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The High Volume Return Premium

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The High Volume Return Premium

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Abstract

The idea that extreme trading activity (as measured by trading volume) contains information about the future evolution of stock prices is investigated. We find that stocks experiencing unusually high (low) trading volume over a period of one day to a week tend to appreciate (depreciate) over the course of the following month. This effect is consistent across firm sizes, portfolio formation strategies, and volume measures. Surprisingly, the effect is even stronger when the unusually high or low trading activity is not accompanied by extreme returns, and appears to be permanent.

The significantly positive returns of our volume-based strategies are not due to compensation for excessive risk taking, nor are they due to firm announcement effects. Previous studies have documented the positive contemporaneous correlation between a stock's trading volume and its return, and the autocorrelation in returns. The high volume return premium that we document in this paper is not an artifact of these results. Finally, we also show that profitable trading strategies can be implemented to take advantage of the information contained in trading volume.

1 Introduction

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) subsequent returns. In other words, a *high volume return premium* seems to exist in stock prices. More importantly, we also document the fact that this premium is even larger for stocks that do not experience abnormal returns at the time of their abnormal trading volume. So, past trading volume appears to contain information that is orthogonal to that contained in past returns, which is evidenced by the return autocorrelation documented by several authors.[1]

The high volume return premium is not the product of risk. We show that (i) market risk does not rise (fall) after a period of unusually large (small) trading activity; (ii) the returns from trading strategies exploiting this volume effect stochastically dominate returns from diversified strategies; (iii) informational risk (as measured by the bid-ask spread) goes in a direction opposite to one which would explain the results. Furthermore, the results are robust to different measures of volume, and are not driven by firm announcements.

Our analysis complements that of Conrad, Hameed and Niden (1994) (CHN, hereafter), who document the fact that the contrarian investment strategies of Lehmann (1990) tend to perform better when conditioning on past trading volume in addition to past returns. First, our paper shows that conditioning on past trading volume alone (as opposed to both volume and returns) can generate positive returns. Indeed, the returns that our volume based strategies generate are of the same magnitude as those documented by CHN, but seem to last for a longer period of time (four weeks vs one week).[2] So, our paper seems to indicate that trading volume alone does contain long-lived information about the future evolution of stock prices; trading volume is not just part of a more complicated joint relationship between current and future returns, as theoretically suggested by Campbell, Grossman and Wang (1993).[3] Quite surprisingly, when we restrict our strategies to stocks whose past price movements are not unusually large or small, our results are even *stronger*. This strengthens the conclusion that trading volume does not just emphasize the autocorrelation in returns, but does contain information of its own.

Also related to this paper is the work of Brennan, Chordia and Subrahmanyam (1998), and Lee and Swaminathan (1998). These two papers document the fact that large trading volume tends to

[1]A few papers from this exhaustive literature include DeBondt and Thaler (1985), Fama and French (1988), Poterba and Summers (1988), Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990), Boudoukh, Richardson and Whitelaw (1994), and Lo and Wang (1997).

[2]In fact, the positive returns generated by their strategies not only die out after the first week, but tend to revert back to zero over the following three weeks, as opposed to our strategies which generate positive returns for up to 100 trading days (20 weeks).

[3]Llorente, Michaely, Saar and Wang (1998) also develop a model in which trading volume of individual stocks interracts dynamically with their returns.

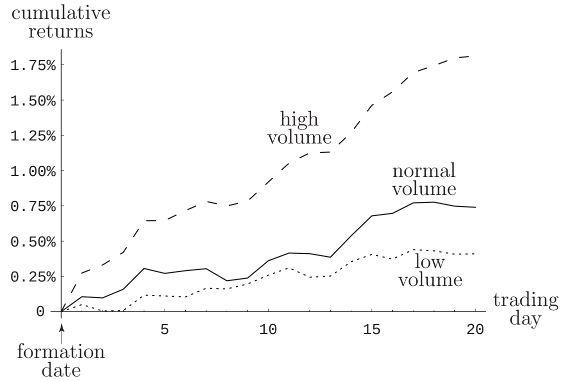

Figure 1: Evolution of the average cumulative returns of stocks chosen according to the trading volume that they experienced the day before this graph starts.

be accompanied by lower expected returns. Indeed, since investors demand a premium for holding illiquid stocks, the stocks with the largest trading volumes (i.e. the most liquid stocks) will not generate returns that are quite as large on average. The apparent contradiction between their results and ours comes from the fact that both these papers measure the *permanent* trading volume of individual stocks, whereas we only consider trading volume *shocks*. In other words, a stock that has a lot of trading activity on average should yield small returns, but a stock that experiences unusually large trading activity over a particular day or a week is expected to subsequently appreciate.

The essence of our paper's results is captured in Figure 1. In this figure, we show the evolution of the average cumulative returns of stocks conditional on the trading volume that they experienced during the trading day preceding the twenty trading day period shown on the x-axis. We see that the stocks which experienced an unusually high (low) trading volume[4] 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 and, although not shown in this figure, does not disappear in the long run.

As mentioned above, numerous papers have been written about the predictability of stock prices from past prices. Depending on the horizons over which returns are measured and on the way portfolios of risky securities are formed, there is vast empirical evidence that stock prices tend to display either positive or negative autocorrelation.[5] Similarly, a number of papers have documented the empirical relationship that seems to exist between a stock's price and its trading volume. A lot of this research is preoccupied with the contemporaneous relationship between trading volume and the absolute change in stock price (or its volatility). For example, using different samples, return intervals, and methods of aggregation, Comiskey, Walkling and Weeks (1985), Wood, McInish and Ord (1985), Harris (1986, 1987), and Gallant, Rossi and Tauchen (1992) all find a positive correlation between contemporaneous trading volume and absolute price changes. A related but

[4] Later sections of the paper will explain precisely what we mean by "unusual trading volume."

[5] See footnote 1 for a list of these studies.

different contemporaneous positive correlation between trading volume and price changes per se has also been documented by Smirlock and Starks (1985), and Harris (1986, 1987).

Although the intertemporal relationship between trading volume and prices is often neglected in these studies, a few authors have documented the Granger causality relationship between stock prices and trading volume through time (Hiemestra and Jones, 1994), as well as the fact that large absolute and nominal price movements tend to be followed by periods of high trading volume (Gallant, Rossi and Tauchen, 1992), that large trading volume is associated with negative autocorrelation in returns (Campbell, Grossman and Wang, 1993), and that volume shocks affect the high order moments of stock prices (Tauchen, Zhang and Liu, 1996). Our work complements these studies in that we are primarily concerned with the informational role of trading volume as it pertains to the direction of future prices.

A theoretical explanation for our results is difficult to find in the current literature, as most models of trading volume concentrate on explaining the contemporaneous relationship between volume and prices. Such models include, among others, Copeland (1976), Tauchen and Pitts (1983), Karpoff (1986), and Wang (1994). Even more disappointing is the fact that in most of this theoretical research, the correlation of trading volume with prices is simply a bi-product of the models, as trading volume does not play any informational role over that of prices.[6] The existing theoretical models that are consistent with and could potentially explain our results are those of Blume, Easley and O'Hara (1994), Bernardo and Judd (1996), Diamond and Verrecchia (1987), and Merton (1987). The first two show that, in the presence of uncertainty about the trading aggressiveness (as measured by the precision of information in these two cases) of some traders, current trading volume may provide information relevant to the evolution of future prices. Diamond and Verrecchia (1987) show that short-sale contraints will create an informational role for trading volume, as traders will be forced to react asymmetrically to positive and negative signals respectively. Finally, Merton (1987) argues that more noticeable stocks tend to experience price increases. Since trading volume arguably makes a stock more prominent or at the very least is correlated with its prominence, this visibility argument may explain part of the effects that we observe.

Our paper is organized as follows. In the next section, we describe the data used for the analysis, and present our methodology. In section 3, we explain our trading strategies whose performance are then evaluated in section 4. We look for risk-based explanations in section 5, and check the robustness of our results in section 6. The economic profitability of our trading strategies is assessed in section 7. Concluding remarks and potential explanations for our results are presented in section 8. Throughout the paper, we use "absolute return" to denote the absolute value of a return, and "return" to denote the return per se. Although all the figures are within the paper, all the tables are located at the end of the paper.

[6] This fact was pointed out by Blume, Easley and O'Hara (1994), who come up with a model in which volume has informational content over and above that of prices. In their model, however, volume does not predict price direction, but only price volatility.

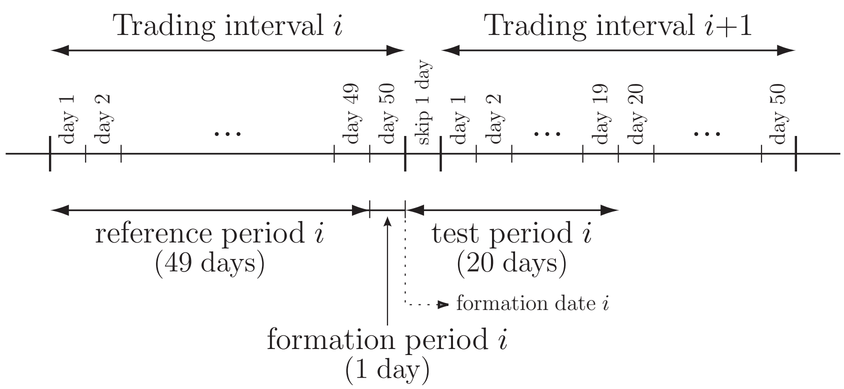

Figure 2: Time sequence for the daily CRSP sample.

2 Data and Methodology

As mentioned in the introduction, the object of this paper is to test whether trading volume has an informational role, and whether that role is orthogonal to that of past 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. To achieve this, we first determine whether trading volume in a stock over a particular interval is high, normal, or low. We then look at the subsequent returns on that stock conditional on the trading volume in that interval.

Our main sample uses daily data on NYSE stocks from the stock database of the Center for Research in Security Prices (CRSP) between August 1963 and December 1996; we shall refer to this sample as the *daily sample*. We construct the sample by splitting the time interval between 15 August 1963 to 31 December 1996 into 161 non-intersecting *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 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 names introduced later in this section, is illustrated in Figure 2.

In each trading interval, we eliminate the stocks for which some data is missing.[7] Also removed from a trading interval were all the stocks for which the firm experienced a merger, a delisting, partial liquidation, or a seasoned equity offerings during, or within one year prior to, that trading interval. 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 \$5 at some point in the first 49 days of that interval (a period that we shall refer to as the *reference period*).[8]

[7]For example, if a stock is missing a closing price on one day during the 50-day trading interval, we simply remove that stock from that trading interval.

[8]Excluding the low price stocks reduces the potential biases resulting from the bid-ask bounce and from price

Every remaining stock in each trading interval is categorized according to two properties: trading volume and size. The three trading volume categories (high, normal and low) seek to identify the stocks which had an unusual trading volume over a particular interval of time, which we refer to as the *formation period*. With this daily sample, the formation period is taken to be the last day of each trading interval, and this period is compared to the 49 days of the reference period. We measure daily trading volume by the dollar value of all the traded shares of a stock on a given day.[9] If the trading volume of a stock during the formation period is among the top (bottom) 10% daily volumes over the whole trading interval, we classify the stock in that trading interval as a high (low) volume stock for that trading interval.[10] Otherwise, the stock is classified as a normal volume stock. As described in section 3, the stock portfolios considered in our study are formed at the *end* of each formation period, a time that we refer to as the *formation date*.

Finally, every stock in each trading interval is assigned to a *size group* 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.

