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Price Momentum and Trading Volume

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ABSTRACT

This study shows that past trading volume provides an important link between "momentum" and "value" strategies. Specifically, we find that firms with high (low) past turnover ratios exhibit many glamour (value) characteristics, earn lower (higher) future returns, and have consistently more negative (positive) earnings surprises over the next eight quarters. Past trading volume also predicts both the magnitude and persistence of price momentum. Specifically, price momentum effects reverse over the next five years, and high (low) volume winners (losers) experience faster reversals. Collectively, our findings show that past volume helps to reconcile intermediate-horizon "underreaction" and long-horizon "overreaction" effects.

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 volume information should be handled and interpreted. Even less is known about how past trading volume interacts with past returns in the prediction of future stock returns. Stock returns and trading volume are jointly determined by the same market dynamics, and are inextricably linked in theory (e.g., Blume, Easley, and O'Hara (1994)). Yet prior empirical studies have generally accorded them separate treatment.

In this study, we investigate the usefulness of trading volume in predicting cross-sectional returns for various price momentum portfolios. The study is organized into two parts. In the first part, we document the interaction between past returns and past trading volume in predicting future returns

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over intermediate and long horizons.[1] In the second part, we evaluate alternative explanations for these empirical regularities. Our findings extend the literature on both price momentum and trading volume. In addition, we establish an important link between intermediate-horizon "momentum" and long-horizon "value" strategies.

We contribute to the literature on price momentum in two ways. First, we show that the price momentum effect documented by Jegadeesh and Titman (1993) reverses over long horizons. Like Jegadeesh and Titman, we find no significant price reversals through the third year following portfolio formation. However, over Years 3 through 5, we find that initial winner portfolios significantly underperform initial loser portfolios. This finding is important because it refutes the common presumption that price momentum is simply a market underreaction. Instead, the evidence suggests that at least a portion of the initial momentum gain is better characterized as an overreaction.[2]

Second, we show that past trading volume predicts both the magnitude and the persistence of future price momentum. Specifically, high (low) volume winners (losers) experience faster momentum reversals. Conditional on past volume, we can create Jegadeesh and Titman–type momentum portfolios (winners minus losers) that either exhibit long-horizon return reversals or long-horizon return continuations. This evidence shows that the information contained in past trading volume can be useful in reconciling intermediate-horizon "underreaction" and long-horizon "overreaction" effects.

Our findings also extend the trading volume literature. Prior research (e.g., Datar, Naik and Radcliffe (1998)) shows that low (high) volume firms earn higher (lower) future returns. We show that this volume effect is long lived (i.e., it is observable over the next three to five years) and is most pronounced among the extreme winner and loser portfolios. More importantly, our evidence contradicts the common interpretation of trading volume as simply a liquidity proxy. These findings instead show that past trading volume is related to various "value" strategies.

Contrary to the liquidity explanation, we find that high (low) volume stocks earn higher (lower) average returns in each of the five years prior to portfolio formation. We show that trading volume is only weakly correlated with traditional liquidity proxies and that the volume effect is robust to various risk adjustments. We find that the volume-based momentum effect holds even in a subsample of the largest 50 percent of New York (NYSE) and American Stock Exchange (AMEX) firms. Finally, we show that most of the excess returns to volume-based strategies is attributable to changes in trad-

[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.

[2] Studies that characterize price momentum as an underreaction include Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999). Conversely, studies that characterize price momentum to be the result of overreaction include DeLong et al. (1990) and Daniel, Hirshleifer, and Subrahmanyam (1998).

ing volume. Firms whose recent volume is higher (lower) than volume four years ago experience significantly lower (higher) future returns. The change in volume measures abnormal trading activity and is unlikely to be a liquidity proxy.

On the other hand, we find that low (high) volume stocks display many characteristics commonly associated with value (glamour) investing. Specifically, lower (higher) trading volume is associated with worse (better) current operating performance, larger (smaller) declines in past operating performance, higher (lower) book-to-market ratios, lower (higher) analyst followings, lower (higher) long-term earnings growth estimates, higher (lower) factor loadings on the Fama–French HML factor, and lower (higher) stock returns over the previous five years.

Further analyses show that the higher (lower) future returns experienced by low (high) volume stocks are related to investor misperceptions about future earnings. Analysts provide lower (higher) long-term earnings growth forecasts for low (high) volume stocks. However, low (high) volume firms experience significantly better (worse) future operating performance. Moreover, we find that short-window earnings announcement returns are significantly more positive (negative) for low (high) volume firms over each of the next eight quarters. The same pattern is observed for both past winners and past losers. Evidently the market is "surprised" by the systematically higher (lower) future earnings of low (high) volume firms.

The fact that a market statistic widely used in technical analysis can provide information about relative under- or over-valuation is surprising and is difficult to reconcile with existing theoretical work. To help explain these results, we evaluate the predictions of several behavioral models. We conclude that each model has specific features that help explain some aspects of our findings but that no single model accommodates all our findings. We also discuss an interesting illustrative tool, dubbed the momentum life cycle (MLC) hypothesis, that captures some of the most salient features of our empirical results.

The remainder of the paper is organized as follows. In the next section, we discuss related literature. In Section II, we describe our sample and methodology. In Section III we present our empirical results. In Section IV, we further explore the information content of trading volume and relate these findings to several behavioral models. Finally, in Section V, we conclude with a summary of the evidence and a discussion of the implications.

I. Related Literature

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 in which long-term past losers outperform long-term past winners over the subsequent three to five years. Similarly, Jegadeesh (1990) and Lehmann (1990) report price reversals at monthly and weekly intervals.

But perhaps the most puzzling results are the intermediate-horizon return continuations reported by Jegadeesh and Titman (1993). Forming portfolios based on past three- to 12-month returns they show that past winners on average continue to outperform past losers over the next three to 12 months. Although many competing explanations have been suggested for the long-horizon price reversal patterns,[3] far fewer explanations have been advanced to explain the intermediate-horizon price momentum effect.

For example, Fama and French (1996) show that a three-factor model of returns 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 that price momentum is not subsumed by earnings momentum. Rouwenhorst (1998) finds a similar pattern of intermediate-horizon price momentum in 12 other countries, suggesting that the effect is not likely due to a data snooping bias.

More recently, Conrad and Kaul (1998) suggest that the momentum effect may be due to cross-sectional variation in the mean returns of individual securities. Moskowitz and Grinblatt (1999) claim that a significant component of firm-specific momentum can be explained by industry momentum. However, the evidence in Grundy and Martin (1998) suggests momentum effects are not explained by time-varying factor exposures, cross-sectional differences in expected returns, or industry effects.[4] None of these studies examine the interaction between past trading volume and past price movements in predicting cross-sectional returns.

At least two theoretical 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, their model focuses on short-run liquidity imbalances (or volume shocks) of a daily or weekly duration and makes no predictions about longer-term returns. Blume et al. (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.

Our study is also tangentially related to Conrad, Hameed, and Niden (1994). Conrad et al. show that, at weekly intervals, the price reversal pattern is observed only for heavily traded stocks; less traded stocks exhibit return

[3] 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-autocorrelations (Lo and MacKinlay (1990)) and transaction costs (Lehmann (1990)).

[4] As we show later, industry adjustments account for approximately 20 percent of the price momentum effect in our sample but have no effect on the predictive power of volume.

continuation.[5] The Conrad et al. study focuses on short-term price movements, because it is motivated by market microstructure concerns raised in Campbell et al. (1993). Our interest lies in the prediction of cross-sectional returns over longer (three-month and longer) horizons. In the intermediate time horizon, the empirical puzzle is not return reversal but return continuation. Given the longer time horizons, these price continuations are unlikely to be due to the short-term liquidity shocks. In fact, we deliberately form our portfolios with a one-week (or a one-month) lag to minimize the effect of bid-ask bounce and short-horizon return reversals.

In a related study, Datar et al. (1998) show that low turnover stocks generally earn higher returns than high turnover stocks. They interpret this result as providing support for the liquidity hypothesis of Amihud and Mendelson (1986).[6] 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 confirm their findings but also present additional evidence, which is difficult to reconcile with the liquidity hypothesis.

In sum, 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. We integrate these two lines of research and report the joint distribution of future returns conditional on both past trading volume and past returns. More importantly, as we show later, our results provide a bridge between past studies on market over- and underreaction, in addition to a link to recent theoretical studies in behavioral finance.

II. Sample and Methodology

Our sample consists of all firms listed on the NYSE and AMEX during the period January 1965 through December 1995 with at least two years of data prior to the portfolio formation date. 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 is 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 average turnover, mixing Nasdaq and NYSE firms will result in inconsistent treatment of firms across these different markets.[7]

[5] Along the same lines, Chordia and Swaminathan (1999) find that at short horizons low volume stocks exhibit more underreaction than high volume stocks.

[6] In a similar study, Brennan, Chordia, and Subrahmanyam (1998) use dollar-trading volume as a proxy of liquidity and find similar results.

[7] We have also replicated our results using a holdout sample consisting of just Nasdaq-NMS firms from 1983 to 1996. The predictive power of trading volume is even stronger among Nasdaq-NMS firms. However, we suspect illiquidity problems are more pervasive with the Nasdaq-NMS sample.

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 price 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. Trading volume (*Volume*) is defined as the average daily turnover in percentage 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.[8] Descriptive statistics that require accounting data (e.g., the B/M ratio and the return-on-equity) are based on the subset of firms in each portfolio that also are in the COMPUSTAT database. Tests involving long-term earnings forecasts or number of analysts are based on firms that are in the I/B/E/S database.

At the beginning of each month, from January 1965 to December 1995, we rank all eligible stocks independently on the basis of past returns and past trading volume. The stocks are then assigned to one of 10 portfolios based on returns over the previous J months and one of three portfolios based on the trading volume over the same time period.[9] 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 ($K = 3$, 6, 9, or 12) and over the next five years.

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 three-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 (approximately) one-third of the portfolio each month and carrying over the rest from the previous month. The technique allows us to use simple t-statistics for monthly returns. To avoid potential microstructure biases, we impose a one-week lag between the end of the portfolio formation period (J) and the beginning of the performance measurement period (K).[10]

III. Results for Volume-Based Price Momentum Strategies

In this section, we discuss the empirical results for volume-based price momentum strategies. In Subsection A, we confirm the price momentum strategy for our sample of firms. We also ensure that our results are con-

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

[9] We have also formed intersections with five momentum and five volume portfolios and three momentum and 10 volume portfolios. These results are presented in Table III.

[10] We have also replicated our tests with a one-month lag and found similar results.

sistent 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 over intermediate horizons. In Subsection C, we provide results of robustness checks for volume-based price momentum strategies. In Subsection D, we provide results from Fama–French three-factor regressions. In Subsection E, we examine long-horizon (one- to five-year) returns to various volume-based price momentum portfolios. Finally in Subsection F, we provide evidence on the usefulness of trading volume in predicting the timing of price momentum reversals.

A. Price Momentum

Table I 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 three, six, nine, and 12 months. 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 papers (Jegadeesh and Titman (1993)) and are omitted for simplicity of presentation.

For each portfolio, Table I reports the mean return volume during the portfolio formation period, the time-series average of the median size decile of the portfolio based on NYSE/AMEX cutoffs (SzRnk), and the time-series average of the median stock price (Price) as of portfolio formation date. At the portfolio formation date, stocks in the winner portfolio are typically larger (column 5) and have higher price (column 6) than stocks in the loser portfolio. This is not surprising given the difference in recent returns. For example, for the six-month formation period ($J = 6$), losers lost an average of 6.36 percent per month over the past six months, whereas winners gained 8.30 percent per month (Column 3).

The results in Columns 3 and 4 confirm 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 volume. For example, the average daily turnover for the R1 and R10 portfolios in the six-month portfolio formation period is 0.17 percent and 0.23 percent, respectively, compared to 0.12 percent 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)).

Columns 7 through 10 report equal-weighted average monthly returns 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 return from a dollar-neutral strategy of buying the extreme winners and selling the extreme losers (R10 − R1). These results confirm the presence of price momentum in our sample. For example, with a six-month portfolio formation period ($J = 6$), past winners gain an average of 1.65 percent per month over the next nine

Table I

Returns to Price Momentum Portfolios

This table presents average monthly and annual returns in percentages for price momentum portfolio strategies involving NYSE/AMEX stocks for the time period from 1965 to 1995. At the beginning of each month starting in January 1965, all stocks in the NYSE and AMEX are sorted based on their previous J months' returns and divided into 10 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. K represents monthly holding periods where K = three, six, nine, or 12 months. Monthly holding period returns are computed as an equal-weighted average of returns from strategies initiated at the beginning of this month and past months. The annual returns (*Year 1*, *Year 2*, *Year 3*, *Year 4*, and *Year 5*) are computed as event time returns for five 12-month periods following the portfolio formation date. *Return* refers to the geometric average monthly return in percentages, and *Volume* represents the average daily turnover in percentages, both measured over the portfolio formation period, J. *SzRnk* represents the time-series average of the median size decile of the portfolio (based on NYSE/AMEX stocks in the sample) on the portfolio formation date. *Price* represents the time-series average of the median stock price of the portfolio in dollars on the portfolio formation date. The numbers in parentheses represent t-statistics. The t-statistics for monthly return (K = three, six nine, or 12) are simple t-statistics, whereas those for annual returns are based on the Hansen–Hodrick (1980) correction for autocorrelation up to lag 11.

J	Portfolio	Return	Volume	SzRnk	Price	Monthly Returns K = 3	Monthly Returns K = 6	Monthly Returns K = 9	Monthly Returns K = 12	Annual Event Time Returns Year 1	Annual Event Time Returns Year 2	Annual Event Time Returns Year 3	Annual Event Time Returns Year 4	Annual Event Time Returns Year 5
3	R1	−8.91	0.1604	3.68	9.91	0.76	0.73	0.77	0.74	8.95	15.86	15.27	14.81	15.82
						(1.88)	(1.81)	(1.93)	(1.86)	(1.91)	(3.46)	(3.40)	(3.53)	(4.13)
	R5	0.08	0.1185	6.09	20.96	1.37	1.36	1.33	1.30	17.11	16.90	15.54	15.19	15.89
						(4.84)	(4.76)	(4.65)	(4.55)	(4.74)	(4.87)	(4.51)	(4.59)	(5.01)
	R10	12.00	0.2403	4.82	17.45	1.42	1.40	1.47	1.46	19.57	15.03	15.51	13.22	13.35
						(4.28)	(4.16)	(4.33)	(4.24)	(4.28)	(3.37)	(3.93)	(3.52)	(3.30)
	R10 − R1					0.66	0.67	0.70	0.72	10.62	−0.84	0.24	−1.59	−2.46
						(3.06)	(3.38)	(3.93)	(4.59)	(5.77)	(−0.69)	(0.15)	(−1.27)	(−2.57)
6	R1	−6.36	0.1671	3.56	9.00	0.59	0.58	0.57	0.65	7.92	15.91	15.46	15.57	15.96
						(1.39)	(1.38)	(1.40)	(1.58)	(1.60)	(3.35)	(3.27)	(3.54)	(4.25)
	R5	0.25	0.1212	6.13	20.79	1.31	1.29	1.31	1.30	16.95	16.98	15.65	14.82	15.50
						(4.66)	(4.55)	(4.59)	(4.52)	(4.73)	(4.96)	(4.49)	(4.46)	(4.91)
	R10	8.30	0.2349	5.05	19.41	1.62	1.62	1.65	1.53	20.41	14.81	15.15	12.81	13.00
						(4.76)	(4.72)	(4.78)	(4.45)	(4.54)	(3.27)	(3.97)	(3.41)	(3.14)
	R10 − R1					1.04	1.05	1.08	0.88	12.49	−1.10	−0.32	−2.77	−2.96
						(3.89)	(4.28)	(4.92)	(4.18)	(5.04)	(−0.66)	(−0.15)	(−1.68)	(−2.46)
9	R1	−5.27	0.1713	3.34	8.34	0.49	0.44	0.55	0.66	7.89	15.91	15.76	16.02	15.77
						(1.15)	(1.06)	(1.32)	(1.57)	(1.57)	(3.26)	(3.18)	(3.56)	(4.19)
	R5	0.31	0.1230	6.12	20.87	1.28	1.28	1.30	1.30	16.81	16.96	16.16	15.32	15.77
						(4.48)	(4.46)	(4.56)	(4.52)	(4.72)	(4.82)	(4.59)	(4.67)	(4.95)
	R10	6.78	0.2304	5.14	20.59	1.85	1.79	1.71	1.54	20.59	14.97	14.88	12.16	12.52
						(5.31)	(5.08)	(4.86)	(4.41)	(4.54)	(3.28)	(3.98)	(3.18)	(3.04)
	R10 − R1					1.36	1.35	1.15	0.88	12.70	−0.95	−0.88	−3.86	−3.26
						(4.85)	(5.29)	(4.71)	(3.72)	(5.10)	(−0.46)	(−0.35)	(−2.12)	(−2.45)
12	R1	−4.61	0.1727	3.28	7.78	0.34	0.45	0.60	0.72	8.14	15.63	16.15	16.23	15.99
						(0.80)	(1.05)	(1.41)	(1.66)	(1.63)	(3.11)	(3.18)	(3.59)	(4.20)
	R5	0.37	0.1239	6.13	20.83	1.24	1.28	1.32	1.31	17.06	17.34	15.83	15.43	15.90
						(4.34)	(4.51)	(4.63)	(4.56)	(4.83)	(4.97)	(4.65)	(4.74)	(4.96)
	R10	5.96	0.2300	5.27	21.79	1.88	1.71	1.61	1.46	19.70	14.93	14.18	11.70	12.24
						(5.29)	(4.84)	(4.59)	(4.15)	(4.37)	(3.26)	(3.82)	(3.02)	(2.99)
	R10 − R1					1.54	1.26	1.01	0.74	11.56	−0.70	−1.96	−4.54	−3.75
						(5.63)	(4.71)	(3.87)	(2.93)	(5.08)	(−0.29)	(−0.70)	(−2.44)	(−2.47)

months ($K = 9$). Past losers gain an average of only 0.57 percent per month over the same time period. The difference between R10 and R1 is 1.08 percent per month. The difference in average monthly returns between R10 and R1 is significantly positive in all (J,K) combinations.

