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The High-Volume Return Premium

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ABSTRACT

The idea that extreme trading activity contains information about the future evolution of stock prices is investigated. We find that stocks experiencing unusually high (low) trading volume over a day or a week tend to appreciate (depreciate) over the course of the following month. We argue that this *high-volume return premium* is consistent with the idea that shocks in the trading activity of a stock affect its visibility, and in turn the subsequent demand and price for that stock. Return autocorrelations, firm announcements, market risk, and liquidity do not seem to explain our results.

THE OBJECTIVE OF THIS PAPER is to investigate the role of trading activity in terms of the information it contains about future prices. More precisely, we are interested in the power of trading volume in predicting the *direction* of future price movements. We find that individual stocks whose trading activity is unusually large (small) over periods of a day or a week, as measured by trading volume during those periods, tend to experience large (small) returns over the subsequent month. In other words, a *high-volume return premium* seems to exist in stock prices. The essence of our paper's results is captured in Figure 1. In this figure, we show the evolution of the average cumulative return of three groups of stocks: stocks that experienced unusually high, unusually low, and normal trading volume, relative to their recent history of trading volume, on the trading day preceding the portfolio formation date. We see that the stocks that experienced unusually high (low) trading volume outperform (are outperformed by) the stocks which had normal trading volume. Moreover, this effect appears to grow over time, especially for the high-volume stocks.

We postulate that the high-volume premium is due to shocks in trader interest in a given stock, that is, the stock's *visibility*. Miller (1977) and

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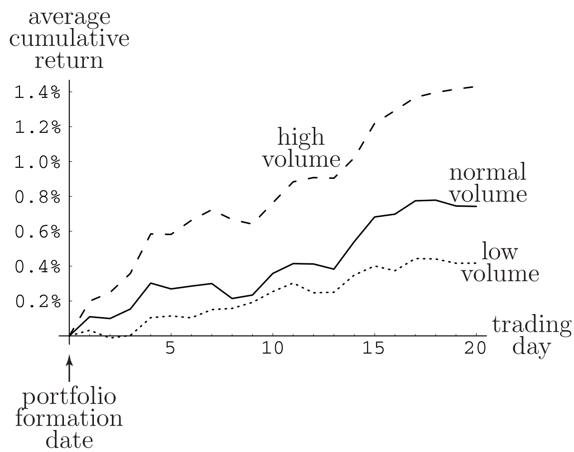


Figure 1. Evolution of the average cumulative return of stocks conditional on their one-day trading volume shocks. At the end of every 50th trading day between August 1963 and December 1996, equally weighted portfolios are formed according to the trading volume (as measured by the number of shares traded) experienced by each stock during that day. A stock whose trading volume that day is among its top (bottom) five daily trading volumes over the last 50 trading days is categorized as a "high-volume" ("low-volume") stock; otherwise, it is categorized as a "normal-volume" stock. The average cumulative return of the three portfolios is plotted in this figure.

Mayshar (1983) claim that the holders of a particular stock will on average tend to be the most optimistic about its prospects. This is especially true if taking negative positions in the stock is rendered difficult by institutional constraints on short-selling. Also, according to these authors, any shock that attracts the attention of investors towards a given stock should result in a subsequent price increase, as the set of potential buyers then includes a larger fraction of the market, whereas the set of potential sellers is largely restricted to current stockholders. Similarly, Arbel and Strebel (1982), Arbel (1985), and Merton (1987) argue that the arrival of additional analysts and traders in the market for a stock should increase its value, because this reduces the estimation risk faced by traders and facilitates risk sharing among them. Our results follow if trading activity shocks, as measured by volume shocks, affect the pool for potential investors through a variety of communication channels like the news, word of mouth, or, more recently, the Internet.

We reinforce the plausibility of this visibility hypothesis by showing that the high-volume return premium is not a simple by-product of the effect that trading volume has on return autocorrelations. In fact, this premium is just as prevalent for stocks that experience little or no price change at the time of their abnormal trading volume. In other words, price movements are not needed for volume shocks to have predictive power over future returns. In that sense, our analysis complements those of Conrad, Hameed, and Niden

(1994) and Cooper (1999), who document the fact that the performance of Lehmann's (1990) contrarian investment strategy is affected when one conditions on past trading volume in addition to past returns.[1] We also show that the high-volume return premium is not just proxying for the momentum effects that Jegadeesh and Titman (1993) document. Indeed, it is not the case that the returns are mainly generated by past winners with positive volume shocks and past losers with negative volume shocks. Instead, we find that past losers, which are more likely to have fallen out of the investors' radar, are especially affected by volume shocks. Moreover, for these stocks, the effects of positive volume shocks are similar in magnitude to the effects of negative volume shocks.

Given the surprising ability of trading volume to predict subsequent price changes, we investigate a number of additional potential explanations for our results. Starting with Beaver's (1968) study of earnings announcements, it is often argued that earnings and dividend announcements are accompanied by unusual changes in price and trading volume. In particular, Bamber and Cheon (1995) document the fact that earnings announcements that are accompanied by large trading volume but small price changes tend to be followed by price increases. To alleviate the possibility that the high-volume premium is explained by firm announcements, we show that the removal of periods around earnings and dividend announcements does not affect our results. Systematic risk does not seem to explain our results either. Indeed, there is no perceptible difference between the betas of stocks that have just experienced unusually high volume and the betas of stocks that have experienced unusually low volume. Similarly, the prediction made by Amihud and Mendelson (1986) that low liquidity (as proxied by large bid-ask spreads) should be associated with large expected returns is rejected, as the returns of our volume-based strategies are unexplained by the stocks' bid-ask spreads. Finally, the high-volume return premium does not depend on how trading volume is measured: share volume, dollar volume, detrended volume, and firm-specific volume all yield the same results.

To our knowledge, the use of trading volume as an exclusive predictor of future prices has only been studied by Ying (1966), who shows that increases (decreases) in daily trading volume on the New York Stock Exchange (NYSE) tend to be followed by a rise (fall) in the price of the S&P500 Composite Index.[2] This paper extends Ying's work in many important directions. First,

[1] Conrad et al. (1994) find that trading volume accentuates negative price autocorrelations, whereas Cooper (1999) finds that trading volume reduces them, and even makes them positive in some case. Cooper (1999) concludes that the apparent contradiction between the two papers is due to the fact that their different stock samples (Nasdaq versus 300 largest NYSE/AMEX stocks) may proxy for firm size, and imply different liquidity and information effects.

[2] Easley, O'Hara, and Srinivas (1998) document the fact that trading volume on options has predictive power about future returns. However, only positive option volume (buy call, sell put) predicts rises in stock prices, and only negative option volume (sell call, buy put) predicts falls in stock prices.

we look at volume effects for individual stocks (as opposed to the market index) over a period of more than 30 years (as opposed to 6 years). Second, we provide tests of several alternative explanations for these results, none of which are suggested or analyzed by Ying. Finally, we assess not only the statistical significance of our results but also their economic significance.

Our paper is organized as follows. In the next section, we describe our main hypothesis, the data, and portfolio formation procedures used to test it. Our main results and how they relate to existing studies on return autocorrelations are presented in Section II. This section also investigates stock visibility as a potential explanation of the high-volume return premium. In Section III, we show that a number of other alternative hypotheses fail to explain our results. Section IV presents additional evidence that visibility effects may be driving the results, and suggests other avenues to further investigate this hypothesis. Finally, in an attempt to measure the economic importance of the high-volume return premium, we study the profitability of volume-based strategies in Section V. Concluding remarks are presented in the final section of the paper.

I. Methodology

A. The Main Hypothesis

Our first objective is to test whether trading volume has any informational role in predicting stock returns. In particular, we are interested in studying how the trading activity in an individual stock is related to the future price evolution of that stock. The efficient market hypothesis predicts that trading volume should not have any predictive power over and above an appropriate measure of risk. This is the main hypothesis tested in this paper.

Miller (1977) and Mayshar (1983) argue that, if traders have diverse opinions about the value of a stock, the traders who end up holding that stock will be the most optimistic about its value. They further argue that if the stock's supply is limited because of constraints on short-selling, the opinions of the pessimistic traders will fail to be incorporated into the stock's price, which will then only reflect the optimistic opinions of the stockholders. In that situation, any positive shock in the number of people paying attention to a given stock (i.e., any increase in the stock's visibility) increases the number of potential buyers, but leaves the number of potential sellers largely unchanged (e.g., if short-selling is impossible, the potential sellers only include the current stockholders). This will tend to increase the stock's price. For example, this is arguably the effect that Shleifer (1986) documents when he shows that the mere inclusion of a stock into the S&P500 index causes its price to rise. As an alternative to our main hypothesis, we conjecture that shocks in the trading activity of a stock affect its visibility and subsequently its price. The essence of this *visibility* hypothesis is in fact captured in Miller's (1977) conclusion:

> In theory, high volume does not indicate that the stock will rise (it may be caused by heavy selling), and merely observing heavy volume should not cause anyone to buy. However, if the volume does attract attention and cause more people to look at a stock, some are likely to persuade themselves that the stock should be bought.

The idea that visibility may impact the price of a stock is not restricted to the above papers. Arbel and Strebel (1982) and Arbel (1985) argue that stocks that are largely neglected by financial analysts should generate larger risk-adjusted returns on average (i.e., sell for a lower price) because of the larger parameter estimation risk faced by investors. Bernardo and Judd (1996) develop a model confirming this intuition. They show that, just like past returns help traders update their beliefs about expected returns, trading volume enables them to update their beliefs about the risk of these returns. This further resolution of uncertainty associated with large trading volume results in the risk-averse traders pushing up the stock's price in later periods. Similarly, Merton (1987) develops a general equilibrium model in which stocks that are ignored by a large fraction of the investors will tend to sell at a discount when compared to otherwise similar stocks, because aggregate risk is then absorbed by fewer agents. All these authors argue that, in such circumstances, it becomes a viable strategy for a firm to "advertise" its stock, even in the absence of news, as this can only increase its investor base and, in turn, its stock price. According to these authors, therefore, if positive shocks in trading activity provide firms with shocks in investor interest through news, word of mouth, or other communication channels, we should expect to subsequently observe an appreciation in the stock's price.

Our hypothesized role for trading volume is novel in that we look at the *intertemporal* role of volume in predicting *directional* price changes. The contemporaneous relation between trading volume and prices is well documented. Epps (1975) develops a model showing that the old Wall Street adage that bull markets are accompanied by large trading volume is not unwarranted, a conclusion that is reinforced in models by Copeland (1976), Tauchen and Pitts (1983), and Karpoff (1986). The predictions of the model are shown to hold empirically by Smirlock and Starks (1985) and Harris (1986, 1987). Another strand of the literature argues that current trading volume should dictate the intensity of future return autocorrelations and volatility. For example, Harris and Raviv (1993) and Shalen (1993) show that large trading volume tends to announce large subsequent *absolute* price changes, that is, high volatility. Similarly, Campbell, Grossman, and Wang (1993) demonstrate that large trading volume induces negative return autocorrelations when the primary motive for trading is liquidity needs. Wang (1994), on the other hand, shows that these autocorrelations will be positive if speculation is the main motive for trading. These last two predictions have been the focus of many empirical studies on trading volume, including Campbell et al. (1993), Conrad et al. (1994), Llorente et al. (1998),

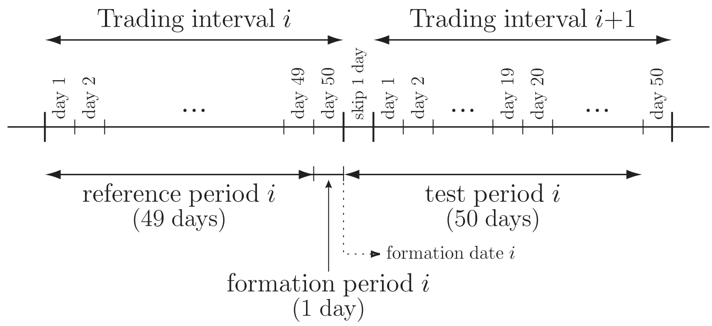


Figure 2. Time sequence for the daily CRSP sample. Each of the 161 trading intervals consists of 50 trading days. In each trading interval, the first 49 days are used to measure whether trading volume during the last day is unusually large (top 10 percent of daily volumes during the trading interval) or small (bottom 10 percent). Based on this measure, portfolios are formed at the end of the last day, and their performance is evaluated over the subsequent 1, 10, 20, 50, or 100 days (50 is depicted here).