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 1 presents some descriptive statistics for our daily 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 volume than stocks in the medium and large firm groups. Also, although the prices in all three size groups have the same order of magnitude, trading volume in the large firms group is much larger than that in the other two groups; this is why we consider these three groups separately.[11]

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discreteness that have been described by Blume and Stambaugh (1983), and Conrad and Kaul (1993), among others. Wood, McInish and Ord (1985), and Hasbrouck (1991) also remove stocks whose prices are below \$4 and \$5 respectively.

[9]Since our data does not include the price of each transaction, we approximate the daily dollar volume by multiplying the share volume by the last trading price. The Trades and Quotes (TAQ) data used in section 6.4 will allow us to measure the dollar volume more precisely. Given the evidence contained in Jones, Kaul, and Lipson (1994), who document the fact that the number of transactions is a better measure of information arrival, we also performed our study using the number of transactions, but the results were similar, if not a bit stronger.

[10]Some stocks, especially for small firms, experience many days without any trade. In some cases, the number of non-trading days for a stock without any trading activity during the formation period may exceed 4 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% of the time. Instead, if we let N denote the number of non-trading 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 $\frac{5}{N+1}$. Note that we also repeated our analysis without the stocks that had no trading activity during the formation period. As this only reduced the small, medium and large firm samples by 2.67%, 0.89% and 0.11% respectively, the results were unaffected.

[11]In fact, Blume, Easley and O'Hara (1994), and CHN suggest that trading volume will have different properties for firms of different sizes.

Panels B and C of Table 1 illustrate the general evolution of the trading intervals by showing prices and trading volumes for the first and last trading intervals.

The second sample uses daily data aggregated in periods of one week extending from the close on Wednesday to the close on the following Wednesday. We refer to it as the *weekly sample*. For this sample, each trading interval is comprised of 10 weeks (totalling 50 trading days), of which the first nine are referred to as the reference period, and the last one as the formation period.[12] 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.[13] 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.[14] Otherwise, the stock is classified as a normal volume stock. The classification of firms to the different size groups is done the same way as in the daily sample. Sample statistics for this weekly sample are not shown here, as they resemble those presented for the daily sample in Table 1.

As mentioned above, our primary objective is to study the evolution of stock prices following periods of unusually large or small trading activity in a stock. To do this, we use the twenty trading days (i.e. about a month) following the formation period of each trading interval to measure the returns following formation periods with large or small trading volume. We refer to this period as the *test period*. Note that since the number of days in the test period is smaller than 50, the timing of the returns that we consider do not intersect for different trading intervals. In other words, we avoid having to adjust our test statistics to account for the potential dependence of overlapping returns.

In what follows, we perform the same analysis separately on each of the three size groups.[15] For a particular size group, we use the subscript "ijt" to denote the trading interval $i = 1, \ldots, 161$ (i goes from 1 to 155 for the weekly sample), the stock j in that trading interval, $j = 1, \ldots, M_i$, and the t-th day of the test period (i.e. the t-th day following the formation date of that trading interval). We can then denote the daily holding return (adjusted for dividends) of stock j in trading interval i over the t-th day following the formation period as r_{ijt}. Similarly, we can calculate the buy and hold return (the *cumulative return*) of stock j in trading interval i over the t days following

[12] We considered another weekly sample with a reference period of 49 weeks and a formation period of 1 week. The results for this sample were almost identical to those with the weekly sample considered here.

[13] Filters similar to those of the daily sample were applied first. The only small difference was that the $5 price minimum filter was only applied over the first 45 days (9 weeks) of the trading interval (which is the reference period for this weekly sample) to avoid an overlap with the formation period.

[14] Notice that, for both the daily and the weekly samples, high (low) volume stocks are the stocks whose trading volume during the formation period is among the top (bottom) 10% of the trading volumes for all the periods of the same length contained in the trading interval.

[15] For that reason, we do not index our variables by size group, as this alleviates the notation.

the formation period as

$$R_{ijt} = \prod_{\tau=1}^{t} (1 + r_{ij\tau}) - 1. \tag{1}$$

We will denote averages over trading intervals, and/or stocks by dropping the relevant subscripts; for example, R_t represents the average cumulative t-day return of all the stocks (in a particular size group) in all trading intervals:

$$R_t \equiv \frac{\sum_{i=1}^{161} \sum_{j=1}^{M_i} R_{ijt}}{\sum_{i=1}^{161} M_i}.$$

To enable us to condition on formation period volume, we let $\Psi_{ij} \in \{1, \ldots, 50\}$ denote the rank of that formation period volume in the 50-day trading interval (a rank of 50 denoting the highest trading volume day), and define[16]

$$\psi_{ij} = \begin{cases} H, & \text{if } \Psi_{ij} \geq 46 \\ L, & \text{if } \Psi_{ij} \leq 5 \\ N, & \text{otherwise} \end{cases} \tag{2}$$

to determine whether the stock is a high (H), low (L), or normal (N) volume stock in that trading interval.

3 Portfolio Formation

To study the effects of trading volume on future returns, we form portfolios of securities at the end of every formation period (i.e. at the formation date) using the volume classifications. In particular, we investigate the possibility for large (small) trading volume to predict high (low) returns. A simplistic approach to do this would be to invest at every formation date a dollar in each security whose formation period gets classified as a high volume period, and to sell a dollar's worth of each security whose formation period gets classified as a low volume period. We could then hold these positions over a fixed horizon, and look at the average returns over all trading intervals and stocks of a size group.[17] This approach, which we refer to as the *unadjusted returns approach*, suffers from the fact that it does not account at all for the difference in risk of the long and short positions. Moreover, it is possible for the long dollar position at a particular formation date to

[16] For the weekly sample, $\Psi_{ij} \in \{1, \ldots, 10\}$ denotes the rank of the formation period volume in the 10-week trading interval, and ψ_{ij} is defined as

$$\psi_{ij} = \begin{cases} H, & \text{if } \Psi_{ij} = 10 \\ L, & \text{if } \Psi_{ij} = 1 \\ N, & \text{otherwise.} \end{cases}$$

[17] This is in fact how Figure 1 was generated, except for the fact that the different size groups were not analyzed separately, and that all the positions illustrated were for $1 long.

be much bigger or much smaller than the short dollar position, making the profits associated with the different trading intervals hard to compare. To deal with these problems, we introduce two portfolio formation approaches.

3.1 The Zero Investment Portfolios

As in the unadjusted returns approach suggested above, the two portfolio formation strategies that we consider throughout the paper involve taking a long position in the high volume stocks and a short position in the low volume stocks of each formation period. However, in doing so, we make sure to control, at least partially, for the risk of these portfolios through the test periods.

The *zero investment portfolios* are formed at the end of every formation period for each size group. At that formation date, we take 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 same size group. Each stock in the high (low) volume category is given equal weight.[18] This position taken at the end of the formation period in each trading interval i is not rebalanced for the whole test period. The returns for the long position in high volume stocks over the ensuing test period (of trading interval i) are thus given by

$$\overline{PR}_{it} = \frac{\sum_{j=1}^{M_i} R_{ijt}\, \mathbf{1}_{\{\psi_{ij}=H\}}}{\sum_{j=1}^{M_i} \mathbf{1}_{\{\psi_{ij}=H\}}}, \tag{3a}$$

and those for the short position in the low volume stocks by

$$\underline{PR}_{it} = -\frac{\sum_{j=1}^{M_i} R_{ijt}\, \mathbf{1}_{\{\psi_{ij}=L\}}}{\sum_{j=1}^{M_i} \mathbf{1}_{\{\psi_{ij}=L\}}}. \tag{3b}$$

The net returns[19] of this portfolio in trading interval i are then given by the sum of these two quantities. We are eventually interested in looking at the overall average (and standard deviation) of these net returns across trading intervals:

$$NPR_t \equiv \overline{PR}_t + \underline{PR}_t \equiv \frac{1}{161}\sum_{i=1}^{161} \overline{PR}_{it} + \frac{1}{161}\sum_{i=1}^{161} \underline{PR}_{it} = \frac{1}{161}\sum_{i=1}^{161} \left(\overline{PR}_{it} + \underline{PR}_{it}\right). \tag{4}$$

3.2 The Reference Return Portfolios

The second portfolio formation approach is similar to that used in Barber, Lyon, and Tsai (1996) and Conrad and Kaul (1993). It consists in taking a long (short) position in each of the high (low)

[18] 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. Since the zero investment portfolio is then not well defined, we simply dropped the only such occurrence (which happened in the large firm group).

[19] Although we, like the rest of the literature, refer to these quantities as returns, it should be understood that they should be referred to more adequately 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."

volume stocks at the end of the formation period of every trading interval i, and an offsetting position in a size adjusted reference portfolio, so that our net investment is exactly zero. This reference portfolio is simply constructed by putting equal weights on each of the securities from the same size group as the high (or low) volume security. Each long (short) position in a high (low) volume stock is for a total of one dollar *per stock* (as opposed to a dollar *per trading interval* in the zero investment portfolios), and this position is held without rebalancing throughout the test period until it is undone at the end of the t-th day of that period. We call each such position a *reference return portfolio*, and we denote its t-day return by $R_{ijt} - R_{it}$ ($R_{it} - R_{ijt}$) for a long (short) position taken at the formation date of trading interval i using high (low) volume security j.

Because the \$1 investment is made per stock in each trading interval, the aggregation for the reference return portfolios is taken over both trading intervals *and* stocks. The average t-day return for all the reference return portfolios constructed from high volume stocks is therefore given by

$$\overline{PR}_t = \frac{\sum_{i=1}^{161} \sum_{j=1}^{M_i} (R_{ijt} - R_{it}) \, \mathbf{1}_{\{\psi_{ij}=H\}}}{\sum_{i=1}^{161} \sum_{j=1}^{M_i} \mathbf{1}_{\{\psi_{ij}=H\}}}. \tag{5a}$$

Similarly, the average t-day return for all the reference return portfolios constructed from low volume stocks is given by

$$\underline{PR}_t = \frac{\sum_{i=1}^{161} \sum_{j=1}^{M_i} (R_{it} - R_{ijt}) \, \mathbf{1}_{\{\psi_{ij}=L\}}}{\sum_{i=1}^{161} \sum_{j=1}^{M_i} \mathbf{1}_{\{\psi_{ij}=L\}}}. \tag{5b}$$

Finally, we are interested in the average profits from a combined long position in the high volume reference portfolios and a short position in the low reference portfolios:

$$NPR_t \equiv \frac{\sum_{i=1}^{161} \sum_{j=1}^{M_i} \left[(R_{ijt} - R_{it}) \, \mathbf{1}_{\{\psi_{ij}=H\}} + (R_{it} - R_{ijt}) \, \mathbf{1}_{\{\psi_{ij}=L\}} \right]}{\sum_{i=1}^{161} \sum_{j=1}^{M_i} \left(\mathbf{1}_{\{\psi_{ij}=H\}} + \mathbf{1}_{\{\psi_{ij}=L\}} \right)}. \tag{6}$$

3.3 Some Comments About the Two Approaches

These two approaches for forming portfolios differ in two important ways. First, the weight assigned to each trading interval in the reference return approach varies with the number of stocks with high (or low) trading volume during the formation period. Indeed, every occurrence of a high (or low) volume formation period in any trading interval receives the same weight in (6). On the other hand, the zero investment approach gives the same weight to every trading interval, whether they contain a lot of high (or low) volume stocks, as seen in (4). In other words, every stock in every trading interval receives the same weight in the reference return approach, whereas every trading interval receives the same weight in the zero investment approach.