The last five columns of Table I report the annual event-time returns for each portfolio for five 12-month periods following the portfolio formation date, with t-statistics based on the Hansen and Hodrick (1980) correction for autocorrelation up to lag 11. In Year 1, the R10 − 1 portfolio yields a statistically significant return of between 10.62 percent and 12.70 percent per year. Consistent with Jegadeesh and Titman (1993), we observe a modest reversal to momentum profits in Years 2 and 3. As in their study, we find that the negative returns in these two years are not statistically significant and are not sufficient to explain the initial momentum gains in Year 1.

When we extend the event time to Years 4 and 5, a pattern of price reversal begins to emerge. The last two columns show that R10 − R1 returns are negative in Years 4 and 5 for all formation periods. The reversal pattern becomes stronger monotonically as the formation period (J) increases. For the longest formation period ($J = 12$), the sum of the losses in Years 2 through 5 (10.95 percent) almost offsets the entire gain from Year 1 (11.56 percent). This reversal pattern is not documented in prior studies that limit return prediction to Year 3.

In sum, Table I confirms prior findings on price momentum. It also extends prior results by documenting significant long-term price reversals in Years 4 and 5. Our results show intermediate-horizon price momentum effects do eventually reverse. Moreover, the longer the estimation period for past returns, the more imminent the future price reversals. We will expand on this theme later when we introduce autocorrelation evidence based on regression tests (see Table VIII).

B. Volume-Based Price Momentum

Table II reports returns to portfolios formed on the basis of a two-way sort between 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 10 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 represents 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 II. 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. For example, with a nine-month portfolio formation period and six month holding period ($J = 9$, $K = 6$), low volume losers outperform high volume losers by 1.02 percent per month, whereas low volume winners outperform high volume winners by 0.26 percent 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 Datar et al. (1998). In that paper, this finding is interpreted as evidence that low volume firms command a greater illiquidity premium. However, Table II also contains evidence that is difficult to explain by the liquidity explanation. 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 $J = 6$ and $K = 6$, the price momentum spread is 1.46 percent for high volume firms and only 0.54 percent for low volume firms. The difference of 0.91 percent per month 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 lower liquidity should earn higher expected returns. 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 percent per month, or approximately 11 percent annualized. For the liquidity hypothesis to hold, high volume winners would have to be much more illiquid than are high volume losers.

A closer examination shows that this counterintuitive result is driven primarily by the return differential in the loser portfolio (R1). Low volume losers (R1V1) rebound strongly in the next 12 months relative to high volume losers, averaging more than one percent per month in virtually all (J,K) combinations. In contrast, high volume losers (R1V3) earn an average return of between −0.21 percent and +0.41 percent per month. The return differential between high and low volume winners is not nearly as large. In most cells the difference in returns between low volume winners and high volume winners is small and statistically insignificant.[11] Nevertheless, high volume winners generally underperform low volume winners, so buying high volume winners does not enhance the performance of the price momentum strategy.

In sum, Table II shows that over the next 12 months, price momentum is more pronounced among high volume stocks. In addition, we find that controlling for price momentum, low volume stocks generally outperform high volume stocks. This effect is most pronounced among losers in the intermediate horizon.

[11] As we show later, this result is specific to the first year after portfolio formation. Table VI reports that low volume winners outperform high volume winners by two percent to six percent per year beyond Year 1.

Table II

Monthly Returns for Portfolios Based on Price Momentum and Trading Volume

This table presents average monthly returns from portfolio strategies based on an independent two-way based on past returns and past average daily turnover for the 1965 to 1995 time period. At the beginning of each month all available stocks in the NYSE/AMEX are sorted independently based on past J month returns and divided into 10 portfolios. K represents monthly holding periods where K = three, six, nine, or 12 months. *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. Monthly returns are computed based on the portfolio rebalancing strategy described in Table I. 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)	(0.44)	(−5.11)	(3.06)	(2.16)	(0.59)	(−5.14)	(3.12)	(2.24)	(0.81)	(−5.02)	(3.06)	(2.06)	(0.85)	(−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	1.25	1.61	1.45	0.20	1.43	1.59	1.36	−0.07	1.54	1.65	1.41	−0.13	1.59	1.65	1.37	−0.23
		(4.12)	(4.93)	(4.05)	(1.09)	(4.68)	(4.87)	(3.77)	(−0.45)	(4.97)	(5.05)	(3.87)	(−0.80)	(5.03)	(5.02)	(3.71)	(−1.38)
	R10 − R1	0.01	0.66	1.26	1.26	0.25	0.73	1.11	0.86	0.33	0.76	1.06	0.73	0.43	0.85	1.01	0.58
		(0.03)	(2.78)	(5.69)	(6.09)	(1.25)	(3.56)	(5.42)	(5.71)	(1.83)	(4.10)	(5.88)	(5.52)	(2.57)	(5.24)	(6.20)	(5.07)
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)	(0.06)	(−5.22)	(2.74)	(1.61)	(0.20)	(−5.19)	(2.58)	(1.66)	(0.36)	(−4.82)	(2.70)	(1.82)	(0.67)	(−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)	(−0.31)	(5.30)	(5.41)	(4.16)	(−0.67)	(5.52)	(5.59)	(4.18)	(−0.89)	(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)	(−0.31)	(−5.87)	(2.35)	(1.31)	(−0.08)	(−5.06)	(2.42)	(1.66)	(0.34)	(−4.50)	(2.59)	(1.82)	(0.71)	(−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)	(−0.85)	(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)	(−0.46)	(−5.20)	(2.25)	(1.37)	(0.01)	(−4.61)	(2.44)	(1.69)	(0.53)	(−4.03)	(2.59)	(1.88)	(0.90)	(−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)	(−0.95)	(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)

C. Robustness Tests

Table III presents various robustness checks on these basic intermediate-horizon results. Panel A confirms these patterns for three subperiods. 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, low volume stocks outperform high volume stocks, and momentum is stronger among high volume stocks. In fact, the result is strongest in the more recent subperiod.

Our earlier results are based on 10 price momentum portfolios and three trading volume portfolios (10×3). Table III shows that our results are not specific to this partitioning. Panel B reports results using three price momentum portfolios and 10 trading volume portfolios (3×10), whereas Panel C reports results using five price momentum and five volume portfolios (5×5). Generally, the volume-based results are as strong as or stronger than those reported in Table II. In fact, in these partitions, low volume winners generally outperform high volume winners by a wider margin than was evident in Table II.

To ensure that these results are not driven by a few small stocks, Panel D of Table III reports the volume-based price momentum results using only the largest 50 percent of all NYSE/AMEX stocks. Not surprisingly, both the momentum and volume effects are weaker for this restricted sample. However, the volume-based results continue to obtain. For example, for $J = 6$, $K = 6$, the momentum spread is 0.95 percent for high volume firms and only 0.24 percent for low volume firms. This effect is again driven by low volume losers that gain 1.09 percent per month, as compared to high volume losers that gain only 0.44 percent per month.[12]

D. Risk Adjustments

Table IV reports descriptive characteristics for various price momentum and volume portfolios. Looking down each column, we see that losers are generally smaller firms with lower stock prices. This is not surprising given the losses they recently sustained. Looking across each row, we see that high and low volume portfolios do not differ significantly in terms of their median stock price or firm size. High volume firms tend to be somewhat larger and more highly priced, but the difference is not large. For example, Panel A shows that high volume losers (R1V3) have a median price of \$10.64 while low volume losers have a median price of \$7.65. In later tests, we provide more formal controls for firm size and industry differences.

[12] We have also replicated the results in Table II using value-weighted portfolio returns. We obtain similar but (not surprisingly) slightly weaker results. For instance, for the ($J = 6$, $K = 6$) strategy, the R10 − R1 returns for low, medium, and high volume portfolios are 0.35 percent, 1.04 percent, and 1.15 percent per month, respectively. The difference in R10 − R1 between high and low volume is 0.80 percent, which is statistically significant at the 1 percent level.

Table V provides additional evidence on the source of abnormal returns for the various volume-based price momentum strategies. In this table, we report the results from time-series regressions based on the Fama–French (1993) three-factor model.[13] Specifically, we run the following time-series regression using monthly portfolio returns:

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

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 book-to-market (value) factor; b_i, s_i, h_i are the corresponding factor loadings; and a_i is the intercept or the *alpha* of the portfolio.[14] For parsimony, we report results for symmetrical combinations of portfolio formation and holding periods (J and K = six 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 cannot be 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 high volume (V3) firms than for low volume (V1) firms. Finally, a strategy of buying low volume winners and selling high volume losers yields average abnormal returns of between one percent and two percent per month in both 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 six-month horizon. Here 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, that is, stocks with high book-to-market ratios. High volume stocks, on the other hand, behave more like glamour stocks, that is, stocks with low book-to-market ratios. In fact, high volume winners (R10V3) tend to have negative loadings on the HML factor.

[13] We have also performed characteristics-based risk adjustment and computed size-adjusted, industry-adjusted, and size- and book-to-market-adjusted returns to check the robustness of results in Table II. These results confirm the basic findings. We do not report these to conserve space.

[14] 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).

Table III

Returns on Portfolios Based on Price Momentum and Trading Volume: Robustness Tests

This table presents subsample period results, results for strategies using only the largest 50% of NYSE/AMEX stocks, and results for two-way sorts involving five price momentum and five trading volume portfolios and three price momentum and 10 trading volume portfolios. We present all these results only for the six-month portfolio formation period (J = 6). For subsample tests we form 10 price momentum and three trading volume portfolios. For strategies involving the largest 50% of NYSE/AMEX stocks, we form five price momentum and five trading volume portfolios. Note that we use turnover as a proxy of trading volum. K represents monthly holding periods where K = three, six, nine or 12 months. *RI* represents the *loser* portfolio. *R10* (*R5*) represents the *winner* portfolio when we form 10 (five) price momentum portfolios. *V1* represents the lowest trading volume portfolio. *V3* (*V5*) represents the highest trading volume portfolio when we form three (five) volume portfolios. The portfolios are rebalanced each month as described in Table I. The numbers in parentheses are simple t-statistics.

Panel A: Subsample Results

	K = 3				K = 6				K = 9				K = 12			
Portfolio	V1	V2	V3	V3 − V1	V1	V2	V3	V3 − V1	V1	V2	V3	V3 − V1	V1	V2	V3	V3 − V1
Sample period: 1965–1975																
R1	0.83	0.82	−0.19	−1.03	1.00	0.75	−0.07	−1.07	0.93	0.78	−0.01	−0.94	0.80	0.76	0.00	−0.81
	(1.00)	(0.92)	(−0.21)	(−2.81)	(1.21)	(0.86)	(−0.08)	(−3.07)	(1.15)	(0.90)	(−0.01)	(−2.76)	(0.98)	(0.87)	(−0.01)	(−2.39)
R5	0.83	0.79	0.57	−0.26	0.80	0.86	0.54	−0.25	0.84	0.93	0.58	−0.25	0.83	0.87	0.50	−0.33
	(1.70)	(1.32)	(0.79)	(−0.75)	(1.59)	(1.42)	(0.75)	(−0.73)	(1.65)	(1.50)	(0.79)	(−0.73)	(1.61)	(1.39)	(0.66)	(−0.94)
R10	1.27	1.48	1.07	−0.20	1.09	1.38	0.97	−0.13	1.11	1.43	1.01	−0.10	0.98	1.29	0.78	−0.20
	(2.37)	(2.57)	(1.55)	(−0.46)	(2.07)	(2.34)	(1.37)	(−0.34)	(2.11)	(2.39)	(1.40)	(−0.25)	(1.82)	(2.09)	(1.07)	(−0.53)
R10 − R1	0.43	0.66	1.26	0.83	0.09	0.62	1.04	0.95	0.17	0.66	1.02	0.85	0.18	0.53	0.79	0.61
	(0.71)	(1.07)	(2.18)	(1.86)	(0.17)	(1.11)	(1.96)	(2.45)	(0.34)	(1.31)	(2.15)	(2.44)	(0.38)	(1.10)	(1.75)	(1.94)
Sample period: 1976–1985																
R1	2.17	1.40	0.87	−1.29	1.95	1.29	0.83	−1.12	1.84	1.22	0.86	−0.98	1.97	1.34	1.06	−0.91
	(3.36)	(2.13)	(1.31)	(−3.43)	(3.13)	(2.02)	(1.27)	(−3.15)	(3.05)	(1.97)	(1.33)	(−3.15)	(3.24)	(2.16)	(1.63)	(−3.11)
R5	2.10	1.93	1.96	−0.14	2.16	1.90	1.87	−0.29	2.14	1.91	1.88	−0.27	2.17	1.91	1.89	−0.28
	(5.14)	(4.23)	(3.40)	(−0.53)	(5.19)	(4.20)	(3.30)	(−1.15)	(5.14)	(4.23)	(3.36)	(−1.12)	(5.17)	(4.27)	(3.40)	(−1.23)
R10	2.45	2.64	2.31	−0.14	2.63	2.60	2.30	−0.33	2.66	2.59	2.27	−0.38	2.59	2.47	2.18	−0.41
	(3.86)	(4.29)	(3.55)	(−0.47)	(4.21)	(4.23)	(3.52)	(−1.18)	(4.28)	(4.25)	(3.49)	(−1.36)	(4.31)	(4.14)	(3.37)	(−1.55)
R10 − R1	0.29	1.23	1.44	1.15	0.68	1.31	1.46	0.79	0.82	1.38	1.41	0.60	0.62	1.13	1.12	0.50
	(0.68)	(3.17)	(4.12)	(3.37)	(1.80)	(3.86)	(4.73)	(2.80)	(2.53)	(4.49)	(4.93)	(2.67)	(2.13)	(4.01)	(4.04)	(2.52)
Sample period: 1985–1995																
R1	0.51	0.09	−0.59	−1.10	0.43	−0.04	−0.48	−0.91	0.33	0.02	−0.38	−0.70	0.49	0.14	−0.16	−0.65
	(0.81)	(0.16)	(−0.88)	(−2.83)	(0.67)	(−0.07)	(−0.72)	(−2.77)	(0.51)	(0.04)	(−0.57)	(−2.44)	(0.77)	(0.23)	(−0.24)	(−2.43)
R5	1.23	1.35	1.10	−0.14	1.15	1.29	1.06	−0.09	1.18	1.23	1.05	−0.13	1.17	1.18	0.99	−0.17
	(3.33)	(3.38)	(2.29)	(−0.64)	(3.12)	(3.17)	(2.22)	(−0.46)	(3.22)	(3.07)	(2.21)	(−0.72)	(3.18)	(2.90)	(2.09)	(−0.94)
R10	1.21	1.37	1.37	0.16	1.32	1.39	1.41	0.09	1.43	1.53	1.42	0.00	1.41	1.49	1.32	−0.09
	(2.60)	(2.77)	(2.54)	(0.58)	(2.86)	(2.83)	(2.56)	(0.33)	(3.13)	(3.13)	(2.59)	(−0.02)	(3.16)	(3.17)	(2.44)	(−0.37)
R10 − R1	0.70	1.27	1.96	1.26	0.89	1.43	1.89	1.00	1.10	1.50	1.80	0.70	0.92	1.36	1.48	0.56
	(1.66)	(3.69)	(4.85)	(3.25)	(2.28)	(4.30)	(4.87)	(2.90)	(2.97)	(5.00)	(4.85)	(2.31)	(2.60)	(4.51)	(3.96)	(2.03)