Lee and Swaminathan (1999), and Cooper (1999). The idea behind this work is to first identify periods of large (positive or negative) price movements *accompanied* by large trading volume, and then look at subsequent price movements. Looking at the existing evidence, Cooper (1999) concludes that periods of high trading volume in smaller (larger) stocks seem to be indicative of liquidity (speculative) trading, as shown by the subsequent return reversals (continuations).

B. Data

Our two main samples use data on NYSE stocks from the stock database of the Center for Research in Security Prices (CRSP) between August 1963 and December 1996. In this section, we shall describe the *daily sample* in detail; the *weekly sample*, which is constructed similarly, is described briefly thereafter. We construct the daily sample by splitting the time interval between August 15, 1963, to December 31, 1996, into 161 nonintersecting *trading intervals* of 50 trading days. For reasons that will be made clear later, we avoid using the same day of the week as the last day in every trading interval by skipping a day in between each of these intervals. We also discard all of the data for the second half of 1968, as the exchange was closed on Wednesdays, affecting the measures of trading volume described below. This time sequence, along with some of the terminology introduced later in this section, is illustrated in Figure 2.

Each trading interval is split into a *reference period* and a *formation period*, which, respectively, consist of the first 49 days and the last day of the interval. The reference period is used to measure how unusually large or small trading volume is in the formation period. The number of shares traded is used as the measure of trading volume. In a given trading interval, a stock is classified as a high- (low-) volume stock if its formation period volume is among the top (bottom) 5 out of 50 daily volumes, that is, top 10 percent, for that trading interval.[3] Otherwise, it is classified as a normal volume stock. At the end of the formation period (at the *formation date*), we form portfolios based on the stock's trading volume classification for that trading interval. We use two different portfolio formation procedures described below: zero investment portfolios and reference return portfolios. After the portfolios are formed, they are held without any rebalancing over the *test period*, which consists of the subsequent 1, 10, 20, 50, or 100 trading days.

All existing NYSE common stocks are considered for every trading interval. However, in each trading interval, we eliminate the stocks for which some data is missing.[4] Also removed from a trading interval are all the stocks for which the firm experienced a merger, a delisting, partial liquidation, or a seasoned equity offering during or within one year prior to the formation period. The stocks with less than one year of trading history on the NYSE at the start of a trading interval were similarly discarded from that interval. Finally, we eliminate from a trading interval the stocks whose price fell below five dollars at some point in the first 49 days of that interval.[5] Every remaining stock in each trading interval is assigned to one of three *size groups* according to the firm's market capitalization decile at the end of the year preceding the formation period: The firms in market capitalization deciles nine and ten are assigned to the *large firm* group, the firms in deciles six through eight are assigned to the *medium firm* group, and those in deciles two to five are assigned to the *small firm* group. We ignore the firms in decile one, as most of these firms do not survive the filters described above. Because Blume, Easley, and O'Hara (1994) postulate that the trading volume properties of large firms will differ from those of small firms, the analysis is done separately on each of these size groups. This also allows us to assess the robustness of the results.

[3] Some stocks, especially for small firms, experience many days without any trade. This is, in fact, why we drop all the stocks from the first size decile below. Still, in some cases, the number of nontrading days for a stock without any trading activity during the formation period may exceed four over a reference period. In those cases, we do not categorize the stock as a low-volume stock automatically, as it would, on average, end up in that category more than 10 percent of the time. Instead, if we let N denote the number of nontrading days in the reference period (where $N > 4$) for a stock that did not trade during the formation period, we classify this stock as a low-volume stock randomly with a probability of $5/(N + 1)$. Note that we also repeated our analysis without the stocks that had no trading activity (i.e., zero volume) during the formation period. As this only reduced the small-, medium-, and large-firm samples by 2.67 percent, 0.89 percent, and 0.11 percent, respectively, the results were unaffected.

[4] For example, if a stock's trading volume is missing in CRSP on any one day during the 50-day trading interval, we simply remove that stock from that trading interval.

[5] Excluding the low price stocks reduces the potential biases resulting from the bid-ask bounce and from price discreteness that have been described by Blume and Stambaugh (1983) and Conrad and Kaul (1993), among others.

As a result of the above classification, for each of the 161 trading intervals, we have three size groups of stocks where each stock is classified according to trading volume in the formation period relative to the reference period. Table I presents some descriptive statistics for our daily CRSP sample. Panel A shows these statistics across all stocks and trading intervals for the three size groups. We see from that panel that, not surprisingly, stocks in the small firm group have lower stock prices and trading volumes than stocks in the medium and large firm groups. Panels B and C of Table I illustrate the general evolution of the trading intervals by showing prices and trading volumes for the first and last trading intervals. Although trading volume increases for all size groups through the years, the change is clearly more dramatic for the large firms. Finally, Panel D shows statistics about the number of stocks that are classified as high and low volume stocks in each trading interval. An interesting aspect of this last panel is the negative correlation between the number of high- and low-volume stocks over the different trading intervals. This reflects the fact that trading volume shocks tend to be correlated across stocks; that is, there seems to be a market component to trading volume. The effect that this can have on our results will be discussed later.

The second sample, the weekly sample, uses daily data aggregated over periods of one week extending from the close on Wednesday to the close on the following Wednesday. For this sample, each trading interval is comprised of 10 weeks (totaling 50 trading days), of which the first 9 are referred to as the reference period, and the last 1 as the formation period. We also skip one week between each trading interval and, as a result, we end up with a total of 155 such trading intervals. Every stock in each trading interval is again classified according to trading volume and size. If the trading volume for a stock during the last week of a trading interval represents the top (bottom) weekly volume for that 10-week interval, we classify that stock as a high- (low-) volume stock in that interval. Otherwise, the stock is classified as a normal volume stock. Sample statistics for this weekly sample are not shown here, as they resemble those presented for the daily sample in Table I.

C. Portfolio Formation

We study the effects of trading volume on future returns by forming portfolios of securities at the end of every formation period using the above volume classifications. In particular, we seek to test the null hypothesis that trading volume does not contain any directional information about future prices. This is tested against the possibility that large (small) trading volume predicts high (low) returns. For this purpose, we introduce two portfolio formation approaches.

At each formation date, we form a *zero investment portfolio* by taking a long position for a total of one dollar in all the high-volume stocks, and a short position for a total of one dollar in all the low-volume stocks of the

Table I

Descriptive Statistics for the Daily CRSP Sample

The daily CRSP sample is comprised of 161 nonoverlapping trading intervals of 50 days. For each interval, a stock is classified in one of three size groups according to its market capitalization decile at the end of the year preceding the formation period. Firms in market capitalization deciles nine and ten are assigned to the large-firm group, firms in deciles six through eight are assigned to the medium-firm group, and those in deciles two to five are assigned to the small-firm group. Volume represents the number of shares traded every day in each stock. The averages and medians in Panel A are taken over all the trading days of all trading intervals. Those in Panels B and C are taken over the trading days of these particular trading intervals. Panel D shows statistics on the number of stocks that are classified as high or low volume stocks in each trading interval.

	Small Firms	Medium Firms	Large Firms
Panel A: Overall Sample—161 Trading Intervals			
Average stock price	$16.40	$25.70	$47.72
Median stock price	$14.25	$23.13	$35.38
Average share volume	12,977	34,661	154,262
Median share volume	3,300	7,700	40,100
Panel B: First Trading Interval (Formation Period: 10/24/63)			
# stocks in subsample	171	421	341
Average stock price	$20.95	$30.71	$55.26
Median stock price	$18.25	$28.63	$44.25
Average share volume	2,597	3,677	9,059
Median share volume	800	1,500	3,600
Panel C: Last Trading Interval (Formation Period: 11/01/96)			
# stocks in subsample	304	571	525
Average stock price	$17.52	$27.13	$106.03
Median stock price	$15.03	$24.50	$39.75
Average share volume	35,447	109,063	545,095
Median share volume	10,950	47,400	301,500

Panel D: Number of High-and Low-volume Stocks in the 161 Trading Intervals

	Volume Classification					
	High	Low	High	Low	High	Low
Average	26.0	24.0	54.4	53.4	49.1	50.1
Median	24	22	51	49	43	43
Standard deviation	15.3	11.9	29.4	26.3	34.6	29.5
Minimum	1	4	5	11	1	4
Maximum	84	81	144	209	217	241
Correlation high-low	−0.392		−0.677		−0.643	

same size group. Each stock in the high- (low-) volume category is given equal weight.[6] This position taken at the end of the formation period in each trading interval i is not rebalanced for the whole test period (of 1, 10, 20, 50, or 100 days). We denote the test period returns of the long (short) position taken at the end of interval i by R_i^h (R_i^l), and the net returns of the combined position by $NR_i = R_i^h + R_i^l$. We can then test our main hypothesis by verifying whether the average net returns of this strategy over all 161 trading intervals (155 trading intervals in the case of the weekly sample), $\overline{NR} \equiv \frac{1}{161}\sum_{i=1}^{161} NR_i$, are significantly positive.[7] Note that, although our tables show the average performance of the long and short positions, that is $\bar{R}^h \equiv \frac{1}{161}\sum_{i=1}^{161} R_i^h$ and $\bar{R}^l \equiv \frac{1}{161}\sum_{i=1}^{161} R_i^l$, it should be clear that our null hypothesis does not predict that these returns will be equal to zero. Instead, given the usual positive drift in stock prices, we expect $\bar{R}^h$ ($\bar{R}^l$) to be positive (negative), and so the zero investment portfolios enable us to test the main hypothesis using net returns only. This is not the case for our second portfolio formation approach, to which we now turn.

The *reference return portfolio* approach is similar to that used by Conrad and Kaul (1993) and Lyon, Barber, and Tsai (1999). This approach implicitly adjusts the weight given to each trading interval according to the number of securities that experience high or low volumes in the interval. This is in contrast to the zero investment portfolio approach, which gives each trading interval the same weight (of 1/161) by adjusting the weight given to each security in each trading interval. More precisely, a dollar is invested long (short) in every stock experiencing high (low) volume. At the same time, every long (short) position is offset by a short (long) position in a size-adjusted reference portfolio to ensure that the net investment is exactly zero at all times. In each trading interval, this reference portfolio is constructed by putting equal weights on each of the securities from the same size group as the high- (or low-) volume security. As before, all positions are held without rebalancing until they are undone at the end of the test period. Because each long and short position is appropriately offset by a reference portfolio, we can test our main hypothesis by looking at the average return of all the long positions and all the short positions separately, something that is not possible with the zero investment portfolios. We can also aggregate the information into one number, which will summarize the profit generated per dollar long. In all cases, because each $1 investment is made for each extreme volume stock in each trading interval, the aggregation for the refer-

[6] It is possible that a size group does not contain any high- (or low-) volume stocks on a particular formation period, but contains low- (or high-) volume stocks. Because the zero investment portfolio is then not well defined, we simply dropped the only such occurrence (which came in the large-firm group's weekly sample).

[7] Although we, like the authors of the rest of the literature, refer to NR_is as returns, it should be understood that they should be more adequately referred to as trading profits. Indeed, strictly speaking, given that the amount invested to generate these profits is zero, the rates of return are infinite. Perhaps a more appropriate designation for them should be "return per dollar long."

ence return portfolios is taken over both trading intervals *and* stocks. We denote the test period return of any long (short) position net of the reference portfolio by R_{ij}^{h} (R_{ij}^{l}), where the subscript i indicates the trading interval, and the subscript $j = 1,\ldots,M_i^h$ ($j = 1,\ldots,M_i^l$) indicates the high- (low-) volume stocks for that interval. We are then interested in knowing whether

$$\bar{R}^h \equiv \frac{\sum_{i=1}^{161}\sum_{j=1}^{M_i^h} R_{ij}^h}{\sum_{i=1}^{161} M_i^h}, \tag{1}$$

$$\bar{R}^l \equiv \frac{\sum_{i=1}^{161}\sum_{j=1}^{M_i^l} R_{ij}^l}{\sum_{i=1}^{161} M_i^l}, \tag{2}$$

and

$$\overline{NR} \equiv \frac{\sum_{i=1}^{161}\left(\sum_{j=1}^{M_i^h} R_{ij}^h + \sum_{j=1}^{M_i^l} R_{ij}^l\right)}{\sum_{i=1}^{161}(M_i^h + M_i^l)} \tag{3}$$

are significantly greater than zero.