Second, the zero investement portfolios are constructed so that every dollar invested in the high volume stocks is offset by a dollar short in the low volume stocks. In the case of the reference return portfolios, this offsetting of both the long and the short positions is performed by a reference portfolio. As a result, it may be the case that (6) puts more weight on the high (or low) volume stocks than on the low (high) volume stocks. More precisely, if

$$\sum_{j=1}^{M_i} \mathbf{1}_{\{\psi_{ij}=H\}} \neq \sum_{j=1}^{M_i} \mathbf{1}_{\{\psi_{ij}=L\}} \text{ for some } i \in \{1, \ldots, 161\},$$

then NPR_t as defined in (6) is not equivalent to $\frac{1}{2}\left(\overline{PR}_t + \underline{PR}_t\right)$, as defined in (5a) and (5b). Of course, the extent of this effect cannot be excessively large as, on average, 10% of the stocks in each trading interval will be considered high volume stocks, and 10% low volume stocks.

Each of these two portfolio formation approaches is used for a specific reason. The zero investment portfolios are similar to those used by CHN in that one side of the position requires an investment of one dollar, whereas the other side of the position generates one dollar at the outset. This will allow us to compare the magnitude of our returns with those of CHN. The problem with this approach is that it is difficult to tell whether the net returns originate from the long, the short, or both positions. The reference return approach solves this problem, as both sides of the position are costless (since they are offset by an equal investment in a reference portfolio).

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), Campbell, Grossman and Wang (1993), and Tauchen, Zhang and Liu (1996) 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.

4 The Main Results

The main results of our analysis are presented in Table 2 for the daily sample, and Table 3 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 periods of 1, 10, and 20 trading days after the formation date. More precisely, the three lines of each panel of Tables 2 and 3 show $\overline{PR}_t$, $\underline{PR}_t$ and NPR_t as defined in (4) for the zero investment portfolios, and as defined in (5a), (5b) and (6) for the reference return portfolios. In both cases, this is done for $t = 1, 10, 20$.

4.1 The Daily Sample

Let us first look at the results obtained with the daily sample in Table 2. As can be seen from that 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 and for all size groups. The average returns from the zero investment portfolio formation strategy range from 0.35% per dollar long over one day to 0.94% over twenty days for the small stocks, and from 0.12% over one day to 0.50% over twenty days for the large stocks. The associated t-statistics are all about 3 or higher. For the reference return portfolio formation strategy, the corresponding numbers are 0.16% to 0.47% for the small stocks, and 0.06% to 0.25% for the large stocks. In this case, the t-statistics are all above 4. Given that the net returns of Table 2 were generated with costless portfolios for both strategies, these statistically significant positive profits indicate that trading volume, *by itself*, contains information about the subsequent evolution of stock prices.

Before we analyze these returns more carefully, let us say a word about the relative sizes of the returns of the zero investment portfolio and the reference return portfolio strategies. From the above numbers, and from comparing the net return lines in each panels, it seems like the zero investment portfolios generate about twice as much returns as the reference return portfolios. As mentioned in section 3, this is simply due to how the average returns are measured for the two strategies. For the zero investment portfolios, the combined long position in the high volume stocks and short position in the low volume stocks counts for only one observation in (4). On the other hand, the reference portfolio returns as calculated in (6) count the long position and the short position as two observations.[20] In other words, the zero investment strategy is effectively betting on the two sides of the volume effect at the same time, whereas the reference return strategy is betting only on one side at a time. This means that the net returns of the zero investment strategy measure "two-way betting" profits, whereas the net returns of the reference return strategy measure "one-way betting" profits.

Our one- and ten-day net profits are comparable in size to the one-week profits documented by Lehmann (1990) who forms his portfolios based on past returns only, and CHN who form theirs based on past trading volume *and* returns. Surprisingly however, our twenty-day profits remain significant, whereas CHN find that their profits disappear after three weeks.[21] More than that, we see from Table 2 that the size of the average profits increases at longer horizons (the 20-day net returns are all larger than the 10-day net returns), which indicates that this volume effect is not just a very short term effect. In fact, although the results are not shown in this table, we verified that for the small and medium firms, even after 100 days, cumulative returns are still significantly positive at about 1% per dollar long, meaning that this shift is permanent.[22]

The size (although not the significance) of the average returns of our two approaches tends to be larger with small firms than with larger firms, confirming some of the evidence found by CHN, and the conjecture by Blume, Easley and O'Hara (1994) that the use of volume information may be particularly useful for small and less widely followed firms. So, although we will postpone the

[20]This is reflected in the fact that the net return lines in Table 2 are exactly equal to the sum of the returns of the high volume and low volume positions for the zero investment strategy, but are close to the average of those returns for the reference return strategy.

[21]This can be seen from their Table VIII.

[22]Of course, with the 100 day test period, the last 49 days of each test period intersect with the subsequent test period, so that the t-statistics have to be adjusted appropriately.

discussion of the economic profitability of our strategies until section 7, we can already conjecture that it will be important to condition on firm size, as well as trading volume, to generate profits that will outweigh trading costs. In fact, given that the net returns of the medium firms are similar to those of the small firms, especially at longer horizons, we can also expect the trading strategies to work best for medium size firms because of the smaller trading costs that they are likely to necessitate relative to small size firms.

Interestingly, these positive returns are not solely due to high volume stocks or low volume stocks. For the reference return portfolios, this can be seen from the first two lines in each panel of Table 2. These lines, which correspond to $\overline{PR}_t$ and $\underline{PR}_t$ as defined in (5a) and (5b), report the performance of the two components of the portfolios, that is the high volume and the low volume positions respectively. They show that the stocks which experienced a high (low) volume formation period significantly outperformed (underperformed) the other stocks in their size group over the following 20 days. In fact, the magnitudes of these over- and underperformances are similar for both the high volume and low volume stocks. For example, a long (short) position of one dollar in a stock which experiences abnormally high (low) volume on a particular day, counterbalanced by a short (long) position of one dollar in the appropriate reference portfolio generates 20-day returns of 0.45% and 0.29% (0.49% and 0.21%) for small stocks and large stocks respectively.

The t-statistics for the two components of the zero investment portfolios are not reported in Table 2, as the relevant return to compare these components to is not zero. This is because each component involves taking a long or a short position of one dollar that is not offset by another position with similar risk. So, unlike the components of the reference return portfolios, the components of the zero investment portfolios require a non-zero investment, and therefore should be more appropriately compared to the average returns of normal volume stocks in order to measure the excess return that they are generating. Although not reported here, these average returns for the normal volume stocks do indeed lie between those of the high and low volume stocks, confirming the fact that high (low) volume stocks outperform (underperform) similar stocks on average.

These results are consistent with the predictions about the intertemporal effects of trading volume on returns made by Diamond and Verrecchia (1987), who construct a model in which short-sale constraints preclude some traders from taking advantage of negative information. Periods without much trading activity will therefore tend to announce that negative information is privately known by some investors. As a result of this increased possibility of bad news, the price level of the stock tends to go down. In fact, this constitutes a potential explanation for this curious high volume return premium.

4.2 The Weekly Sample

Table 3 is the analogue of Table 2 for the weekly sample. It shows that the positive net returns (NPR_t) generated using the information contained in a formation period's volume does not crucially depend on the length of that formation period.[23] 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 than with the daily sample (1.36% compared to 0.94% per dollar long for the small stocks, and 0.90% compared to 0.50% for the large stocks, in the case of the zero investment strategy).

The main difference between Tables 2 and 3 comes from the origin of these positive returns. This is especially obvious for the reference return portfolios. Indeed, for the weekly sample, the high volume stocks outperformed their size group by less than the low volume stocks underperformed it. In other words, the returns for the weekly sample are resulting mainly from selling the stocks with low volume formation periods.

As mentioned in the introduction, CHN document the fact that contrarian strategies based on last week's returns generate profits (losses) when applied on stocks that experienced a positive (negative) trading volume shock last week. In other words, the "double-conditioning" on past returns and trading volume generates additional profits that cannot be generated by conditioning on past returns alone. Interestingly, the profits that their strategies generate only last for one week, and even tend to revert to zero over the following three weeks. In contrast, our strategies, which condition on trading volume exclusively, generate significant returns for horizons as long as 100 trading days, that is 20 weeks. So, it appears that the trading volume effect is a permanent one, whereas the return autocorrelation effect is only temporary. We will come back to these issues in section 4.3.

Brennan, Chordia and Subrahmanyam (1998), and Lee and Swaminathan (1998) 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. Our results in Tables 2 and 3 seem to contradict this evidence. However, this is not the case because the above two papers use a long-run measure of trading activity, as opposed to our short-run measure. In other words, Brennan, Chordia and Subrahmanyam (1998), and Lee and Swaminathan (1998) 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 certain period; these stocks tend to appreciate.

So, in short, it appears that daily and weekly trading volume contains information about the future evolution of stock prices, and this is the case unconditionally (i.e. without conditioning on other variables). Also, this information seems to be useful for at least one month (20 trading days); this is somewhat surprising given the short-term effects documented by CHN, who look at the joint role of trading volume and returns in predicting future returns. Also, although it is not clear whether our portfolio formation strategies could be exploited profitably on their own, it is clear

[23]In fact, we repeated the analysis with formation periods of half a day, and found essentially the same results as with the daily sample.

that traders would benefit from incorporating the information contained in trading volume into their trading strategies.[24]

4.3 The Role of Formation Period Returns

As postulated by Campbell, Grossman and Wang (1993) and as documented by CHN, extreme stock returns, positive or negative, will tend to be later reversed when they are associated with large trading volume. The effect that we describe in this paper is different in the sense that the net returns of our portfolios are not the result of the autocorrelation that may exist in returns. Instead, we want to document the fact that "normal" returns associated with "unusually" high (low) trading activity tend to be followed by large (small) returns.

To document this better, we restrict our two samples to include only those stocks that experience returns that are not unusually high or low during the formation period. More precisely, from the current strategies, we eliminate all the stocks whose formation period returns are in the top or bottom 30% of returns during the trading interval. So, for the daily sample, let Φ_{ij} denote the formation period return rank for stock $j = 1, \ldots, M_i$ in trading interval $i = 1, \ldots, 161$, when compared to the 49 daily returns of the associated reference period. In each trading interval, stocks are classified as high (low) return stocks if their formation period return is among the top (bottom) 30% of the daily returns for that trading interval. Otherwise, they are considered normal return stocks. The analogue to equation (2) for returns is therefore defined as

$$\phi_{ij} = \begin{cases} H, & \text{if } \Phi_{ij} \geq 36 \\ L, & \text{if } \Phi_{ij} \leq 15 \\ N, & \text{otherwise.} \end{cases} \tag{7}$$

This variable is similarly defined for the weekly sample. The portfolio formation strategies developed in section 3 can then be altered to only include those stocks that experienced a normal return during the formation period by multiplying every indicator function in (3a)-(6) by $\mathbf{1}_{\{\phi_{ij}=N\}}$. The net returns of our two strategies for the two subsamples (daily and weekly) are presented in Table 4.

The evidence from this table is remarkable. Indeed, not only are most of the net returns of both strategies significantly positive, but these returns are now approaching values that can be profitably exploited, even after transaction costs. For example, the ten and twenty day net returns of 1.55% and 2.02% generated by the zero investment portfolios using the weekly sample with small firms are now quite sizeable (they are up from 1.00% and 1.36% in Table 3). In fact, it is the case that most of the net returns in Table 4 for these normal return subsamples are up from the corresponding full sample net returns in Tables 2 and 3, especially for the ten and twenty day returns.

These results emphasize the difference between our study and that of CHN. To illustrate this difference, let us categorize stocks according to whether their return and trading volume during the formation period are high, normal, or low. As shown in Figure 3, CHN refine the return-based

[24] A similar argument was made by CHN when discussing the profitability of their contrarian portfolio strategy.