Panel B: Three Price Momentum, 10 Trading Volume Portfolios

	$K = 3$				$K = 6$				$K = 9$				$K = 12$			
Portfolio	V1	V5	V10	V10 − V1	V1	V5	V10	V10 − V1	V1	V5	V10	V10 − V1	V1	V5	V10	V10 − V1
R1	1.22	1.15	0.01	−1.21	1.25	1.07	0.12	−1.13	1.25	1.04	0.20	−1.06	1.28	1.07	0.30	−0.98
	(3.74)	(3.31)	(0.01)	(−4.75)	(3.83)	(3.12)	(0.27)	(−4.61)	(3.93)	(3.09)	(0.45)	(−4.46)	(4.02)	(3.16)	(0.71)	(−4.25)
R2	1.39	1.34	0.71	−0.68	1.42	1.34	0.71	−0.71	1.44	1.37	0.80	−0.64	1.44	1.34	0.79	−0.65
	(5.79)	(4.73)	(1.83)	(−2.78)	(5.82)	(4.74)	(1.83)	(−2.99)	(5.88)	(4.82)	(2.07)	(−2.78)	(5.90)	(4.69)	(2.03)	(−2.94)
R3	1.42	1.45	1.13	−0.29	1.57	1.52	1.19	−0.38	1.63	1.60	1.20	−0.43	1.56	1.55	1.09	−0.48
	(5.74)	(5.13)	(2.98)	(−1.25)	(6.21)	(5.29)	(3.10)	(−1.65)	(6.39)	(5.53)	(3.11)	(−1.95)	(6.16)	(5.37)	(2.82)	(−2.22)
R3 − R1	0.20	0.30	1.13	0.92	0.32	0.46	1.08	0.75	0.38	0.56	1.00	0.63	0.28	0.48	0.78	0.50
	(1.04)	(1.65)	(5.42)	(4.77)	(1.81)	(2.77)	(5.83)	(4.54)	(2.42)	(3.89)	(5.95)	(4.42)	(1.89)	(3.48)	(4.84)	(3.88)

Panel C: Five Price Momentum, Five Trading Volume Portfolios

	$K = 3$				$K = 6$				$K = 9$				$K = 12$			
Portfolio	V1	V3	V5	V5 − V1	V1	V3	V5	V5 − V1	V1	V3	V5	V5 − V1	V1	V3	V5	V5 − V1
R1	1.23	1.00	0.12	−1.11	1.24	0.88	0.22	−1.02	1.20	0.87	0.29	−0.91	1.25	0.91	0.39	−0.86
	(3.32)	(2.64)	(0.27)	(−4.87)	(3.40)	(2.36)	(0.51)	(−4.75)	(3.38)	(2.38)	(0.68)	(−4.50)	(3.51)	(2.47)	(0.92)	(−4.38)
R3	1.40	1.39	0.98	−0.42	1.41	1.37	0.98	−0.43	1.44	1.38	1.01	−0.43	1.44	1.34	0.98	−0.46
	(5.81)	(4.86)	(2.67)	(−2.10)	(5.71)	(4.79)	(2.66)	(−2.21)	(5.82)	(4.80)	(2.75)	(−2.29)	(5.83)	(4.64)	(2.66)	(−2.47)
R5	1.56	1.64	1.39	−0.16	1.66	1.67	1.41	−0.25	1.73	1.74	1.42	−0.31	1.66	1.65	1.28	−0.37
	(5.73)	(5.38)	(3.77)	(−0.82)	(6.00)	(5.40)	(3.78)	(−1.26)	(6.15)	(5.59)	(3.76)	(−1.60)	(5.93)	(5.37)	(3.41)	(−1.97)
R5 − R1	0.33	0.64	1.28	0.95	0.42	0.79	1.19	0.77	0.53	0.87	1.13	0.60	0.40	0.75	0.89	0.49
	(1.38)	(2.85)	(5.76)	(4.86)	(1.91)	(3.90)	(6.02)	(4.59)	(2.73)	(4.79)	(6.21)	(4.19)	(2.20)	(4.30)	(5.07)	(3.66)

Panel D: Largest 50% of NYSE/AMEX Stocks (5 × 5)

	$K = 3$				$K = 6$				$K = 9$				$K = 12$			
Portfolio	V1	V3	V5	V5 − V1	V1	V3	V5	V5 − V1	V1	V3	V5	V5 − V1	V1	V3	V5	V5 − V1
R1	1.15	1.12	0.42	−0.73	1.09	0.99	0.44	−0.66	1.06	0.95	0.43	−0.63	1.05	0.96	0.53	−0.52
	(4.11)	(3.73)	(1.06)	(−3.38)	(4.03)	(3.38)	(1.11)	(−3.15)	(3.99)	(3.29)	(1.11)	(−3.08)	(3.95)	(3.31)	(1.35)	(−2.59)
R3	1.15	1.23	0.93	−0.22	1.19	1.22	0.97	−0.22	1.20	1.24	0.99	−0.21	1.22	1.20	0.96	−0.26
	(5.38)	(4.76)	(2.67)	(−1.11)	(5.50)	(4.74)	(2.80)	(−1.12)	(5.50)	(4.85)	(2.85)	(−1.09)	(5.60)	(4.66)	(2.74)	(−1.39)
R5	1.26	1.42	1.31	0.05	1.33	1.43	1.39	0.06	1.41	1.49	1.42	0.01	1.36	1.43	1.28	−0.07
	(4.98)	(5.14)	(3.75)	(0.24)	(5.24)	(5.20)	(3.91)	(0.30)	(5.49)	(5.38)	(3.95)	(0.06)	(5.33)	(5.20)	(3.58)	(−0.39)
R5 − R1	0.11	0.30	0.89	0.78	0.24	0.44	0.95	0.71	0.34	0.54	0.98	0.64	0.31	0.47	0.76	0.45
	(0.54)	(1.59)	(4.37)	(3.99)	(1.24)	(2.75)	(5.16)	(4.16)	(1.92)	(3.63)	(5.81)	(4.10)	(1.88)	(3.42)	(4.79)	(3.21)

Table IV

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 Tables II and III. The strategies are based on this six-month portfolio formation period ($J = 6$). The sample period is 1965 to 1995. Portfolio characteristics are presented for 10 price momentum and three trading volume portfolios involving all NYSE/AMEX stocks (Table II and Table III, Panel A), five price momentum and five trading volume portfolios involving only the largest 50% of NYSE/AMEX stocks (Table III, Panel B), and three price momentum and 10 trading volume portfolios (Table III, Panel C). *R1* represents the *loser* portfolio. *R10* (*R5*) represents the *winner* portfolio when we form 10 (five) price momentum portfolios. *V1* represents the lowest trading volume portfolio. *V3* (*V5*) represents the highest trading volume portfolio when we form three (five) volume portfolios. *Return* refers to the geometric average monthly return in percentages during the last six months, and *Volume* represents the average daily turnover in percentages during the last six months. *SzRnk* represents the time-series average of the median size decile of the portfolio on the portfolio formation date. *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.

Panel A: 10 Price Momentum, Three Trading Volume Portfolios

	V1					V2					V3				
Portfolio	Return	Volume	SzRnk	Price	*N*	Return	Volume	SzRnk	Price	*N*	Return	Volume	SzRnk	Price	*N*
R1 (loser)	−5.84	0.0588	2.7	7.65	57	−6.14	0.1430	3.3	8.51	57	−6.84	0.3232	4.5	10.64	84
R5	0.25	0.0608	5.4	19.41	78	0.25	0.1381	6.6	22.25	71	0.25	0.2822	6.4	20.59	49
R10 (winner)	7.46	0.0661	4.3	17.39	35	7.71	0.1480	4.8	18.77	50	8.79	0.3653	5.4	20.74	112

Panel B: Three Price Momentum, 10 Trading Volume Portfolios

	V1					V5					V10				
Portfolio	Return	Volume	SzRnk	Price	N	Return	Volume	SzRnk	Price	N	Return	Volume	SzRnk	Price	N
R1 (loser)	−2.98	0.0309	3.5	11.10	75	−3.11	0.1267	4.7	13.98	64	−4.70	0.5085	5.4	15.00	63
R2	0.62	0.0310	4.7	17.58	75	0.67	0.1265	6.7	23.28	74	0.70	0.4925	6.2	20.74	38
R3 (winner)	4.02	0.0316	4.8	19.65	48	4.35	0.1271	6.1	23.06	61	6.85	0.5254	5.8	21.93	96

Panel C: Five Price Momentum, Five Trading Volume Portfolios

	V1					V3					V5				
Portfolio	Return	Volume	SzRnk	Price	N	Return	Volume	SzRnk	Price	N	Return	Volume	SzRnk	Price	N
R1 (loser)	−4.22	0.0439	3.1	9.37	80	−4.47	0.1411	4.1	11.13	73	−5.51	0.3886	5.0	12.90	90
R2	0.66	0.0450	5.0	18.78	92	0.67	0.1397	6.8	23.17	86	0.67	0.3650	6.2	20.66	53
R5 (winner)	5.48	0.0471	4.6	18.62	50	5.80	0.1420	5.5	21.58	68	7.39	0.4155	5.7	21.69	131

Panel D: Largest 50% of NYSE/AMEX Stocks (5 × 5)

	V1					V3					V5				
Portfolio	Return	Volume	SzRnk	Price	N	Return	Volume	SzRnk	Price	N	Return	Volume	SzRnk	Price	N
R1 (loser)	−2.70	0.0598	7.5	23.37	33	−2.83	0.1523	8.1	25.11	37	−4.08	0.3857	7.4	21.61	50
R3	0.99	0.0627	7.7	29.77	50	1.00	0.1503	8.6	31.81	42	1.01	0.3695	7.7	28.61	23
R5 (winner)	4.90	0.0597	7.6	32.85	25	5.08	0.1533	8.1	34.63	33	6.67	0.4165	7.5	31.74	68

Table V

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 and volume portfolios for (J = 6, K = 6) and (J = 12, K = 12) portfolio strategies. J represents the months before the portfolio formation date, and K represents in months after the portfolio formation date. K represents monthly holding periods where K = three, six, nine, or 12 months. *R1* represents the *loser* portfolio. *R10* represents the *winner* portfolio. *V1* represents the lowest trading volume portfolio. *V3* represents the highest trading volume portfolio. The three-factor regression is as follows:

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

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 January 1965 to December 1995.

Panel A: 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)
	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)	(−0.78)	(−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)								

Panel B: $J = 12$, $K = 12$

Portfolio	a V1	a V2	a V3	a V3 − V1	b V1	b V2	b V3	b V3 − V1	s V1	s V2	s V3	s V3 − V1
R1	−0.59	−0.86	−1.28	−0.69	1.02	1.12	1.25	0.22	1.60	1.61	1.69	0.09
	(−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	0.17	0.02	−0.30	−0.47	0.88	1.04	1.18	0.30	0.71	0.75	1.03	0.32
	(2.51)	(0.39)	(−3.94)	(−4.40)	(31.42)	(44.06)	(47.42)	(8.24)	(16.11)	(19.69)	(26.40)	(5.80)
R10	0.42	0.47	0.12	−0.30	0.95	1.08	1.18	0.23	0.93	0.85	1.03	0.10
	(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	0.39	−0.07	−0.05	−0.06	0.01	−0.68	−0.75	−0.66	0.02
	(4.28)	(6.06)	(6.98)	(2.05)	(−0.89)	(−0.68)	(−0.85)	(0.12)	(−4.39)	(−5.21)	(−4.79)	(0.17)

Portfolio	h V1	h V2	h V3	h V3 − V1	Adj. R^2 V1	Adj. R^2 V2	Adj. R^2 V3	Adj. R^2 V3 − V1
R1	0.82	0.66	0.55	−0.27	0.76	0.83	0.87	0.16
	(7.21)	(6.59)	(5.87)	(−3.23)				
R5	0.44	0.38	0.23	−0.21	0.92	0.96	0.96	0.51
	(8.39)	(8.90)	(6.18)	(−3.76)				
R10	0.30	0.02	−0.22	−0.52	0.81	0.90	0.91	0.34
	(4.36)	(0.42)	(−3.07)	(−7.05)				
R10 − R1	−0.52	−0.64	−0.77	−0.25	0.18	0.26	0.29	0.02
	(−3.74)	(−4.66)	(−5.34)	(−2.92)				

The magnitudes of the HML loadings correspond to those obtained for value and glamour stocks (highest and lowest 40 percent by book-to-market ratio) in Fama and French (1993). For (J = 6, K = 6), the difference in estimated HML loadings for our low and high volume winner portfolios (R10V3 − R10V1) is −0.51. This is comparable to the spread Fama and French obtain when they separate firms on the basis of high versus low book-to-market ratios.[15] In short, low (high) volume stocks earn positive (negative) excess returns when high B/M stocks do well. These results lay a foundation for our attempt to interpret the findings of the paper and understand the nature of the information provided by trading volume (see Section III).

The factor loadings on SMB also provide interesting information. Table V 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 have no explanatory power for a stock's sensitivity to firm size. In the intermediate return portfolio (R5), there is in fact some evidence that high volume stocks actually behave more like small stocks than low volume stocks. Because small stocks are generally more illiquid, this evidence runs counter to the liquidity explanation for the volume effect.

E. Long-Horizon Results

Table VI presents long-term (event time) annual returns to various trading volume and price momentum portfolios over the next five years. These results are based on the six-month portfolio formation period (J = 6), 10 momentum portfolios, and three volume portfolios (10 × 3). Year 1, Year 2, Year 3, Year 4, and Year 5 represent the annual returns of each portfolio in the five 12-month periods following the portfolio formation date. To correct for spurious autocorrelation from overlapping observations, we compute t-statistics using the Hansen and Hodrick (1980) correction for autocorrelation up to lag 11. Panel A presents raw returns, Panel B reports industry-adjusted returns, and Panel C reports size-adjusted returns.

The industry adjustment is based on 25 equal-weighted industry portfolios formed by grouping two-digit SIC codes (see the Appendix).[16] The size adjustment is based on equal-weighted size decile portfolios. The benchmark portfolios are formed monthly using all NYSE/AMEX firms available at that time. Each firm's benchmark-adjusted return is computed by subtracting the annual return of the appropriate benchmark portfolio (a portfolio that corresponds to the industry grouping of the stock, or the size decile of the

[15] See Fama and French (1993, 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.

[16] Our industry partitions are slightly finer than the 20 industries used by Moskowitz and Grinblatt (1999) but not as fine as the 48 industries used by Fama and French (1997).

stock, as of the portfolio formation date) from the individual stock's annual return. Annual benchmark-adjusted portfolio returns are computed as an equal-weighted average of the adjusted returns of individual stocks.

The bottom row of each panel reports the annual returns to the price momentum strategy, after controlling for trading volume (R10 − R1). The results in Panels A, B, and C show that the price momentum effect dissipates after 12 months in all three volume groups. As we noted earlier, the spread between winners and losers (R10 − R1) is higher for high volume firms in the first year. However, this effect does not persist beyond Year 1.

The last five columns of Table VI report the difference between high and low volume firms (V3 − V1), controlling for price momentum. The results show that low volume losers outperform high volume losers for each of the next five years. On the winner side, low volume stocks take a little longer to outperform high volume stocks. As we saw earlier, the difference in returns between high and low volume winners is not significant in the first year. However, low volume winners begin to outperform high volume winners in Year 2, and this difference is seen through to Year 5.

Moskowitz and Grinblatt (1999) show that a portion of the returns from momentum strategies is due to industry effects. Panel B shows that industry adjustment decreases first year price momentum returns in our sample from 12.5 percent to an average of 10.1 percent (also see Table VII), a decline of about 20 percent. More importantly, industry adjustments have virtually no effect on the volume results. The last five columns of Panel B show that low volume firms continue to outperform high volume firms in the next five years even after industry adjustment. This effect is clearly seen in both winner and loser portfolios and is also robust to firm size adjustments (Panel C). Thus, trading volume does not appear to be a proxy for firm size or industry effects.