Note that, in any given trading interval, only the stocks that experience a large enough trading volume shock (positive or negative) are included in the zero investment portfolio. Similarly, only the stocks that experience these large enough volume shocks prompt the formation of reference return portfolios. In this respect, our portfolio formation approaches are similar in nature to that of Cooper (1999). The zero investment portfolios are also similar to those used by Conrad et al. (1994) in that the high-volume side of the position requires an investment of exactly one dollar, whereas the low-volume side of the position generates exactly one dollar at the outset. This will make the magnitude of our returns comparable to those of Conrad et al. (1994). The reference return approach has the advantage of better controlling for risk over the sample period, especially if the (market, liquidity, or other) risk of every security does not vary much through time. Indeed, because each security is expected to be classified as a high- (low-) volume security 10 percent of the time by construction, equally weighting each such occurrence ensures that the average risk of each security will be properly accounted for. Of course, this does not ensure that we properly control for risk shifts, an issue that we address in detail in Section III. The difference between the two portfolio formation approaches is further illustrated with a simple numerical example in the Appendix.

Finally, we want to emphasize the fact that our two portfolio formation approaches have the advantage of being implementable, as they only make use of past data. Indeed, unlike Gallant, Rossi, and Tauchen (1992), and Campbell et al. (1993), who detrend the whole time series of trading volume using ex post data prior to manipulating it, we restrict our information set at the formation date to include only data that is then available. In addition to allowing us to document the statistical relationship between prices and trading volume through time, this will enable us to verify whether profits from our strategies are both statistically and economically significant.

II. Data Analysis

A. The Main Results

The main results of our analysis are presented in Table II for the daily sample and Table III for the weekly sample. Both these tables show the average cumulative returns of the zero investment portfolios and the reference return portfolios for each of the three size groups over horizons of 1, 10, 20, 50, and 100 trading days after the formation date.

Let us first look at the results obtained with the daily sample in Table II. As can be seen from this table, the average net returns from both strategies (third line of each panel) are significantly positive at horizons of 1, 10, and 20 trading days for all size groups. The average returns from the zero investment portfolio formation strategy range from 0.41 percent per dollar long over 1 day to 0.96 percent over 20 days for the small stocks, and from 0.14 percent over 1 day to 0.55 percent over 20 days for the large stocks. The associated t-statistics are all above 3. For the reference return portfolio formation strategy, the corresponding numbers are 0.17 percent to 0.50 percent for the small stocks, and 0.08 percent to 0.29 percent for the large stocks.[8] In this case, the t-statistics all exceed 4. These statistically significant positive profits indicate that trading volume, *by itself*, contains information about the subsequent evolution of stock prices. In other words, it appears that our main hypothesis that trading volume does not have any predictive power over returns is rejected. This conclusion is reinforced by the separate long and short positions of the reference return portfolios, which all generate

[8] The fact that the zero investment portfolios seem to generate about twice as much net returns as the reference return portfolios is an artifact of the way the portfolios are formed. Indeed, the zero investment portfolios use low-volume stocks as the offsetting position for long positions in high-volume stocks before the net returns are aggregated. The average net returns of the reference return portfolios are obtained by aggregating both long and short positions that are already offset by a reference portfolio. The difference between the two portfolio formation strategies is better seen through the numerical example in the Appendix.

Table II
Average Returns of the Zero Investment and the Reference Return Portfolio Formation Strategies for the Daily CRSP Sample

In each trading interval, stocks are classified according to size and trading volume. The size groups are based on the firms' market capitalization decile at the close of the year prior to each formation period: The firms in market capitalization deciles nine and ten are assigned to the large-firm group, the firms in deciles six through eight are assigned to the medium-firm group, and those in deciles two to five are assigned to the small-firm group. The volume classification is based on whether the stock's trading volume during the formation period (last day of each trading interval) is among the top (high volume) or bottom (low volume) 10% of the 50 daily volumes in the whole trading interval. For both the zero investment and the reference return portfolio formation strategies, the three lines in each size group panel correspond to $\bar{R}^h$, $\bar{R}^l$, and $\overline{NR}$ as defined in Section I.C. We display the percentage test period returns over five different horizons following the formation date: 1, 10, 20, 50, and 100 trading days. The numbers in parentheses are t-statistics. For the cases where returns should not be compared to zero, "n/a" indicates that the t-statistic is not applicable.

	Zero Investment					Reference Returns				
Test Period (in days):	1	10	20	50	100	1	10	20	50	100
Panel A: Small Firms										
High volume ($\bar{R}^h$)	0.28	1.04	1.65	4.13	7.78	0.14	0.39	0.50	0.39	0.58
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(2.99)	(3.16)	(3.03)	(1.48)	(1.44)
Low volume ($\bar{R}^l$)	0.12	−0.14	−0.69	−3.10	−6.60	0.19	0.49	0.50	0.44	0.10
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(5.74)	(4.70)	(3.34)	(1.88)	(0.28)
Net returns ($\overline{NR}$)	0.41	0.90	0.96	1.03	1.17	0.17	0.44	0.50	0.42	0.33
	(5.90)	(4.30)	(3.04)	(2.23)	(1.83)	(5.84)	(5.49)	(4.50)	(2.37)	(1.25)
Panel B: Medium Firms										
High volume ($\bar{R}^h$)	0.23	0.89	1.35	3.54	6.65	0.12	0.35	0.46	0.51	0.70
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(4.47)	(4.92)	(4.87)	(3.38)	(3.15)
Low volume ($\bar{R}^l$)	0.04	−0.01	−0.15	−2.26	−5.20	0.10	0.37	0.54	0.47	0.35
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(5.00)	(5.74)	(6.16)	(3.34)	(1.78)
Net returns ($\overline{NR}$)	0.27	0.88	1.20	1.28	1.45	0.11	0.36	0.50	0.49	0.53
	(5.43)	(6.21)	(6.92)	(4.61)	(3.89)	(6.62)	(7.51)	(7.77)	(4.75)	(3.52)
Panel C: Large Firms										
High volume ($\bar{R}^h$)	0.15	0.52	0.96	2.69	5.00	0.08	0.27	0.43	0.31	0.23
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(3.65)	(4.72)	(5.47)	(2.53)	(1.32)
Low volume ($\bar{R}^l$)	−0.01	0.01	−0.41	−2.23	−4.86	0.07	0.19	0.15	0.15	0.12
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(4.28)	(3.50)	(1.88)	(1.24)	(0.71)
Net returns ($\overline{NR}$)	0.14	0.53	0.55	0.47	0.15	0.08	0.23	0.29	0.23	0.18
	(3.39)	(3.94)	(3.27)	(1.68)	(0.35)	(5.53)	(5.83)	(5.24)	(2.68)	(1.45)

significantly positive returns. In fact, this shows that our main hypothesis is rejected on two grounds: stocks experiencing positive volume shocks subsequently generate positive abnormal returns, whereas stocks experiencing negative volume shocks subsequently generate negative abnormal returns. The combined effect is what we call the *high-volume return premium*.

The results for the longer-term returns are not quite as strong. At horizons of 50 and 100 trading days, the profits seem to level off (and even clearly start declining for the large firms), and their significance is also diminished.[9] Because the results for the 200-day horizon are similar to those of the 100-day horizon, they are not presented here, but they force us to conclude that the permanence of the high-volume return premium is ambiguous when the volume shocks are measured daily.

Table III is the analogue of Table II for the weekly sample. It shows that the positive 1-, 10-, and 20-day net returns generated using the information contained in a formation period's volume do not crucially depend on the length of that formation period. In fact, the returns generated with the weekly sample are comparable in size to the returns generated with the daily sample, except perhaps for the 20-day returns, which seem to be higher with the weekly sample (1.44 percent compared to 0.96 percent per dollar long for the small stocks, and 1.07 percent compared to 0.55 percent for the large stocks, in the case of the zero investment strategy). Unlike the daily sample, the net returns of the two portfolio formation strategies based on weekly volume shocks persist past the 50- and 100-day test periods. The net returns of the zero investment portfolios even reach 2.21 percent and 1.52 percent after 100 days for the small and medium firms respectively.

Our 1- and 10-day net profits for both portfolio formation strategies and for both samples are comparable in size to the 1-week profits documented by Lehmann (1990), who forms his portfolios based on past returns only, and by Conrad et al. (1994) and Cooper (1999) who form theirs based on past trading volume *and* returns. Surprisingly, however, our 20-day profits remain significant, whereas Conrad et al. (1994) find that their profits disappear after three weeks.[10] More than that, we see from Table III that the size of the average profits increases at longer horizons, which indicates that this volume effect is not just a very short-term effect. As mentioned above, it is not clear whether our net returns are permanent when they are associated with daily volume shocks, but they certainly seem permanent when they are associated with volume shocks over one week, the formation period used by Conrad et al. (1994) and Cooper (1999). Given that our strategies condition on trading volume exclusively, it appears that the trading volume effect is a

[9] The t-statistics with the 100-day test period suffer from a bias. Indeed, because the last 49 days of each test period intersect with the subsequent test period, the intersecting periods' returns of the stocks that experience a high- (or low-) volume shock for two trading intervals in a row are considered twice. However, this bias is minimal as it only occurs 10 percent of the time by construction, and it only affects half of the 100-day return horizon each time.

[10] This can be seen from their Table VIII. It is impossible to tell whether Cooper's profits persist past the one-week test period that he considers throughout his paper.

Table III
Average Returns of the Zero Investment and the Reference Return Portfolio Formation Strategies for the Weekly CRSP Sample

In each trading interval, stocks are classified according to size and trading volume. The size groups are based on the firms' market capitalization decile at the close of the year prior to each formation period: the firms in market capitalization deciles nine and ten are assigned to the large-firm group, the firms in deciles six through eight are assigned to the medium-firm group, and those in deciles two to five are assigned to the small-firm group. The volume classification is based on whether the stock's trading volume during the formation period (last week of each trading interval) is the highest (high volume) or lowest (low volume) of the 10 weekly volumes in the whole trading interval. For both the zero investment and the reference return portfolio formation strategies, the three lines in each size group panel correspond to $\bar{R}^h$, $\bar{R}^l$, and $\overline{NR}$ as defined in Section I.C. We display the percentage test period returns over five different horizons following the formation date: 1, 10, 20, 50, and 100 trading days. The numbers in parentheses are t-statistics. For the cases where returns should not be compared to zero, "n/a" indicates that the t-statistic is not applicable.

	Zero Investment					Reference Returns				
Test Period (in days):	1	10	20	50	100	1	10	20	50	100
					Panel A: Small Firms					
High volume ($\bar{R}^h$)	0.19	0.92	1.26	4.18	7.95	0.07	0.31	0.45	0.41	0.71
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(1.48)	(2.43)	(2.68)	(1.61)	(1.90)
Low volume ($\bar{R}^l$)	0.06	0.08	0.17	−2.57	−5.74	0.16	0.53	0.71	0.96	1.02
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(4.62)	(4.92)	(4.71)	(3.99)	(2.79)
Net returns ($\overline{NR}$)	0.25	1.00	1.44	1.61	2.21	0.11	0.42	0.58	0.69	0.87
	(4.06)	(4.20)	(4.66)	(3.40)	(3.47)	(4.01)	(5.05)	(5.17)	(3.93)	(3.32)
					Panel B: Medium Firms					
High volume ($\bar{R}^h$)	0.18	0.76	0.91	3.37	6.44	0.07	0.33	0.32	0.34	0.41
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(2.57)	(4.64)	(3.43)	(2.28)	(1.88)
Low volume ($\bar{R}^l$)	0.04	0.18	0.22	−2.18	−4.92	0.10	0.51	0.70	0.76	0.85
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(4.78)	(8.18)	(8.15)	(5.61)	(4.29)
Net returns ($\overline{NR}$)	0.22	0.94	1.13	1.19	1.52	0.08	0.42	0.51	0.56	0.64
	(4.08)	(7.04)	(6.27)	(4.28)	(4.20)	(5.01)	(8.96)	(8.11)	(5.51)	(4.31)
					Panel C: Large Firms					
High volume ($\bar{R}^h$)	0.17	0.66	0.80	2.75	5.44	0.06	0.25	0.29	0.28	0.43
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(2.64)	(4.28)	(3.60)	(2.17)	(2.32)
Low volume ($\bar{R}^l$)	−0.02	−0.03	0.27	−1.66	−4.28	0.06	0.31	0.55	0.64	0.78
	(n/a)	(n/a)	(n/a)	(n/a)	(n/a)	(3.46)	(5.23)	(6.95)	(4.97)	(4.22)
Net returns ($\overline{NR}$)	0.14	0.63	1.07	1.09	1.15	0.06	0.28	0.42	0.46	0.60
	(3.45)	(5.36)	(6.15)	(3.67)	(2.89)	(4.25)	(6.72)	(7.41)	(5.03)	(4.61)

permanent one. In contrast, the return autocorrelation effect and the impact that trading volume has on it only seem temporary. We will come back to these issues in Section II.B.