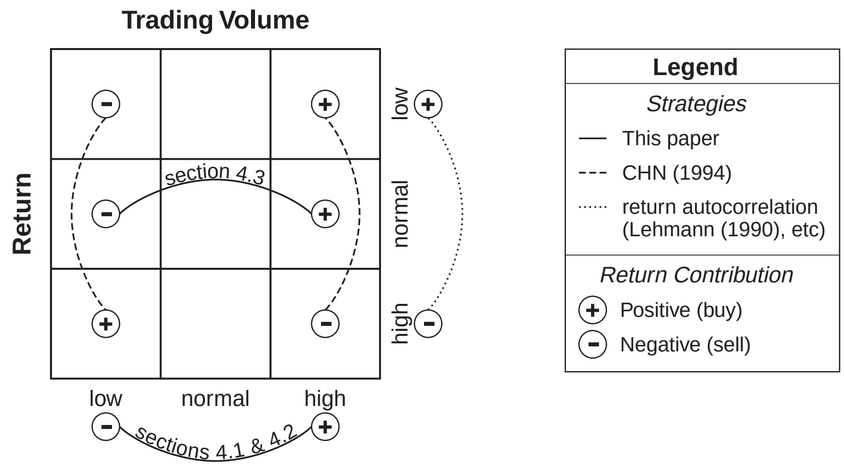


Figure 3: After categorizing stocks according to their return and trading volume in a formation period (a day or a week), we can represent the different profitable strategies considered by this and other papers by adjoining their positive and negative contributions. Strategies conditioning on both return and trading volume lie inside the three by three diagram; strategies conditioning only on one variable lie outside that diagram.

contrarian strategies of Lehmann (1990) by further conditioning on volume. We, on the other hand, first show in sections 4.1 and 4.2 that strategies based purely on volume generate profits, and in this section that these profits do note depend on extreme returns. As a result, we feel quite confident that the high volume return premium is not a product of the joint contemporaneous relationship between trading activity and returns. Instead, trading volume *by itself* does predict future returns, and the information it contains is *orthogonal* to that contained in returns.

5 Risk Issues

At this point, section 4 leads us to conclude that high (low) volume announces large (small) subsequent returns. Of course, it may be the case that this conclusion is justified by risk. For example, it is possible that the positive returns generated by the portfolios analyzed in section 3 simply represent a compensation for risk. The purpose of this section is to assess the extent to which the returns of our volume-based strategies are explained by risk.

5.1 Market Risk

The first measure of risk that we consider is systematic risk. Using the daily sample, we assess whether it explains 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 ($\overline{PR}_{it}$ and $\underline{PR}_{it}$ as defined in (3a) and (3b) respectively). 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 the returns on a value-weighted market index, an equal-weighted market index, and the S&P500. We denote these returns over the first t days of the test period of interval i by R_{it}^m. For a given investment horizon t, we estimate the following joint model across all 161 trading intervals,[25] which are indexed by $i = 1, \ldots, 161$:

$$\begin{aligned} \overline{PR}_{it} &= \alpha_t^H + \beta_t^H R_{it}^m + \varepsilon_{it}^H; &\text{(8a)} \\ \underline{PR}_{it} &= \alpha_t^L + \beta_t^L R_{it}^m + \varepsilon_{it}^L. &\text{(8b)} \end{aligned}$$

The estimated market return coefficients (β_t^H and β_t^L) for these regression are shown in Table 5 for the same three investment horizons as in section 4, namely $t = 1, 10, 20$. That same table also shows the difference between these coefficients, a quantity that effectively represents the beta of the zero investment portfolios of section 3. Finally, the numbers in curly brackets show the p-values for three tests: $\beta_t^H = 1$, $\beta_t^L = 1$, and $\beta_t^H - \beta_t^L = 0$. As can be seen from this last test, the betas of the zero investment portfolios are at most indistinguishable from zero, and even significantly negative in some cases. In fact, all of the estimated β_t^H coefficients are smaller than the corresponding β_t^L coefficients for the ten and twenty-day investment horizons. These results confirm that the significantly positive returns generated by the zero investment portfolios cannot be explained by their systematic risk.

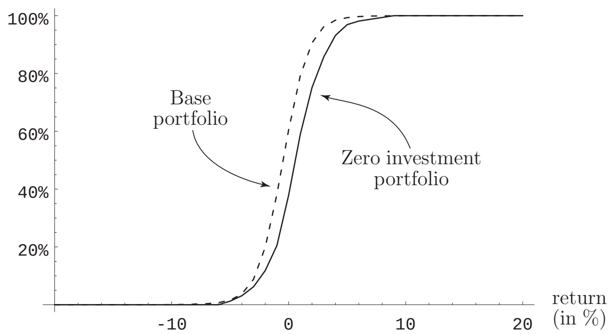
5.2 Stochastic Dominance

Another way to assess the relationship between the returns generated by our trading strategies and their underlying risk is to compare these returns with those of similar unconditional strategies. More precisely, this comparison will be made using the notion of first-order stochastic dominance.[26] If we can show that the returns of our trading strategies come from a distribution which first-order stochastically dominates that of the returns from similar strategies which do not condition on trading volume, we can then be confident that investors will prefer conditioning their purchases and sales of stocks on trading activity when this is possible. This would also be additional evidence that the risk underlying our trading strategies is not unusual.

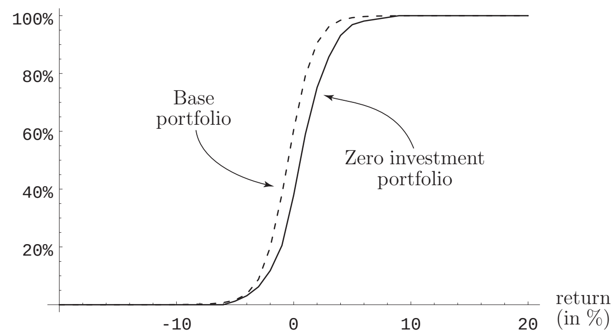
To perform the tests, we use the twenty-day net returns of our zero investment portfolios. We compare them to the returns from portfolios containing the same number of long and short positions, but not based on trading volume. More precisely, for every zero investment portfolio formed in section 3 (one per trading interval for each size group), we construct a *base portfolio* by replacing each security of the zero investment portfolio by another randomly chosen from the same size group. For each size group, we then check if the distribution of net returns of the zero

[25] There are only 160 trading intervals for the large firm group since, as mentioned in footnote 18, one such zero investment portfolio could not be formed in a trading interval without any low volume stock.

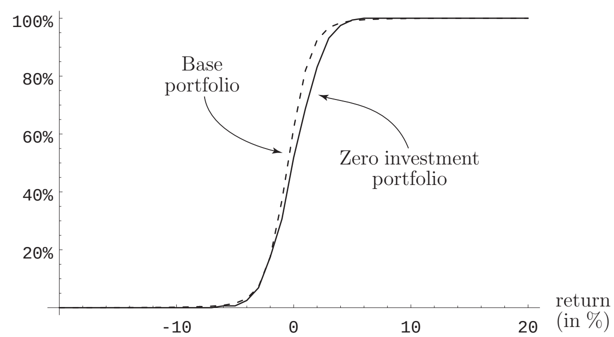
[26] For a definition of first-order stochastic dominance, see for example Shaked and Shanthikumar (1994).



(a) Small stocks.



(b) Medium stocks.



(c) Large stocks.

Figure 4: Empirical cumulative distribution functions for the twenty-day net returns of the zero investment portfolios and those of the base portfolios.

investment portfolios dominates those of the base portfolios by performing two first-order stochastic dominance tests. The details of how we perform these tests are included in the appendix.[27]

The essence of these tests is captured in Figure 4, 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 portfolio. The tests described in the appendix reinforce this evidence. Indeed, for both tests and with all three size groups, we find that the distribution of the zero investment returns first-order stochastically dominates that of the base portfolio returns.

This finding, and its implications for the risk of our strategies, is quite important. Since 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 cannot explain the abnormal returns generated by our volume-based strategies.

[27]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.

5.3 Bid-Ask Spread

The last measure of risk that we consider is the bid-ask spread, as quoted by the specialist in each stock. As argued by many authors,[28] the size of the bid-ask spread will reflect the likelihood that some information has not been made public (i.e. the risk that some private information will be used by some market participants). Looking at the intertemporal effects of unusual volume on spreads will therefore tell us about the information asymmetry risk in stock prices. Since we require a measure of the bid-ask spread to assess these effects, we introduce another sample that we construct from a different dataset, namely the Trades and Quotes (TAQ) data from the New York Stock Exchange (NYSE).

The details of how we construct this dataset are relegated to section 6.4, which makes a more extensive use of this data. For now, we simply report the following fact: during the test periods of high (low) volume stocks, the average bid-ask spread is systematically lower (higher) than (i) the average bid-ask spread during the formation period, (ii) the average bid-ask spread during the five trading days preceding that formation period, (iii) the unconditional average bid-ask spread. This finding is also consistent across all three size groups.[29] Thus it seems like high trading volume in a day not only reduces the incidence of asymmetric information for that day,[30] but also for the subsequent few days. In other words, once the private information floods the market (with high volume), the trading crowd (including the specialist) becomes less nervous about the possible existence of more such private information.

These results seem to contradict the predictions about the intertemporal effects of trading volume on spreads made by Easley and O'Hara (1992), who construct a model based on the likelihood that information events occur. Since information-based trading is more likely to take place when an information event has occurred, the lack of trading activity in their model tends to be associated with low asymmetric information between market participants. So, they also predict that the bid-ask spread will go down after periods of low trading activity. However, according to their model, the price level of the stock should remain stable. Our findings that the bid-ask spread tends to decrease (increase) after a period of high (low) trading activity indicate that the information flow is related to volume, but not through the occurence of news events, as postulated by these authors.

[28]For example, see Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987).

[29]The details of how this analysis was performed, along with the tables that accompany it, are available from the authors upon request.

[30]This has been empirically documented by Easley, Kiefer, O'Hara, and Paperman (1996).

6 Robustness of Results

The results documented in Tables 2-4 suggest that past trading volume contains information about the future evolution of a stock price. Since this result is far from intuitive[31] and cannot be explained by risk, it is necessary to investigate its robustness. In particular, we would like to make sure that our findings do not depend on how we rank trading volume across days/weeks, on potential announcements made by the firms, or on volume proxying for some other relevant variable in the economy. The current section looks at these issues in turn. Unless we state otherwise, we use the daily sample to study the robustness of our results.

6.1 Volume Ranks

In determining the rank of the trading volume during the formation period in section 2, 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 non-stationary[32] or if it displays persistence and trends,[33] using a large number of past daily volumes could result in misclassifying volume as high or low.[34] In order 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, each of the three 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, where $n = 2, 4, 8$. As this is done progressively through the reference period, this means that the t-th day of the reference period will be given a relative weight of $w_t(n) = 1 + \left(\frac{n-1}{48}\right)(t-1)$. As in the original analysis, the stocks whose trading volume on the formation period is in the top (bottom) 10% of the last 49

[31] In fact, very few theoretical models predict that trading volume can be useful to predict the future evolution of a stock's price. For example, Easley and O'Hara (1992), Campbell, Grossman and Wang (1993), and Wang (1994) find a role for volume, but not a role of predicting future stock prices. On the other hand, Diamond and Verrecchia (1987), Blume, Easley and O'Hara (1994), and Bernardo and Judd (1996) come up with models in which trading volume has some predicting power.

[32] For example, Hiemestra and Jones (1994) show that volume dynamics contain a unit root.

[33] 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, Rossi and Tauchen (1992), Campbell, Grossman and Wang (1993), and Lo and Wang (1997) among others.