F. Price Momentum Reversals

Table VI results (see Panels B and C) suggest that the magnitude and persistence of price momentum are a function of past trading volume. Price reversals are more pronounced among low volume losers (R1V1) and high volume winners (R10V3). Conversely, price momentum is more pronounced among high volume losers (R1V3) and low volume winners (R10V1). These observations suggest two volume-based price momentum strategies. We refer to the first, which involves buying low volume winners and selling high volume losers, as the *early-stage* strategy, to capture the idea that stocks in these portfolios exhibit future price momentum over a longer horizon. We refer to the second strategy, which involves buying high volume winners and selling low volume losers, as the *late-stage* momentum strategy to capture the notion that the price momentum in these stocks reverses faster.

Table VII compares the annual returns of the simple price momentum strategy (*simple*) to those of the early stage (*early*) and the late stage (*late*) strategies. Panel A shows that the *simple* strategy earns 12.5 percent in

Table VI

Annual Returns for Portfolios Based on Price Momentum and Trading Volume

This table presents annual returns for portfolios based on price momentum and trading volume using data on NYSE/AMEX stocks from 1965 to 1995. The portfolio strategies are based on the six-month portfolio formation period ($J = 6$). *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. *Year 1*, *Year 2*, *Year 3*, *Year 4*, and *Year 5* represent the annual returns of price momentum portfolios in the five 12-month periods following the portfolio formation date. The industry adjustment is based on 25 equal-weighted industry portfolios (described in the text) formed by grouping two-digit SIC codes. The size adjustment is based on equal-weighted size decile portfolios. The benchmark portfolios are formed on the portfolio formation date using all NYSE/AMEX firms available at that time. The benchmark-adjusted returns are computed by subtracting the annual returns of the appropriate benchmark portfolio (a portfolio that corresponds to the industry grouping of the stock or the size decile of the stock at the time of the portfolio formation) from the individual stock's annual returns. The annual portfolio returns are computed as an equal-weighted average of annual returns of the individual stocks in the portfolio. The numbers in parentheses represent t-statistics based on the Hansen–Hodrick correction for autocorrelation up to lag 11.

	V1					V2					V3					V3 − V1				
Portfolio	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Panel A: Raw Returns																				
R1	12.35	18.50	17.55	18.19	17.29	9.38	17.37	17.38	16.56	15.75	3.93	13.39	12.36	13.37	14.93	−8.42	−5.11	−5.19	−4.82	−2.36
	(2.36)	(4.15)	(3.74)	(4.08)	(4.70)	(1.71)	(3.31)	(3.26)	(3.74)	(4.15)	(0.85)	(2.75)	(2.76)	(2.95)	(3.80)	(−5.24)	(−2.64)	(−2.90)	(−2.60)	(−1.58)
R5	17.74	17.57	16.67	16.13	16.26	17.34	17.60	15.61	14.82	14.95	15.43	15.09	14.21	12.64	14.44	−2.31	−2.47	−2.46	−3.49	−1.82
	(5.28)	(5.83)	(5.13)	(5.26)	(5.50)	(4.76)	(4.85)	(4.47)	(4.34)	(4.64)	(3.54)	(3.44)	(3.53)	(3.32)	(3.89)	(−1.04)	(−1.16)	(−1.91)	(−2.73)	(−1.28)
R10	20.64	19.58	18.21	14.89	14.82	23.44	17.47	17.04	13.91	14.25	19.20	13.14	13.64	11.86	12.52	−1.44	−6.44	−4.57	−3.03	−2.31
	(4.99)	(4.14)	(4.63)	(4.59)	(4.18)	(5.18)	(3.80)	(4.31)	(3.78)	(3.33)	(4.03)	(2.86)	(3.41)	(2.95)	(2.96)	(−0.65)	(−3.15)	(−2.46)	(−1.84)	(−1.48)
R10 − R1	8.28	1.08	0.66	−3.30	−2.47	14.06	0.10	−0.34	−2.66	−1.50	15.26	−0.25	1.28	−1.51	−2.42	6.98	−1.33	0.62	1.79	0.05
	(2.48)	(0.51)	(0.27)	(−1.31)	(−1.77)	(4.17)	(0.05)	(−0.13)	(−1.39)	(−0.95)	(7.13)	(−0.15)	(0.72)	(−0.86)	(−1.92)	(2.50)	(−0.58)	(0.32)	(0.69)	(0.04)

Panel B: Industry-Adjusted Returns																				
R1	−3.07	1.97	1.83	3.01	2.15	−5.77	0.95	1.88	1.62	0.51	−11.33	−3.35	−3.09	−1.21	−0.34	−8.27	−5.31	−4.92	−4.22	−2.49
	(−1.54)	(1.19)	(1.11)	(2.10)	(1.97)	(−2.53)	(0.54)	(0.93)	(1.37)	(0.62)	(−10.44)	(−2.83)	(−2.78)	(−1.11)	(−0.43)	(−5.83)	(−3.29)	(−3.08)	(−2.75)	(−1.90)
R5	1.34	0.94	1.08	1.23	0.70	0.85	0.95	−0.16	0.15	−0.16	−1.22	−1.39	−1.28	−1.94	−0.52	−2.56	−2.32	−2.36	−3.17	−1.22
	(1.34)	(0.96)	(1.70)	(2.00)	(1.21)	(1.48)	(1.57)	(−0.38)	(0.33)	(−0.37)	(−1.60)	(−2.00)	(−2.01)	(−3.62)	(−0.91)	(−1.59)	(−1.50)	(−2.49)	(−3.39)	(−1.23)
R10	3.00	3.10	1.95	0.29	0.05	5.60	1.23	1.16	−0.65	−0.62	1.62	−2.88	−2.09	−2.30	−2.45	−1.38	−5.99	−4.05	−2.59	−2.50
	(2.39)	(2.10)	(1.34)	(0.29)	(0.05)	(4.17)	(1.35)	(1.15)	(−0.93)	(−0.67)	(1.44)	(−3.20)	(−3.02)	(−3.32)	(−3.13)	(−0.80)	(−3.29)	(−2.56)	(−1.85)	(−1.84)
R10 − R1	6.07	1.14	0.12	−2.72	−2.10	11.37	0.28	−0.72	−2.27	−1.13	12.95	0.46	1.00	−1.09	−2.11	6.89	−0.67	0.88	1.63	−0.01
	(2.30)	(0.71)	(0.07)	(−1.36)	(−1.58)	(3.90)	(0.17)	(−0.35)	(−1.67)	(−0.91)	(7.99)	(0.32)	(0.74)	(−0.97)	(−2.37)	(2.95)	(−0.34)	(0.48)	(0.72)	(−0.01)
Panel C: Size-Adjusted Returns																				
R1	−4.35	0.16	−0.19	1.70	1.14	−7.62	−0.53	0.39	1.08	0.32	−13.04	−3.92	−3.81	−1.32	−0.27	−8.70	−4.08	−3.63	−3.03	−1.41
	(−3.56)	(0.12)	(−0.16)	(1.62)	(1.16)	(−4.62)	(−0.45)	(0.25)	(0.91)	(0.45)	(−10.89)	(−3.55)	(−3.03)	(−0.85)	(−0.30)	(−7.06)	(−2.47)	(−2.61)	(−1.88)	(−1.03)
R5	1.93	1.44	1.18	1.32	0.81	1.20	1.59	0.40	0.58	0.15	−1.59	−1.60	−1.21	−1.62	−0.45	−3.52	−3.04	−2.39	−2.94	−1.26
	(1.81)	(1.41)	(1.60)	(1.68)	(1.10)	(2.41)	(3.77)	(1.00)	(1.62)	(0.36)	(−1.96)	(−2.19)	(−1.68)	(−3.03)	(−0.69)	(−2.02)	(−1.83)	(−1.89)	(−2.48)	(−0.98)
R10	3.45	2.74	1.35	−0.43	−0.50	6.14	0.57	0.74	−0.69	−0.65	2.04	−3.60	−2.20	−2.44	−2.43	−1.41	−6.34	−3.55	−2.01	−1.92
	(2.57)	(1.64)	(0.92)	(−0.36)	(−0.52)	(4.36)	(0.62)	(0.77)	(−0.94)	(−0.80)	(1.43)	(−3.47)	(−2.19)	(−2.82)	(−2.54)	(−0.79)	(−3.02)	(−1.95)	(−1.21)	(−1.23)
R10 − R1	7.80	2.58	1.54	−2.13	−1.64	13.76	1.10	0.35	−1.76	−0.96	15.08	0.32	1.62	−1.11	−2.15	7.28	−2.26	0.08	1.02	−0.51
	(3.44)	(1.34)	(0.83)	(−1.16)	(−1.28)	(5.46)	(0.72)	(0.18)	(−1.08)	(−0.84)	(7.28)	(0.24)	(1.04)	(−0.63)	(−2.04)	(3.16)	(−1.08)	(0.05)	(0.46)	(−0.32)

Table VII

Early and Late Stage Strategies Based on Price Momentum and Trading Volume

This table summarizes annual returns from *early* (*R10V1 − R1V3* or *R5V1 − R1V5*) and *late* stage (*R10V3 − R1V1* or *R5V5 − R1V1*) price momentum-trading volume strategies and compares them to the returns from a *simple* price momentum strategy (*R10 − R1* or *R5 − R1*) for the time period 1965 to 1995. *Early* represents a zero investment portfolio that is long low volume winners (R10V1 or R5V1) and short high volume losers (R1V3 or R1V5). *Late* represents a zero investment portfolio that is long high volume winners (R10V3 or R5V5) and short low volume losers (R1V1). *R1* represents the *loser* portfolio with the lowest returns and *R10* represents the *winner* portfolio with the highest returns during the previous six months. *V1* represents the portfolio with the lowest trading volume, and *V3* (*V5*) represents the portfolio with the highest trading volume when three (five) volume portfolios are formed. The volume is computed as the average daily turnover over the previous six months. *Year 1*, *Year 2*, *Year 3*, *Year 4*, and *Year 5* represent the compounded returns in each of the five 12-month periods following the portfolio formation month. The number of monthly observations is 325, except for Panel D, where it is 265. The numbers within parentheses are *t*-statistics computed with the Hansen–Hodrick autocorrelation correction up to 11 lags.

Strategy	Year 1	Year 2	Year 3	Year 4	Year 5
Panel A: Raw Returns					
R10 − R1 (simple)	12.49	−1.10	−0.32	−2.77	−2.96
	(5.04)	(−0.66)	(−0.15)	(−1.68)	(−2.46)
R10V3 − R1V1 (late)	6.84	−5.35	−3.91	−6.33	−4.78
	(2.53)	(−2.17)	(−1.53)	(−3.54)	(−2.64)
R10V1 − R1V3 (early)	16.70	6.19	5.85	1.53	−0.11
	(5.85)	(3.16)	(2.56)	(0.64)	(−0.06)
(R10V3 − R1V1) − (R10 − R1)	−5.65	−4.25	−3.59	−3.56	−1.81
	(−5.21)	(−3.00)	(−2.93)	(−3.14)	(−1.37)
(R10V1 − R1V3) − (R10 − R1)	4.21	7.29	6.17	4.29	2.85
	(2.40)	(3.40)	(2.91)	(2.92)	(1.73)
Panel B: Industry-Adjusted Returns					
R10 − R1 (simple)	10.11	−0.82	−0.65	−2.27	−2.67
	(5.19)	(−0.57)	(−0.41)	(−2.20)	(−3.33)
R10V3 − R1V1 (late)	4.69	−4.85	−3.92	−5.31	−4.60
	(2.04)	(−2.33)	(−2.04)	(−3.99)	(−3.21)
R10V1 − R1V3 (early)	14.33	6.45	5.05	1.50	0.39
	(7.34)	(4.23)	(2.77)	(0.92)	(0.27)
(R10V3 − R1V1) − (R10 − R1)	−5.42	−4.03	−3.28	−3.05	−1.94
	(−6.09)	(−3.23)	(−3.25)	(−3.42)	(−1.65)
(R10V1 − R1V3) − (R10 − R1)	4.22	7.27	5.69	3.77	3.05
	(3.02)	(3.82)	(3.05)	(3.13)	(2.11)
Panel C: Size-Adjusted Returns					
R10 − R1 (simple)	12.17	−0.21	0.52	−1.84	−2.30
	(6.25)	(−0.16)	(0.31)	(−1.32)	(−2.61)
R10V3 − R1V1 (late)	6.39	−3.76	−2.01	−4.14	−3.57
	(3.24)	(−1.91)	(−1.08)	(−3.10)	(−2.32)
R10V1 − R1V3 (early)	16.49	6.66	5.17	0.89	−0.23
	(7.43)	(3.18)	(2.32)	(0.39)	(−0.15)
(R10V3 − R1V1) − (R10 − R1)	−5.78	−3.55	−2.53	−2.30	−1.26
	(−7.00)	(−2.68)	(−2.35)	(−2.02)	(−1.06)
(R10V1 − R1V3) − (R10 − R1)	4.33	6.87	4.65	2.73	2.07
	(3.13)	(3.18)	(2.32)	(1.83)	(1.31)

Table 7—*Continued*

Strategy	Year 1	Year 2	Year 3	Year 4	Year 5
Panel D: Size- and Book-to-Market-Adjusted Returns					
R3 − R1 (simple)	11.50	1.70	2.62	−0.17	−1.68
	(5.98)	(1.29)	(1.49)	(−.08)	(−1.55)
R3V10 − R1V1 (late)	7.14	−0.24	1.16	−1.94	−2.96
	(3.86)	(−0.15)	(0.67)	(−0.84)	(−1.60)
R3V1 − R1V10 (early)	15.03	4.39	3.83	1.08	−2.95
	(6.55)	(2.46)	(1.52)	(0.35)	(−1.68)
(R3V10 − R1V1) − (R3 − R1)	−4.36	−1.95	−1.46	−1.77	−1.28
	(−4.13)	(−1.75)	(−1.27)	(−1.19)	(−0.87)
(R3V1 − R1V10) − (R3 − R1)	3.54	2.68	1.21	1.25	−1.28
	(2.59)	(2.16)	(0.79)	(0.67)	(−0.83)
Panel E: Three Price Momentum, 10 Volume Portfolios					
R3 − R1 (simple)	6.98	−0.61	−0.22	−1.48	−2.08
	(4.30)	(−0.58)	(−0.15)	(−1.35)	(−2.05)
R3V10 − R1V1 (late)	−0.39	−5.85	−4.93	−5.12	−5.42
	(−0.14)	(−2.20)	(−2.31)	(−3.03)	(−2.81)
R3V1 − R1V10 (early)	15.53	5.95	7.00	3.97	0.22
	(6.40)	(2.34)	(3.18)	(1.61)	(0.11)
(R3V10 − R1V1) − (R3 − R1)	−7.37	−5.23	−4.71	−3.63	−3.34
	(−3.09)	(−2.54)	(−2.39)	(−2.00)	(−1.83)
(R3V1 − R1V10) − (R3 − R1)	8.55	6.57	7.22	5.45	2.31
	(3.96)	(2.45)	(3.82)	(2.75)	(1.16)
Panel F: Five Price Momentum, Five Volume Portfolios					
R5 − R1 (simple)	9.42	−0.55	−0.10	−2.10	−2.44
	(4.62)	(−0.40)	(−0.06)	(−1.53)	(−2.02)
R5V5 − R1V1 (late)	2.96	−4.91	−4.72	−5.90	−4.99
	(1.18)	(−2.05)	(−2.31)	(−3.77)	(−2.92)
R5V1 − R1V5 (early)	16.00	5.96	7.42	1.86	−1.05
	(6.11)	(3.05)	(3.23)	(0.75)	(−0.55)
(R5V5 − R1V1) − (R5 − R1)	−6.46	−4.37	−4.62	−3.80	−2.55
	(−3.67)	(−2.64)	(−3.63)	(−2.78)	(−1.86)
(R5V1 − R1V5) − (R5 − R1)	6.58	6.50	7.52	3.96	1.39
	(3.27)	(2.92)	(3.60)	(2.30)	(0.75)
Panel G: Largest 50% of NYSE/AMEX Stocks (5 × 5)					
R5 − R1 (simple)	7.71	−0.92	−0.49	−0.98	−2.10
	(3.83)	(−0.74)	(−0.33)	(−0.72)	(−1.81)
R5V5 − R1V1 (late)	5.42	−2.68	−2.23	−2.27	−4.72
	(1.61)	(−1.18)	(−1.33)	(−1.19)	(−2.74)
R5V1 − R1V5 (early)	11.16	2.19	3.64	0.62	−2.10
	(3.87)	(1.04)	(1.52)	(0.27)	(−0.99)
(R5V5 − R1V1) − (R5 − R1)	−2.29	−1.75	−1.74	−1.29	−2.62
	(−1.04)	(−1.13)	(−1.22)	(−0.84)	(−1.87)
(R5V1 − R1V5) − (R5 − R1)	3.45	3.11	4.13	1.60	−0.01
	(1.34)	(1.25)	(2.00)	(0.95)	(0.00)