Brennan, Chordia, and Subrahmanyam (1998) and Lee and Swaminathan (1999) present some evidence that large trading volume tends to be accompanied by smaller expected returns. They show that the most active stocks tend to generate smaller returns on average than comparable stocks that are traded less heavily, an effect resulting from the fact that investors require a higher expected return for holding illiquid stocks, as suggested by Amihud and Mendelson (1986). Our results in Tables II and III seem to contradict this evidence. However, this is probably a consequence of the fact that the above two papers use a long-run measure of trading activity, as opposed to our measure of unusual short-run volume. In other words, Brennan et al. (1998) and Lee and Swaminathan (1999) identify stocks that are very active *on average*; these stocks trade at a premium. On the other hand, we identify stocks that experience a *shock* in their trading activity over a relatively short period; as we argue next, these stocks tend to appreciate as they become more visible.

B. The Interactions of Stock Returns and Trading Volume

Many authors have documented the fact that stock returns and trading volume are generally correlated. Starting with Epps' (1975) formalization of the old Wall Street adage that bull (bear) markets are associated with large (small) trading volume, most of the early literature concentrates on the contemporaneous relationship between stock returns and trading volume. This adage was later confirmed empirically by Smirlock and Starks (1985), and Harris (1986, 1987) among others. More recently, the rapid growth of the literature on the autocorrelation of returns has prompted financial economists to think about the effects that trading volume should have on these autocorrelations. Campbell et al. (1993) postulate that, if the main motive for trading is informationless hedging, then extreme short-term stock returns, positive or negative, will tend to be later reversed when they are associated with large trading volume. This is in fact verified empirically by Conrad et al. (1994) for Nasdaq stocks. However, Wang (1994) argues that these tendencies can be opposite when the main motive for trading is to take advantage of private information. Cooper (1999) shows that this is the case for large NYSE/AMEX stocks. Lee and Swaminathan (1999) complement these results for medium-term (three-month) autocorrelations by showing that the momentum strategies documented by Jegadeesh and Titman (1993) are more profitable for high-volume stocks.

There are two ways by which the high-volume return premium can be affected or explained by the above studies and results. First, our portfolio formation strategies are based on the trading volume that stocks experience during a short time interval (a day or a week). The performance of these strategies is also evaluated over a short period of time (a day to 100 days).

If the effect that trading volume has on short-term return autocorrelations is stronger for stocks that experience low (high) formation period returns, Conrad et al.'s (1994) reversal (Cooper's momentum) results could be a partial explanation for our results, although our effects' persistence would remain unexplained. Second, it is possible that returns and volume implicitly interact with each other throughout the entire reference period that serves as a measure for normal trading volume.[11] The medium-term (three-month) momentum results originally documented by Jegadeesh and Titman (1993) could then possibly imply our volume results.

Incidentally, these possibilities provide us with an opportunity to assess visibility as an explanation for the high-volume return premium. If visibility shocks are the main force behind the subsequent price movements, contemporaneous shocks in returns should not be required for the high-volume return premium to exist. The unusual volume during the formation period should be sufficient. Furthermore, visibility shocks should be particularly important for stocks that Arbel (1985) refers to as "generic stocks." These stocks, largely ignored by analysts and investors, have essentially fallen out of fashion. It is not unreasonable to proxy a stock's level of genericity by its recent return, as large losers do not typically generate much analyst and investor interest. More than that, given that short-selling is only possible on up ticks at the NYSE, these stocks are probably harder to short-sell than other stocks. We therefore expect the high-volume return premium to be stronger for stocks that have recently underperformed.

In this section, we take a closer look at these possibilities and, at the same time, show how our work relates to the aforementioned papers. Also, given that the high-volume return premium is clearly present at horizons of 20 or fewer trading days, but less clearly so for longer horizons (in the case of the daily sample), we focus the rest of our analysis on test periods of 1, 10, and 20 trading days exclusively. This also makes our analysis comparable to the work of Lehmann (1990), Conrad et al. (1994), and Cooper (1999), who all consider test periods of less than one month.

B.1. Short-term Interactions

In this section, we show that the net returns of our portfolios are not the result of short-term autocorrelations that may exist in returns or the impact that trading volume has on these autocorrelations. Instead, the high-volume return premium reflects the fact that "normal" returns associated with "unusually" high (low) trading activity tend to be followed by large (small) returns.

To show this, we restrict each of our two data samples to *normal return subsamples* based on the formation period return experienced by each stock. A stock is said to have experienced a normal formation period return if that return is not unusually high or low. We consider two alternative definitions of normal returns. For the *middle 40 percent* definition, the high and low

[11] We are grateful to an anonymous referee and to René Stulz for pointing this out.

returns are separated from the normal returns using a method similar to the one that was implemented for trading volume in Section I. Using the daily (weekly) sample, we therefore compare the formation period return of each stock to the previous 49 daily (9 weekly) returns; the normal return subsample consists of those stocks whose formation period return is not in the top or bottom 30 percent of the distribution for the trading interval. The more restrictive *middle 20 percent* subsample is similarly obtained by removing the stocks whose formation period return is not in the top or bottom 40 percent. The net returns ($\overline{NR}$, as defined in Section I) for the two volume-based portfolio formation strategies applied to these subsamples are shown in Table IV, where Panel A uses the daily sample, and Panel B the weekly sample.

As in Tables II and III, most of the 10- and 20-day net returns are significantly positive despite the fact that sample sizes have been greatly reduced for these normal return subsamples. In fact, these returns are all of the same magnitude as before, and many exceed their counterparts from Tables II and III. Many of the one-day net returns are also still significant. Moreover, some of the zero investment (reference return) 20-day net returns are now close to two percent (one percent), and approaching economically significant values. Because our normal subsample stocks would have received very little or no weight in the portfolios considered by Conrad et al. (1994) and Cooper (1999), we can safely say that the phenomenon described here is orthogonal to theirs. At the same time, shifts in visibility and the ensuing effect they have on the demand for a stock seem to be an attractive explanation for the high-volume return premium.

This is not to say that our findings are inconsistent with those documented by Cooper (1999), who also uses data on NYSE stocks for his analysis. Although he does not emphasize it, Cooper finds that the high-volume stocks subsequently outperform the low-volume stocks, when conditioning on small absolute returns and large changes in weekly volume (see the left-most columns in his Table 3). This is exactly the essence of the results we find in Table IV, of which the large firms of Panel B are the most comparable to Cooper's weekly data on large NYSE/AMEX firms.

B.2. Medium-term Interactions

Although we feel confident that the high-volume return premium is not the product of return autocorrelations at daily or weekly frequencies, it is still possible that return autocorrelations at lower frequencies are responsible for its existence. To assess this possibility, we split each of our two main samples into two *momentum subsamples*. These subsamples are based on the return experienced by each stock during the reference period, as opposed to the formation period (as was done in Section B.1). In particular, in any given trading interval, a stock is classified as a *winner* (*loser*) if its reference period return is larger (smaller) than the median return of all

Table IV

Average Net Returns of the Zero Investment and the Reference Return Strategies Using Formation Period Return Subsamples of the Daily and Weekly CRSP Samples

In each trading interval, stocks are classified according to size and trading volume as in Tables II and III. We only use the subsample of stocks whose returns during the formation period are classified as normal. Two definitions of normal returns are considered: (1) middle 40%: returns that are not in the top 30% or bottom 30% when compared to the daily (Panel A) or weekly (Panel B) returns of the reference period; (2) middle 20%: returns that are not in the top 40% or bottom 40% when compared to the daily (Panel A) or weekly (Panel B) returns of the reference period. All the entries refer to the average net returns ($\overline{NR}$) of the strategies, as defined in Section I.C. For both portfolio formation strategies, we display the percentage test period returns over three different horizons following the formation date: 1, 10, and 20 trading days. The numbers in parentheses are t-statistics.

	Zero Return			Reference Returns		
Test Period (in days):	1	10	20	1	10	20
Panel A: Daily CRSP Sample						
Small firms						
Middle 40%	0.30	0.59	0.36	0.12	0.53	0.56
	(1.96)	(1.30)	(0.55)	(2.07)	(3.26)	(2.52)
Middle 20%	−0.06	1.13	1.68	0.08	0.59	0.68
	(−0.44)	(2.63)	(2.93)	(1.56)	(4.17)	(3.37)
Medium firms						
Middle 40%	0.13	1.01	1.89	0.01	0.39	0.76
	(1.63)	(3.88)	(6.52)	(0.42)	(4.08)	(6.06)
Middle 20%	0.10	1.02	1.46	0.09	0.52	0.57
	(1.07)	(3.56)	(4.56)	(2.85)	(5.57)	(4.47)
Large firms						
Middle 40%	−0.01	0.22	0.46	0.01	0.15	0.28
	(−0.21)	(1.02)	(1.47)	(0.21)	(2.05)	(2.64)
Middle 20%	0.18	1.08	0.86	0.07	0.32	0.31
	(2.03)	(4.48)	(2.24)	(2.59)	(4.02)	(2.79)
Panel B: Weekly CRSP Sample						
Small firms						
Middle 40%	0.20	0.68	1.21	0.13	0.40	0.61
	(1.46)	(1.84)	(2.22)	(2.37)	(2.54)	(2.86)
Middle 20%	0.26	0.87	1.74	0.19	0.66	1.03
	(1.52)	(1.53)	(2.67)	(3.08)	(3.62)	(4.42)
Medium firms						
Middle 40%	0.08	1.09	1.16	0.07	0.54	0.70
	(0.86)	(4.00)	(2.97)	(2.49)	(6.10)	(5.94)
Middle 20%	0.12	0.67	0.96	0.08	0.50	0.57
	(1.21)	(2.62)	(2.82)	(2.41)	(4.97)	(4.08)
Large firms						
Middle 40%	0.04	0.51	1.23	0.04	0.21	0.40
	(0.43)	(2.13)	(3.28)	(1.27)	(2.66)	(3.75)
Middle 20%	0.20	0.65	1.17	0.07	0.27	0.43
	(2.54)	(2.49)	(3.36)	(2.26)	(2.91)	(3.49)

stocks in that period.[12] We then apply the reference return portfolio strategy on each of these subsamples. The zero investment portfolios are not investigated because we are ultimately interested in how the long and short positions perform.

Table V, which shows the results, uncovers many interesting insights. First, looking at the last three columns of the table, we can see that almost all of the net returns are positive. However, the high-volume return premium is much stronger for stocks that have performed relatively poorly over the 49 trading days (9 weeks in the case of the weekly sample) of the reference period. Indeed, the net returns of the loser portfolios are all significantly positive and all larger than their unconditional counterparts in Tables II and III. The size of these returns is particularly striking for the weekly sample: the 20-day net returns of 0.93 percent, 0.66 percent, and 0.69 percent for the small, medium, and large firms, respectively, are probably large enough to yield economic profits. Although the net returns of the winner portfolios are mostly positive, they are all smaller than the unconditional net returns. Also, many of them are not statistically significant. Thus, the high-volume return premium is mainly a phenomenon for losers. This leads us to conclude that medium-term momentum does not explain the whole story.

A look at the performance of the long and short positions of the loser portfolios in Table V further reinforces this conclusion. All but one of the long ($\bar{R}^h$) and short ($\bar{R}^l$) positions generate significantly positive returns at the 1-, 10-, and 20-day horizons, showing that the high-volume return premium is not primarily driven by one side of the portfolios. Incidentally, this, in fact, also rules out institutional investor herding as a potential explanation for our results. Nofsinger and Sias (1999) and Wermers (1999) find that buy-side (sell-side) mutual fund herding tends to be accompanied and followed by larger (smaller) returns. Both the absence of momentum and the prevalence of the high-volume return premium for losers are inconsistent with these findings. However, once again, the visibility hypothesis fits the data quite nicely. Indeed, it is more than conceivable that subperforming stocks fall out of investors' and analysts' interest more than their overperforming counterparts. Shifts in visibility, as proxied by volume shocks, are likely to have a bigger effect on the demand for these stocks, as they seem to have in the data.