[34] For example, an upward trend in trading volume would result in putting a stock in the high volume category in more than 10% of the formation periods. 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%.

weighted daily trading volumes is considered a high (low) volume stock for that trading interval.[35]

The first three rows in each size group panel of Table 6 present the average net returns (NPR_t) of our two strategies for each of the three weighting schemes. Comparison of these three rows with the third row of each panel in Table 2 shows that the potential non-stationarities, trends and persistence in trading volume do not account for the significantly positive returns of our two portfolio formation approaches. Indeed, we can see that the returns generated by our strategies are unaffected both in size and significance when weighting the recent past more. For example, the average net returns of the zero investment portfolio strategy for the medium firms go from their original values of 0.24%, 0.74% and 1.07% per dollar long at horizons of 1, 10 and 20 days respectively to 0.25%, 0.77% and 1.02% with the "$n = 8$" weighting scheme.

Another concern with trading volume is whether it is correlated cross-sectionally between securities on a given day. This would mean that stocks would tend to be picked for the high or low volume categories in the same formation periods. In other words, it is possible that abnormal market volume is driving the results of section 4, as opposed to firm specific abnormal volume. To control for this possibility, we rank the 50 days of the trading interval for each stock according to the fraction of the daily market volume that they account for.[36] 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.

The "market volume" line in each size group panel of Table 6 shows our results. Again, a direct comparison of the net returns (NPR_t) for both strategies to those in the third line of each panel in Table 2 reveals that both the size and the significance of the returns are not affected by this alternative measure of trading volume. Using the zero investment strategy with the medium firms as an example again, we can see that the average net returns go from 0.24%, 0.74% and 1.07% in the original analysis to 0.25%, 0.70% and 1.04% with this new measure of trading activity. We can therefore conclude that the driving force behind the results of section 4 is not market volume but firm specific volume. This in turn implies that studies seeking to document the relationships between volume and return using some kind of aggregated data (like portfolio volume, or market volume) may not capture the essential effects of volume, which are more firm specific.[37]

The last potential correction that we need to make is due to the interdaily patterns of trading volume during the week. Jain and Joh (1988) document an inverse U-shape in daily trading volume across days of the week, with a peek on Wednesdays. To avoid miscategorizing normal

[35] To be perfectly precise, let V_{ij}^t denote stock j's trading volume on the t-th day of trading interval i ($t = 50$ referring to the formation period). The formation date is considered a high (low) volume date if

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

[36] Such a measure has been suggested by Tkac (1996). Here, market volume is proxied by the total dollar volume for all the stocks in our sample.

[37] It is in fact the case that authors using aggregate measures of trading volume do not find much of a relationship between volume and subsequent returns; see for example Gallant, Rossi, and Tauchen (1992).

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.[38]

The fifth and last row in each of the three panels of Table 6 show how this last adjustment affects our results. We see that for the small and the medium size groups, the adjustment slightly accentuates our results (with 20-day returns of 1.06% and 1.19% versus the 0.94% and 1.07% of Table 2) whereas, for the large size group, our results are somewhat weakened (the 20-day return went down to 0.44% from 0.50% on Table 2). Given the relatively small size of the differences however, we can safely say that the results of section 4 were not driven by interdaily patterns in trading volume.

As explained in section 2, we skip a day in between each trading interval, so that every day of the week is used as a formation period. In doing this, 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. The bottom line is that our results do not seem to crucially depend on how we measure trading volume.

6.2 Firm Announcements and Outlyers

Given the numerous studies documenting the effects of firm announcements on trading volume and stock returns,[39] we would like to remove these potential effects from our sample for two reasons. First, we want to make sure that the volume-return premiums of section 4 are not simply due to a few firm announcements. Second, as emphasized in section 4.3, our study is not so much about "unusual" days, as it is about "regular" days with unusual volume.

To deal with these issues, we first remove from each trading interval of our daily sample all the stocks which had a dividend or an earnings announcement either the day before, the day of, or the day after the formation period.[40] We consider the days preceding and following the formation

[38] More precisely, we calculate the mean adjusting factors using only the stocks that existed during the whole 1963-1996 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 $d = 1, \ldots, 5$ of week $w = 1, \ldots, N$. Then the deflating factors for each day d of the week are given by $DF_d = \frac{1/\alpha_d}{\sum_{\delta=1}^{5} 1/\alpha_\delta}$, $d = 1, \ldots, 5$, where

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

[39] See for example Bamber (1987), Bernard and Thomas (1989, 1990), Lang (1991), and Chiang, Davidson and Okunev (1997).

[40] To be perfectly precise, the earnings annoucements 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

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.[41] We then use this subsample of the daily CRSP data and perform the same analysis as in section 3. The average returns from the two portfolio formation strategies are shown in the "no event" portions of Table 7.

These returns can then be directly compared with those in Table 2. Little or no effect results from removing firm announcements from the daily sample. For example, the 20-day net returns (NPR_t) from the zero investment portfolios go from 0.94%, 1.07% and 0.50% for the small, medium and large firms respectively in Table 2 to 0.99%, 1.10% and 0.47% in Table 7. Since all the returns, including those of the components of the two strategies ($\overline{PR}_t$ and $\underline{PR}_t$), are also essentially the same as before, we conclude that the results of section 4 are not driven by firm announcements around formation periods. In other words, abnormal volume is not proxying for the effects that periods of major announcements can have on stock returns.

Even if firm announcements do not seem to play a role in the results that we document in section 4, it is still useful to analyze whether trading volume contains similar information around firm announcements. To investigate this, we construct two alternative daily samples. Both samples use every single trading day as a formation period of a 50-day trading interval (with the previous 49 days as the reference period, and the subsequent 20 days as the test period); this results in around 8,000 total trading intervals. Then, for the first sample, we remove from each such trading interval all the stocks that did *not* make a dividend announcement during its formation period. Similarly, the second sample removes from each trading interval all the stocks that did *not* make an earnings announcement during its formation period.[42] Using these two new samples, we calculate the average returns from our portfolio formation strategies as usual. The results of this analysis are presented in the "dividend" and "earnings" portions of Table 7.

Interestingly, we find that both strategies, when the portfolio formation period coincide with a firm announcement, generate higher average net returns (NPR_t) for small firms. Indeed, the zero investment portfolio (reference return) strategy generated 20-day net returns of 1.99% and 5.10% (0.86% and 1.18%) on average for the dividend and earnings announcement samples respectively compared to the 0.94% (0.47%) that the original daily sample generated. However, this effect on net returns does not appear to be present for the medium and large firm groups. Surprisingly, although the net returns are not extremely affected for these latter two firm groups, it now seems like the returns are being generated mainly from the long position in high volume stocks ($\overline{PR}_t$), unlike those in Table 2. For example, the 20-day net returns of the reference return portfolio only increased slightly from 0.25% to 0.28% (0.29%) when considering the dividend (earnings)

starts on 01/20/83.

[41] We also repeated the same control analysis by removing the stocks which had a dividend or an earnings announcement in the period of one week around the formation period, in order to control better for the post-announcement drift documented by many authors (see footnote 39). The results were essentially the same.

[42] Note that it does not matter that the trading intervals now intersect each other, as no stock is ever included in two formation periods separated by less than 50 trading days because of the low frequency of dividend and earnings announcements.

announcement sample with large firms. At the same time, the high volume portion ($\overline{PR}_t$) of that return increased from 0.29% to 0.41% (0.38%), while the low volume portion ($\underline{PR}_t$) decreased from 0.21% to 0.05% (-0.22%).

Although Table 7 shows that the returns of our portfolios did not originate from firm announcements, it is still possible that these returns are the product of just a few outlyers. To assess this possibility, we simply look at the empirical distribution of the zero investment strategy. Using the daily CRSP sample, this strategy consists in forming a portfolio of long and short positions on the formation date of each of the 161 trading intervals, and hold that position for a given horizon, which we take to be twenty days in this case. As a result, we end up with a sample of 161 twenty-day net returns for each of the size groups. The empirical distribution of these net returns is shown in Table 8 for the three size groups. More precisely, the three graphs show how many trading intervals generated returns of different sizes. That same table also shows some sample statistics for these distributions.

As can be seen from this table, it is not true that the positive returns of the zero investment portfolio strategy are generated from a few extreme positive returns. Instead, we find that the net returns are distributed evenly on both sides of the average, as evidence by the symmetric empirical distributions, the small (and even negative in some cases) skewness coefficients, and the fact that the means are essentially equal to the medians. We can therefore conclude that the positive returns documented Table 2 are not driven by a firm announcements or just a few outlyers.

6.3 Volume as a Proxy for Returns

Several authors have documented the contemporaneous positive correlation between a stock's trading volume and its return,[43] as well as the autocorrelation in returns.[44] In this section, we seek to emphasize the results of section 4.3 by showing explicitly that the high volume return premium is not a bi-product of these two effects. In order to show this, we first apply a methodology similar to the one we have been using so far, but we use formation period *returns* instead of *trading volumes* to classify stocks. More formally, we alter our definition of high, low, and normal formation period returns in (7) to include only the top (bottom) 10% of the daily returns in the high (low) return category:

$$\phi_{ij} = \begin{cases} H, & \text{if } \Phi_{ij} \geq 46 \\ L, & \text{if } \Phi_{ij} \leq 5 \\ N, & \text{otherwise,} \end{cases} \tag{9}$$

and similarly for the weekly sample.

[43] See, among others, Smirlock and Starks (1985), Harris (1986, 1987), and Jain and Joh (1988). Karpoff (1987) provides an excellent survey of this literature. In fact, the contemporaneous correlation between the formation periods' trading volume ranks and returns is 0.11, 0.09 and 0.08 for the small, medium and large size groups respectively.

[44] See, for example, Lehmann (1990), and Conrad, Kaul and Nimalendran (1991) for negative autocorrelations, and Lo and MacKinlay (1988) for positive autocorrelations.

Portfolios analogous to those formed in section 3 with trading volume ranks are formed using these return ranks (i.e. by replacing ψ_{ij} by ϕ_{ij} in all the equations of that section). Table 9 presents the average net returns (NPR_t) for both portfolio formation strategies and the three size groups. Observe that, as documented by previous studies, returns tend to be mean reverting in the short run. Specifically, stocks that had an extremely high return during the formation period tend to depreciate, and stocks that had an extremely low return tend to appreciate. This is in fact true for both the daily and the weekly sample. This can be seen from the negative net returns of our strategies in Table 9.[45] Indeed, we can see from that table that our strategies, which are long (short) in stocks that just experienced a high return in the formation period (one day in Panel A, and one week in Panel B) tend to generate negative net returns over the subsequent ten or twenty days. Moreover, most of these negative returns tend to be significant.

In contrast, our earlier results show that stocks that experienced extreme high volume tend to appreciate over the subsequent 20 trading days, whereas stocks that experienced extreme low volume tend to depreciate over that period. So, not only is it not the case that the high volume return premium that we document exists just because of the contemporaneous correlation between trading volume and returns, but it exists *despite* it.

Some studies have shown that volume is also correlated with absolute returns.[46] It is therefore possible that the high volume premium in returns is driven by some intertemporal correlation between current absolute returns and future returns. In fact, as absolute returns closely proxy stock volatility, our high volume premium could simply represent the usual risk premium. To see if that is the case, we repeat the same analysis as above, but we now base it on absolute returns (instead of returns per se) during the formation period. So, let Γ_{ij} denote the formation period absolute return rank for stock $j = 1, \ldots, M_i$ in trading interval $i = 1, \ldots, 161$, when compared to the 49 daily absolute returns of the associated reference period. Again, we are interested in identifying the stocks whose absolute returns in the formation period is unusually high or low by defining

$$\gamma_{ij} = \begin{cases} H, & \text{if } \Gamma_{ij} \geq 46 \\ L, & \text{if } \Gamma_{ij} \leq 5 \\ N, & \text{otherwise.} \end{cases} \tag{10}$$

Both Γ_{ij} and γ_{ij} are similarly defined for the weekly sample.