Year 1 but the momentum dissipates after 12 months. The *late* strategy earns 6.8 percent in Year 1 but immediately begins losing in subsequent years. In contrast, the *early* strategy earns significant positive returns for

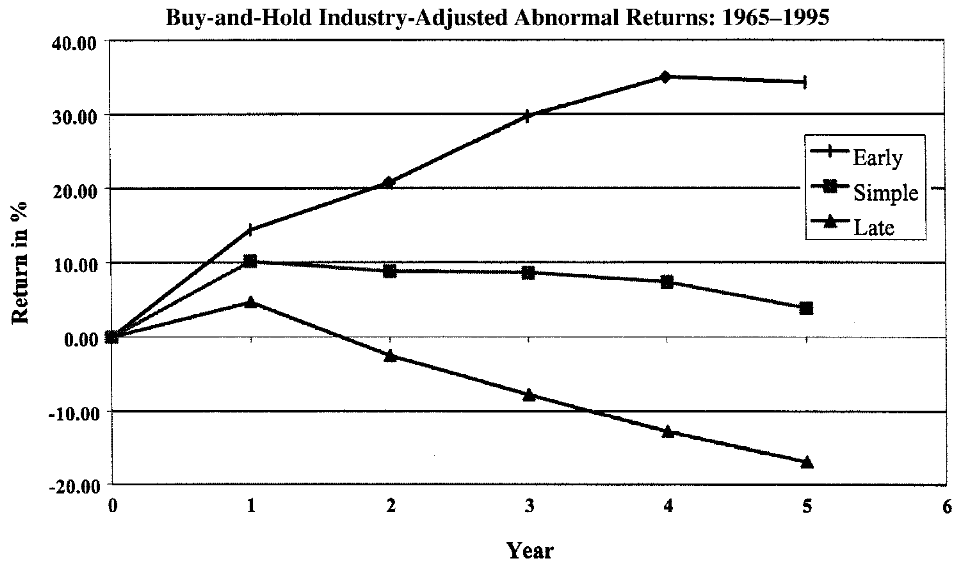


Figure 1. Buy-and-hold industry-adjusted long-term returns to various momentum strategies. This graph depicts buy-and-hold industry-adjusted returns to three price momentum strategies, formulated using past returns and trading volume from the previous six months ($J = 6$). Each month, stocks are independently sorted into 10 price momentum portfolios and three volume portfolios. The simple price momentum strategy (simple) buys top decile winners and sells bottom decile losers (R10 − R1). The early stage momentum strategy (early) buys low volume winners and sells high volume losers (R10V1 − R1V3). The late stage momentum strategy (late) buys high volume winners and sells low volume losers (R10V3 − R1V1). The industry adjustment is based on 25 equal-weighted industry portfolios formed by grouping two-digit SIC codes (see the Appendix). Each firm's benchmark-adjusted return is computed by subtracting the annual return of the appropriate benchmark portfolio (a portfolio that corresponds to the industry grouping of the stock as of the portfolio formation date) from the individual stock's annual return.

Years 1, 2, and 3 before the effect dissipates. Compared to the *simple* strategy, *early* (*late*) momentum strategies earn significantly higher (lower) returns in each of the next four years. Panels B and C show that these effects are robust when returns are adjusted for industry and size effects. Panel D shows the effect is weaker but still quite evident when both firm size and book-to-market are controlled for. Similarly, Panels E through G show this effect holds for various alternative partitions of the data and even for firms in the largest 50 percent of the NYSE/AMEX population.

Figures 1 and 2 provide graphical representations of buy-and-hold returns to these three strategies.[17] Figure 1 reports buy-and-hold industry-adjusted

[17] The buy-and-hold abnormal returns (BHAR) are computed as follows:

$$\mathrm{BHAR}_i = \prod_{i=1}^{T}(1 + r_{it}) - \prod_{i=1}^{T}(1 + r_{mt})$$

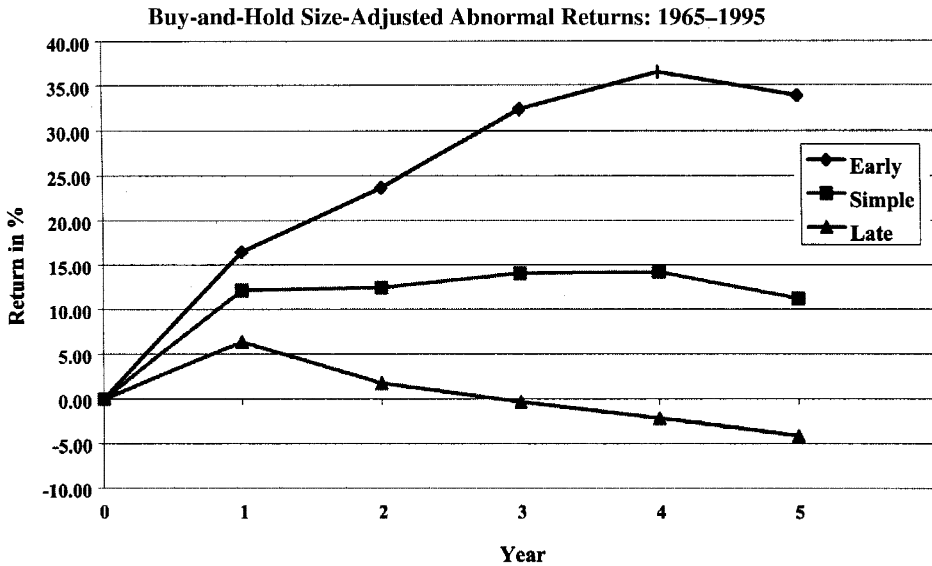


Figure 2. Buy-and-hold size-adjusted long-term returns to various momentum strategies. This graph depicts the buy-and-hold size-adjusted returns to three price momentum strategies, formulated using past returns and trading volume from the previous six months ($J = 6$). Each month, stocks are independently sorted into 10 price momentum portfolios and three volume portfolios. The simple price momentum strategy (simple) buys top decile winners and sells bottom decile losers (R10 − R1). The early stage momentum strategy (early) buys low volume winners and sells high volume losers (R10V1 −R1V3). The late stage momentum strategy (late) buys high volume winners and sells low volume losers (R10V3 − R1V1). The size adjustment is based on 10 equal-weighted sizes. Each firm's benchmark-adjusted return is computed by subtracting the annual return of the appropriate benchmark portfolio (a portfolio that corresponds to the size decile of the stock as of the portfolio formation date) from the individual stock's annual return.

returns, whereas Figure 2 reports buy-and-hold size-adjusted returns. These graphs show that both long-horizon *underreaction* and *overreaction* can occur in the data and indeed can be reconciled through judicious use of past trading volume. Looking at the returns for late stage stocks in isolation, we might be tempted to conclude that price momentum is an overreaction to fundamental news. Yet the same graph shows that the early stage momentum stocks exhibit price continuation for three to five years. Looking at the early stage momentum stocks in isolation, we might conclude markets generally underreact to information. In fact, both effects are part of a more general process by which information is incorporated into prices. More gen-

where r_{it} is the annual return in stock i and r_{mt} is the annual return on the benchmark. The benchmark annual returns are computed by equally weighting the annual returns of constituent securities. The time-series average of the cross-sectional mean buy-and-hold abnormal return is depicted in Figures 2 and 3.

erally, this evidence shows that the duration and magnitude of price momentum can be predicted based on firm characteristics, such as trading volume.

Table VIII provides additional evidence on the timing of momentum reversals conditional on trading volume and firm size. This table reports the time-series average of slope coefficients estimated from monthly Fama–MacBeth cross-sectional regressions of the following model:

$$r_{t+K,i} = a_K + b_K r_{t,i} + u_{t+K,i}$$

where subscript i refers to stock i, $r_{t+K,i}$ is the annual return K years ahead, and $r_{t,i}$ is the prior year's (pre–portfolio formation) return, where $K = 1$, 2, 3, 4, or 5. The time-series average of b_K is an estimate of the average autocorrelation (across all stocks) between last year's return and future returns. The cross-sectional regression is run each month using all stocks available at the beginning of the month, and the standard errors of the time-series means are computed using the Hansen and Hodrick (1980) correction with 11 lags.

Reported table values represent the average slope coefficient estimated with various subsamples. The first two columns provide a more formal test of the momentum reversal phenomenon reported in Table I. In column 1, which involves all stocks, the slope coefficient is positive and significant in Year 1, negative and insignificant in Years 2 and 3, and negative and significant in Years 4 and 5. These return autocorrelation patterns confirm the presence of price momentum in Year 1 and strong price reversals in Years 4 and 5. Column 2 provides similar evidence using only winner and loser stocks.

Columns 3 and 4 report slope coefficient estimates when only early stage or late stage stocks, based on past trading volume, are included in the regressions. These results show that the Year 1 price momentum is much stronger for early stage firms. Moreover, early stage firms show significant price momentum up to the third year, whereas late stage firms show strong price reversal starting in Year 2. Evidently, the magnitude and persistence of price momentum are a function of trading volume. We obtain similar results using size- or industry-adjusted returns (not reported in the paper).

Columns 5 and 6 conduct the same test using firm size rather than trading volume as the conditioning variable. The results for this subset of firms are weak and inconsistent, indicating that firm size is not a good substitute for trading volume in the prediction of return autocorrelation patterns. In other words, the information conveyed by trading volume about the persistence of future price momentum is not driven by its correlation with firm size.

It is useful to summarize the empirical facts at this point. Thus far we have seen that low volume stocks generally earn higher returns than high volume stocks. This fact is consistent with the liquidity effect. However, we have also seen that the price momentum effect is stronger among high volume stocks, raising questions about the liquidity explanation. We find that

Table VIII

Regression Tests of Return Continuation and Reversals Involving Simple, Early Stage, and Late Stage Price Momentum Strategies

This table reports time-series average of slope coefficients estimated from monthly Fama–MacBeth cross-sectional regressions run from January 1965 to January 1992. The regression model is

$$r_{t+K,i} = a_K + b_K r_{t,i} + u_{t+K,i},$$

where the subscript i refers to stock i. $r_{t+K,i}$ is annual return K years ahead, and $r_{t,i}$ is the previous year's (pre–portfolio formation) return where K = 1, 2, 3, 4, or 5. The cross-sectional regression is run each month, which results in the estimated slope coefficients being autocorrelated (due to the overlap) up to lag 11. Therefore, the standard errors of the time-series means are computed using the Hansen–Hodrick (1980) correction. The resulting t-statistics are presented in parentheses. The number of monthly observations is 324. *R5* and *R1* refer to past 12-month momentum quintile winners and losers. *V5* and *V1* refer to past 12-month high volume and low volume quintiles. S5 and S1 refer to largest and smallest size quintiles based on market cap at the time of portfolio formation. Regressions are run using several different samples: all stocks, stocks in extreme price momentum portfolios (R1 and R5) only, stocks in *early stage* portfolios (R5V1 and R1V5) only, and stocks in *late stage* portfolios (R5V5 and R1V1) only. For comparison, regressions are also run using size-based price momentum portfolios where firm size, rather than trading volume, is used as an indicator of early and late stage momentum.

	Time-Series Average Slope Coefficients, b_K					
	Simple Price Momentum		Volume Based Momentum Strategies		Size Based Momentum Strategies	
K	All Stocks	Stocks in R1 and R5 only	Early Stage (R5V1 and R1V5)	Late Stage (R5V5 and R1V1)	Early Stage (R5S1 and R1S5)	Late Stage (R5S5 and R1S1)
1	0.0673	0.0685	0.1303	0.0229	0.0840	0.0210
	(4.37)	(4.57)	(4.69)	(1.73)	(2.72)	(0.41)
2	−0.0072	−0.0074	0.0388	−0.0219	0.0148	−0.0517
	(−0.44)	(−0.46)	(1.50)	(−1.61)	(0.45)	(−1.20)
3	−0.0073	−0.0088	0.0629	−0.0367	−0.0069	−0.0552
	(−0.43)	(−0.53)	(2.37)	(−3.11)	(−0.31)	(−1.16)
4	−0.0288	−0.0270	0.0254	−0.0436	0.0060	−0.0610
	(−2.27)	(−2.10)	(1.00)	(−4.14)	(0.28)	(−1.97)
5	−0.0321	−0.0292	−0.0067	−0.0305	−0.0154	−0.0502
	(−2.58)	(−2.54)	(−0.33)	(−2.25)	(−0.75)	(−1.67)

past trading volume predicts the magnitude and timing of price momentum reversals. Finally, we have seen evidence that the information in trading volume is not about firm size or industry effects. In the next section, we provide additional evidence on the nature of the information provided by trading volume.

IV. Information Content of Trading Volume

Why does trading volume predict future returns? Is it a proxy for differences in liquidity, or the rate of information diffusion, or something else? In this section, we conduct additional tests to help answer these questions. Our goal is to better understand the information content of trading volume and to evaluate this evidence in the light of existing models of investor behavior.

A. Volume as a Liquidity Proxy

First we explore the relationship between trading volume (turnover) and other proxies of liquidity. Although average daily dollar volume is an intuitive proxy for liquidity, it does not necessarily follow that the average daily turnover is also a liquidity proxy. The turnover measure we use is, in effect, average daily dollar volume scaled by a firm's total market capitalization. The effect of dividing by firm size is to create a volume measure that may not have strong correlations with traditional liquidity proxies.

To provide more direct evidence on the relation between liquidity and turnover, the following table reports cross-sectional Spearman rank correlations of trading volume to firm size, stock price, and relative spread.[18] The sample period is 1964 to 1995, except for the relative spread results, which are based on the 1979 to 1989 time period (the data is the same as that used in Eleswarapu and Reinganum (1993)).

	Firm Size	Stock Price	Relative Spread
Turnover	0.20	0.11	−0.12

This chart shows that trading volume (as measured by average daily turnover) is not highly correlated with common proxies for market liquidity. The low degree of correlation with these variables suggests turnover may be providing information about something other than market liquidity.

Guidance on where to look emerges from the results in Table V. Recall Table V shows that the returns on low volume stocks are more positively correlated with HML than are returns on high volume stocks. In other words, high volume stocks behave like glamour stocks, whereas low volume stocks

[18] These results are based on annual pooled cross-sectional data measured as of June 30 each year; computing year-by-year correlations and averaging the annual estimates yields similar results.

behave like value stocks. Thus, trading volume seems to provide information about relative under- or overvaluation of stocks. In the next subsection, we investigate this possibility by conducting additional tests that focus on a possible link between trading volume and measures of under- or overvaluation.

B. Firm Characteristics Related to Profitability and Under- or Overvaluation

Table IX reports the pattern of past and future profitability and firm characteristics that proxy for under- or overvaluation across high and low volume portfolios. Panel A reports the results when firms are divided into 10 price momentum and three volume portfolios (the 10×3 partition), and Panel B reports the results when firms are divided into five price momentum and five volume portfolios (the 5×5 partition).

Each panel reports the number of analysts following the firm (NANA), the forecasted long-term earnings growth rate (Ltg), the cumulative buy-and-hold returns over the five years prior to the portfolio formation date (LtRet), and the book-to-market ratio just before the formation date (B/M). In addition, Table IX provides the return on equity from the most recent fiscal year end (ROE(0)) and also the change in ROE over the last three years (DROE(−)) and the next three years (DROE(+)). All values represent time-series averages of portfolio medians. For NANA and Ltg, we used the subset of firms covered by I/B/E/S (sample period 1979 to 1995).

The most striking fact that emerges from Table IX is that high volume stocks are generally *glamour* stocks and low volume stocks are generally *value* or *neglected* stocks. For example, Panel B shows that high volume stocks have greater analyst coverage (NANA is 3.6 for low volume losers and 9.6 for high volume losers), have higher forecasted earnings (long-term growth per year, Ltg, is 9.33 percent for low volume losers and 12.85 percent for high volume losers), lower book-to-market ratios (B/M is 0.815 for high volume losers and 1.125 for low volume losers), and higher return-on-equity (ROE(0) is 11.3 percent for high volume losers and 7.3 percent for low volume losers). These differences are all statistically significant. The results for winner portfolios are symmetrical and comparable in magnitude.

