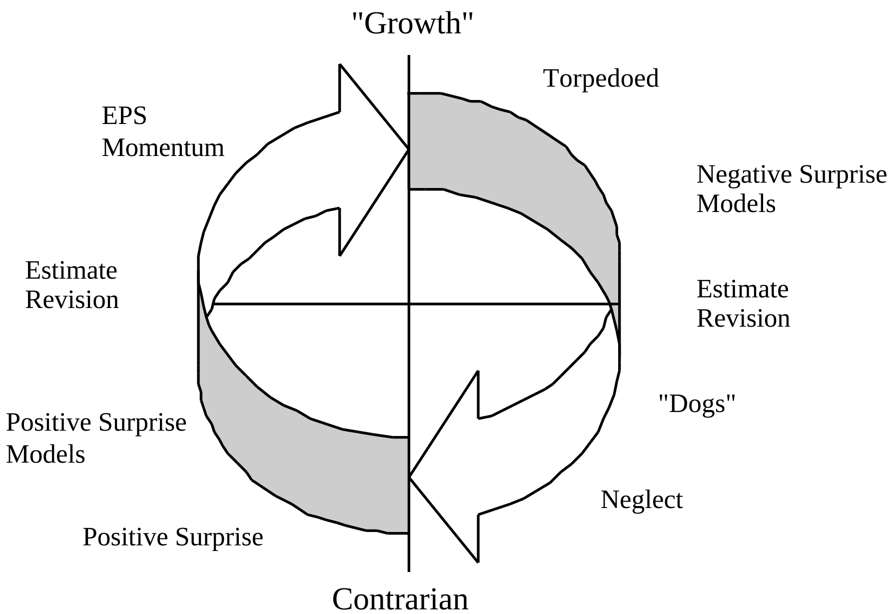
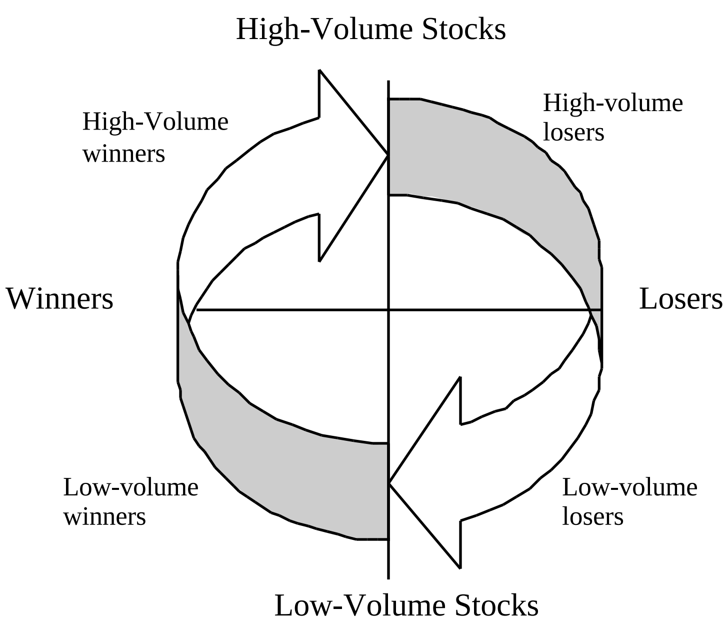
Figure 1a. Earnings Expectations Life Cycle*

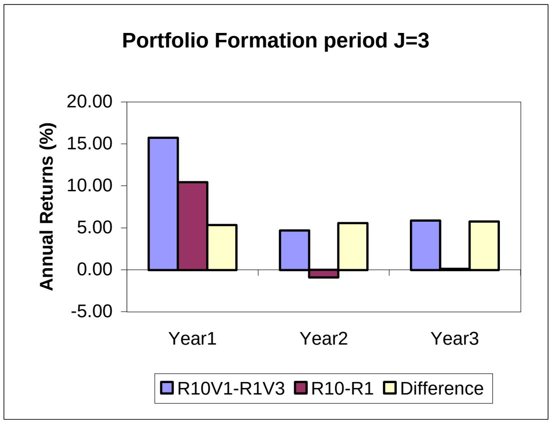


* Source: Bernstein, Richard, 1995, *Style Investing*, page 36.

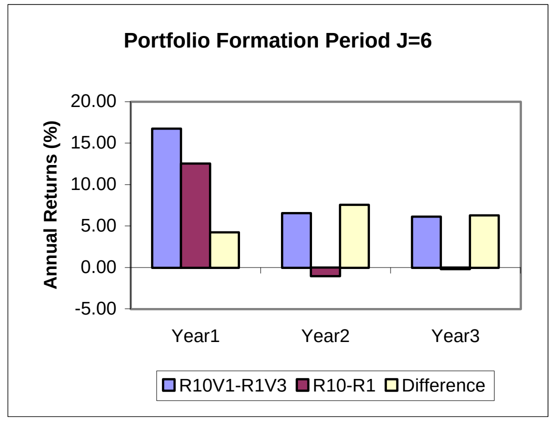
Figure 1b. Momentum Investing Based on Past Price and Volume Information



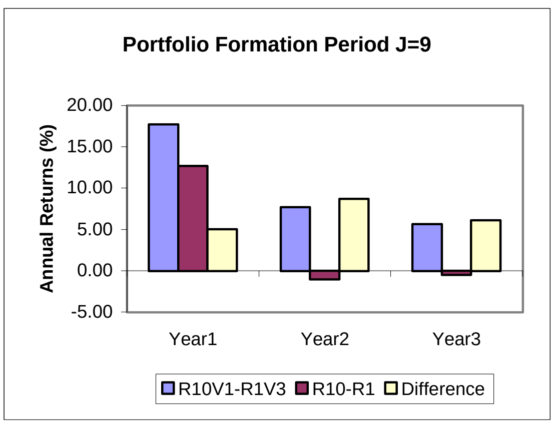
Buy Low-Volume Winners and Sell High-Volume Losers



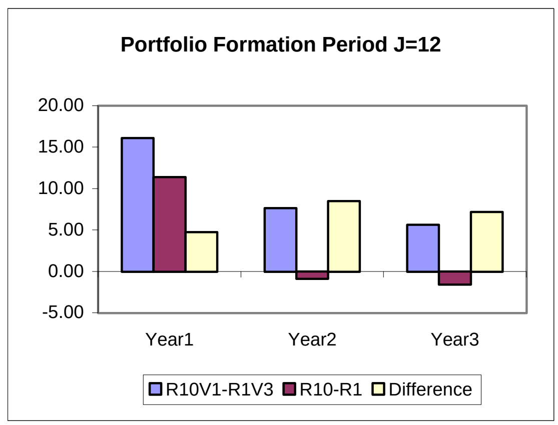
J=3	Year1	Year2	Year3
R10V1-R1V3	15.75*	4.68*	5.85*
R10-R1	10.42*	-0.88	0.11
Difference	5.33*	5.56*	5.74*



J=6	Year1	Year2	Year3
R10V1-R1V3	16.77*	6.55*	6.11*
R10-R1	12.53*	-1.01	-0.18
Difference	4.25*	7.56*	6.29*