Using one lag of weekly return and volume, Conrad et al. (1994) and Cooper (1999) also analyze the interaction of past returns and past trading volume in predicting subsequent price movements. Unfortunately, comparing their results to ours in Panel B of Table V, which also conditions on one week of trading volume, is problematic. Indeed, instead of using the same week (i.e., the formation period) to identify price momentum, we use the nine weeks

[12] We do this ranking for stocks of all sizes all at once in a given interval to conform with the momentum literature. We repeated the analysis ranking each stock relative to its own size group, and found essentially the same results.

preceding it (i.e., the reference period) to conform more closely to the medium-term momentum literature started by Jegadeesh and Titman (1993). As a result, the returns of our portfolios during the formation period week are not as extreme as those in Conrad et al. (1994) and Cooper (1999). They are therefore not subject to the strong weekly mean reversion discussed by these authors, making our momentum analysis very different from theirs.

III. Other Potential Explanations and Alternative Hypotheses

In this section, we investigate whether some other existing theories and empirical facts can account for the existence of the high-volume return premium. In particular, the current section shall show that, like return autocorrelations, firm announcements, market risk, liquidity, and trading volume patterns all fall short in explaining this premium.

A. Firm Announcements and Outliers

Numerous studies have documented the effects of firm announcements on trading volume and stock returns. Beaver (1968) finds that there are significant and abnormal changes in price and trading volume around earnings announcements. Ball and Brown (1968) and Bernard and Thomas (1989, 1990) among others show that earnings announcements tend to be followed by price drifts in the direction of the earnings surprise. More importantly for us, Bamber and Cheon (1995) find that, when earnings announcements are accompanied by large trading volume but small price changes, they tend to be followed by price increases. It is therefore possible that the volume-price relation is driven by firm announcements. To investigate this possibility and at the same time the more general possibility that our results are affected by a few outliers, we conduct two tests.

First, we remove from each trading interval of our daily sample all the stocks that had a dividend or an earnings announcement either the day before, the day of, or the day after the formation period.[13] We consider the days preceding and following the formation period to account for the possibilities that some announcements are only recorded the next day in our data, or do not have their effects felt until the day following the announcement.[14] We then use this subsample of the daily CRSP data and perform the same analysis as in Section II.A. The average net returns from the two portfolio formation strategies are shown in Table VI. These returns can then be directly compared with those in Table II. Little or no effect results from re-

[13] To be perfectly precise, the earnings announcements were extracted from the Institutional Broker Estimate System (I/B/E/S) data, which only starts in 1983. The first trading interval considered for earnings announcements therefore starts on January 20, 1983.

[14] We also repeated the same analysis by removing the stocks that had a dividend or an earnings announcement in the period of one week around the formation period. The results were essentially the same.

Table V

Average Net Returns of the Reference Return Strategies Using Momentum Subsamples of the Daily and Weekly CRSP Samples

In each trading interval, stocks are classified according to size and trading volume. In both cases, this classification is done exactly the same way it was done in Tables II and III. We further split the stocks into two mutually exclusive subsamples: those stocks whose reference period returns are in the top ("winner") and bottom ("loser") halves when compared to the entire cross section of reference period returns for all stocks. The "High Volume," "Low Volume" and "Net Returns" columns refer to $\bar{R}^h$, $\bar{R}^l$, and $\overline{NR}$ for the reference return strategy, as defined in Section I.C. We display the percentage test period returns over three different horizons following the formation date: 1, 10, and 20 trading days. The numbers in parentheses are t-statistics.

	High Volume ($\bar{R}^h$)			Low Volume ($\bar{R}^l$)			Net Returns ($\overline{NR}$)		
Test Period (in days):	1	10	20	1	10	20	1	10	20
Panel A: Daily CRSP Sample									
Small firms									
Winners	0.00	−0.04	0.21	0.16	0.36	0.32	0.08	0.16	0.27
	(0.03)	(−0.22)	(0.91)	(3.42)	(2.44)	(1.53)	(2.06)	(1.44)	(1.72)
Losers	0.29	0.83	0.80	0.22	0.56	0.64	0.25	0.69	0.71
	(4.10)	(4.77)	(3.41)	(4.46)	(3.86)	(3.04)	(5.97)	(6.13)	(4.56)
Medium firms									
Winners	−0.01	−0.09	0.08	0.15	0.34	0.37	0.07	0.13	0.23
	(−0.33)	(−0.97)	(0.63)	(5.34)	(3.88)	(3.08)	(3.02)	(1.93)	(2.56)
Losers	0.26	0.82	0.87	0.06	0.41	0.71	0.16	0.61	0.79
	(6.34)	(7.73)	(6.24)	(1.94)	(4.38)	(5.71)	(6.14)	(8.66)	(8.46)
Large firms									
Winners	−0.01	−0.15	0.12	0.08	0.16	0.01	0.04	0.01	0.05
	(−0.32)	(−1.87)	(1.05)	(3.62)	(2.17)	(0.13)	(2.06)	(0.17)	(0.66)
Losers	0.15	0.65	0.72	0.06	0.23	0.32	0.11	0.45	0.53
	(5.29)	(8.06)	(6.53)	(2.45)	(2.74)	(2.73)	(5.66)	(7.73)	(6.59)

Panel B: Weekly CRSP Sample									
Large firms									
Winners	−0.08	−0.12	−0.10	0.18	0.49	0.48	0.06	0.21	0.21
	(−1.26)	(−0.66)	(−0.41)	(3.98)	(3.27)	(2.31)	(1.52)	(1.77)	(1.32)
Losers	0.19	0.68	0.91	0.13	0.57	0.95	0.16	0.63	0.93
	(3.08)	(3.73)	(3.94)	(2.63)	(3.73)	(4.36)	(4.04)	(5.24)	(5.85)
Medium firms									
Winners	−0.04	0.03	−0.04	0.12	0.58	0.72	0.05	0.32	0.36
	(−1.11)	(0.30)	(−0.26)	(4.54)	(6.88)	(6.13)	(1.98)	(4.96)	(4.11)
Losers	0.17	0.60	0.64	0.07	0.44	0.68	0.12	0.52	0.66
	(4.56)	(6.03)	(4.96)	(2.32)	(4.71)	(5.39)	(4.99)	(7.64)	(7.31)
Large firms									
Winners	−0.03	−0.10	−0.18	0.05	0.23	0.44	0.01	0.08	0.15
	(−1.12)	(−1.18)	(−1.57)	(2.24)	(3.02)	(4.27)	(0.66)	(1.39)	(1.99)
Losers	0.14	0.55	0.69	0.08	0.40	0.69	0.11	0.48	0.69
	(4.32)	(6.59)	(6.05)	(2.65)	(4.33)	(5.54)	(5.03)	(7.78)	(8.21)

Table VI

Average Net Returns of the Zero Investment and the Reference Return Strategies for the Daily CRSP Sample Controlling for Firm Announcements

In each trading interval, stocks are classified according to size and trading volume the same way they were in Table II. We further reduce this daily sample in each trading interval by eliminating all the stocks that had a dividend or an earnings announcement either the day before, the day of, or the day after the formation period. For all three size groups and both portfolio formation strategies, we display the percentage net returns ($\overline{NR}$), as defined in Section I.C, for three different test periods: 1, 10, and 20 trading days. The numbers in parentheses are t-statistics.

	Zero Investment			Reference Returns		
Test Period (in days):	1	10	20	1	10	20
Small firms	0.41	0.89	1.04	0.18	0.40	0.48
	(6.05)	(4.09)	(3.04)	(5.96)	(4.90)	(4.18)
Medium firms	0.26	0.85	1.20	0.11	0.36	0.51
	(4.93)	(5.87)	(6.79)	(6.10)	(7.23)	(7.60)
Large firms	0.13	0.52	0.51	0.07	0.24	0.28
	(3.14)	(3.88)	(2.95)	(5.39)	(5.76)	(4.96)

moving firm announcements from the daily sample. For example, the 20-day net returns from the zero investment portfolios go from 0.96 percent, 1.20 percent, and 0.55 percent for the small, medium, and large firms, respectively, in Table II to 1.04 percent, 1.20 percent, and 0.51 percent in Table VI. Similarly, the 20-day net returns from the reference return portfolios go from 0.50 percent, 0.50 percent, and 0.29 percent for the small, medium, and large firms, respectively, in Table II to 0.48 percent, 0.51 percent, and 0.28 percent in Table VI. In all cases, the significance of these returns is hardly affected. It therefore seems unlikely that the high-volume return premium is driven by firm announcements.

More generally, to address the possibility that just a few extreme observations are generating our results, we take a closer look at the empirical distribution of the zero investment strategy. Using our initial daily sample, this strategy consists of forming a portfolio of long and short positions on the formation date of each of the 161 trading intervals, and holding that position for a given horizon, which we take to be 20 days in this case. As a result, we end up with a sample of 161 20-day net returns. The empirical distribution of these net returns is shown in Table VII for each of the three size groups. That same table also shows some sample statistics for these distributions. We find that the net returns are distributed evenly on both sides of the average, as evidenced by the symmetric empirical distributions, the small absolute skewness coefficients, and the fact that the sample means

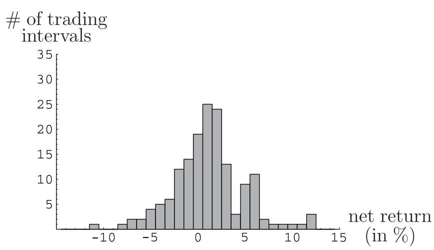
Table VII

Empirical Distribution and Sample Statistics for the 20-day Net Returns of the Zero Investment Portfolios Using the Daily CRSP Sample

In each trading interval, stocks are classified according to size and daily trading volume as in Table II. The empirical distribution and sample statistics of the following table are then obtained from the 20-day net returns (for each of the 161 trading intervals) of the zero investment portfolios.

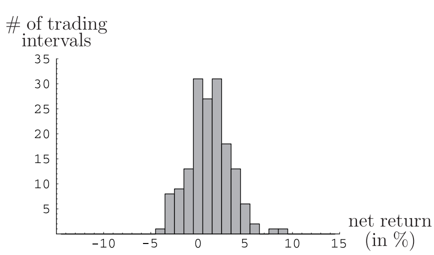
Empirical Distribution | Sample Statistics (in %)

Panel A: Small Firms



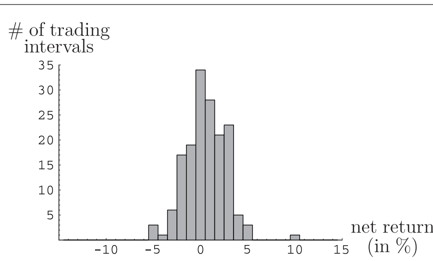
Sample Statistics (in %)	
Minimum	−16.40
Maximum	12.03
Mean	0.96
25th percentile	−1.18
Median	0.85
75th percentile	2.73
Std. deviation	4.01
Skewness	−0.28
Trimmed mean	1.01

Panel B: Medium Firms



Sample Statistics (in %)	
Minimum	−3.64
Maximum	8.70
Mean	1.20
25th percentile	−0.19
Median	1.21
75th percentile	2.59
Std. deviation	2.20
Skewness	0.24
Trimmed mean	1.16

Panel C: Large Firms



Sample Statistics (in %)	
Minimum	−5.23
Maximum	10.23
Mean	0.55
25th percentile	−0.73
Median	0.51
75th percentile	2.09
Std. deviation	2.13
Skewness	0.31
Trimmed mean	0.54

and medians are similar. Removing the five most extreme observations on each side yields trimmed means that are also essentially equal to the sample means. We conclude that the positive returns documented in Table II are not driven by firm announcements or just a few outliers.

B. Systematic Risk

Because higher systematic risk commands higher expected returns, it would be natural to find that positive trading volume shocks precede large average returns if such shocks proxy for positive shifts in stock betas. Using the daily sample, we assess whether such shifts in betas can explain the positive returns of the zero investment portfolios by estimating a joint market model for the test period returns of both the high and low volume portions of these portfolios' returns (R_i^h and R_i^l as defined in Section I.C). This joint model, which we estimate using a seemingly unrelated regression (SURE), allows the disturbance terms for the two portions of the zero investment portfolio in each trading interval to be correlated. For the return on the market, we use in turns a value-weighted market index, an equally weighted market index, and the S&P500 as the market portfolio. Because the results do not depend on which index we use, we report our results based on the value-weighted index only. We denote the market returns over the test period of interval i by R_i^m. For a given test period, we estimate the following joint model across all 161 trading intervals, which are indexed by $i = 1, \ldots, 161$:

$$R_i^h = \alpha^h + \beta^h R_i^m + \varepsilon_i^h; \tag{4a}$$

$$R_i^l = \alpha^l + \beta^l R_i^m + \varepsilon_i^l. \tag{4b}$$

The estimated market return coefficients (β^h and β^l) for these regressions, as well as their difference, are shown in Table VIII. If the positive net returns of the zero investment portfolios are the product of shifts in systematic risk, we should observe $\beta^h > \beta^l$. The p-values for the test that $\beta^h - \beta^l = 0$ are shown in curly brackets in Table VIII. As can be seen from this test, the betas of the long positions are at most indistinguishable from the betas of the short positions, and perhaps even smaller. In fact, all of the estimated β^h coefficients are smaller than the corresponding β^l coefficients for the 10- and 20-day test periods. We therefore conclude that the high-volume return premium cannot be explained by systematic risk.