Table IX shows that high volume firms and low volume firms also differ significantly in terms of their past operating and price performance. In general, low volume losers have experienced a greater decline in ROE over the past three years compared to high volume losers. The pattern is symmetrical, but reversed in direction, among winners: high volume winners have experienced an increase in ROE, whereas low volume winners have experienced a decline in ROE. In spite of this, high volume stocks—both winners and losers—have significantly worse operating performance (significantly lower ROE increases) in the future than low volume stocks. This result is striking, because, ex ante, analysts forecast higher earnings growth (Ltg) for high volume firms. High volume firms have also experienced a recent in-

Table IX

Long-Term Performance Characteristics for Price Momentum and Trading Volume Portfolios

This table reports average number of analysts, long-term growth forecasts, long-term past returns, book-to-market ratio, and return on equity based on time-series of cross-sectional medians for price momentum and 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. Because of data unavailability in COMPUSTAT before 1970, there are missing observations due to the absence of sufficient number of observations in portfolios. *R1* represents the *loser* portfolios, and *R10* or *R5* 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* or *V5* 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* in percentages defined as $\mathrm{ROE}(t) = 100 * NI(t)/[0.5 * [B(t)+B(t-1)]]$, where $NI(t)$ is net income before extraordinary items for period t, and $\mathrm{B}(t)$ is book value for period t. $\mathrm{DROE}(-) = \mathrm{ROE}(0) - \mathrm{ROE}(-3)$ and $\mathrm{DROE}(+) = \mathrm{ROE}(3) - \mathrm{ROE}(0)$ represent changes in ROE over the last three years and the next three years, respectively. *LtRet* represents the cumulative buy-and-hold return in percentages for a 60-month (five-year) period prior to the portfolio formation date and represents the long-term stock performance. *NANA* represents time-series average of portfolio median number of security analysts making annual earnings forecasts as of the portfolio formation data, and *Ltg* represents analyst consensus long-term growth estimates obtained from IBES in percentages. The portfolios for this data item are based only on stocks that are covered by IBES and cover the 1979 to 1995 time period. Numbers in parentheses represent t-statistics computed using Hansen–Hodrick standard errors with 60 lags, that is, autocorrelation up to 60 months. The number of time-series observations ranges between 330 and 368.

Portfolio	NANA	Ltg	LtRet	B/M	ROE(−3)	ROE(0)	ROE(3)	DROE(−)	DROE(+)
Panel A: 10 Price Momentum, Three Trading Volume Portfolios									
R1V1 (LV − Loser)	4.17	9.50	18.31	1.167	10.47	5.22	6.82	−5.25	1.61
								(−3.96)	(1.90)
R1V3 (HV − Loser)	8.02	12.54	82.38	0.899	13.21	9.77	6.95	−3.44	−2.81
								(−2.75)	(−4.35)
R1V1 − R1V3 (LV − HV)	−3.85	−3.04	−64.07	0.268	−2.74	−4.55	−0.13	−1.81	4.42
	(−4.44)	(−5.29)	(−6.45)	(4.49)	(−3.13)	(−4.38)	(−0.18)	(−2.98)	(6.09)
R10V1 (LV − Winner)	3.11	9.84	149.07	0.689	11.28	10.55	12.84	−0.73	2.29
								(−1.02)	(2.12)
R10V3 (HV − Winner)	8.11	12.66	252.75	0.512	11.20	12.17	12.68	0.97	0.51
								(1.00)	(0.54)
R10V1 − R10V3 (LV − HV)	−5.00	−2.82	−103.68	0.177	0.08	−1.62	0.16	−1.71	1.78
	(−6.02)	(−4.24)	(−5.13)	(5.42)	(0.21)	(−2.01)	(0.28)	(−2.23)	(3.52)
Panel B: Five Price Momentum, Five Trading Volume Portfolios									
R1V1 (LV − Loser)	3.59	9.33	28.97	1.125	11.15	7.30	8.42	−3.85	1.13
								(−4.90)	(2.30)
R1V5 (HV − Loser)	9.62	12.85	108.87	0.815	13.35	11.31	7.68	−2.04	−3.64
								(−2.22)	(−6.14)
R1V1 − R1V5 (LV − HV)	−6.03	−3.52	−79.90	0.309	−2.20	−4.02	0.75	−1.82	4.76
	(−6.24)	(−7.15)	(−5.42)	(4.73)	(−2.45)	(−4.57)	(0.97)	(−4.01)	(10.49)
R5V1 (LV − Winner)	3.26	9.80	133.53	0.736	12.36	11.30	13.10	−1.06	1.80
								(−2.15)	(2.48)
R5V5 (HV − Winner)	8.97	12.71	247.62	0.524	11.42	12.26	12.27	0.84	0.02
								(0.94)	(0.02)
R5V1 − R5V5 (LV − HV)	−5.71	−2.91	−114.09	0.212	0.94	−0.96	0.82	−1.90	1.78
	(−7.59)	(−5.23)	(−4.67)	(4.38)	(2.07)	(−1.11)	(1.14)	(−2.79)	(4.45)

crease in ROE. In other words, analysts seem to consistently overestimate (underestimate) the future profitability of high (low) volume firms, perhaps because they naively extrapolate recent operating performance.

Finally, over the past five years, high volume losers (winners) have significantly outperformed low volume losers (winners). For example, in Panel B, LtRet is 28.97 percent for low volume losers and 108.87 percent for high volume losers. Among winners, LtRet is 133.53 percent for low volume stocks and 247.62 percent for high volume stocks. Thus, high volume winners and low volume losers are long-term winners and long-term losers, respectively, whereas low volume winners and high volume losers are more recent winners and losers.

Figure 3 provides further evidence on the past and future performance of volume based portfolio strategies. This figure examines the average annual return for various volume portfolios from Year -4 to Year $+5$ around the portfolio formation date. Figure 3A shows that whereas high volume firms (V5) underperform low volume firms (V1) in the future they have outperformed low volume firms in the past. Thus, high volume stocks appear to be long-term winners relative to low volume stocks. This is consistent with the result in Table IX that high volume stocks have lower B/M ratios than low volume stocks.

The pattern across high volume and low volume stocks is seen in winner (Figure 3B) and loser (Figure 3C) portfolios also. Once again, high volume stocks earned higher returns than low volume firms in each of the past five years.[19] Figure 3B shows that among winners the difference in performance between low volume and high volume stocks is most pronounced in the immediate past (Year 0). Specifically, high volume winners have been "long-term" winners, whereas low volume winners are only "recent" winners.

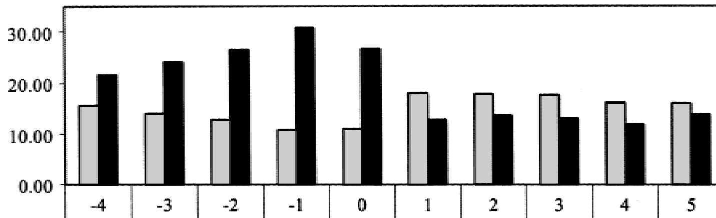
Figure 3C shows that among losers the performance gap is most pronounced in the more distant past (on or before Year -1). Specifically, this figure provides striking evidence that prior to Year 0, high volume losers have in fact been big winners ($+37.34$ percent in Year -1 versus -16.20 percent in Year 0). Therefore, it is very appropriate to refer to high volume losers as "recent" losers. In contrast, low volume losers have been underperforming consistently over the last five years, indicating that they are "long-term" losers.

These results fit our earlier characterization of volume-based momentum strategies as *early* and *late* stage strategies. Specifically, low volume winners only became winners in the recent past, and they exhibit positive momentum for a longer time in the future. Similarly, high volume losers only became losers in the recent past and exhibit negative momentum for a longer time in the future. In contrast, high volume winners and low volume losers are "long-term" winners and losers, respectively. Our earlier results show they tend to exhibit faster reversals in the future.

[19] Table IX provides formal tests that these differences in past returns are statistically significant.

PANEL A

Low Volume Stocks (V1) and High Volume Stocks (V5)

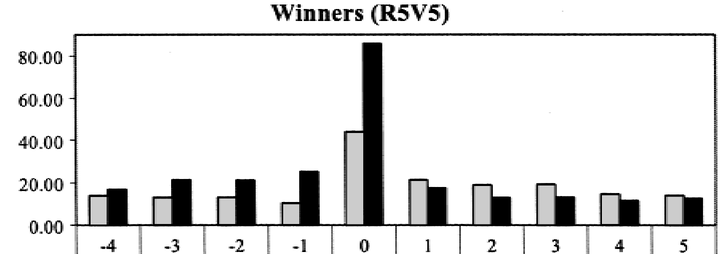


	-4	-3	-2	-1	0	1	2	3	4	5
□V1	15.68	14.05	12.88	10.84	10.98	18.04	17.87	17.66	16.16	16.07
■V5	21.72	24.20	26.49	30.71	26.56	12.84	13.65	13.09	12.00	13.80

Annual Return in %, Figure 3a.

PANEL B

Low Volume Winners (R5V1) and High Volume Winners (R5V5)

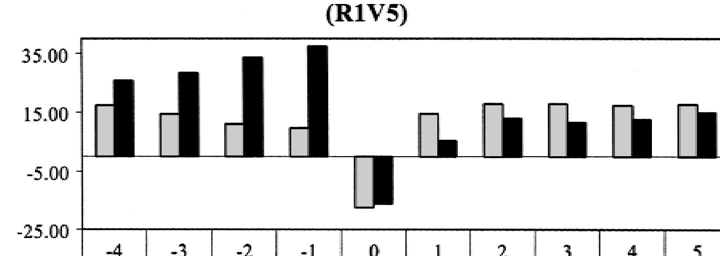


	-4	-3	-2	-1	0	1	2	3	4	5
□R5V1	13.94	13.07	13.03	10.48	43.91	21.37	18.88	19.07	14.56	13.78
■R5V5	16.79	21.31	21.07	25.09	85.62	17.46	12.92	13.13	11.45	12.57

Annual Return in %, Figure 3b.

PANEL C

Low Volume Losers (R1V1) and High Volume Losers (R1V5)



	-4	-3	-2	-1	0	1	2	3	4	5
□R1V1	17.34	14.41	11.14	9.64	-17.30	14.49	17.84	17.86	17.35	17.56
■R1V5	25.77	28.33	33.52	37.34	-16.20	5.37	12.92	11.65	12.69	14.83

Annual Return in %, Figure 3c.

Figure 3. Annual returns from Year −4 to Year +5 for various volume portfolios. These charts report the annual returns for various volume and volume-based momentum portfolios from Year −4 to Year +5 around the portfolio formation date. Figure 3A reports the average annual return for high (V5) and low (V1) volume quintile firms. Figures 3B and 3C report similar statistics for winner portfolios (R5) and loser portfolios (R1), respectively. Price momentum and volume are based on past six-month data in Year 0.

In sum, Table IX shows that past trading volume is related to a firm's past performance measures, current valuation ratios, and analysts' future forecast errors. Along all these dimensions, low (high) volume firms display value (glamour) characteristics. Controlling for price momentum, low (high) volume firms have underperformed their peers in the past; they possess lower (higher) valuation ratios today and tend to over- (under-) perform analyst expectations in the future.

C. Abnormal Returns around Quarterly Earnings Announcements

Table IX shows that analysts are more optimistic (pessimistic) for high (low) volume stocks but future changes in profitability fail to meet expectations. Thus, trading volume seems to provide information about investors' misperception of future earnings. In this subsection, we further explore this issue by examining the stock price reactions around future quarterly earnings announcements. If trading volume serves as a proxy for investor misperceptions of future earnings, these misperceptions should correct themselves around subsequent earnings announcement dates. Specifically, we might expect to see more negative (positive) price reactions for high (low) volume stocks. Risk differences should have little effect on short-window returns. Therefore, this technique provides a direct test that distinguishes between the mispricing hypothesis and other risk-based explanations.

Table X reports the abnormal returns around quarterly earnings announcements for various price momentum and trading volume portfolios. Table values represent four-day (day -2 to $+1$) cumulative abnormal returns (CAR) in percentages around quarterly earnings announcements. Returns are reported for the eight quarters before and after the most recent earnings announcement date just prior to portfolio formation. The NYSE/AMEX/Nasdaq value-weighted index is used as the benchmark in computing the CAR. The numbers in parentheses are t-statistics computed using the Hansen and Hodrick (1980) autocorrelation correction with six moving average lags. The six-month strategy ($J = 6$, $K = 6$) results are reported. Results for other holding and formation periods are similar.

Row 1 of Panel A shows that loser (R1) portfolios have significant negative earnings announcement abnormal returns in the past three quarters (-2 to 0). These losers continue to exhibit losses in the next two quarters, before staging a modest recovery in quarters $t + 4$ to $t + 8$. The next two rows show that the recovery among losers is driven almost entirely by the low volume (late stage) stocks. The high volume losers keep losing for three quarters and exhibit no significant CARs beyond quarter $t + 3$. The difference in CARs between high volume and low volume losers averages more than one percent per announcement and is highly significant for each of the next eight quarters.

Panel B shows a similar pattern for the winner portfolios. Specifically, low volume (early stage) winners experience significant positive announcement period CARs for the next eight quarters. High volume (late stage) winners, on the other hand, experience negative CARs starting from quarter $t + 4$. The difference in CARs between low volume winners and high volume winners averages between 0.50 percent and 1.22 percent per announcement and is highly significant for each of the next eight quarters. Taken together, the evidence in Panels A and B shows clearly that the ability of low volume stocks to outperform high volume stocks is related to the better earnings news received by the low volume stocks in the future.

Panel C reports abnormal returns when firms are sorted only on the basis of past trading volume. The bottom row shows that high volume (V3) and low volume (V1) firms do not have significantly different returns around earnings announcements in the past (quarters -8 to -1). However, low (high) volume firms exhibit significantly more positive (negative) earnings announcement returns in the future (quarters 0 to $+8$). On average, V1 firms earn approximately 0.60 percent more than do V3 firms around each of the next eight quarterly announcements. Although significant, this difference is much lower than what was reported in Panels A and B. In sum, Panel C shows that an independent volume effect exists but that the volume effect is most pronounced among extreme winners and losers.

Panel D augments these findings by comparing the announcement period CARs from three different trading strategies. The results in this panel show that the early stage momentum strategy (R10V1 − R1V3) has significantly more positive announcement period returns than a simple price momentum strategy (R10 − R1) in each of the next eight quarters. Conversely, the late stage strategy (R10V3 − R1V1) results in sharply lower earnings announcement period returns than the simple price momentum strategy.

In sum, we find that the short-window returns also support the view that trading volume provides information about market misperceptions of future earnings. Specifically, short-window earnings announcement returns are more positive for low volume stocks than for high volume stocks. We observe this difference for the next eight quarters. The effect is strong for both winners and losers.

D. Changes in Trading Volume

As a final test, we form portfolios based on price momentum and *changes* in trading volume. Our goal is to compute a volume measure that purges each firm of its normal level of trading activity (i.e., a measure of the abnormal trading volume). If the information content of trading volume is due to intertemporal variations in a firm's normal trading activity, this measure should also predict returns. Furthermore, by using changes in trading volume, we address any lingering concern that our original results are driven by liquidity effects.

In Table XI, we replicate our industry-adjusted return prediction tests, replacing trading volume with the actual change in trading volume. To construct this table, firms are independently sorted into five price momentum portfolios and five portfolios based on changes in trading volume over the

Table X

Abnormal Returns around Quarterly Earnings Announcements for Price Momentum and Trading Volume Portfolios

This table reports four-day (from day −2 to day +1) cumulative abnormal returns (CAR) in *percentages* around quarterly earnings announcement dates for (J = 6, K = 6) price momentum and trading volume portfolios. The sample time period is 1974 to 1995 and contains 264 monthly observations. The returns are reported for eight quarters before and eight quarters after the most recent earnings announcement date just prior to the portfolio formation date. The NYSE/AMEX/Nasdaq value-weighted index is used as the benchmark in computing the CAR. The numbers in parentheses are t-statistics using the Hansen–Hodrick autocorrelation correction with six moving average lags. *R1* represents the *loser* portfolio, *R10* represents the *winner* portfolio, *V1* represents low volume and *V3* represents high volume. The most recent quarter is represented by *0*. Quarters prior to the most recent quarter are represented as $-k$ whereas quarters after the most recent quarter are represented as $+k$, where k = 1 to 8. *Early* represents a zero investment portfolio that is long low volume winners (R10V1) and short high volume losers (R1V3). *Late* represents a zero investment portfolio that is long high volume winners (R10V3) and short low volume losers (R1V1).