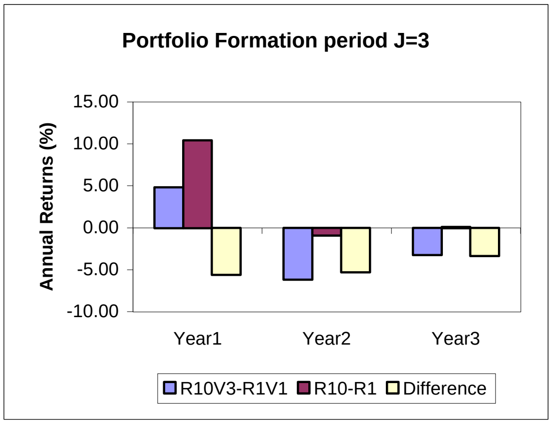
J=9	Year1	Year2	Year3
R10V1-R1V3	17.71*	7.68*	5.64**
R10-R1	12.67*	-1.02	-0.48
Difference	5.04*	8.70*	6.12*

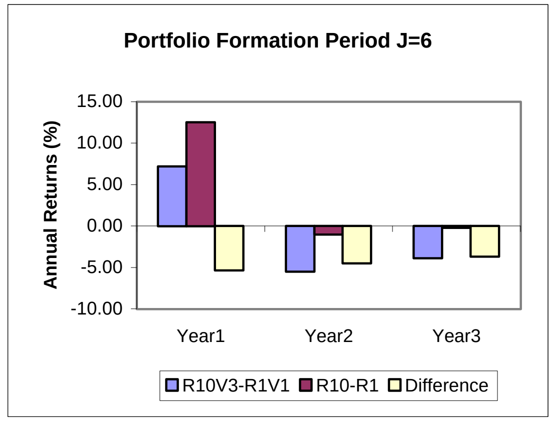


J=12	Year1	Year2	Year3
R10V1-R1V3	16.11*	7.64*	5.62**
R10-R1	11.39*	-0.87	-1.55
Difference	4.72**	8.50*	7.17*

Figure 2. Long-term returns on price momentum and volume-price momentum strategies. These graphs compare future returns from a simple price momentum strategy (*R10-R1*) to the returns from a volume-price momentum strategy of buying low-volume winners and selling high-volume losers, (*R10V1-R1V3*). *Difference* is the return differential between the two strategies. *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous *J* months. *V3* represents the portfolio with the highest trading volume. *Year1*, *Year2*, and *Year 3* represent the compounded returns in each of the three 12-month periods following the portfolio formation month. * - significance at 1% level; ** - significance at 5% level; *** - significance at 10% level. The significance levels correspond to two-tail tests.

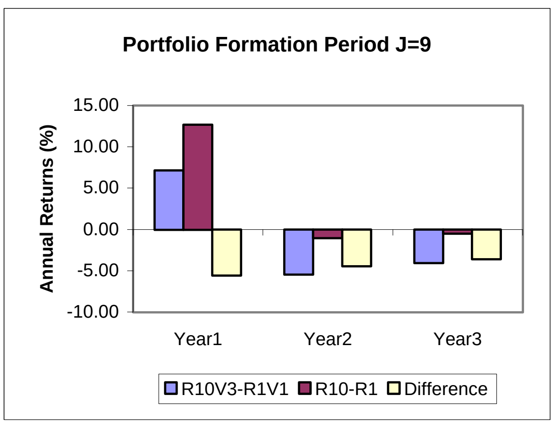
Buy High-Volume Winners and Sell Low-Volume Losers

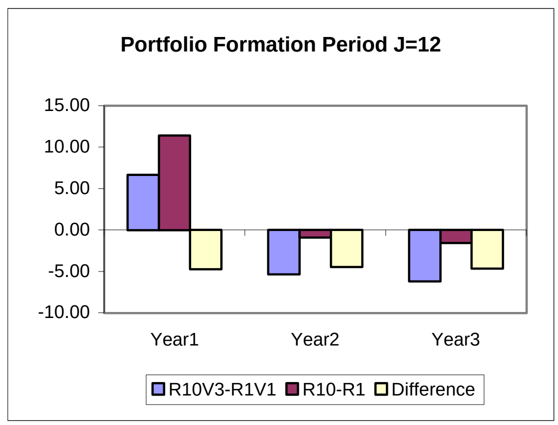




J=3	Year1	Year2	Year3
R10V3-R1V1	4.83**	-6.16*	-3.21***
R10-R1	10.42*	-0.88	0.11
Difference	-5.59*	-5.28*	-3.32*

J=6	Year1	Year2	Year3
R10V3-R1V1	7.21*	-5.49**	-3.86
R10-R1	12.53*	-1.01	-0.18
Difference	-5.32*	-4.48*	-3.68*





J=9	Year1	Year2	Year3
R10V3-R1V1	7.13*	-5.43**	-4.04
R10-R1	12.67*	-1.02	-0.48
Difference	-5.54*	-4.41*	-3.56*

J=12	Year1	Year2	Year3
R10V3-R1V1	6.67*	-5.31***	-6.16**
R10-R1	11.39*	-0.87	-1.55
Difference	-4.73*	-4.44*	-4.61*

Figure 3. Long-term returns on price momentum and volume-price momentum strategies. These graphs compare future returns from a simple price momentum strategy (*R10-R1*) to the returns from a volume-price momentum strategy of buying high volume winners and selling low volume losers, (*R10V3-R1V1*). *Difference* is the return differential between the two strategies. *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous *J* months. *V3* represents the portfolio with the highest trading volume. *Year1*, *Year2*, and *Year 3* represent the compounded returns in each of the three 12-month periods following the portfolio formation month. * - significance at 1% level; ** - significance at 5% level; *** - significance at 10% level. The significance levels correspond to two-tail tests.

Table 1
Returns to Price Momentum Portfolios

This table summarizes results from price momentum portfolio strategies using monthly returns on NYSE/AMEX stocks from 1965-1995. Each month from January 1965 all stocks in NYSE and AMEX are sorted based on their previous *J* month returns and divided into ten equal-weighted portfolios. *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous *J* months. The portfolios are held over the next *K* months and arithmetic mean monthly returns over the holding period are presented below. For example, the monthly return for a 3-month holding period is based on an equal-weighted average of portfolio returns from this month's strategy, last month's strategy, and the strategy from two months ago. This is equivalent to revising the weights of 1/3[rd] of the portfolio each month and carrying over the rest from the previous month. To avoid potential microstructure biases, we introduced a one-week lag between the portfolio formation period and the beginning of the portfolio measurement period. *Return* refers to the geometric average monthly return (for each security) in percent and *Volume* represents the average daily turnover in percent both during the portfolio formation period, *J*. The numbers in parentheses represent simple t-statistics.