The net returns for the portfolio strategies based on these absolute returns appear in Table 10. The net returns for both the zero investment portfolios and the reference return portfolios are insignificantly different from zero after 10 and 20 trading days. This is true both when the formation period is a day or a week.[47] Based on this evidence, it is clear that the high volume premium is

[45] Given the studies by Lehmann (1990), and CHN, the results for the weekly sample in Panel B are not surprising.

[46] See, for example, Comiskey, Walkling and Weeks (1985), Wood, McInish and Ord (1985), Harris (1986, 1987), and Gallant, Rossi and Tauchen (1992).

[47] The only exception is for small stocks in the zero investment strategy, when the formation period is a day.

not simply a risk premium. Of course, this is consistent with the results of section 5 that the risk of the positions taken with our original strategies cannot explain the returns that they generate.

6.4 Regression Analysis

To further assess the robustness of our results, we go back to the TAQ dataset, which we briefly mentioned in section 5.3. For the purpose of our regression analysis, this dataset has two main advantages over the CRSP dataset used in most of our analysis so far. First, the TAQ dataset allows us to remove the potential bias introduced by the bid-ask bounce. Indeed, as opposed to the CRSP data, the TAQ data contains quote information, and it is therefore possible to dampen the effect of the bid-ask spread by using the mid-quote as a proxy for the true price. Second, as the TAQ data contains the trade by trade account of the activity on the NYSE, it is possible to figure out the exact dollar value of the trading volume for a stock over a day. Using CRSP data, this quantity could only be approximated using the price of the last trade of the day, along with the number of shares traded that day. We feel that these two properties of the TAQ dataset are essential for performing the regression analysis of this section.[48]

The only drawback in using the TAQ dataset is its shorter horizon. In fact, for this study, we use data that spans the period from January 1993 to December 1994. As a result, we are forced to make the different trading intervals overlapping. However, in order to keep the test periods from overlapping, we make every fourth day a formation period and consider the returns over the subsequent three days.[49] We end up with 113 trading intervals. Apart from this last consideration and the slight adjustments made to the way we measure trading volume and stock returns in the previous paragraph, the rest of the *TAQ sample* is constructed the same way the daily sample was constructed in section 2. Our regressions seek to test whether trading volume has any explanatory power for subsequent returns. Given the numerous studies documenting the power of past returns to explain future returns, all of our regressions include an independent variable for formation period return (R_{ij0}), along with different sets of independent variables for formation period volume. This way, we should be able to see the *incremental* power of past volume over past returns in explaining stock returns during the test period.

We consider two sets of volume terms in our regressions. The first set is a pair of indicator variables: the first variable takes a value of one if the volume in the formation period is classified as low ($\psi_{ij} = L$) and zero otherwise, and the second takes a value of one if that volume is high ($\psi_{ij} = H$) and zero otherwise. The second set simply consists of a volume rank (Ψ_{ij}) for the stock in the formation period. In order to make the intercept a_{it} and its t-statistic informative, we center the volume rank, which takes values of $1, \dots, 50$, around zero by subtracting 25.5 from it. We

[48]We also produced all the previous tables using this TAQ dataset. These tables are not reported here, as the results were essentially the same as those of the CRSP daily sample.

[49]The fact that the 49-day reference periods preceding the formation periods are then overlapping is less problematic than intersecting test periods. Indeed, under the null hypothesis that the high volume return premium does not exist, this overlap does not bias the formation of our portfolios.

do not use the actual trading volume directly in our regressions in order to make all the different stocks comparable. This allows us to run a cross-sectional regression in each trading interval, and then to average the coefficients over all 113 trading intervals.[50]

For each set of independent variables and each trading interval i, we run a cross-sectional regression over all M_i stocks (index by $j = 1, \ldots, M_i$) in the size group. First, we use the one-day stock returns after the formation date (R_{ij1}) as the dependent variable for each regression:

$$R_{ij1} = a_{i1} + b_{i1} R_{ij0} + c_{i1} \mathbf{1}_{\{\psi_{ij}=L\}} + d_{i1} \mathbf{1}_{\{\psi_{ij}=H\}} + \varepsilon_{ij1}, \tag{11a}$$

$$R_{ij1} = a_{i1} + b_{i1} R_{ij0} + e_{i1} (\Psi_{ij} - 25.5) + \epsilon_{ij1}. \tag{11b}$$

We then run similar regressions using the three-day stock returns (R_{ij3}) as the left-hand side variable:

$$R_{ij3} = a_{i3} + b_{i3} R_{ij0} + c_{i3} \mathbf{1}_{\{\psi_{ij}=L\}} + d_{i3} \mathbf{1}_{\{\psi_{ij}=H\}} + \varepsilon_{ij3}, \tag{11c}$$

$$R_{ij3} = a_{i3} + b_{i3} R_{ij0} + e_{i3} (\Psi_{ij} - 25.5) + \epsilon_{ij3}. \tag{11d}$$

We then aggregate the results of these regressions over the 113 trading intervals by calculating

$$a_t \equiv \frac{1}{113} \sum_{i=1}^{113} a_{it}, \quad t = 1, 3,$$

and similarly for $b_t, \ldots, e_t$. If volume has any explanatory power over returns for subsequent price changes, we would expect to find that c_t, d_t, and e_t are all significantly different from zero. More precisely, if high (low) volume announces positive (negative) future returns, we would expect c_t to be significantly negative, and d_t and e_t to be significantly positive.

Table 11 shows the estimated coefficients resulting from the above regressions. As anticipated, the coefficients c_t (d_t, e_t) are significantly negative (positive) for $t = 1, 3$ and all size groups. This confirms the fact that trading volume does have explanatory power for future returns, that is higher current trading volume tends to announce positive returns. Moreover, we can see that all the coefficients for the three-day returns are larger (in absolute value) than the coefficients for the one-day returns, confirming the increase in returns over the test period documented in section 4.

Another interesting aspect of Table 11 concerns the coefficients on formation period returns (b_t). Although these coefficients are mostly statistically insignificant, it is the case that they are positive when explaining the one-day returns, but negative when explaining the three-day returns. In other words, daily stock returns have a momentum effect over the following day, but a reversal effect over the following few days, as documented by Hasbrouck and Ho (1987). Since the volume effect described in the previous paragraph coexists with these return effects, we can safely say that past trading volume contains information about future prices not contained in past returns. This

[50] Also, in all cases, we use volume as a fraction of total daily market volume (as in section 6.1) to rank a stock's daily volume in each trading interval.

reinforces the results from section 4.3 that trading volume does contain some information that is orthogonal to prices.

In sum, the evidence shows that the positive (negative) information contained in periods of high (low) volume is very robust. In particular, it does not seem to be affected by how trading volume is measured, it is not driven by firm announcements, it is not proxying for return effects that have been previously documented, and it appears to have been present for the past 30 years or so.[51]

7 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 3. 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.[52] 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% would be wiped out by one-way transaction costs of 0.2%. These estimates would seem to indicate on the one hand that, although the positive returns documented in Tables 2 and 3 help us describe the evolution of stock prices, these positive returns are probably not directly exploitable by market participants. On the other hand, the sizeable returns of the strategies involving only normal return stocks (section 4.3 and Table 4) 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 will take advantage of that same information, but will do 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 reversed. 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) orders. With the twenty-day horizon, we close our positions by sending cancelling sell (buy) limit orders at the ask (bid) price prevailing at the end of the twentieth day of the test period. We then check over the next two days[53] whether the limit

[51] We also checked to see if the high volume return premium was a recent phenomenon, or if it has prevailed since the 1960's. To do this, we used the daily CRSP sample, and divided the whole time interval into two subintervals of 80 and 81 trading intervals respectively (the cutoff date was 21 April 1980). We find that the volume effect documented in section 4 is very consistent across the two periods.

[52] 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. In any event, this potential bias was mitigated in section 6.4, where we used Trades and Quotes (TAQ) data.

[53] The waiting period is restricted to a day for opening the positions in order to take full advantage of the high

orders are hit. Those that are still outstanding are again converted into market-on-close orders.

Since the Lee and Ready (1991) algorithm requires a transaction by transaction account of the trading activity, we use the TAQ sample introduced in section 6.4 to perform this analysis.[54] The results are shown in Panel A of Table 12. 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 destroy 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 2. At the other end of the spectrum, the third column incorporates very explicitly the transaction costs discussed by Lehmann (1990), and by Conrad, Gultekin and Kaul (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.

Since Table 4 shows that the extreme formation period returns reduce the extent of the high volume return premium, we again restrict our sample to only include the normal (middle 40%) formation period returns. Panel B of Table 12 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 twenty-day net returns that our strategies generate are of the order of 0.89% and 0.73% per dollar long *after transaction costs* for the small and medium firms 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. Since 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 too aggressively. For example, the positive net returns described in Table 12 will translate into economic profits, as long as the strategies are not implemented with order sizes so

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.

[54] There is one small difference between the way we construct the TAQ sample in this section and that in section 6.4. In order 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 excluded from the sample for a period of four days.

large that their price impact destroys the profit opportunities. This is especially true for the price impact of sell orders placed in times of low trading activity.

8 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 extreme high volume contain positive information, whereas periods of extreme low volume contain negative information. 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. Remarkably, the results are *stronger* for stocks which experience returns that are not unusually high or low during these extreme volume periods, suggesting that past trading volume contains information about future prices changes that is orthogonal to that contained in past returns.

The additional 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. 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 risk-based explanations for our results difficult. Furthermore, the stocks' bid-ask spreads following periods of high (low) volume are significantly smaller (larger) than average bid-ask spreads, suggesting that information risk also goes down (up) after periods of unusually high (low) trading activity. The results are shown to be robust to the way trading volume is measured, and do not rely on a few outlyers generated around firm announcements. We also demonstrate that the high volume return premium is clearly a phenomenon that is independent from the well known contemporaneous correlation between trading volume and returns (as well as absolute returns), and the autocorrelation in stock returns. 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 option.

The fact that, after periods of extreme high volume, stocks tend to outperform their counterparts is consistent with the work of Merton (1987), who predicts that observability induces positive returns. So, it is possible that a stock becomes more "noticeable" after undergoing a period of unusually high trading volume, and hence subsequently experiences positive excess returns. Also, given that trading volume is determined endogenously, it appears that good (bad) information about the future prospects of a firm tends to be associated with higher (lower) volume. This would imply that investors have asymmetric reactions to good versus bad news, as suggested by the short-sale constraint model by Diamond and Verrecchia (1987). So, it is our view that the high volume return premium is probably related to stock visibility and trading constraints. However, the construction of a model that reconciles all the empirical facts documented in this paper represents a challenge for future research.

Appendix

In this appendix, we describe in more details the two tests of first-order stochastic dominance used in section 5.2. These tests seek to document the fact that the returns generated by our volume-based investment strategies dominate those that could be obtained with a similar but unconditional investment in the firms of the same size group. The tests are applied to the twenty-day net returns of the zero investment portfolios using the daily CRSP sample.

For this strategy, we already have one net return per trading interval, that is 161 net returns for each size group.[55] Assuming that these 161 outcomes are drawn from the same distribution (whose actual and empirical cumulative density functions are denoted by F and F^e respectively), we want to determine whether this distribution first-order stochastically dominates the distribution of net returns generated by zero investment portfolios formed without conditioning on trading volume during the formation period. To this end, for every size group in each trading interval, we construct 1,000 *simulated portfolios* as follows. Each security that was originally purchased or sold in the zero investment portfolio is replaced randomly by a security from the same trading interval and size group. The 161,000 twenty-day net returns generated by these portfolios are also assumed to orignate from the same distribution (whose actual and empirical cumulative density functions are denoted by G and G^e respectively).