	Quarters																
Strategy	−8	−7	−6	−5	−4	−3	−2	−1	0	1	2	3	4	5	6	7	8
Panel A: Loser Portfolios																	
R1	0.16	0.39	0.46	0.40	0.26	0.25	−0.33	−2.19	−2.42	−0.64	−0.29	0.10	0.33	0.49	0.65	0.50	0.56
	(1.69)	(4.47)	(4.75)	(4.08)	(2.12)	(2.21)	(−3.40)	(−24.72)	(−18.88)	(−5.40)	(−2.65)	(1.04)	(2.92)	(4.23)	(5.28)	(4.74)	(3.61)
Low volume (R1V1)	0.19	0.46	0.48	0.37	0.32	0.57	0.10	−1.58	−1.79	0.02	0.44	0.77	1.08	1.26	1.30	1.10	1.08
	(1.18)	(2.95)	(2.26)	(2.69)	(2.03)	(2.79)	(0.73)	(−15.21)	(−13.20)	(0.13)	(2.64)	(4.90)	(5.41)	(6.97)	(6.96)	(7.77)	(5.58)
High volume (R1V3)	0.23	0.43	0.62	0.52	0.30	0.01	−0.69	−2.79	−2.93	−1.06	−0.68	−0.45	−0.12	0.08	0.23	0.12	0.15
	(2.12)	(4.20)	(5.03)	(4.24)	(2.17)	(0.05)	(−5.60)	(−20.07)	(−16.58)	(−6.71)	(−5.24)	(−4.47)	(−1.11)	(0.57)	(1.56)	(0.92)	(0.92)
Difference (R1V1 − R1V3)	−0.05	0.02	−0.14	−0.15	0.02	0.57	0.79	1.22	1.14	1.08	1.12	1.22	1.20	1.18	1.08	0.98	0.93
	(−0.29)	(0.14)	(−0.61)	(−1.02)	(0.12)	(2.77)	(4.95)	(7.18)	(6.94)	(6.13)	(7.09)	(7.68)	(5.77)	(6.18)	(6.03)	(6.19)	(4.09)

Panel B: Winner Portfolios																	
R10	0.51	0.52	0.45	0.36	0.50	0.91	1.37	3.23	2.95	0.89	1.01	0.56	0.09	0.10	0.17	0.09	0.10
	(5.52)	(5.19)	(4.83)	(4.69)	(5.20)	(8.44)	(10.70)	(19.67)	(18.48)	(9.09)	(8.71)	(6.68)	(1.04)	(1.40)	(1.99)	(1.17)	(1.32)
Low volume (R10V1)	0.90	0.64	0.75	0.36	0.52	0.91	1.49	3.57	4.08	1.70	1.77	1.15	0.37	0.56	0.68	0.69	0.47
	(5.47)	(3.53)	(3.74)	(2.33)	(2.93)	(5.30)	(6.26)	(17.75)	(19.12)	(7.81)	(7.89)	(6.79)	(2.08)	(3.62)	(4.23)	(3.66)	(2.53)
High volume (R10V3)	0.41	0.41	0.40	0.30	0.59	0.96	1.43	3.16	2.54	0.48	0.67	0.31	−0.13	−0.14	−0.17	−0.18	−0.17
	(4.06)	(3.76)	(4.22)	(3.63)	(4.42)	(7.38)	(9.99)	(16.25)	(15.47)	(4.93)	(6.15)	(3.41)	(−1.30)	(−1.53)	(−1.82)	(−1.95)	(−1.75)
Difference (R10V1 − R10V3)	0.49	0.24	0.35	0.06	−0.06	−0.04	0.06	0.41	1.54	1.22	1.09	0.84	0.50	0.70	0.85	0.87	0.64
	(3.29)	(1.26)	(1.79)	(0.41)	(−0.32)	(−0.27)	(0.23)	(1.88)	(8.37)	(5.55)	(5.42)	(4.85)	(2.72)	(4.43)	(5.69)	(4.27)	(3.16)
Panel C: Volume Portfolios																	
Low volume (V1)	0.37	0.51	0.42	0.39	0.33	0.43	0.36	0.41	0.48	0.61	0.63	0.62	0.61	0.71	0.67	0.63	0.62
	(5.27)	(6.84)	(6.06)	(6.49)	(4.56)	(5.77)	(5.46)	(6.17)	(6.98)	(8.17)	(8.68)	(8.75)	(6.99)	(8.44)	(8.99)	(8.89)	(7.45)
High volume (V3)	0.34	0.43	0.45	0.41	0.42	0.46	0.41	0.33	0.10	0.01	0.08	0.05	−0.02	0.01	0.04	0.02	0.18
	(4.64)	(6.60)	(6.89)	(6.38)	(5.33)	(6.23)	(5.24)	(4.44)	(1.41)	(0.16)	(1.23)	(0.90)	(−0.34)	(0.17)	(0.59)	(0.38)	(1.49)
Difference (V1 − V3)	0.03	0.08	−0.02	−0.03	−0.09	−0.03	−0.06	0.08	0.37	0.60	0.55	0.57	0.63	0.70	0.63	0.61	0.44
	(0.47)	(1.22)	(−0.37)	(−0.45)	(−1.29)	(−0.41)	(−0.73)	(1.19)	(5.71)	(9.77)	(10.28)	(9.62)	(7.84)	(9.39)	(12.68)	(8.25)	(6.62)
Panel D: Comparing Trading Strategies																	
Simple price momentum (R10 − R1)	0.36	0.12	−0.02	−0.04	0.24	0.66	1.70	5.41	5.37	1.53	1.30	0.46	−0.24	−0.39	−0.48	−0.41	−0.46
	(3.51)	(1.58)	(−0.15)	(−0.45)	(2.17)	(5.57)	(14.21)	(29.89)	(27.13)	(12.61)	(10.14)	(4.47)	(−2.03)	(−3.48)	(−3.53)	(−3.47)	(−3.09)
Early-stage price momentum (R10V1 − R1V3)	0.66	0.21	0.12	−0.16	0.22	0.91	2.17	6.36	7.00	2.76	2.44	1.60	0.50	0.48	0.46	0.56	0.28
	(3.70)	(1.15)	(0.56)	(−0.82)	(1.13)	(4.20)	(8.59)	(26.09)	(23.75)	(11.54)	(11.26)	(7.65)	(2.39)	(2.35)	(2.35)	(2.37)	(1.14)
Late-stage price momentum (R10V3 − R1V1)	0.22	−0.05	−0.08	−0.07	0.27	0.38	1.33	4.73	4.32	0.46	0.23	−0.45	−1.18	−1.47	−1.43	−1.27	−1.25
	(1.62)	(−0.39)	(−0.40)	(−0.53)	(1.63)	(1.92)	(7.76)	(23.55)	(23.23)	(2.79)	(1.40)	(−2.83)	(−5.60)	(−7.15)	(−6.81)	(−8.50)	(−5.30)

Table XI

Annual Industry Adjusted Returns of Portfolios Based on Price Momentum and Change in Trading Volume

This table presents annual industry-adjusted returns for portfolios based on price momentum and change in trading volume using data on NYSE/AMEX stocks from 1968 to 1995. The portfolio strategies are based on the six month portfolio formation period ($J = 6$). *R1* represents the *loser* portfolio with the lowest returns, and *R5* represents the *winner* portfolio with the highest returns during the previous six months. $\Delta V1$ represents the portfolio with the smallest increase (or the largest decrease) in trading volume, and $\Delta V5$ represents the portfolio with the largest increase in trading volume over the past four years. Specifically, if the 12-month period just prior to the portfolio formation date is defined as year t, then we define change in volume as the average daily turnover in the past six months (the final six months of year t) minus the average daily turnover in year $t - 4$, $\Delta V = V(6, t) - V(t - 4)$. *Year 1*, *Year 2*, *Year 3*, *Year 4*, and *Year 5* represent the annual returns of price momentum portfolios in the five 12-month periods following the portfolio formation date. The industry adjustment is based on 25 equal-weighted industry portfolios (described in the text) formed by grouping two-digit SIC codes. The benchmark portfolios are formed on the portfolio formation date using all NYSE/AMEX firms available at that time. The benchmark-adjusted returns are computed by subtracting the annual returns of the appropriate benchmark portfolio (a portfolio that corresponds to the industry grouping of the stock at the time of the portfolio formation) from the individual stock's annual returns. The annual portfolio returns are computed as an equal-weighted average of annual returns of the individual stocks in the portfolio. The numbers in parentheses represent t-statistics based on the Hansen–Hodrick correction for autocorrelation up to lag 11.

	$\Delta V1$					$\Delta V3$					$\Delta V5$					$\Delta V5 - \Delta V1$				
Portfolio	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
R1	−4.29	−1.82	0.14	2.84	1.90	−3.39	−0.05	0.33	−0.77	0.04	−9.40	−3.85	−3.04	−2.12	−1.43	−5.11	−2.04	−3.18	−4.95	−3.33
	(−3.17)	(−1.55)	(0.10)	(2.04)	(1.85)	(−3.96)	(−0.06)	(0.36)	(−0.97)	(0.06)	(−10.72)	(−4.66)	(−2.71)	(−1.86)	(−2.27)	(−3.09)	(−1.31)	(−2.21)	(−3.26)	(−3.04)
R3	1.91	1.21	1.01	1.93	1.12	2.29	0.94	0.35	0.58	0.33	−2.70	−2.06	−1.95	−3.49	−1.64	−4.61	−3.27	−2.96	−5.42	−2.76
	(2.54)	(1.86)	(1.38)	(2.47)	(1.74)	(3.90)	(1.57)	(0.59)	(0.97)	(0.74)	(−3.25)	(−2.36)	(−2.63)	(−5.55)	(−2.96)	(−3.17)	(−2.29)	(−2.43)	(−4.43)	(−2.71)
R5	4.03	0.24	0.61	2.00	1.13	4.64	0.91	0.63	−0.05	−0.25	−1.45	−2.12	−2.23	−3.14	−2.70	−5.49	−2.36	−2.84	−5.14	−3.83
	(3.01)	(0.23)	(0.51)	(2.14)	(1.07)	(5.28)	(1.49)	(0.73)	(−0.09)	(−0.39)	(−1.54)	(−2.35)	(−3.47)	(−4.29)	(−3.23)	(−3.75)	(−1.94)	(−2.01)	(−3.71)	(−3.73)
R5 − R1	8.32	2.05	0.47	−0.84	−0.77	8.03	0.96	0.30	0.72	−0.29	7.94	1.73	0.81	−1.03	−1.27	−0.38	−0.32	0.34	−0.19	−0.50
	(5.22)	(1.70)	(0.26)	(−0.51)	(−0.58)	(5.87)	(0.80)	(0.20)	(0.66)	(−0.27)	(5.91)	(1.61)	(0.64)	(−0.98)	(−1.66)	(−0.26)	(−0.24)	(0.22)	(−0.12)	(−0.43)

past four years (ΔV). Specifically, if the 12-month period just prior to the portfolio formation date is defined as year t, then we define change in volume as the average daily turnover over the past six months minus the average daily turnover in year $t-4$ ($\Delta V = V(6,t) - V(t-4)$).[20] Using percentage change in trading volume rather than actual change (($\Delta V = (V(6,\ t) - V(t-4))/V(t-4)$) yields very similar results. We find that the level of trading volume is positively correlated with the change in trading volume. The Spearman rank correlation between these two variables is 0.48.

Table XI shows that portfolios ranked on price momentum and changes in trading volume exhibit the same patterns in future returns as those ranked on price momentum and level of trading volume. For example, the bottom row shows that returns to simple price momentum strategies dissipate in 12 months. However, the last five columns show that firms with the most increase in volume significantly underperform firms with the least increase (or the most decline) in volume. The difference ranges from two percent to five percent over the next five years and is equally strong in winner and loser portfolios.

Table XII compares the predictive power of the following: (1) average trading volume from the past six months, (2) changes in trading volume over the past four years, and (3) lagged trading volume from four years ago (we ensure comparability by using only a subsample of stocks for which all three volume measures are available). Panel A reports early and late strategy returns based on last six-month trading volume. Panel B reports the results for changes in trading volume measured relative to the trading volume in Year $t - 4$. Finally, Panel C reports the results using only trading volume from Year $t - 4$.

The last two rows of each panel reports the incremental returns to the volume metric, controlling for price momentum. These results show that most of the predictive power comes from changes in trading volume, rather than lagged volume. The last two rows of Panel C show that lagged volume from four years ago has some predictive power for future returns but the effect is not statistically significant in any of the next five years. Conversely, Panel B shows that the change in trading volume has significant incremental predictive power. With two exceptions (Years 2 and 3 in the early strategy), this predictive power is statistically significant over each of the next five years for both the late strategy and the early strategy.

It is important to recognize the imprecise nature of this test. Specifically, this test assumes that we can parse past trading volume into a "normal" and an "abnormal" component using a fixed time interval of four years for all firms. This is a strong assumption, and the imprecision it introduces may

[20] We chose the four-year horizon because it measures changes in trading volume over a fairly long period but not so long that we have data availability problems. The use of a longer horizon is also driven by the empirical fact that the level of trading volume (turnover) is a very slowly mean reverting process. Changes measured over a three-year horizon also provide similar results.

Table XII

Early and Late Strategies Based on Price Momentum and Current, Lagged, and the Change in Trading Volume

This table summarizes raw annual returns from *early* (*R5V1 − R1V5*) and *late* stage (*R5V5 − R1V1*) price momentum and trading volume strategies and compares them to the returns from a *simple* price momentum strategy (*R5 − R1*) for the sample period 1965 to 1995. *Early* represents a zero investment portfolio that is long low volume winners (R5V1) and short high volume losers (R1V5). *Late* represents a zero investment portfolio that is long high volume winners (R5V5) and short low volume losers (R1V1). *R1* represents the *loser* portfolio with the lowest returns, and *R5* represents the *winner* portfolio with the highest returns during the previous six months. *V1* represents the portfolio with the lowest trading volume, and *V5* represents the portfolio with the highest trading volume. Trading volume is measured in three ways: (a) the average daily turnover during the past six months, (b) the change in trading volume, defined as the average daily turnover during the past six months *minus* the average daily turnover four years ago, and (c) the average daily turnover four years ago. *Year 1*, *Year 2*, *Year 3*, *Year 4*, and *Year 5* represent the compounded returns in each of the five 12-month periods following the portfolio formation month. The number of monthly observations is 289. The numbers within parentheses are *t*-statistics computed with the Hansen–Hodrick (1980) autocorrelation correction up to 11 lags.

Strategy	Year 1	Year 2	Year 3	Year 4	Year 5
Panel A: Last Six-Month Trading Volume					
R5 − R1 (simple)	8.38	0.26	0.90	−1.57	−2.40
	(4.75)	(0.20)	(0.51)	(−1.09)	(−1.77)
R5V5 − R1V1 (late)	0.00	−4.23	−4.10	−6.04	−5.19
	(0.00)	(−1.87)	(−2.27)	(−3.97)	(−2.59)
R5V1 − R1V5 (early)	15.39	5.23	6.67	2.42	−0.80
	(6.94)	(2.60)	(2.72)	(0.94)	(−0.40)
(R5V5 − R1V1) − (R5 − R1)	−8.38	−4.49	−5.00	−4.47	−2.78
	(−4.60)	(−2.79)	(−3.99)	(−2.97)	(−1.85)
(R5V1 − R1V5) − (R5 − R1)	7.02	4.97	5.77	4.00	1.60
	(3.35)	(2.30)	(2.99)	(2.26)	(0.84)
Panel B: Change in Trading Volume					
R5 − R1 (simple)	8.38	0.26	0.90	−1.57	−2.40
	(4.75)	(0.20)	(0.51)	(−1.09)	(−1.77)
R5V5 − R1V1 (late)	4.00	−0.82	−2.30	−6.71	−5.11
	(1.63)	(−0.37)	(−0.97)	(−3.09)	(−2.80)
R5V1 − R1V5 (early)	15.64	3.59	3.68	4.24	2.96
	(6.65)	(2.26)	(1.61)	(1.87)	(2.25)
(R5V5 − R1V1) − (R5 − R1)	−4.38	−1.08	−3.21	−5.14	−2.71
	(−3.29)	(−0.78)	(−2.55)	(−3.68)	(−3.31)
(R5V1 − R1V5) − (R5 − R1)	7.26	3.33	2.78	5.82	5.36
	(3.06)	(1.76)	(1.51)	(3.15)	(4.03)
Panel C: Trading Volume Lagged Four Years					
R5 − R1 (simple)	8.38	0.26	0.90	−1.57	−2.40
	(4.75)	(0.20)	(0.51)	(−1.09)	(−1.77)
R5V5 − R1V1 (late)	4.56	−3.69	−0.97	−0.21	−0.68
	(1.67)	(−1.63)	(−0.43)	(−0.11)	(−0.33)
R5V1 − R1V5 (early)	11.44	2.69	2.23	−2.36	−3.01
	(4.21)	(1.09)	(0.78)	(−0.85)	(−1.52)
(R5V5 − R1V1) − (R5 − R1)	−3.81	−3.96	−1.87	1.37	1.73
	(−1.54)	(−1.87)	(−1.02)	(0.60)	(0.83)
(R5V1 − R1V5) − (R5 − R1)	3.07	2.42	1.33	−0.78	−0.61
	(1.53)	(1.21)	(0.65)	(−0.41)	(−0.42)

explain why both the changes and lagged volume variables have some predictive power. Despite this limitation, Table XII results show that most of the predictive power of trading volume is attributable to recent *changes* in the level of trading activity rather than lagged volume. This evidence further supports the notion that past turnover is a measure of fluctuating investor sentiment and not a liquidity proxy.