J	Portfolio	Return	Volume	K=3	K=6	K=9	K=12
3	R1	-8.91	0.1604	0.76	0.73	0.77	0.74
				(1.88)	(1.81)	(1.93)	(1.86)
	R5	0.08	0.1185	1.37	1.36	1.33	1.30
				(4.84)	(4.76)	(4.65)	(4.55)
	R10	12.00	0.2403	1.42	1.40	1.47	1.46
				(4.28)	(4.16)	(4.33)	(4.24)
	R10-R1			0.66	0.67	0.70	0.72
				(3.06)	(3.38)	(3.93)	(4.59)
6	R1	-6.36	0.1671	0.59	0.58	0.57	0.65
				(1.39)	(1.38)	(1.40)	(1.58)
	R5	0.25	0.1212	1.31	1.29	1.31	1.30
				(4.66)	(4.55)	(4.59)	(4.52)
	R10	8.30	0.2349	1.62	1.62	1.65	1.53
				(4.76)	(4.72)	(4.78)	(4.45)
	R10-R1			1.04	1.05	1.08	0.88
				(3.89)	(4.28)	(4.92)	(4.18)
9	R1	-5.27	0.1713	0.49	0.44	0.55	0.66
				(1.15)	(1.06)	(1.32)	(1.57)
	R5	0.31	0.1230	1.28	1.28	1.30	1.30
				(4.48)	(4.46)	(4.56)	(4.52)
	R10	6.78	0.2304	1.85	1.79	1.71	1.54
				(5.31)	(5.08)	(4.86)	(4.41)
	R10-R1			1.36	1.35	1.15	0.88
				(4.85)	(5.29)	(4.71)	(3.72)
12	R1	-4.61	0.1727	0.34	0.45	0.60	0.72
				(0.80)	(1.05)	(1.41)	(1.66)
	R5	0.37	0.1239	1.24	1.28	1.32	1.31
				(4.34)	(4.51)	(4.63)	(4.56)
	R10	5.96	0.2300	1.88	1.71	1.61	1.46
				(5.29)	(4.84)	(4.59)	(4.15)
	R10-R1			1.54	1.26	1.01	0.74
				(5.63)	(4.71)	(3.87)	(2.93)

Table 2
Portfolio Characteristics and Long-Term Returns of Price Momentum Portfolios

This table summarizes the portfolio characteristics and returns in future years for price momentum portfolios using data on NYSE/AMEX stocks from 1965-1995. *J* represents the portfolio formation period. *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous *J* months. *Size* represents the time-series average of median market capitalization of the portfolio on the portfolio formation date in millions of dollars. *SzRnk* represents the time-series average of the median size decile of the portfolio at the end of the calendar year prior to the calendar year in which the portfolio was formed. *Price* represents the time-series average of the median stock price of the portfolio in dollars on the portfolio formation date. *Year1, Year2,* and *Year 3* represent the annual returns of price momentum portfolios in the three 12-month periods following the portfolio formation month. The numbers in parentheses represent t-statistics based on the Hansen-Hodrick correction for autocorrelation up to lag 11.

J	Portfolio	Size	SzRnk	Price	Year 1	Year 2	Year 3
3	R1	49.85	6.14	9.91	9.49	15.85	15.50
					(2.16)	(3.69)	(3.69)
	R5	201.72	7.88	20.96	16.96	16.62	15.83
					(5.03)	(5.12)	(4.91)
	R10	94.63	6.03	17.45	19.91	14.97	15.60
					(4.65)	(3.59)	(4.23)
	R10-R1				10.42	-0.88	0.11
					(6.04)	(-0.78)	(0.07)
6	R1	43.28	6.25	9.00	8.34	15.85	15.58
					(1.81)	(3.57)	(3.52)
	R5	216.28	7.88	20.79	16.74	16.58	15.96
					(4.99)	(5.16)	(4.89)
	R10	107.38	5.96	19.41	20.86	14.84	15.40
					(4.93)	(3.51)	(4.30)
	R10-R1				12.53	-1.01	-0.18
					(5.39)	(-0.64)	(-0.09)
9	R1	39.37	6.23	8.34	8.41	15.92	15.75
					(1.79)	(3.48)	(3.40)
	R5	209.88	7.89	20.87	16.66	16.60	16.40
					(4.99)	(5.05)	(4.97)
	R10	111.14	5.92	20.59	21.08	14.89	15.27
					(4.93)	(3.50)	(4.33)
	R10-R1				12.67	-1.02	-0.48
					(5.42)	(-0.53)	(-0.20)
12	R1	36.31	6.29	7.78	8.72	15.66	16.19
					(1.87)	(3.32)	(3.42)
	R5	211.31	7.91	20.83	16.89	17.01	16.03
					(5.11)	(5.20)	(5.03)
	R10	119.84	5.92	21.79	20.11	14.79	14.64
					(4.74)	(3.46)	(4.19)
	R10-R1				11.39	-0.87	-1.55
					(5.32)	(-0.38)	(-0.59)

Table 3

Returns on Portfolios Based on Price Momentum and Trading Volume

This table presents results from portfolio strategies based on an independent two-way sort based on past returns and past average daily turnover. At the beginning of each month all available stocks in NYSE/AMEX are sorted independently based on past *J* month returns and divided into ten portfolios. *R1* represents the *loser* portfolio and *R10* represents the winner portfolio. The stocks are then independently sorted based on the average daily volume over the past *J* months and divided into three portfolios, where we use turnover as a proxy of trading volume. *V1* represents the lowest trading volume portfolio and *V3* represents the highest trading volume portfolio. The stocks at the intersection of the two sorts are grouped together to form portfolios based on past returns and past trading volume. The portfolios are rebalanced each month as described in Table 1. The numbers in parentheses are simple t-statistics.