C. Liquidity

Amihud and Mendelson (1986) predict that liquidity, as proxied by the bid-ask spread, should contribute to a stock's expected return. If periods of unusual trading volume announce changes in the stock's liquidity, it is therefore plausible that they will also predict returns, explaining the high-volume return premium. Testing for this explanation requires that we test whether the stocks' bid-ask spreads during the test period are positively associated with the test period returns of our strategies. However, this cannot be achieved using the data that we have used so far, as it contains no information concerning bid-ask spreads. This is why we introduce another sample that we construct from a different dataset, the Trade and Quote (TAQ) database from the New York Stock Exchange.

Table VIII

Regression Slopes of the High- and Low-volume Portions of the Zero Investment Portfolios on the Market Index Using the Daily CRSP Sample

Using the 161 zero investment portfolios formed for each size group in Section I.C, we estimate a joint market model. This is done using the following seemingly unrelated regression (SURE) model, where $i = 1,\ldots,161$ indexes the trading periods:

$$R_i^h = \alpha^h + \beta^h R_i^m + \varepsilon_i^h,$$

$$R_i^l = \alpha^l + \beta^l R_i^m + \varepsilon_i^l.$$

The two equations for this model describe the two portions of the zero investment portfolios, R_i^h and R_i^l, as defined in Section I.C. The corresponding returns on the market (R_i^m) are taken to be the returns on a value-weighted index. In all cases, the model is estimated for three different test periods: 1, 10, and 20 trading days. For each such regression, we show the estimated slopes β^h and β^l, as well as their difference. The numbers in curly brackets show the p-values testing for the null hypothesis that $\beta^h - \beta^l = 0$ against the alternative that $\beta^h - \beta^l \neq 0$.

	Test Period (in days):		
	1	10	20
Panel A: Small Firms			
β^h	0.886	0.960	1.111
β^l	0.793	1.081	1.176
$\beta^h - \beta^l$	0.093	−0.121	−0.065
	{0.1895}	{0.0715}	{0.3457}
Panel B: Medium Firms			
β^h	0.861	1.072	1.123
β^l	0.780	1.095	1.132
$\beta^h - \beta^l$	0.081	−0.023	−0.009
	{0.1169}	{0.6172}	{0.8127}
Panel C: Large Firms			
β^h	0.927	0.983	1.048
β^l	0.945	0.990	1.053
$\beta^h - \beta^l$	−0.019	−0.007	−0.005
	{0.6489}	{0.8728}	{0.9886}

This dataset enables us to measure the average spread over an interval of time by taking the average of the spreads quoted at the end of every half-hour in that interval (i.e., 13 spreads a day). In all cases, the spread is measured as a percentage of the stock's midquote price to make the stocks with different price levels comparable for aggregation purposes. The drawback in using the TAQ dataset is its shorter span. In fact, for this study, we use data that spans the period from January 1993 to December 1994. We alleviate this problem by making every fourth day a formation period, and

Table IX

Average Net Returns of the Reference Return Strategy Using Percentage Spread Subsamples of the Daily TAQ Sample

In each trading interval during the period covered by the TAQ sample (1993 to 1994), stocks are classified according to size and trading volume. This classification is done exactly the same way it was done in Tables II and III. Stocks are further classified according to their average percentage bid-ask spread during each test period, which is taken to be five trading days. For this calculation, percentage spreads are computed every half hour for each stock, that is, the average spread during the test period is an average of $5 \times 13 = 65$ spreads. In Panel A, we consider two subsamples based on each stock's time series of percentage spreads over the whole sample period: (1) stocks whose test period spread is above the median spread for the whole period; (2) stocks whose test period spread is below the median spread for the whole period. In Panel B, we consider two subsamples based on the cross-sectional distribution of percentage spreads in each test period: (1) stocks whose test period spread is above the median cross-sectional spread for the test period; (2) stocks whose test period spread is above the median cross-sectional spread for the test period. The entries in the "Low Spread" and "High Spread" columns refer to the percentage net returns ($\overline{NR}$) of the reference return strategy applied to these subsamples over the test period. The "Difference" column shows the difference between the two subsamples' net returns. The numbers in parentheses are t-statistics.

	High Spread	Low Spread	Difference
	Panel A: Time Series Classification		
Small firms	0.47	0.35	0.12
	(6.63)	(5.37)	(1.31)
Medium firms	0.28	0.22	0.06
	(7.03)	(5.98)	(1.07)
Large firms	0.08	0.04	0.04
	(2.44)	(1.59)	(0.81)
	Panel B: Cross-Sectional Classification		
Small firms	0.43	0.37	0.06
	(6.20)	(5.56)	(0.65)
Medium firms	0.27	0.22	0.05
	(6.86)	(6.12)	(0.88)
Large firms	0.08	0.04	0.04
	(2.50)	(1.54)	(0.83)

by restricting the test periods to five days. We end up with 113 trading intervals. In every trading interval, we classify each stock as a high-spread (low-spread) stock if its average test period spread is above (below) its median spread for all of 1993 and 1994. We then form the reference return portfolios separately on each of these two subsamples. The net returns of these portfolios, and the difference between the two subsamples, are shown in Panel A of Table IX. The slightly (but insignificantly) larger net returns of the high-spread subsample indicate that liquidity may play a (limited) role in explaining the high-volume return premium. However, it is evident from this table that liquidity does not fully explain our results: The net returns of the strategies applied to both the low-spread and high-spread subsamples are highly significant for the small and medium stocks. Panel B of Table IX shows analogous results when we construct the high- and low-spread subsamples using the cross-sectional median spread of all stocks in each test period (instead of the time series median spread for each stock in Panel A). The conclusion is unaffected by this alternative specification.

D. Other Risks

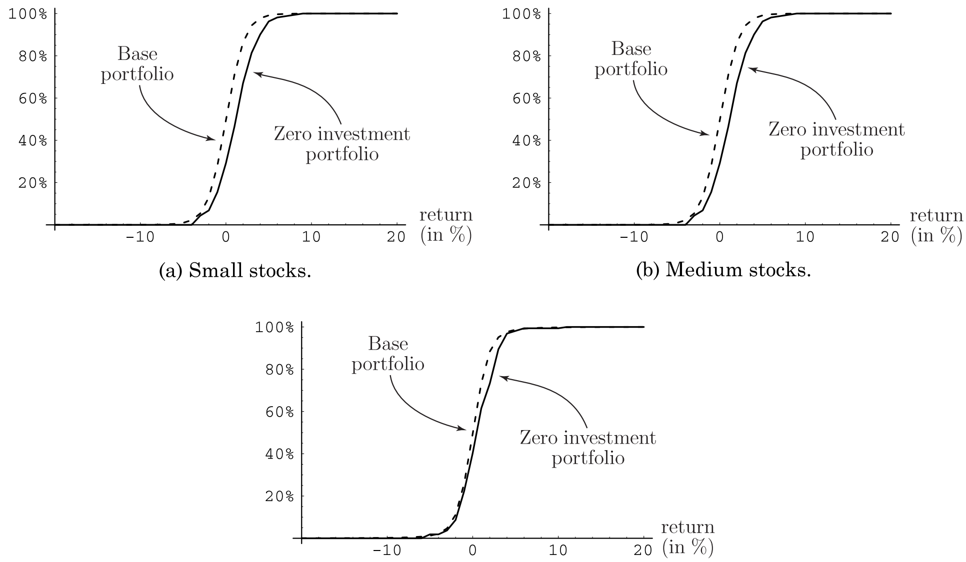
The preceding two sections investigate the possibility for the high-volume return premium to be explained by systematic risk and liquidity. To reinforce those results and at the same time remove the possibility that other types of risk are generating the results, we take a closer look at the distribution of returns obtained by the zero investment portfolios. We do this by comparing the 20-day net returns of these portfolios to 20-day net returns of similar portfolios constructed without conditioning on trading volume. More precisely, for every zero investment portfolio, we construct a *base portfolio* by replacing each security of the zero investment portfolio by another randomly chosen from the same size group. We then compare the returns of these portfolios with first-order stochastic dominance tests. For all three size groups, we find that the distribution of the zero investment returns first-order stochastically dominates that of the base portfolio returns at a significance level of one percent.[15]

The essence of these tests is captured in Figure 3, which shows the empirical cumulative density functions (CDF) for the net returns of the zero investment portfolios and the base portfolios. As can be seen from that figure, the CDF for the base portfolios tends to lie above that of the zero investment portfolios. This finding, and its implications for the risk of our strategies, is quite important. Because our strategies first-order stochastically dominate base portfolios constructed randomly, our strategies should be preferred by all rational investors with increasing utility functions, whether they are risk averse or not. Of course, this implies that risk, of any type, is not likely to explain the abnormal returns generated by our volume-based strategies.

E. Volume Measure

We finish this section by assessing the robustness of our results. In particular, we would like to ensure that our results are robust to different measures of trading volume, and are not sensitive to well-known patterns in this variable. We present these robustness checks only for the daily CRSP sample for brevity purposes. Before we start, it is worthwhile to note that all the results and tables in this paper, including those contained in this section, were also generated using dollar volume as the measure of trading volume; the findings were essentially identical.

[15] The details of how we perform these tests are available upon request. We are extremely grateful to Gordon Anderson for providing us with his computer codes for one of the tests, and for helpful discussions about this test.



(a) Small stocks.

(b) Medium stocks.

(c) Large stocks.

Figure 3. Empirical cumulative density functions for the 20-day net returns of the zero investment and base portfolios. For each of the 161 zero investment portfolios formed between August 1963 and December 1996, we construct a base portfolio by replacing each security of the zero investment portfolio by another randomly chosen from the same size group. The empirical cumulative density functions for the 20-day net returns of these two portfolios is plotted for each of the three size groups.

In determining the rank of the trading volume during the formation period in Section I.C, equal weight was given to each of the 49 days preceding that period. In choosing this length for the reference period, our concern was twofold. First, we wanted to make sure to identify only *unusual* volume days by making the reference period long enough. Second, we wanted to make sure that the volume classification was local enough to avoid biasing the analysis with time-series patterns in volume. Indeed, if daily trading volume is nonstationary (Hiemstra and Jones (1994)) or if it displays persistence and trends,[16] using a large number of past daily volumes could result in misclassifying volume as high or low.[17] To correct for these potential effects, we consider weighting schemes that will put progressively more weight on the later days (i.e., the days closer to the formation period). More precisely,

[16] The average autocorrelation of daily trading volume during the reference period varied between 0.22 and 0.25 for the different size groups. This is not surprising given the persistence in daily trading volume documented in Gallant et al. (1992), Campbell et al. (1993), and Lo and Wang (2000) among others.

[17] For example, an upward trend in trading volume would result in putting a stock in the high-volume category in more than 10 percent of the formation periods on average. In fact, ex post, the fraction of formation periods in which stocks were actually classified as high-volume stocks using the CRSP daily sample was about 11 percent.

each of the weighting schemes that we consider puts n times more weight on the volume of the reference period's last (49th) day than on its first day. As this is done progressively through the reference period, this means that the tth day of the reference period will be given a relative weight of $w_t(n) = 1 + ((n - 1)/48)(t - 1)$. As in the original analysis, the stocks whose trading volume on the formation period is in the top (bottom) 10 percent of the last 49 *weighted* daily trading volumes is considered a high- (low-) volume stock for that trading interval.[18] The first row in each size group panel of Table X presents the average net returns ($\overline{NR}$) of our two strategies using the "$n = 4$" weighting scheme. Comparison of these three rows with the third row of each panel in Table II shows that the potential nonstationarities, trends, and persistence in trading volume do not account for the significantly positive returns of our two portfolio formation approaches. Indeed, the returns generated by our strategies are unaffected both in size and significance when weighting the recent past more. We repeated the same analysis with $n = 2$ and $n = 8$ only to find essentially the same results.