E. Relation to Existing Behavioral Models of Under- and Overreaction

Our results show trading volume is an important empirical link between intermediate-horizon momentum and long-horizon return reversal. Recently, several behavioral models have attempted to provide a framework for integrating these two empirical phenomena (e.g., Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999)). In this subsection, we briefly summarize each model and discuss their relation to our findings.

Daniel et al. (1998) focus on the *overconfidence bias*. They argue that stocks that are more difficult to value tend to generate greater overconfidence among investors. Therefore, according to their model, mispricing should be more severe among securities that are hard to value (i.e., growth or glamour stocks) or where feedback is slow or ambiguous (i.e., small, illiquid stocks). If high volume stocks tend to be growth or glamour stocks, then Daniel et al. would predict that price momentum profits should be stronger among the high volume stocks. This is consistent with our finding that high volume stocks tend to behave like glamour stocks (see Table V and, for more direct evidence, Table VIII). It may also help explain our intermediate-horizon finding that momentum spreads (profits on R10 − R1 strategies) are greater among high volume firms.

In Barberis et al. (1998), the *conservatism bias* of the representative investor causes him to update his priors insufficiently when he observes new public information about a firm. This leads to an initial market underreaction. However, due to the *representativeness bias*, when an investor receives a long sequence of good (or bad) news he tends to become too optimistic (or pessimistic) about the future profitability of the firm. As a result, firms experiencing prolonged periods of increasing earnings tend to become overvalued, and those experiencing long periods of declining earnings tend to become undervalued. The prices of these stocks ultimately undergo reversals as realized earnings fail to meet expectations.

In Hong and Stein (1999) there are two types of investors: news watchers and momentum traders. The news watchers trade only on private information about fundamentals, whereas the momentum traders trade only on past price movements. Both are boundedly rational in the sense they ignore all other information. Given these rationality constraints, Hong and Stein show that if firm-specific information diffuses gradually across news watchers, there will be an initial underreaction. This underreaction in turn allows momentum traders to make money by trend chasing. As more and more momentum traders arrive in the market, the initial underreaction inevitably turns into overreaction at longer horizons. In short, Hong and Stein provide a context for reconciling the dynamics of intermediate-horizon underreaction and long-horizon overreaction.

The main appeal of these models is their synthesis of intermediate-horizon underreaction and long-horizon overreaction. Each model presents a plausible explanation for these empirical observations. In addition, each model has specific features that help explain some aspect of our findings. However, the main limitation of these models, as they pertain to our tests, is that none have an explicit role for trading volume. Therefore, the directional predictions we discuss below are inferred from each model's underlying assumptions.

The models fall into two camps in terms of their explanation of the intermediate-horizon momentum effect. In Daniel et al. (1998) (and also in DeLong et al. (1990)), prices initially overreact to news about fundamentals, and continue to move further away, before ultimately reverting to fundamentals. Therefore, in Daniel et al. (1998) and DeLong et al. (1990), the positive autocorrelation in intermediate-horizon returns is due to a market *overreaction*. In contrast, both Barberis et al. (1998) and Hong and Stein (1999) characterize the intermediate-horizon momentum effect as a market *underreaction*. In Barberis et al. (1998), the underreaction arises because the representative investor does not update sufficiently when he observes a firm-specific public news event. In Hong and Stein (1999), insufficient diffusion of information across news watchers results in a gradual incorporation of information into prices.

Our volume-based results do not fit neatly into either of these frameworks. For example, the Hong and Stein (1999) model predicts that momentum profits should be larger for stocks with slower information diffusion. If we make the assumption that scarcity of trading leads to insufficient diffusion of information, then the Hong and Stein model would predict a greater momentum effect among low volume stocks. Our results indicate this to be true among winners but not among losers. That is, low volume winners have greater momentum, but low volume losers actually have less momentum. In addition, our results show that price momentum strategies actually perform better among high volume stocks. Therefore, the evidence does not seem to support the view that volume is an *information diffusion* proxy at intermediate and long horizons.

Conversely, in Daniel et al. (1998) and DeLong et al. (1990), the implicit assumption is that high trading volume will "fuel" momentum. For example, in Daniel et al. (1998), momentum arises from positive feedback traders that seek to capitalize on an initial price move by buying (selling) on good (bad) news. If we assume that trading volume is a proxy for positive feedback trading, or the activity of overconfident traders, then these models predict greater momentum among high volume stocks (in the case of Daniel et al. this is because high volume stocks are glamour stocks that are more difficult to value). We find this is true among losers but not among winners both in intermediate and long horizons. High volume losers do continue to lose

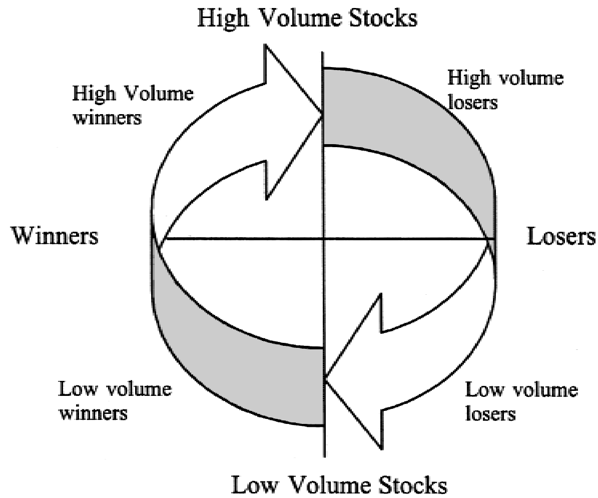


Figure 4. Momentum investing based on past price and volume information. This figure illustrates some of the more salient features of our empirical findings. We find that low volume stocks generally outperform high volume stocks. Among winners, low volume stocks show greater persistence in price momentum. Among losers, high volume stocks show greater persistence in price momentum. In addition, low volume (high volume) firms exhibit many characteristics most commonly associated with value (glamour) stocks.

longer (and lose more) than low volume losers. However, among winners, the opposite is true: high volume winners continue to win for a shorter period than low volume winners; indeed, high volume winners do worse than low volume winners over the next two to five years. Thus, the fact that at intermediate horizons, momentum profits (R10 − R1) are higher among high volume stocks is not because volume "fuels" price momentum.

F. Momentum Life Cycle (MLC)

An intriguing explanation for the above findings is depicted in Figure 4. This figure presents a simple conceptual diagram that helps to integrate the evidence in this paper. We refer to this diagram as the momentum life cycle (MLC) hypothesis.[21] The main benefit of this graph is that it presents the interaction between price momentum, reversals, and trading volume in a single framework. The main disadvantage is that it implies more rigidity and regularity than are warranted by the evidence to date. We present it here as an intriguing possibility that merits further research.

According to this hypothesis, stocks experience periods of investor favoritism and neglect. A stock with positive price and/or earning momentum (past winner) would be on the left half of the cycle, whereas a stock with

[21] This diagram closely parallels the intuition presented in Bernstein (1993, 1995). However, Bernstein does not discuss the role of trading volume.

negative price and/or earning momentum (past loser) would be on the right half of the cycle. Growth stocks that experience positive news move up the cycle, but eventually these stocks disappoint the market and are "torpedoed." Stocks that disappoint begin a downward slide and eventually experience general neglect. If they fall far enough in price, they may become attractive to contrarian investors.

Given this framework, our evidence suggests trading volume may provide information useful in locating a given stock in its momentum/expectation life cycle. Generally, when a stock falls into disfavor, its trading volume declines. Conversely, when a stock is popular, its trading volume increases. Viewed in this light, trading volume provides information on the degree of investor favoritism (or neglect) in a stock, or more precisely, the extent to which market sentiment favors the stock at a particular point in time.

The MLC would characterize high volume winners and low volume losers as *late stage* momentum stocks, in the sense that their price momentum is more likely to reverse in the near future. Conversely low volume winners and high volume losers are *early stage* momentum stocks, in the sense that their momentum is more likely to persist in the near future. The MLC also implies that trading volume should be correlated with value/glamour characteristics. As a stock moves up the cycle, trading volume increases and it becomes more "expensive" in terms of price-to-value measures. The higher (lower) number of analysts following high (low) volume stocks is also consistent with this explanation. In fact, many of the relations between volume and value characteristics are difficult to accommodate in any other explanation that we are aware of.

We wish to stress the limitations of Figure 4. We have shown that, *on average*, firms in each of the four quadrants of this cycle exhibit characteristics that are consistent with the MLC hypothesis. However, these results describe general tendencies at the portfolio level. For individual firms, things are far less deterministic than the figure implies. Individual firms do not necessarily exhibit expectation cycles of the same frequency. Nor does each firm need to pass through all phases of the cycle each time. The turning points for individual firms may appear random and difficult to pinpoint, even though the portfolios in each quadrant conform to the predictions of the MLC hypothesis.

The MLC diagram also does not explain the asymmetric volume effect in Year 1. Specifically, the fact that the price momentum effect is more pronounced among high volume stocks is not predicted by this explanation. Nor does the diagram explain why volume might decline as a stock falls out of favor. There are no extant models that formally address this question. One possibility is the disposition effect, or the tendency of investors to hold on to losing investments too long (see Odean (1998)). According to the disposition effect, as a stock falls out of favor, investors who own the stock become more reluctant to realize their losses. This unwillingness to sell by its owners, coupled with general neglect from potential investors, may be the reason for the decline in trading volume.

Another possibility, suggested by asymmetric information models, is that trading volume captures investors' disagreement about a stock's intrinsic value. In general, glamour stocks tend to be high growth stocks that are difficult to value. This could result in greater disagreement among investors about their intrinsic values and therefore higher trading volume. Interpreted in this context, stocks at the bottom of the MLC tend to have less investor disagreement, whereas stocks at the top of their MLC (late winners and early losers) tend to have more investor disagreement. The question that remains is why the degree of investor disagreement would vary over the MLC. Clearly, a more complete theoretical framework would be helpful.

V. Conclusion

Price and volume are simultaneously determined in equilibrium. Whatever process generates price also gives rise to the accompanying trading volume. Trading volume is also a widely available market statistic. Therefore, it is perhaps not surprising that both financial academics (e.g., Blume et al. (1994)) and practitioners (e.g., various technical chartists) have recognized the potential usefulness of trading volume in investment decisions. What is surprising is how little we really know about trading volume.

In this study, we have begun the process of understanding the role of trading volume in the prediction of cross-sectional stock returns. Our findings establish several important regularities about the role of trading volume in predicting cross-sectional returns. First, we show that trading volume, as measured by the turnover ratio, is unlikely to be a liquidity proxy. Although high (low) volume firms earn lower (higher) future returns, the opposite is true in the past. Trading volume is not highly correlated with firm size or relative bid-ask spread, and the volume effect is independent of the firm size effect.

Rather, our evidence shows that the information content of trading volume is related to market misperceptions of firms' future earnings prospects. Specifically, we provide strong evidence that low (high) volume stocks tend to be under- (over-) valued by the market. This evidence includes past operating and market performance, current valuation multiples and operating performance, and future operating performance and earnings surprises. One implication of our finding is that investor expectations affect not only a stock's returns but also its trading activity.

Second, our results show that the effect of trading volume on price momentum is more complex than prior research suggests. Neither of the two most common views about volume's effect on price momentum (i.e., the "fueling" hypothesis and the "diffusion" hypothesis) captures the stylized facts. In fact, we find volume "fuels" momentum only for losers and it helps information "diffusion" only for winners. These facts should provide further guidance to researchers interested in modeling the market dynamics that give rise to returns and volume.

Third, we show that the price momentum effect reported by Jegadeesh and Titman (1993) eventually reverses and that the timing of this reversal is predictable based on past trading volume. Specifically, we show that it is possible to create Jegadeesh and Titman–type momentum portfolios (winners minus losers) that exhibit long-horizon return reversals of the type first documented by DeBondt and Thaler (1985). This finding represents an important conceptual shift in the literature. Previous studies have generally viewed intermediate-horizon momentum and long-horizon price reversal as two separate phenomena. Our results show that trading volume provides an important link between these two effects.

Finally, we show that existing theories of investor behavior do not fully account for all of the evidence. Models presented in Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999) capture the spirit of our findings, in that they model prices as initially underreacting, and ultimately overreacting, to fundamental news. However, none of these models incorporate trading volume explicitly and, therefore, they cannot fully explain why trading volume is able to predict the magnitude and persistence of future price momentum.

To summarize our results, we suggest a simple conceptual diagram, which we have dubbed the momentum life cycle (MLC) hypothesis. According to the MLC hypothesis, firms move through periods of relative glamour and neglect. We suggest that trading volume may play a useful role in identifying where a stock is in this cycle. When stocks decline in popularity, their trading volume drops and they become neglected. When stocks increase in popularity, their trading volume increases.[22]

Our findings have important implications for the debate on market efficiency. The ability of past trading volume to predict future returns (and earnings surprises) implies prices do not generally equal fundamental values. Indeed, our results suggest that the market is better characterized as being in a constant state of convergence toward intrinsic value.[23] Viewed in this light, intermediate-horizon "underreaction" and long-horizon "overreaction" are simply two elements of the same continuous process by which prices impound new information. This characterization of the price adjustment process is consistent with our findings and with the behavioral models we discuss in this paper.

Our results also raise at least three interesting questions for future research. First, the asymmetry in the timing of momentum reversals between winners and losers remains a puzzle. We show that low volume losers rebound quickly and outperform high volume losers within the next three to

[22] We stress that this framework applies only at the portfolio level. We show that the firms in each quadrant of the cycle behave, *on average*, as predicted by the MLC hypothesis. However, these results reflect mean behavior at the portfolio level. At the individual firm level, things are far less deterministic than the figure implies, and turning points are far less predictable.

[23] See Lee, Myers, and Swaminathan (1999) for a more formal econometric specification of this concept.

12 months. However, it takes low volume winners longer (more than 12 months) to significantly outperform high volume winners. We know of no explanation for this timing difference. Second, with the possible exception of the disposition effect from the behavioral literature, we know of no explanation for why trading volume should decline when firms fall out of favor. We believe more robust models of investor behavior, which incorporate fluctuations in the level of trading activity, are needed to explain this finding.

Finally, we find it remarkable that measures as readily available as past returns and trading volume can have such strong predictive power for returns. The magnitude of these returns is likely to be lower under practical implementation. However, given the popularity of price momentum strategies, the improvement gained by also conditioning on past volume appears economically significant. Why this information is not fully reflected in current prices is another puzzle we leave for future research. In the meantime, we remain agnostic as to the prediction that this phenomenon will yield positive abnormal returns in future periods.

Appendix. Industry Benchmarks

To control for industry effects in our return calculations, we construct 25 equal-weighted industry portfolios. The industry portfolios are formed monthly, from January 1965 to December 1995, using two-digit CRSP SIC codes. The following table lists the industry groupings and their corresponding SIC codes. All NYSE/AMEX firms available at the time of portfolio formation are included. The benchmark-adjusted returns are computed by subtracting the annual returns of the appropriate benchmark portfolio (a portfolio that corresponds to the industry grouping of the stock at the time of the portfolio formation) from each individual stock's annual returns. The annual portfolio returns are computed as an equal-weighted average of the returns of individual stocks.

	Industry	SIC Code
1	Agriculture, forestry, and fishing	01–09
2	Mining, minerals, oil, and gas	10–14
3	Construction	15–17, 25, 32
4	Food and beverage	20
5	Tobacco products	21
6	Textile and apparel	22–23
7	Paper products	26
8	Printing and publishing	27
9	Chemicals	28
10	Petroleum	29
11	Rubber	30
12	Leather	31
13	Primary and fabricated metals	33–34
14	Machinery and electrical equipment	35–36
15	Transportation equipment	37

	Industry	SIC Code
16	Manufacturing	38–39
17	Transportation	40–47
18	Communication and utilities	48–49
19	Wholesale	50–51
20	Retail	52–59
21	Finance and real estate	60–67
22	Services	70–76, 81–89
23	Entertainment	78–79
24	Health care	80
25	Other	>89

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