		K=3				K=6				K=9				K=12			
J	Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
3	R1	1.24	0.96	0.19	-1.05	1.19	0.87	0.25	-0.93	1.21	0.89	0.34	-0.86	1.17	0.81	0.36	-0.81
		(3.17)	(2.32)	(.44)	(-5.11)	(3.06)	(2.16)	(.59)	(-5.14)	(3.12)	(2.24)	(.81)	(-5.02)	(3.06)	(2.06)	(.85)	(-4.98)
	R5	1.41	1.45	1.20	-0.20	1.42	1.38	1.23	-0.19	1.40	1.34	1.19	-0.21	1.40	1.31	1.14	-0.26
		(5.62)	(5.02)	(3.40)	(-1.28)	(5.62)	(4.77)	(3.48)	(-1.20)	(5.54)	(4.62)	(3.38)	(-1.38)	(5.54)	(4.50)	(3.23)	(-1.72)
	R10	1.26	1.61	1.45	0.19	1.45	1.59	1.36	-0.09	1.55	1.65	1.41	-0.14	1.60	1.65	1.37	-0.23
		(4.15)	(4.93)	(4.05)	(1.02)	(4.71)	(4.87)	(3.77)	(-.53)	(4.99)	(5.05)	(3.87)	(-.85)	(5.04)	(5.02)	(3.71)	(-1.43)
	R10-R1	0.02	0.66	1.26	1.24	0.26	0.73	1.11	0.84	0.34	0.76	1.06	0.72	0.43	0.85	1.01	0.58
		(.09)	(2.78)	(5.69)	(6.03)	(1.31)	(3.56)	(5.42)	(5.66)	(1.87)	(4.10)	(5.88)	(5.54)	(2.62)	(5.24)	(6.20)	(5.10)
6	R1	1.16	0.77	0.03	-1.14	1.12	0.67	0.09	-1.04	1.03	0.67	0.16	-0.88	1.09	0.74	0.30	-0.79
		(2.80)	(1.82)	(.06)	(-5.22)	(2.74)	(1.61)	(.20)	(-5.19)	(2.58)	(1.66)	(.36)	(-4.82)	(2.70)	(1.82)	(.67)	(-4.54)
	R5	1.37	1.34	1.19	-0.18	1.36	1.34	1.15	-0.21	1.38	1.35	1.16	-0.22	1.39	1.32	1.13	-0.26
		(5.50)	(4.64)	(3.39)	(-1.10)	(5.37)	(4.63)	(3.28)	(-1.33)	(5.44)	(4.65)	(3.32)	(-1.41)	(5.44)	(4.53)	(3.19)	(-1.72)
	R10	1.63	1.82	1.57	-0.06	1.67	1.78	1.55	-0.12	1.72	1.85	1.56	-0.16	1.66	1.75	1.42	-0.23
		(5.12)	(5.55)	(4.28)	(-.31)	(5.30)	(5.41)	(4.16)	(-.67)	(5.52)	(5.59)	(4.18)	(-.89)	(5.35)	(5.34)	(3.82)	(-1.34)
	R10-R1	0.47	1.05	1.55	1.07	0.54	1.11	1.46	0.91	0.69	1.17	1.41	0.71	0.57	1.00	1.13	0.56
		(1.64)	(3.79)	(5.78)	(4.68)	(2.07)	(4.46)	(5.93)	(4.61)	(2.93)	(5.28)	(6.28)	(4.18)	(2.59)	(4.72)	(5.20)	(3.60)
9	R1	1.16	0.65	-0.14	-1.30	0.99	0.54	-0.04	-1.02	1.01	0.69	0.15	-0.86	1.09	0.77	0.32	-0.77
		(2.68)	(1.51)	(-.31)	(-5.87)	(2.35)	(1.31)	(-.08)	(-5.06)	(2.42)	(1.66)	(.34)	(-4.50)	(2.59)	(1.82)	(.71)	(-4.13)
	R5	1.39	1.33	1.04	-0.35	1.37	1.31	1.09	-0.28	1.40	1.33	1.13	-0.27	1.41	1.31	1.10	-0.31
		(5.44)	(4.63)	(2.89)	(-2.10)	(5.41)	(4.55)	(3.04)	(-1.77)	(5.53)	(4.61)	(3.16)	(-1.75)	(5.56)	(4.52)	(3.08)	(-2.01)
	R10	1.91	2.09	1.73	-0.17	1.92	2.00	1.67	-0.26	1.86	1.94	1.57	-0.29	1.75	1.79	1.39	-0.35
		(5.81)	(6.20)	(4.59)	(-.85)	(5.85)	(5.89)	(4.36)	(-1.31)	(5.78)	(5.80)	(4.11)	(-1.54)	(5.50)	(5.40)	(3.65)	(-1.96)
	R10-R1	0.74	1.44	1.87	1.13	0.94	1.46	1.70	0.77	0.85	1.25	1.42	0.57	0.66	1.02	1.07	0.41
		(2.31)	(4.87)	(6.75)	(4.72)	(3.20)	(5.57)	(6.62)	(3.49)	(3.11)	(4.95)	(5.72)	(2.90)	(2.54)	(4.18)	(4.46)	(2.24)
12	R1	0.92	0.47	-0.21	-1.13	0.95	0.58	0.00	-0.94	1.04	0.73	0.24	-0.80	1.10	0.81	0.41	-0.69
		(2.20)	(1.13)	(-.46)	(-5.20)	(2.25)	(1.37)	(.01)	(-4.61)	(2.44)	(1.69)	(.53)	(-4.03)	(2.59)	(1.88)	(.90)	(-3.56)
	R5	1.28	1.33	1.07	-0.21	1.36	1.35	1.10	-0.26	1.40	1.38	1.12	-0.29	1.43	1.34	1.08	-0.35
		(5.09)	(4.56)	(3.03)	(-1.28)	(5.38)	(4.68)	(3.10)	(-1.58)	(5.57)	(4.77)	(3.15)	(-1.84)	(5.62)	(4.61)	(3.04)	(-2.30)
	R10	1.94	2.09	1.74	-0.20	1.91	1.89	1.57	-0.33	1.82	1.84	1.45	-0.37	1.71	1.67	1.31	-0.40
		(5.81)	(6.07)	(4.53)	(-.95)	(5.82)	(5.61)	(4.08)	(-1.71)	(5.66)	(5.53)	(3.78)	(-1.92)	(5.37)	(5.04)	(3.39)	(-2.16)
	R10-R1	1.02	1.62	1.95	0.92	0.96	1.31	1.57	0.61	0.78	1.11	1.21	0.43	0.60	0.86	0.90	0.29
		(3.33)	(5.58)	(7.10)	(3.82)	(3.24)	(4.63)	(5.83)	(2.74)	(2.73)	(4.06)	(4.64)	(2.06)	(2.17)	(3.21)	(3.52)	(1.47)

Table 4

Comparing Returns on Winners Minus Losers Portfolio Conditional on Volume To Returns on Unconditional Winners Minus Losers Portfolio

This table compares returns of winner-minus-loser portfolios conditional on trading volume to returns on unconditional winner-minus-loser portfolios using monthly returns in percent from 1965 to 1995. The zero-investment portfolio *R10-R1* is the unconditional winner-minus-loser portfolio, the zero-investment portfolio *R10V3-R1V3* is the winner-minus-loser portfolio using only high volume stocks, and the zero-investment portfolio *R10V1-R1V3* longs the low-volume winner and shorts the high-volume loser. *Diff1=(R10V3-R1V3)-(R10-R1), Diff2=(R10V1-R1V3)-(R10-R1), Diff3=(R10V1-R1V3)-(R10V3-R1V3). Prop1*, *Prop2*, and *Prop3* represent the proportion of total months *NMON* during the sample period, when *Diff1*, *Diff2*, and *Diff3* were respectively greater than zero. The numbers in parentheses in every column except those representing *Prop1*, *Prop2*, and *Prop3* represent ordinary t-statistics for the null hypothesis of zero difference. The numbers in parentheses in columns corresponding to *Prop1*, *Prop2*, and *Prop3* represent non-parametric Z-statistics testing the null hypothesis that the corresponding proportions are equal to 0.5, i.e., the first zero-investment portfolio outperforms the second zero-investment portfolio only 50% of the times. The Z-statistic is computed as follows: $Z = NMON^{1/2} \times (Prop - 0.5)/[0.5\times(1-0.5)]^{1/2}$.