Test #1

The first test is based on Whitemore (1978). The null hypothesis (H_0) is that neither F nor G first-order stochastically dominates the other. We test this against the following two possible alternatives:

$$\begin{aligned} &H_1: \ F \text{ first-order stochastically dominates } G; \\ &H_2: \ G \text{ first-order stochastically dominates } F. \end{aligned}$$

To do this, we first compute the Kolmogorov-Smirnov test statistics comparing the two empirical distributions:

$$\begin{aligned} T^{FG} &= \sup_{x \in \mathbb{R}} \left[F^e(x) - G^e(x) \right]; \\ T^{GF} &= \sup_{x \in \mathbb{R}} \left[G^e(x) - F^e(x) \right]. \end{aligned}$$

We reject the null hypothesis in favor of H_1 (H_2) if $T^{FG} \leq A_d \leq T^{GF}$ ($T^{GF} \leq A_d \leq T^{FG}$) where, for a confidence level d, the quantity A_d satisfies

$$\Pr\left\{ \text{not rejecting } H_0 \mid F \overset{\text{dist}}{\sim} G \right\} = 1 - d. \tag{A.1}$$

[55] As before, there are only 160 trading intervals for the large firm group.

Since neither F or G is known, we estimate A_d from the simulated portfolios. To do this, we denote the empirical cumulative density function for each of the 1,000 sets of 161 net returns by G_k^e, $k = 1, \ldots, 1{,}000$. Then, for each $k = 1, \ldots, 1{,}000$, we calculate

$$
\begin{aligned}
T_k^{FG} &= \sup_{x \in \mathbb{R}} \left[G_k^e(x) - G^e(x) \right], \quad \text{and} \\
T_k^{GF} &= \sup_{x \in \mathbb{R}} \left[G^e(x) - G_k^e(x) \right].
\end{aligned}
$$

From these simulated series of T^{FG}'s and T^{GF}'s, we can finally estimate A_d, so that (A.1) is satisfied empirically.

For our test in section 5.2, we chose $d = 5\%$. Using the above procedure, we estimate $A_{5\%}$ to be 0.095, 0.085 and 0.085 for the small, medium, and large firm groups respectively. We calculate $T^{FG} = 0.008, 0.009, 0.00525$ and $T^{GF} = 0.1409, 0.2042, 0.161$ for these three size groups. In all three cases, we find that $T^{FG} \leq A_d \leq T^{GF}$, so we can reject null hypothesis in favor of the alternative that F first-order stochastically dominates G.

Test #2

This test follows the procedure developed by Anderson (1996), and is an extension of the Pearson's goodness of fit test. The idea behind the test is as follows. If two empirical distributions are from a common underlying distribution, and if we partition each empirical distribution into a number of mutually exclusive and exhaustive intervals of the real line, then the cumulative proportion of observations of the two empirical distributions should be similar for all intervals. On the other hand, we can reject that hypothesis for a first-order stochastic dominance alternative if the cumulative proportion of observations from one empirical distribution is not significantly more than that of the other empirical distribution for all the partitions, but is significantly less for at least one partition.

As described by Anderson (1996), with a suitable partition of the real line, the difference in the cumulative proportion of observations for two empirical distributions has a well defined distribution. It is therefore possible, given a confidence level, to find the appropriate confidence intervals using the studentized maximum modulus distribution described in Stoline and Ury (1979). We chose to use a ten-interval partition: $(-\infty, r_1]$, $(r_1, r_2]$, $\ldots$, (r_9, ∞), where $r_1, \ldots, r_9$ are chosen so that 10% of the 161,161 combined observations from the empirical distribution of the zero investment portfolios and the simulated portfolios are contained in each interval.

The rest of the test involves comparing the empirical cumulative density functions. To do this, we calculate ($r_{10} = \infty$ in these expressions)

$$
\begin{aligned}
M &= \max_{n=1,\ldots,10} \frac{G^e(r_n) - F^e(r_n)}{\sigma_n}, \quad \text{and} \\
m &= \min_{n=1,\ldots,10} \frac{G^e(r_n) - F^e(r_n)}{\sigma_n},
\end{aligned}
$$

where $\{\sigma_n^2\}_{n=1}^{10}$ correspond to the diagonal elements of the 10×10 variance-covariance matrix

$$\frac{161{,}161}{(161{,}000)(161)} I_f \Omega I_f',$$

and

$$\Omega = \begin{bmatrix} 0.09 & 0.01 & 0.01 & \cdots & 0.01 \\ 0.01 & 0.09 & 0.01 & \cdots & 0.01 \\ 0.01 & 0.01 & 0.09 & \cdots & 0.01 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0.01 & 0.01 & 0.01 & \cdots & 0.09 \end{bmatrix}, \quad I_f = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix}.$$

The null and alternative hypotheses (H_0, H_1, and H_2) are the same as in the first test. The null hypothesis is rejected in favor of H_1 (H_2) if $M \geq A_d$ and $m > -A_d$ ($m \leq -A_d$ and $M < A_d$). At a significance level of 1%, the partition that we chose implies that $A_{1\%} = 3.29$. For the small (medium, large) firm group, we calculate $M = 3.71$ ($M = 6.54$ and $M = 4.14$) and $m = 0.29$ ($m = 1.60$ and $m = 0.40$). We can therefore reject the null hypothesis in favor of the alternative that F first-order stochastically dominates G for all three size groups.

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Table 1
Descriptive statistics of the daily CRSP sample.

The daily CRSP sample is comprised of 161 non-overlapping 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 date. 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 dollar value of the shares of each stock traded every day. 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.

	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 volume	$207,222	$817,378	$6,440,099
Median volume	$47,025	$172,138	$1,380,400
	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 volume	$58,367	$107,419	$495,413
Median volume	$12,675	$38,850	$163,300
	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 volume	$663,010	$2,888,940	$24,979,804
Median volume	$172,756	$1,112,300	$11,272,650

Table 2
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 date: 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 the zero investment portfolio formation strategy, the three lines in each size group panel correspond to $\overline{PR}_t$, $\underline{PR}_t$, and NPR_t as defined in equation (4). For the reference return portfolio formation strategy, the three lines in each size group panel correspond to $\overline{PR}_t$, $\underline{PR}_t$, and NPR_t as defined in equations (5a), (5b), and (6). For both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) 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		
days after formation (t):	1	10	20	1	10	20
			Panel A: Small Firms			
High Volume ($\overline{PR}_t$)	0.25	0.95	1.61	0.12	0.28	0.45
	(n/a)	(n/a)	(n/a)	(2.54)	(2.21)	(2.65)
Low Volume ($\underline{PR}_t$)	0.11	-0.18	-0.67	0.19	0.46	0.49
	(n/a)	(n/a)	(n/a)	(5.53)	(4.42)	(3.24)
Net Returns (NPR_t)	0.35	0.77	0.94	0.16	0.37	0.47
	(5.07)	(3.56)	(2.98)	(5.34)	(4.58)	(4.15)
			Panel B: Medium Firms			
High Volume ($\overline{PR}_t$)	0.22	0.79	1.31	0.12	0.26	0.41
	(n/a)	(n/a)	(n/a)	(4.42)	(3.68)	(4.36)
Low Volume ($\underline{PR}_t$)	0.02	-0.05	-0.24	0.08	0.31	0.45
	(n/a)	(n/a)	(n/a)	(3.92)	(4.71)	(5.00)
Net Returns (NPR_t)	0.24	0.74	1.07	0.10	0.28	0.43
	(4.93)	(5.25)	(5.77)	(5.90)	(5.91)	(6.60)
			Panel C: Large Firms			
High Volume ($\overline{PR}_t$)	0.13	0.43	0.78	0.06	0.18	0.29
	(n/a)	(n/a)	(n/a)	(2.78)	(3.23)	(3.80)
Low Volume ($\underline{PR}_t$)	-0.01	0.04	-0.28	0.07	0.20	0.21
	(n/a)	(n/a)	(n/a)	(3.81)	(3.48)	(2.63)
Net Returns (NPR_t)	0.12	0.46	0.50	0.06	0.19	0.25
	(3.16)	(3.49)	(3.11)	(4.58)	(4.74)	(4.56)

Table 3
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 date: 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 the zero investment portfolio formation strategy, the three lines in each size group panel correspond to $\overline{PR}_t$, $\underline{PR}_t$, and NPR_t as defined in equation (4). For the reference return portfolio formation strategy, the three lines in each size group panel correspond to $\overline{PR}_t$, $\underline{PR}_t$, and NPR_t as defined in equations (5a), (5b), and (6). For both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) 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		
days after formation (t):	1	10	20	1	10	20
Panel A: Small Firms						
High Volume ($\overline{PR}_t$)	0.20	0.92	1.28	0.06	0.24	0.40
	(n/a)	(n/a)	(n/a)	(1.31)	(1.87)	(2.44)
Low Volume ($\underline{PR}_t$)	0.02	0.08	0.08	0.15	0.56	0.67
	(n/a)	(n/a)	(n/a)	(4.23)	(5.18)	(4.42)
Net Returns (NPR_t)	0.22	1.00	1.36	0.10	0.40	0.54
	(3.46)	(4.26)	(4.66)	(3.62)	(4.79)	(4.80)
Panel B: Medium Firms						
High Volume ($\overline{PR}_t$)	0.17	0.72	0.89	0.04	0.25	0.27
	(n/a)	(n/a)	(n/a)	(1.55)	(3.64)	(2.96)
Low Volume ($\underline{PR}_t$)	0.06	0.11	0.22	0.10	0.47	0.66
	(n/a)	(n/a)	(n/a)	(4.80)	(7.37)	(7.72)
Net Returns (NPR_t)	0.23	0.84	1.10	0.07	0.36	0.47
	(3.90)	(6.20)	(5.81)	(4.24)	(7.71)	(7.50)
Panel C: Large Firms						
High Volume ($\overline{PR}_t$)	0.13	0.65	0.75	0.02	0.18	0.21
	(n/a)	(n/a)	(n/a)	(1.14)	(3.22)	(2.58)
Low Volume ($\underline{PR}_t$)	-0.03	-0.09	0.15	0.05	0.29	0.55
	(n/a)	(n/a)	(n/a)	(2.78)	(4.90)	(6.88)
Net Returns (NPR_t)	0.10	0.56	0.90	0.04	0.24	0.38
	(2.37)	(4.52)	(4.93)	(2.70)	(5.75)	(6.66)

Table 4
Average net returns of the zero investment and the reference return strategies using normal return 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 2 and 3. We only use the subsample of stocks whose returns during the formation period of one day (week) in Panel A (Panel B) are classified as normal, that is not in the top or bottom 30% of the 50 daily (10 weekly) returns in the whole trading interval. All the entries refer to the average net returns (NPR_t) of the strategies, as defined in equation (4) for the zero investment portfolios and in equation (6) for the reference return portfolios. For both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) trading days. The numbers in parentheses are t-statistics.