As discussed in Section I.B, trading volume tends to be correlated across stocks over a given day. This means that stocks tend to be picked for the high or low volume categories in the same formation periods. As a result, the number of stocks that are classified as high volume tends to be negatively correlated with the number of stocks that are classified as low volume across trading intervals: From Panel D of Table I, we see that these correlations are -0.392, -0.677, and -0.643 for the small, medium, and large firms, respectively. To ascertain the possibility that this affects our results, we change our measure of trading volume to the fraction of the daily market volume that a stock accounts for, as suggested by Tkac (1999). For this measure, market volume is proxied by the total share volume for all the stocks in our sample. When trading activity is measured this way, the high- (low-) volume stock category will most likely be comprised of stocks which experienced high (low) *firm-specific* volume. Moreover, we should see less correlation between the number of high-volume stocks and the number of low-volume stocks across trading intervals; this is indeed the case, as the correlations become 0.092, -0.204, and 0.064 for the small, medium, and large firms. The "firm-specific volume" line in each panel of Table X shows our results. Again, a direct comparison of the average net returns ($\overline{NR}$) for both strategies to those in the third line of each panel in Table II reveals that the size and the significance of the returns are not affected by this alternative measure of trading volume. We can therefore conclude that the driving force behind the results of Section I is not shocks in market volume but in firm-specific volume.

[18] To be perfectly precise, let V_j^t denote stock j's trading volume on the tth day of a trading interval ($t = 50$ referring to the formation period). The formation period is considered a high- (low-) volume period if

$$\sum_{t=1}^{49} \mathbf{1}_{\{V_j^{50} < V_j^t\}} \frac{w_t(n)}{\sum_{\tau=1}^{49} w_\tau(n)} < 10\% \qquad \left(\sum_{t=1}^{49} \mathbf{1}_{\{V_j^{50} > V_j^t\}} \frac{w_t(n)}{\sum_{\tau=1}^{49} w_\tau(n)} < 10\% \right).$$

Table X

Average Net Returns of the Zero Investment and the Reference Return Strategies for the Daily CRSP Sample Using Alternative Volume Ranking Methods

In each trading interval, stocks are classified according to size and trading volume. The size groups are the same as in Tables II and III. The volume classification is based on whether the stock's trading volume during the formation period (last day of each trading interval) is among the top (high volume) or bottom (low volume) 10% of the 50 daily volumes in the whole trading interval. For the "volume weight" analysis, the volume of the last trading day of the reference period is weighted four times more than the volume of the first day of that period when ranking the formation period volume. For the "firm specific volume" analysis, the measure of a stock's daily volume is taken to be the ratio of the daily trading volume for that stock over that of the market. For the "day of the week" analysis, each stock's daily volume is premultiplied by a factor adjusting for the differences in expected volume across days of the week. For both portfolio formation strategies, we display the percentage net returns ($\overline{NR}$, as defined in Section I.C) over three different test periods following the formation date: 1, 10, and 20 trading days. The numbers in parentheses are t-statistics.

	Zero Investment			Reference Returns		
Test Period (in days):	1	10	20	1	10	20
Panel A: Small Firms						
Volume weight	0.42 (6.25)	0.78 (3.92)	1.00 (3.28)	0.18 (6.01)	0.38 (4.70)	0.50 (4.44)
Firm specific volume	0.42 (5.98)	0.91 (4.79)	0.92 (3.33)	0.18 (6.23)	0.40 (5.00)	0.44 (3.90)
Day of the week	0.41 (6.19)	0.92 (4.25)	1.13 (3.46)	0.18 (6.04)	0.41 (5.07)	0.50 (4.53)
Panel B: Medium Firms						
Volume weight	0.27 (5.39)	0.83 (5.93)	1.10 (6.56)	0.11 (6.49)	0.33 (6.88)	0.48 (7.36)
Firm specific volume	0.25 (6.03)	0.76 (5.87)	1.05 (6.58)	0.12 (6.86)	0.36 (7.28)	0.48 (7.30)
Day of the week	0.27 (5.32)	0.80 (5.70)	1.10 (6.69)	0.12 (6.72)	0.35 (7.23)	0.47 (7.30)
Panel C: Large Firms						
Volume weight	0.11 (2.66)	0.50 (3.77)	0.62 (3.69)	0.06 (4.32)	0.22 (5.45)	0.30 (5.38)
Firm specific volume	0.17 (5.15)	0.57 (5.42)	0.82 (5.64)	0.09 (6.29)	0.28 (6.86)	0.39 (7.01)
Day of the week	0.13 (3.20)	0.61 (4.56)	0.61 (3.63)	0.07 (5.48)	0.24 (6.07)	0.29 (5.21)

Jain and Joh (1988) document an inverse U-shape in daily trading volume across days of the week, with a peak on Wednesdays. To avoid the systematic categorization of normal volume Wednesdays (Mondays and Fridays) as high (low) volume days, we normalize the trading volume on each day by a factor that will make the mean volume across days of the week identical over the

33 years of our sample.[19] The last row of each panel in Table X shows that the results are largely unaffected by this adjustment. Recall also from Section I.B that we skip a day in between each trading interval, so that every day of the week is used as a formation period. In doing so, we seek to avoid forming all of our portfolios on the same day of the week, as our analysis could then be biased by some weekly patterns in stock returns or trading volume. In a final check on the day-of-the-week effect, we need to make sure that a similar bias is not driving the positive returns generated by our trading strategies, that is, we need to check that our returns were not concentrated on portfolios formed on a particular day of the week. Using an F-test, we find that we cannot reject the hypothesis that the returns generated from positions taken on each of the five days of the week are equal to each other. We can therefore safely say that the high-volume return premium is not driven by interdaily patterns in trading volume.

IV. Further Exploration of the Visibility Hypothesis

So far, the only serious candidate to explain the high-volume return premium is the visibility hypothesis discussed in Sections I and II. In this section, we make a slight return to this hypothesis. First, we gather additional data that will help assess its validity. Then we discuss how it relates to some of the existing literature, and how it could be further explored in the future.

As noted in Section I, the visibility argument is especially relevant when selling a stock is difficult for pessimistic traders who do not own it. The data that we have used so far do not allow us to directly measure the difficulty with which traders can take negative positions on a given stock. However, the NYSE publishes a report of the short positions held in each stock in the middle of every month.[20] The presence of short-selling in some stocks should reflect the fact that it is easier for traders to take negative positions, and so we conjecture that visibility shocks will have less impact on these stocks. In an attempt to verify this prediction, we divide the stocks into two categories: the stocks that showed some short interest at any time between 1989 and

[19] More precisely, we calculate the mean adjusting factors using only the stocks that existed during the whole 1963 to 1996 period and only the weeks with five trading days (let the number of such weeks be denoted by N). Let V_{dw} denote the total volume for all these stocks on day $d = 1,\dots,5$ of week $w = 1,\dots,N$. Then the deflating factors for each day d of the week are given by $DF_d = (1/\alpha_d)/(\sum_{\delta=1}^{5} 1/\alpha_\delta)$, $d = 1,\dots,5$, where

$$\alpha_d \equiv \frac{1}{N}\sum_{w=1}^{N}\frac{V_{dw}}{\sum_{\delta=1}^{5} V_{\delta w}}.$$

[20] As carefully described by Asquith and Meulbroek (1996), the data included in these reports is much more comprehensive than the data used in prior studies of short interest, which used reports from the *Wall Street Journal*, Barron's, and *The New York Times* (e.g., see Senchack and Starks (1993)). In particular, the set of firms included in the NYSE reports is much larger: Only firms with no or very small short interest are not listed in these reports.

Table XI

Average Net Returns of the Reference Return Strategy Using Short Interest Subsamples of the Daily and Weekly CRSP Samples for 1989–1996

In each trading interval during the period 1989 to 1996, stocks are classified according to trading volume only (i.e., all size groups are aggregated). This volume classification is done exactly the same way it was done in Tables II and III. We consider two subsamples: (1) stocks that did not show any short interest in any of the monthly NYSE short interest data files in years 1989 to 1996; (2) stocks that appeared in at least one of these files. The entries in the "No short interest" and "Some short interest" rows refer to the percentage net returns ($\overline{NR}$) of the reference return strategy applied to these subsamples over three different test periods following the formation date: 1, 10, and 20 trading days. The "Difference" row refers to the difference in net returns between the two subsamples. The numbers in parentheses are t-statistics.

	Test Period (in days)		
	1	10	20
Panel A: Daily CRSP Sample			
No Short Interest	0.10	0.53	0.55
Some Short Interest	0.08	0.34	0.44
Difference	0.02	0.19	0.11
	(0.42)	(1.41)	(0.59)
Panel B: Weekly CRSP Sample			
No Short Interest	0.12	0.61	0.55
Some Short Interest	0.12	0.33	0.48
Difference	0.00	0.27	0.07
	(0.05)	(1.97)	(0.37)

1996, the period for which we have short-interest data, and the stocks that did not. We then apply the reference return strategy separately on these two subsamples. To keep sample sizes large enough, we pool all three size groups together for this particular test. The results, shown in Table XI, indicate that the stocks that do not experience short sales tend to be affected more by the high-volume return premium than other stocks, confirming our conjecture.[21] However, the difference is not statistically significant, and so these results only provide partial support for the visibility hypothesis.

Thus the high-volume return premium and the hypothesized role that stock visibility plays remain topics for future research. First, although the asso-

[21] Our priors were that the NYSE short-interest reports would exclude small firms more systematically than large firms because, as mentioned in footnote 20, firms with very small short interest are often neglected. In that case, our results could have been driven by the fact that the high-volume return premium is stronger for small stocks. We verified that this is not the case as the average size decile for both subsamples were essentially the same: 7.49 versus 7.57.

ciation of visibility shocks with volume shocks appears to be consistent with our empirical findings, it is unclear how this association comes about. In fact, only the model suggested by Bernardo and Judd (1996) directly predicts that trading volume should contain some statistical information about future price movements. Because the economy in their model is restricted to only one stock and two trading periods, it is difficult to reconcile all the empirical facts that we document here (e.g., the results on past losers). Clearly, a better understanding of the high-volume return premium will necessitate more modeling. Second, it remains unclear how long the price movements associated with visibility shocks should last, that is, how long it takes for the demand adjustments to be completed. Although our results suggest that the shock is felt for over 20 trading days, future work on the high-volume return premium should help assess this question. Such work has actually been initiated by some authors. For example, Cao, Chen, and Griffin (2000) document that purchasing call options that exhibit extreme high trading volume on a given day yields significantly positive returns for a four-week holding period. Mingelgrin (2000) also documents an intraday high-volume return premium for both NYSE and Nasdaq stocks. Finally, it may be possible to learn more about the effects of trading volume on stock visibility by looking at other markets. For example, Miller (1977) and Merton (1987) suggest that the existence of a liquid market for put options on a given stock should make it easier for (pessimistic) traders to take negative positions. They would therefore also predict that visibility shocks will have less of an impact on these stocks, that is, the high-volume return premium should be smaller for optioned stocks. In our view, testing this prediction would be the natural next step in investigating the high-volume return premium. An information effect of volume, which is potentially related to the visibility hypothesis, is also discussed by Chan and Lakonishok (1993). These authors postulate that, when making their selling decisions, investors typically only consider the assets that they currently hold; thus the decision of which asset to sell does not convey much information to the market, as it is usually interpreted as being liquidity motivated. On the other hand, the opportunity set for buying includes every possible asset on the market; the choice of which asset to pick then conveys a lot of information. As a result, large trading volume initiated by sellers should not have much of a price impact, but large trading volume initiated by buyers does. Unconditionally, large trading volume should therefore be accompanied by price increases. The study of insider trading by Chowdhury, Howe, and Lin (1993) corroborates this view. They find that stock returns depend significantly on insider purchases but not on insider sales, and suggest that seller-initiated transactions are simply more likely to be regarded as liquidity motivated. The high-volume return premium is potentially a product of these findings. Large trading volume initiated by sellers should not have much of a price impact, but large trading volume initiated by buyers does. Unconditionally, positive (negative) trading volume shocks should be followed by positive (negative) returns.

The role of volume in assessing information-based trading is also studied by Diamond and Verrecchia (1987), who show that the absence of trade is bad news when informed traders are constrained from selling short. At first sight, this model does not seem to be consistent with the high-volume return premium. In particular, the model shows that the price reactions to volume shocks should be contemporaneous and unbiased, as rational traders should remove any potential price or return bias through their trading activities. However, if one relaxes the rational expectations assumption that all traders learn simultaneously from trading volume, it is feasible that this model would deliver predictions that resemble our empirical findings and those of Chan and Lakonishok (1993).