Panel A: J=3										
K	R10-R1	R10V3-R1V3	R10V1-R1V3	Diff1	Diff2	Diff3	Prop1>0	Prop2>0	Prop3>0	NMON
3	.66	1.26	1.07	.60	.41	-.19	.64	.58	.49	370
	(3.06)	(5.69)	(4.12)	(6.32)	(2.03)	(-1.02)	(5.30)	(3.12)	(-.31)	
6	.67	1.11	1.19	.43	.52	.09	.62	.60	.52	367
	(3.38)	(5.42)	(5.05)	(5.78)	(2.88)	(.53)	(4.54)	(3.81)	(.89)	
9	.70	1.06	1.20	.37	.51	.14	.60	.60	.53	364
	(3.93)	(5.88)	(5.35)	(5.53)	(2.82)	(.85)	(3.67)	(3.67)	(1.05)	
12	.72	1.01	1.24	.28	.52	.23	.60	.60	.55	361
	(4.59)	(6.20)	(5.80)	(5.09)	(2.92)	(1.43)	(3.95)	(3.63)	(1.74)	
Panel B: J=6										
K	R10-R1	R10V3-R1V3	R10V1-R1V3	Diff1	Diff2	Diff3	Prob1>0	Prob2>0	Prob3>0	NMON
3	1.04	1.55	1.61	.51	.57	.06	.59	.57	.49	370
	(3.89)	(5.78)	(5.46)	(4.87)	(2.71)	(.31)	(3.54)	(2.70)	(-.31)	
6	1.05	1.46	1.58	.41	.53	.12	.59	.57	.51	367
	(4.28)	(5.93)	(5.80)	(4.46)	(2.78)	(.67)	(3.50)	(2.77)	(.47)	
9	1.08	1.41	1.57	.32	.49	.16	.58	.60	.54	364
	(4.92)	(6.28)	(6.08)	(4.06)	(2.57)	(.89)	(3.14)	(3.77)	(1.57)	
12	.88	1.13	1.36	.25	.48	.23	.59	.58	.54	361
	(4.18)	(5.20)	(5.57)	(3.33)	(2.62)	(1.34)	(3.53)	(2.89)	(1.42)	
Panel C: J=9										
K	R10-R1	R10V3-R1V3	R10V1-R1V3	Diff1	Diff2	Diff3	Prob1>0	Prob2>0	Prob3>0	NMON
3	1.36	1.87	2.05	.51	.69	.17	.60	.62	.54	370
	(4.85)	(6.75)	(6.61)	(5.03)	(3.30)	(.85)	(3.74)	(4.57)	(1.35)	
6	1.35	1.70	1.96	.35	.61	.26	.56	.60	.54	367
	(5.29)	(6.62)	(6.85)	(3.76)	(3.10)	(1.31)	(2.24)	(3.91)	(1.51)	
9	1.15	1.42	1.71	.27	.55	.29	.57	.59	.55	364
	(4.71)	(5.72)	(6.25)	(2.99)	(2.88)	(1.54)	(2.62)	(3.35)	(2.10)	
12	.88	1.07	1.43	.19	.54	.35	.56	.59	.57	361
	(3.72)	(4.46)	(5.42)	(2.31)	(2.90)	(1.96)	(2.26)	(3.32)	(2.68)	
Panel D: J=12										
K	R10-R1	R10V3-R1V3	R10V1-R1V3	Diff1	Diff2	Diff3	Prob1>0	Prob2>0	Prob3>0	NMON
3	1.54	1.95	2.15	.41	.61	.20	.58	.60	.54	370
	(5.63)	(7.10)	(7.07)	(4.12)	(2.85)	(.95)	(3.22)	(3.95)	(1.35)	
6	1.26	1.57	1.90	.30	.64	.33	.56	.59	.55	367
	(4.71)	(5.83)	(6.51)	(3.16)	(3.22)	(1.71)	(2.14)	(3.39)	(1.83)	
9	1.01	1.21	1.58	.21	.57	.37	.56	.57	.57	364
	(3.87)	(4.64)	(5.58)	(2.27)	(2.94)	(1.92)	(2.31)	(2.62)	(2.83)	
12	.74	.90	1.30	.15	.55	.40	.53	.58	.58	361
	(2.93)	(3.52)	(4.67)	(1.77)	(2.90)	(2.16)	(1.21)	(3.21)	(2.89)	

Table 5
Long-Term Returns for Portfolios Based on Price Momentum and Trading Volume

This table summarizes the returns in future years for portfolios based on price momentum and trading volume using data on NYSE/AMEX stocks from 1965-1995. *J* represents the portfolio formation period. *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous *J* months. *V1* represents the portfolio with the lowest trading volume and *V3* represents the portfolio with the highest trading volume. *Year1*, *Year2*, and *Year 3* represent the annual returns of price momentum portfolios in the three 12-month periods following the portfolio formation month. The numbers in parentheses represent t-statistics based on the Hansen-Hodrick correction for autocorrelation up to lag 11.

J	Portfolio	V1			V2			V3			V3-V1		
		Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
3	R1	14.32	19.22	17.50	10.46	16.29	16.87	5.33	13.59	13.11	-8.99	-5.63	-4.39
		(3.04)	(4.57)	(4.13)	(2.26)	(3.53)	(3.78)	(1.28)	(3.05)	(3.19)	(-6.43)	(-3.25)	(-3.00)
	R5	17.87	17.18	16.67	16.95	17.02	15.91	15.82	14.95	14.29	-2.05	-2.23	-2.38
		(5.66)	(5.96)	(5.43)	(4.94)	(5.03)	(4.89)	(3.92)	(3.75)	(3.92)	(-1.09)	(-1.27)	(-1.91)
	R10	21.08	18.27	18.96	22.24	18.40	17.48	19.15	13.06	14.29	-1.93	-5.21	-4.67
		(5.04)	(4.52)	(4.96)	(5.15)	(4.28)	(4.76)	(4.21)	(3.06)	(3.71)	(-1.21)	(-3.57)	(-2.67)
	R10-R1	6.76	-0.95	1.46	11.78	2.11	0.61	13.82	-0.53	1.18	5.86	0.16	-0.28
		(2.89)	(-.70)	(.82)	(5.81)	(1.54)	(.34)	(8.10)	(-.44)	(.95)	(3.78)	(.11)	(-.17)
6	R1	12.68	18.51	17.77	9.76	17.27	17.19	4.47	13.26	12.49	-8.21	-5.25	-5.28
		(2.60)	(4.42)	(4.05)	(1.90)	(3.51)	(3.45)	(1.04)	(2.91)	(2.98)	(-5.49)	(-2.85)	(-3.06)
	R5	17.55	17.32	16.91	16.99	17.00	15.88	15.44	14.81	14.67	-2.11	-2.51	-2.24
		(5.57)	(6.13)	(5.56)	(4.98)	(4.96)	(4.86)	(3.80)	(3.61)	(3.89)	(-1.00)	(-1.25)	(-1.85)
	R10	21.24	19.81	18.60	23.41	17.47	17.14	19.89	13.02	13.91	-1.35	-6.79	-4.69
		(5.43)	(4.47)	(5.02)	(5.52)	(4.06)	(4.64)	(4.41)	(3.03)	(3.71)	(-.65)	(-3.52)	(-2.67)
	R10-R1	8.56	1.30	0.84	13.65	0.21	-0.04	15.42	-0.24	1.42	5.72	-2.04	0.58
		(2.73)	(.65)	(.37)	(4.32)	(.11)	(-.02)	(7.51)	(-.15)	(.85)	(2.73)	(-.93)	(.31)
9	R1	12.34	18.20	17.84	9.95	17.37	17.51	4.72	13.33	12.48	-7.62	-4.86	-5.36
		(2.59)	(4.14)	(3.95)	(1.89)	(3.48)	(3.24)	(1.07)	(2.82)	(2.93)	(-4.77)	(-2.43)	(-3.32)
	R5	17.68	17.09	16.91	16.92	17.13	16.98	14.80	15.16	14.72	-2.89	-1.93	-2.19
		(5.78)	(6.02)	(5.58)	(4.89)	(4.83)	(4.99)	(3.64)	(3.69)	(3.93)	(-1.38)	(-1.04)	(-1.71)
	R10	22.43	21.01	18.12	24.20	17.43	16.77	19.47	12.77	13.79	-2.95	-8.24	-4.32
		(5.42)	(4.53)	(5.07)	(5.80)	(3.90)	(4.70)	(4.25)	(2.98)	(3.64)	(-1.27)	(-4.07)	(-2.05)
	R10-R1	10.08	2.82	0.28	14.25	0.06	-0.74	14.75	-0.56	1.31	4.14	-3.86	1.03
		(3.20)	(1.14)	(.11)	(4.30)	(.03)	(-.24)	(7.14)	(-.31)	(.71)	(1.75)	(-1.57)	(.52)
12	R1	11.72	18.20	19.17	10.34	16.90	18.01	5.67	12.87	12.19	-6.05	-5.33	-6.98
		(2.54)	(4.12)	(4.04)	(2.01)	(3.31)	(3.34)	(1.26)	(2.63)	(2.80)	(-3.64)	(-2.52)	(-4.14)
	R5	18.11	17.26	16.38	17.37	17.41	16.58	14.69	16.00	14.90	-3.41	-1.26	-1.48
		(5.99)	(5.99)	(5.63)	(5.05)	(5.12)	(5.09)	(3.50)	(3.94)	(3.98)	(-1.44)	(-.70)	(-1.09)
	R10	21.78	20.51	17.81	22.77	17.01	16.50	18.39	12.89	13.01	-3.39	-7.62	-4.80
		(5.69)	(4.08)	(5.25)	(5.60)	(3.82)	(4.60)	(4.06)	(3.00)	(3.43)	(-1.60)	(-3.18)	(-2.06)
	R10-R1	10.06	2.31	-1.36	12.42	0.11	-1.51	12.72	0.02	0.82	2.66	-2.29	1.90
		(3.67)	(.79)	(-.43)	(4.12)	(.04)	(-.49)	(6.66)	(.01)	(.39)	(1.19)	(-.70)	(.74)

Table 6

Characteristics of Portfolios Based on Price Momentum and Trading Volume

This table presents portfolio characteristics for portfolios based on price momentum and trading volume. The way these portfolios are formed is described in Table 3. using data on NYSE/AMEX stocks from 1965-1995. *J* represents the portfolio formation period. *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous *J* months. *V1* represents the low trading volume portfolio and *V3* represents high trading volume portfolio. *Return* refers to the average monthly return in percent during the portfolio formation period and *Volume* represents the average daily turnover in percent both during the portfolio formation period. *Size* represents the time-series average of median market capitalization of the portfolio on the portfolio formation date in millions of dollars. *SzRnk* represents the time-series average of the median size decile of the portfolio at the end of the calendar year prior to the calendar year in which the portfolio was formed. *Price* represents the time-series average of the median stock price of the portfolio in dollars on the portfolio formation date. N represents the average number of firms in each portfolio.

		V1						V2						V3					
J	Portfolio	Return	Volume	Size	SzRnk	Price	N	Return	Volume	Size	SzRnk	Price	N	Return	Volume	Size	SzRnk	Price	N
3	R1	-8.27	0.0556	35.21	5.0	8.15	59	-8.59	0.1385	55.62	6.0	9.53	58	-9.57	0.3243	95.38	7.0	11.98	81
	R5	0.07	0.0579	107.80	7.3	19.29	78	0.08	0.1355	348.98	8.2	22.46	71	0.08	0.2780	373.34	7.7	21.10	49
	R10	10.71	0.0630	75.30	5.4	15.82	35	11.04	0.1428	98.72	5.9	16.55	49	12.76	0.3754	139.64	6.3	18.85	114
6	R1	-5.84	0.0588	35.71	5.0	7.65	57	-6.14	0.1430	42.45	6.0	8.51	57	-6.84	0.3232	79.16	7.1	10.64	84
	R5	0.25	0.0608	113.52	7.3	19.41	78	0.25	0.1381	360.69	8.2	22.25	71	0.25	0.2822	397.86	7.8	20.59	49
	R10	7.46	0.0661	93.76	5.4	17.39	35	7.71	0.1480	114.44	5.9	18.77	50	8.79	0.3653	153.38	6.2	20.74	112
9	R1	-4.84	0.0602	34.13	4.9	7.07	55	-5.08	0.1451	38.52	5.9	7.73	58	-5.69	0.3225	71.75	7.2	9.88	85
	R5	0.31	0.0629	113.97	7.4	19.54	78	0.31	0.1394	360.82	8.2	22.58	71	0.31	0.2805	368.70	7.7	20.31	49
	R10	6.11	0.0675	99.78	5.4	18.55	36	6.35	0.1487	113.85	5.9	20.47	51	7.18	0.3583	154.68	6.1	21.60	111
12	R1	-4.19	0.0613	31.14	4.9	6.53	53	-4.44	0.1465	33.85	5.9	7.32	59	-4.99	0.3209	64.57	7.2	9.22	86
	R5	0.37	0.0640	115.81	7.4	19.83	78	0.37	0.1403	371.56	8.2	22.34	71	0.36	0.2822	364.26	7.7	19.87	49
	R10	5.37	0.0687	112.65	5.4	20.70	36	5.61	0.1502	125.99	5.9	21.76	51	6.28	0.3531	168.88	6.1	22.58	111

Table 7

Three-Factor Regressions of Monthly Excess Returns on Price Momentum-Volume Portfolios

This table summarizes three-factor regression results for monthly returns on price momentum-volume portfolios based on four different portfolio strategies: (J=3,K=3), (J=6,K=6), (J=9,K=9), and (J=12, K=12). J represents the months before the portfolio formation date and K represents months after the portfolio formation date. The three-factor regression is as follows:

$$r_i - r_f = a_i + b_i\left(r_m - r_f\right) + s_i SMB + h_i HML + e_i$$

where r_m is the return on the NYSE/AMEX/NASDAQ value-weighted market index, SMB is the small firm factor and HML is the value factor. The numbers within parentheses represent White heteroskedasticity corrected t-statistics. There are 372 total months from Jan. 1965 to Dec. 1995.