V. Economic Profitability of the Strategies

At this point, it is still difficult to infer whether positive economic profits could be generated by undertaking the investment strategies of Section I. First, the prices used for calculating the returns on these strategies come from the closing daily prices. As discussed in Blume and Stambaugh (1983), and Conrad and Kaul (1993), the fact that these prices could be either bid or ask prices causes an upward bias in the observed returns.[22] Second, our analysis does not consider the transaction costs associated with the formation and the redemption of the different portfolios. Lehmann (1990) and Conrad, Gultekin, and Kaul (1991) estimate that one-week returns of less than 1 percent on zero investment portfolios would be wiped out by one-way transaction costs of 0.2 percent. These estimates would seem to indicate on the one hand that, although the positive returns documented in Tables II and III help us describe the evolution of stock prices, these positive returns are probably not directly exploitable by market participants. On the other hand, the sizable returns of the strategies involving only normal formation period return stocks in Table IV may provide investors with profitable opportunities.

To see if the information contained in trading volume can be used profitably, we construct one last strategy, which takes advantage of that same information, but does so more efficiently. In particular, using limit orders, we modify the zero investment strategy in order to reduce the transaction costs associated with the bid-ask spread at the times that the positions are taken and undone. More precisely, we open our positions at the end of the formation period by sending buy (sell) limit orders at the prevailing bid (ask) price. Using the Lee and Ready (1991) algorithm to sign orders, we then check over the next day whether the limit orders are hit. The orders that have not been hit at the end of that day are converted into market-on-close orders, which are cleared at the then prevailing ask (bid) price for buy (sell)

[22] As this potential bias accentuates the returns generated from long positions with high-volume stocks, but attenuates the returns from short positions with low-volume stocks, it is not clear whether our strategies benefit from or are hurt by it.

orders. With the 20-day horizon, we close our positions by sending canceling sell (buy) limit orders at the ask (bid) price prevailing at the end of the 20th day of the test period. We then check over the next two days[23] whether the limit orders are hit. Those that are still outstanding are again converted into market-on-close orders.

Because this strategy requires the knowledge of bid and ask prices, and because Lee and Ready's (1991) algorithm requires a transaction-by-transaction account of the trading activity, we use the TAQ sample introduced in Section III.C to perform this analysis.[24] The results are shown in Panel A of Table XII. The leftmost column shows that this new strategy is mildly profitable with the small and medium stocks. The fact that we still find positive profits with this modified strategy is remarkable. Indeed, by making use of bid and ask prices, this strategy endogenously incorporates transaction costs. So the returns found in this table could actually translate into economic profits, as long as the strategies are not implemented with order sizes so large that their price impact destroys these profit opportunities.

The second and third columns of this table are included for comparison purposes. Both of these columns show the net returns of the above strategy using, as before, market orders exclusively. The second column uses the day's last quote midpoints as prices, whereas the third column uses the day's last ask (bid) price for buy (sell) orders. Essentially, the net returns of the second column do not incorporate any transaction cost, and are therefore comparable to the net returns of the zero investment portfolios in Table II. At the other end of the spectrum, the third column incorporates very explicitly the transaction costs discussed by Lehmann (1990), and by Conrad et al. (1991). As can be seen from that third column, these transaction costs are detrimental to the strategy. The fact that a similar strategy based on limit orders may be profitable simply shows that the price impact of implementing a strategy designed to take advantage of the high-volume return premium will be crucial for its profitability.

Because Table IV shows that the high-volume return premium is stronger for normal (middle 40 percent) formation period returns, we again restrict our sample to only those stocks that experience normal returns during the formation period. Panel B of Table XII shows the analogue of Panel A using this subsample. The evidence becomes quite shocking: using limit orders, it is possible to systematically take advantage of the high-volume return premium with the small- and medium-firm stocks. More precisely, the 20-day

[23] The waiting period is restricted to a day for opening the positions in order to take full advantage of the high-volume premium. Longer waiting periods to close the positions make the results better, as they give our limit orders more time to be hit. However, we felt that a waiting period longer than two days may affect the risk of our strategy.

[24] There is one small difference between the way we construct the TAQ sample in this section and that in Section III.C. To increase the sample size without compromising the requirement that every stock's test periods do not intersect, every day covered by our TAQ data is considered as a formation period, but stocks that are purchased or sold on a given formation date are not considered on the subsequent four formation days.

Table XII

Average Net Returns of the Zero Investment Portfolio Formation Strategy Using Limit Orders and the Daily TAQ Sample

Using the daily TAQ sample described in Section III.C, we repeat the zero investment strategy using limit orders. In each trading interval, stocks are classified according to size and trading volume as done in Section I.C. In Panel A, we condition only on formation period volume to form the portfolios (as in Table II). In Panel B, we only use the stocks that had normal returns during the formation period, where a normal return is taken to be the middle 40% (as in Table IV). For the first column ("Limit Orders"), the zero investment portfolios are formed at the end of the formation period using limit orders at the bid (ask) price for buy (sell) orders. The orders that are not filled within one day are turned into market orders at the end of that day. The positions are canceled at the end of 20 days using similar limit orders that, when still outstanding, turn into market orders two days later. The positions for the second column are taken using market orders at the midquote price of the day's last bid/ask quotes. The positions for the third column are also taken using market orders; however, they incorporate transaction costs by using the day's last ask (bid) price for buy (sell) orders. All the entries refer to the average 20-day percentage net returns of the zero investment strategy as defined in Section I.C. The numbers in parentheses are t-statistics.

	20-Day Net Returns		
Size Group	Limit Orders	Market Orders at Midpoint	Market Orders at Bid/Ask
Panel A: No Conditioning on Return			
Small firms	0.44	1.45	−2.98
	(1.97)	(7.14)	(−14.74)
Medium firms	0.35	0.98	−1.27
	(2.72)	(8.19)	(−10.60)
Large firms	−0.11	0.44	−0.74
	(−0.89)	(3.97)	(−6.67)
Panel B: Conditioning on Normal Return			
Small firms	0.84	1.49	−2.86
	(2.37)	(4.50)	(−8.63)
Medium firms	0.80	1.26	−0.95
	(4.27)	(7.35)	(−5.55)
Large firms	0.07	0.55	−0.62
	(0.44)	(3.63)	(−4.10)

net returns that our strategies generate are of the order of 0.84 percent and 0.80 percent per dollar long *after transaction costs* for the small and medium firms, respectively. These figures translates in annual excess returns of 11.0 percent and 10.4 percent, respectively.

Of course, the transaction costs considered in this section represent the direct bid-ask spread costs. In particular, brokerage and price impact costs are not explicitly part of our analysis. Because large traders and floor brokers face minimal brokerage costs, ignoring these costs is not a bad approximation. However, because of the impact that purchase and sell orders have on prices, it should be clear that all the strategies described throughout the paper will not be profitable if they are undertaken on a large scale. This is especially true for the price impact of sell orders placed in times of low trading activity.

VI. Conclusion

This paper shows that periods in which individual stocks experience extreme trading volume, relative to their usual trading volume, contain important information about subsequent stock returns. Specifically, periods of extremely high volume tend to be followed by positive excess returns, whereas periods of extremely low volume tend to be followed by negative excess returns. This effect, which we refer to as the *high-volume return premium*, holds when the formation period for identifying extreme trading volume is a day or a week. It lasts for at least 20 trading days, and possibly for as long as 100 trading days. It also holds consistently across all stock sizes.

Many authors, including Miller (1977) and Merton (1987), predict that an increase in a stock's visibility will tend to be followed by a rise in its price. This prediction is highly consistent with the high-volume return premium, as visibility and demand shifts seem to be prompted by trading volume shocks. The plausibility of this explanation is reinforced by two findings: (1) the returns on the day/week of the volume shocks do not seem to affect the existence of the high-volume return premium; (2) past losers, which have arguably fallen out of investors' interest, tend to be particularly affected by shocks in their trading activity.

These findings can also be used to show that the price movements implied by trading volume shocks are not simple products of the short- and medium-term return autocorrelations documented by other authors. For example, we can safely say that the high-volume return premium is not driven by the usual impact that trading activity has on short-term return autocorrelations, as studied by Conrad et al. (1994) and Cooper (1999). Indeed, even volume shocks accompanied by little or no price changes have the same effect on subsequent prices, suggesting that volume shocks contain information about future price changes that is orthogonal to that contained in past returns. Longer-term autocorrelations, like those documented by Jegadeesh and Titman (1993), do not explain the high-volume return premium either: Although past losers are more affected by volume shocks, they are equally affected by positive and negative shocks.

Many other alternative hypotheses come up short in explaining the high-volume return premium. For example, the possibility that our findings are driven by unusual conditions around earnings and dividend announcements is rejected, as the removal of such periods does not affect the results. The additional stock returns are not a compensation for additional risk: The high volume components of our volume-based portfolios actually have lower systematic risk than the low volume components. Because the stocks' bid-ask

Table AI
Stock Returns for the Two Trading Intervals

Trading Interval 1		Trading Interval 2	
Stock	Test Period Return	Stock	Test Period Return
High-volume stocks		High-volume stocks	
A	1.50%	D	1.70%
B	1.30%	Low-volume stocks	
Low-volume stocks		E	0.40%
C	0.60%	F	0.60%
		G	0.50%

spreads do not seem to explain the returns of our volume-based strategies, the liquidity explanation postulated by Amihud and Mendelson (1986) is also rejected. In fact, the return of our strategies are shown to first-order stochastically dominate the returns of random portfolios constructed on the same dates, rendering any risk-based explanation to our results unlikely. Finally, the results are robust to different measures of volume, accounting for volume trends, market-wide effects on volume, and weekly volume patterns.

Although the main objective of this paper is not to come up with profitable trading strategies based on trading volume, we do present some evidence that shows that our strategies could potentially be profitably exploited with an appropriate use of limit orders. At the very least, traders placing buy (sell) orders should do so after a period of large (small) trading volume, if they have that flexibility.

APPENDIX

In this Appendix, we describe the two portfolio formation strategies of Section I.C with the help of a numerical example. Suppose that there are only two trading intervals, and that all the stocks that are classified as high- or low-volume in each of these intervals are as listed in Table AI. Furthermore, suppose that the average test period return of all stocks is 1.04 percent in trading interval 1, and 1.10 percent in trading interval 2.

Zero Investment Portfolio Strategy

Given that there are two trading intervals, the zero investment portfolios will generate two data points. The average high-volume, low-volume, and net returns ($\bar{R}^h$, $\bar{R}^l$, and $\overline{NR}$) are calculated as shown in Table AII.

Reference Return Portfolio Strategy

The offsetting reference portfolio for both sides of this strategy is the average of all stocks, so that the reference test period return is 1.04 per-

Table AII

Calculation of Returns for the Zero Investment Portfolio Strategy

Trading Interval	Position/ Calculation	Return
High volume		
1	Buy $\$\frac{1}{2}$ of each A and B	1.40%
2	Buy \$1 of D	1.70%
	Average ($\bar{R}^h$):	1.55%
Low volume		
1	Sell \$1 of each C	−0.60%
2	Sell $\$\frac{1}{3}$ of each E, F, G	−0.50%
	Average ($\bar{R}^h$):	−0.55%
Net returns		
1	1.40% + (−0.60%)	0.80%
2	1.70% + (−0.50%)	1.20%
	Average ($\overline{NR} = \bar{R}^h + \bar{R}^l$):	1.00%

cent in trading interval 1 (Ref-1), and 1.10 percent in trading interval 2 (Ref-2). The high volume side of the strategy consists of three data points, whose average yields $\bar{R}^h = 0.44\%$. Similarly, the low volume side of the strategy consists of four data points, whose average yields $\bar{R}^l = 0.56\%$ (see Table AIII). The average net return $\overline{NR}$ for this strategy is simply the average of all seven high- and low-volume data points in Table AIII, namely 0.509 percent.

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Table AIII

Calculation of Returns for the Reference Return Portfolio Strategy

Data Point	Position/Calculation	Return
High volume		
1	Buy \$1 of A and sell \$1 of Ref-1	0.46%
2	Buy \$1 of B and sell \$1 of Ref-1	0.26%
3	Buy \$1 of D and sell \$1 of Ref-2	0.60%
	Average ($\bar{R}^h$):	0.44%
Low volume		
1	Sell \$1 of C and buy \$1 of Ref-1	0.44%
2	Sell \$1 of E and buy \$1 of Ref-2	0.70%
3	Sell \$1 of F and buy \$1 of Ref-2	0.50%
4	Sell \$1 of G and buy \$1 of Ref-2	0.60%
	Average ($\bar{R}^l$):	0.56%

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