Panel A: Portfolio strategy J=3, K=3

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	a				b				s			
R1	-.42	-.71	-1.40	-.98	1.02	1.18	1.29	.27	1.44	1.45	1.41	-.04
	(-2.44)	(-4.47)	(-9.63)	(-5.66)	(16.83)	(19.72)	(23.99)	(4.23)	(15.03)	(15.35)	(17.63)	(-.42)
R5	.13	.13	-.16	-.29	.86	1.05	1.18	.32	.73	.73	1.03	.30
	(1.86)	(1.85)	(-1.89)	(-2.49)	(32.95)	(38.34)	(35.41)	(7.91)	(17.21)	(20.73)	(25.25)	(5.68)
R10	-.07	.28	.15	.23	.89	1.02	1.12	.23	.95	.99	1.03	.08
	(-.50)	(2.41)	(1.32)	(1.39)	(25.00)	(29.46)	(24.74)	(4.06)	(14.72)	(15.96)	(13.76)	(.88)
R10-R1	.35	1.00	1.56	1.21	-.13	-.16	-.17	-.04	-.49	-.46	-.37	.11
	(1.57)	(4.67)	(7.77)	(6.27)	(-1.80)	(-1.99)	(-2.04)	(-.53)	(-4.09)	(-3.36)	(-2.75)	(1.16)

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	h				Adj. R^2			
R1	.72	.59	.31	-.41	.80	.85	.89	.21
	(6.35)	(5.59)	(3.28)	(-3.37)				
R5	.43	.34	.14	-.29	.92	.95	.95	.52
	(8.47)	(7.98)	(3.30)	(-5.86)				
R10	.39	.23	.03	-.36	.79	.87	.89	.21
	(6.33)	(3.89)	(.31)	(-3.66)				
R10-R1	-.33	-.36	-.29	.05	.14	.14	.12	.00
	(-2.66)	(-2.56)	(-1.74)	(.31)				

Panel B: Portfolio strategy J=6, K=6

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	a				b				s			
R1	-0.56	-0.96	-1.54	-0.98	1.02	1.12	1.26	0.24	1.51	1.50	1.55	0.04
	(-2.96)	(-5.78)	(-9.97)	(-5.65)	(16.24)	(19.18)	(23.39)	(4.46)	(12.88)	(15.04)	(15.88)	(0.49)
R5	0.09	0.02	-0.21	-0.30	0.86	1.04	1.17	0.31	0.72	0.75	0.99	0.27
	(1.29)	(0.26)	(-2.55)	(-2.57)	(29.37)	(47.21)	(46.57)	(7.53)	(16.93)	(20.36)	(26.39)	(4.69)
R10	0.30	0.47	0.28	-0.02	0.95	1.06	1.15	0.20	0.93	0.93	1.03	0.10
	(2.20)	(4.16)	(2.32)	(-0.12)	(22.15)	(28.98)	(25.77)	(3.91)	(13.32)	(14.28)	(14.32)	(1.21)
R10-R1	0.86	1.42	1.82	0.96	-0.07	-0.06	-0.11	-0.04	-0.58	-0.58	-0.52	0.06
	(3.48)	(6.24)	(8.56)	(5.00)	(-0.86)	(-0.68)	(-1.28)	(-0.74)	(-3.88)	(-3.85)	(-3.58)	(0.63)

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	h				Adj. R^2			
R1	0.77	0.53	0.38	-0.39	0.77	0.83	0.87	0.20
	(6.86)	(5.45)	(4.11)	(-4.33)				
R5	0.42	0.36	0.16	-0.26	0.92	0.96	0.95	0.47
	(7.60)	(8.88)	(4.23)	(-3.93)				
R10	0.44	0.21	-0.06	-0.51	0.80	0.88	0.89	0.29
	(6.17)	(3.17)	(-.78)	(-5.72)				
R10-R1	-0.33	-0.32	-0.44	-0.11	0.13	0.14	0.15	0.00
	(-2.58)	(-2.26)	(-2.91)	(-1.21)				

Table 7 continued on to the next page.

Panel C: Portfolio strategy J=9, K=9

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	a				b				s			
R1	-.70	-.97	-1.53	-.83	1.01	1.12	1.23	.22	1.58	1.53	1.61	.03
	(-3.71)	(-5.84)	(-9.85)	(-5.01)	(15.13)	(20.62)	(23.54)	(4.29)	(13.93)	(16.00)	(16.70)	(.37)
R5	.13	.01	-.30	-.42	.87	1.03	1.20	.34	.72	.74	1.01	.29
	(1.89)	(.12)	(-3.58)	(-3.87)	(31.95)	(45.35)	(45.29)	(9.02)	(16.31)	(19.72)	(24.89)	(4.93)
R10	.49	.65	.31	-.18	.97	1.08	1.18	.21	.93	.90	1.04	.11
	(3.56)	(5.97)	(2.59)	(-1.18)	(23.08)	(29.69)	(28.21)	(4.72)	(12.23)	(14.03)	(15.57)	(1.53)
R10-R1	1.20	1.62	1.84	.64	-.04	-.04	-.06	-.01	-.65	-.62	-.56	.08
	(4.95)	(7.32)	(8.74)	(3.48)	(-.51)	(-.48)	(-.77)	(-.32)	(-4.14)	(-4.34)	(-4.14)	(.81)
	h				Adj. R^2							
R1	.76	.56	.44	-.32	.77	.83	.87	.17				
	(6.38)	(6.24)	(5.03)	(-3.65)								
R5	.41	.34	.24	-.17	.92	.96	.95	.50				
	(7.82)	(8.18)	(6.58)	(-2.93)								
R10	.38	.11	-.14	-.52	.80	.89	.90	.31				
	(4.85)	(1.64)	(-1.90)	(-6.88)								
R10-R1	-.38	-.45	-.58	-.20	.15	.18	.20	.02				
	(-2.48)	(-3.23)	(-4.12)	(-2.53)								

Panel D: Portfolio strategy J=12, K=12

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	a				b				s			
R1	-.59	-.86	-1.28	-.69	1.02	1.12	1.25	.22	1.60	1.61	1.69	.09
	(-3.09)	(-5.01)	(-8.09)	(-4.07)	(15.95)	(20.12)	(23.45)	(4.53)	(14.01)	(15.76)	(16.40)	(1.03)
R5	.17	.02	-.30	-.47	.88	1.04	1.18	.30	.71	.75	1.03	.32
	(2.51)	(.39)	(-3.94)	(-4.40)	(31.42)	(44.06)	(47.42)	(8.24)	(16.11)	(19.69)	(26.40)	(5.80)
R10	.42	.47	.12	-.30	.95	1.08	1.18	.23	.93	.85	1.03	.10
	(3.17)	(4.57)	(1.05)	(-1.99)	(26.70)	(35.65)	(29.41)	(5.58)	(13.02)	(14.54)	(16.28)	(1.48)
R10-R1	1.01	1.33	1.40	.39	-.07	-.05	-.06	.01	-.68	-.75	-.66	.02
	(4.28)	(6.06)	(6.98)	(2.05)	(-.89)	(-.68)	(-.85)	(.12)	(-4.39)	(-5.21)	(-4.79)	(.17)
	h				Adj. R^2							
R1	.82	.66	.55	-.27	.76	.83	.87	.16				
	(7.21)	(6.59)	(5.87)	(-3.23)								
R5	.44	.38	.23	-.21	.92	.96	.96	.51				
	(8.39)	(8.90)	(6.18)	(-3.76)								
R10	.30	.02	-.22	-.52	.81	.90	.91	.34				
	(4.36)	(.42)	(-3.07)	(-7.05)								
R10-R1	-.52	-.64	-.77	-.25	.18	.26	.29	.02				
	(-3.74)	(-4.66)	(-5.34)	(-2.92)								

Table 9
Book-to-Market Ratios and Profitability Measures for Price Momentum-Trading Volume Portfolios

This table reports accounting profitability measures and the book-to-market ratio based on time-series of cross-sectional medians for price momentum-trading volume portfolios. The sample period is January 1965 to December 1995. The accounting numbers are obtained from COMPUSTAT annual files for all NYSE/AMEX firms that had data available in COMPUSTAT. *R1* represents the *loser* portfolios and *R10* represents the winner portfolio. The most recent fiscal year ending at least four months before the portfolio formation date is assumed to be year 0 for accounting numbers. *V1* represents the lowest trading volume portfolio and *V3* represents the highest trading volume portfolio. B/ M is the book-to-market ratio just before the portfolio formation date where B represents the book value of equity and M represents the market value of equity on the portfolio formation date. ROE represents the *return on equity* defined as ROE(t) = NI(t) / [0.5*[B(t)+B(t-1)]], where NI(t) is net income before extraordinary items for period t, and B(t) is book value for period t. DROE(-) = ROE (0) D ROE(-3) and DROE(+) = ROE(3) D ROE(0) represent changes in ROE over the last three years and the next three years respectively. Numbers in parentheses represent t-statistics computed using Hansen-Hodrick standard errors with sixty lags, i.e., autocorrelation up to sixty months. The number of time-series observations ranges between 330 and 368.

J=6

Portfolio	B/M	ROE(-3)	ROE(0)	ROE(3)	DROE(-)	DROE(+)
R1V1	1.167	10.47	5.22	6.82	-5.25	1.61
(LV-Loser)					(-3.96)	(1.90)
R1V3	.899	13.21	9.77	6.95	-3.44	-2.81
(HV-Loser)					(-2.75)	(-4.35)
R1V1-R1V3	.268	-2.74	-4.55	-.13	-1.81	4.42
(LV-HV)	(4.49)	(-3.13)	(-4.38)	(-.18)	(-2.98)	(6.09)
R10V1	.689	11.28	10.55	12.84	-.73	2.29
(LV-Winner)					(-1.02)	(2.12)
R10V3	.512	11.20	12.17	12.68	.97	.51
(HV-Winner)					(1.00)	(.54)
R10V1-R10V3	.177	.08	-1.62	.16	-1.71	1.78
(LV-HV)	(5.42)	(.21)	(-2.01)	(.28)	(-2.23)	(3.52)

J=12

Portfolio	B/M	ROE(-3)	ROE(0)	ROE(3)	DROE(-)	DROE(+)
R1V1	1.253	10.54	2.84	6.00	-7.70	3.16
(LV-Loser)					(-4.58)	(2.63)
R1V3	1.018	13.46	7.36	6.11	-6.10	-1.25
(HV-Loser)					(-3.52)	(-1.47)
R1V1-R1V3	.235	-2.92	-4.52	-.11	-1.60	4.41
(LV-HV)	(2.77)	(-2.75)	(-5.06)	(-.17)	(-1.81)	(5.66)
R10V1	.584	11.54	12.52	14.02	.98	1.50
(LV-Winner)					(1.66)	(1.50)
R10V3	.458	10.51	13.60	13.49	3.09	-.11
(HV-Winner)					(3.82)	(-.11)
R10V1-R10V3	.126	1.03	-1.08	.53	-2.12	1.61
(LV-HV)	(4.27)	(1.59)	(-1.36)	(.77)	(-4.95)	(2.05)

Panel C: Portfolio strategy J=9, K=9

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	a				b				s			
R1	-.70	-.97	-1.53	-.83	1.01	1.12	1.23	.22	1.58	1.53	1.61	.03
	(-3.71)	(-5.84)	(-9.85)	(-5.01)	(15.13)	(20.62)	(23.54)	(4.29)	(13.93)	(16.00)	(16.70)	(.37)
R5	.13	.01	-.30	-.42	.87	1.03	1.20	.34	.72	.74	1.01	.29
	(1.89)	(.12)	(-3.58)	(-3.87)	(31.95)	(45.35)	(45.29)	(9.02)	(16.31)	(19.72)	(24.89)	(4.93)
R10	.49	.65	.31	-.18	.97	1.08	1.18	.21	.93	.90	1.04	.11
	(3.56)	(5.97)	(2.59)	(-1.18)	(23.08)	(29.69)	(28.21)	(4.72)	(12.23)	(14.03)	(15.57)	(1.53)
R10-R1	1.20	1.62	1.84	.64	-.04	-.04	-.06	-.01	-.65	-.62	-.56	.08
	(4.95)	(7.32)	(8.74)	(3.48)	(-.51)	(-.48)	(-.77)	(-.32)	(-4.14)	(-4.34)	(-4.14)	(.81)
	h				Adj. R^2							
R1	.76	.56	.44	-.32	.77	.83	.87	.17				
	(6.38)	(6.24)	(5.03)	(-3.65)								
R5	.41	.34	.24	-.17	.92	.96	.95	.50				
	(7.82)	(8.18)	(6.58)	(-2.93)								
R10	.38	.11	-.14	-.52	.80	.89	.90	.31				
	(4.85)	(1.64)	(-1.90)	(-6.88)								
R10-R1	-.38	-.45	-.58	-.20	.15	.18	.20	.02				
	(-2.48)	(-3.23)	(-4.12)	(-2.53)								

Panel D: Portfolio strategy J=12, K=12

Portfolio	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1	V1	V2	V3	V3-V1
	a				b				s			
R1	-.59	-.86	-1.28	-.69	1.02	1.12	1.25	.22	1.60	1.61	1.69	.09
	(-3.09)	(-5.01)	(-8.09)	(-4.07)	(15.95)	(20.12)	(23.45)	(4.53)	(14.01)	(15.76)	(16.40)	(1.03)
R5	.17	.02	-.30	-.47	.88	1.04	1.18	.30	.71	.75	1.03	.32
	(2.51)	(.39)	(-3.94)	(-4.40)	(31.42)	(44.06)	(47.42)	(8.24)	(16.11)	(19.69)	(26.40)	(5.80)
R10	.42	.47	.12	-.30	.95	1.08	1.18	.23	.93	.85	1.03	.10
	(3.17)	(4.57)	(1.05)	(-1.99)	(26.70)	(35.65)	(29.41)	(5.58)	(13.02)	(14.54)	(16.28)	(1.48)
R10-R1	1.01	1.33	1.40	.39	-.07	-.05	-.06	.01	-.68	-.75	-.66	.02
	(4.28)	(6.06)	(6.98)	(2.05)	(-.89)	(-.68)	(-.85)	(.12)	(-4.39)	(-5.21)	(-4.79)	(.17)
	h				Adj. R^2							
R1	.82	.66	.55	-.27	.76	.83	.87	.16				
	(7.21)	(6.59)	(5.87)	(-3.23)								
R5	.44	.38	.23	-.21	.92	.96	.96	.51				
	(8.39)	(8.90)	(6.18)	(-3.76)								
R10	.30	.02	-.22	-.52	.81	.90	.91	.34				
	(4.36)	(.42)	(-3.07)	(-7.05)								
R10-R1	-.52	-.64	-.77	-.25	.18	.26	.29	.02				
	(-3.74)	(-4.66)	(-5.34)	(-2.92)								