	Zero Investment			Reference Returns		
days after formation (t):	1	10	20	1	10	20
			Panel A: Daily CRSP sample			
Small firms	0.31	0.63	1.15	0.12	0.46	0.52
	(2.88)	(1.64)	(2.25)	(3.14)	(3.96)	(3.15)
Medium firms	0.14	0.88	1.25	0.08	0.39	0.52
	(2.17)	(4.38)	(4.53)	(3.44)	(5.29)	(5.08)
Large firms	0.09	0.62	0.60	0.05	0.23	0.21
	(1.45)	(3.02)	(2.24)	(2.66)	(3.56)	(2.38)
			Panel B: Weekly CRSP sample			
Small firms	0.42	1.55	2.02	0.18	0.65	0.89
	(3.59)	(4.20)	(3.82)	(4.43)	(4.96)	(4.91)
Medium firms	0.25	0.87	1.17	0.10	0.46	0.56
	(3.29)	(4.14)	(4.56)	(3.86)	(6.34)	(5.57)
Large firms	0.14	0.50	0.99	0.06	0.27	0.51
	(2.54)	(2.41)	(3.55)	(3.07)	(4.16)	(5.79)

Table 5
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 3, we estimate a joint market model. This is done using the following seemingly unrelated regression (SURE) model:

$$\begin{aligned} \overline{PR}_{it} &= \alpha_t^H + \beta_t^H R_{it}^m + \varepsilon_{it}^H, \quad i = 1, \dots, 161; \\ \underline{PR}_{it} &= \alpha_t^L + \beta_t^L R_{it}^m + \varepsilon_{it}^L, \quad i = 1, \dots, 161. \end{aligned}$$

The two equations for this model describe the two portions of the zero investment portfolios, $\overline{PR}_{it}$ and $\underline{PR}_{it}$, as defined in (3a) and (3b) respectively. The corresponding returns on the market (R_{it}^m) are taken to be the returns on a value-weighted index, an equal-weighted index, and the S&P500. In all cases, the model is estimated for three investment horizons: $t = 1, 10, 20$. For each such regression, we show the estimated slopes β_t^H and β_t^L, as well as their difference. The numbers in curly brackets show the p-values testing for $\beta_t^H = 1$, $\beta_t^L = 1$, and $\beta_t^H - \beta_t^L = 0$.

	Value-weighted index			Equal-weighted index			S&P500		
days after formation (t):	1	10	20	1	10	20	1	10	20
Panel A: Small Firms									
β_t^H	0.858	0.946	1.095	1.020	0.970	1.029	0.802	0.919	1.065
	{0.0254}	{0.3676}	{0.1304}	{0.7581}	{0.4721}	{0.4625}	{0.0019}	{0.1915}	{0.3306}
β_t^L	0.799	1.090	1.193	0.984	1.095	1.102	0.741	1.059	1.152
	{0.0006}	{0.1704}	{0.0043}	{0.7789}	{0.0523}	{0.0218}	{0.0000}	{0.3911}	{0.0366}
$\beta_t^H - \beta_t^L$	0.059	-0.144	-0.098	0.036	-0.125	-0.073	0.062	-0.140	-0.087
	{0.4163}	{0.0326}	{0.1458}	{0.6591}	{0.0428}	{0.1981}	{0.3751}	{0.0374}	{0.1992}
Panel B: Medium Firms									
β_t^H	0.813	1.090	1.122	0.953	1.031	0.985	0.758	1.071	1.101
	{0.0000}	{0.0329}	{0.0026}	{0.2400}	{0.3427}	{0.5723}	{0.0000}	{0.1170}	{0.0250}
β_t^L	0.765	1.108	1.140	0.941	1.083	1.024	0.710	1.078	1.112
	{0.0000}	{0.0154}	{0.0020}	{0.1469}	{0.0027}	{0.3628}	{0.0000}	{0.1100}	{0.0277}
$\beta_t^H - \beta_t^L$	0.048	-0.017	-0.018	0.012	-0.052	-0.039	0.048	-0.007	-0.010
	{0.3420}	{0.6945}	{0.6535}	{0.8351}	{0.2037}	{0.2486}	{0.3217}	{0.8749}	{0.7979}
Panel C: Large Firms									
β_t^H	0.899	0.997	1.043	0.982	0.891	0.848	0.856	0.987	1.036
	{0.0002}	{0.9249}	{0.1045}	{0.5993}	{0.0002}	{0.0000}	{0.0000}	{0.6583}	{0.2200}
β_t^L	0.980	1.019	1.076	1.080	0.892	0.872	0.929	1.011	1.067
	{0.5131}	{0.5954}	{0.0173}	{0.0325}	{0.0064}	{0.0001}	{0.0320}	{0.7635}	{0.0582}
$\beta_t^H - \beta_t^L$	-0.080	-0.022	-0.033	-0.098	-0.001	-0.024	-0.073	-0.024	-0.030
	{0.0359}	{0.6118}	{0.3548}	{0.0213}	{0.9838}	{0.4213}	{0.0480}	{0.5739}	{0.3966}

Table 6
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 2 and 3. 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 weighting function analysis ($n = 2$, $n = 4$, and $n = 8$), the volume of the last trading day of the reference period is weighted n times more than the volume of the first day of that period when ranking the formation date volume. For the "market 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 pre-multiplied by a factor adjusting for the differences in expected volume across days of the week. For the zero investment portfolio formation strategy, every number in the table corresponds to NPR_t as defined in equation (4). For the reference return portfolio formation strategy, every number in the table corresponds to NPR_t as defined in equation (6). For both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) trading days. The numbers in parentheses are t-statistics.

	Zero Investment			Reference Returns		
days after formation (t):	1	10	20	1	10	20
Panel A: Small Firms						
Weights $n = 2$	0.33	0.68	0.89	0.16	0.34	0.46
	(4.95)	(3.30)	(2.88)	(5.58)	(4.20)	(4.12)
Weights $n = 4$	0.37	0.63	0.78	0.17	0.30	0.42
	(5.29)	(3.21)	(2.57)	(5.78)	(3.78)	(3.76)
Weights $n = 8$	0.39	0.72	0.92	0.18	0.30	0.40
	(5.56)	(3.65)	(3.06)	(6.08)	(3.71)	(3.60)
Market volume	0.41	0.74	0.87	0.17	0.33	0.42
	(5.52)	(3.75)	(3.38)	(5.86)	(4.13)	(3.72)
Day of the week	0.36	0.80	1.06	0.15	0.37	0.50
	(5.10)	(3.74)	(3.25)	(5.15)	(4.57)	(4.45)
Panel B: Medium Firms						
Weights $n = 2$	0.23	0.72	1.04	0.09	0.28	0.43
	(4.61)	(5.28)	(5.71)	(5.44)	(5.79)	(6.63)
Weights $n = 4$	0.25	0.75	1.05	0.10	0.28	0.42
	(5.04)	(5.51)	(6.12)	(5.71)	(5.73)	(6.49)
Weights $n = 8$	0.25	0.77	1.02	0.10	0.29	0.43
	(4.85)	(5.70)	(6.08)	(5.78)	(6.06)	(6.73)
Market volume	0.25	0.70	1.04	0.12	0.32	0.46
	(6.15)	(5.60)	(6.62)	(6.76)	(6.56)	(7.02)
Day of the week	0.26	0.80	1.19	0.11	0.32	0.48
	(5.29)	(5.62)	(6.25)	(6.31)	(6.65)	(7.36)
Panel C: Large Firms						
Weights $n = 2$	0.12	0.51	0.59	0.06	0.19	0.27
	(3.19)	(3.99)	(3.80)	(4.11)	(4.85)	(4.96)
Weights $n = 4$	0.09	0.49	0.52	0.05	0.18	0.25
	(2.54)	(3.96)	(3.28)	(3.61)	(4.61)	(4.61)
Weights $n = 8$	0.09	0.43	0.50	0.05	0.17	0.25
	(2.26)	(3.55)	(3.22)	(3.43)	(4.43)	(4.54)
Market volume	0.16	0.44	0.64	0.07	0.21	0.31
	(4.71)	(4.20)	(4.48)	(5.50)	(5.23)	(5.46)
Day of the week	0.10	0.44	0.44	0.06	0.19	0.23
	(2.80)	(3.26)	(2.87)	(4.33)	(4.69)	(4.22)

Table 7
Average 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 2. The "No event" subsample eliminates all the stocks which had a dividend or an earnings announcement either the day before, the day of, or the day after the formation period. The "Dividend" ("Earnings") sample uses every trading day as a formation period, but only includes the stocks which had a dividend (earnings) announcement on that day. For all three size groups and all three samples, three lines are shown. For the zero investment portfolio formation strategy, these three lines correspond to $\overline{PR}_t$, $\underline{PR}_t$, and NPR_t as defined in equation (4). For the reference return portfolio formation strategy, they correspond to $\overline{PR}_t$, $\underline{PR}_t$, and NPR_t as defined in equations (5a), (5b), and (6). For both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) 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		
	days after formation (t):	1	10	20	1	10	20
				Panel A: Small Firms			
No event	High Volume ($\overline{PR}_t$)	0.25	0.93	1.60	0.13	0.26	0.44
		(n/a)	(n/a)	(n/a)	(2.61)	(2.04)	(2.52)
	Low Volume ($\underline{PR}_t$)	0.11	-0.16	-0.61	0.21	0.46	0.47
		(n/a)	(n/a)	(n/a)	(6.02)	(4.30)	(3.06)
	Net Returns (NPR_t)	0.37	0.77	0.99	0.17	0.37	0.46
		(5.20)	(3.54)	(3.00)	(5.69)	(4.39)	(3.93)
Dividend	High Volume ($\overline{PR}_t$)	0.18	1.51	2.78	0.36	0.88	1.08
		(n/a)	(n/a)	(n/a)	(6.53)	(6.68)	(6.42)
	Low Volume ($\underline{PR}_t$)	0.10	0.13	-0.79	0.09	0.37	0.47
		(n/a)	(n/a)	(n/a)	(1.70)	(2.67)	(2.45)
	Net Returns (NPR_t)	0.28	1.65	1.99	0.26	0.70	0.86
		(1.66)	(4.35)	(3.74)	(6.54)	(7.09)	(6.71)
Earnings	High Volume ($\overline{PR}_t$)	-0.24	3.04	5.05	0.04	0.78	1.19
		(n/a)	(n/a)	(n/a)	(0.49)	(3.98)	(4.73)
	Low Volume ($\underline{PR}_t$)	0.15	0.49	0.05	0.11	0.77	1.20
		(n/a)	(n/a)	(n/a)	(0.96)	(2.41)	(2.67)
	Net Returns (NPR_t)	-0.08	3.53	5.10	0.05	0.78	1.18
		(-0.35)	(3.57)	(3.96)	(0.74)	(4.51)	(5.34)

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Table 7 (cont'd)

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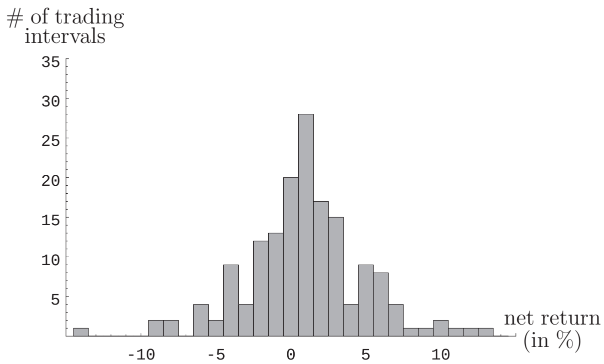
		Zero Investment			Reference Returns		
	days after formation (t):	1	10	20	1	10	20
		Panel B: Medium Firms					
No event	High Volume ($\overline{PR}_t$)	0.21	0.76	1.29	0.11	0.25	0.41
		(n/a)	(n/a)	(n/a)	(3.89)	(3.43)	(4.12)
	Low Volume ($\underline{PR}_t$)	0.02	-0.02	-0.19	0.08	0.31	0.45
		(n/a)	(n/a)	(n/a)	(3.70)	(4.59)	(4.90)
	Net Returns (NPR_t)	0.23	0.74	1.10	0.09	0.28	0.43
		(4.52)	(5.14)	(5.83)	(5.36)	(5.65)	(6.36)
Dividend	High Volume ($\overline{PR}_t$)	0.29	1.17	1.78	0.24	0.62	0.66
		(n/a)	(n/a)	(n/a)	(8.01)	(8.64)	(7.08)
	Low Volume ($\underline{PR}_t$)	0.05	-0.18	-0.56	0.07	0.18	0.29
		(n/a)	(n/a)	(n/a)	(2.34)	(2.27)	(2.64)
	Net Returns (NPR_t)	0.33	0.99	1.23	0.17	0.45	0.52
		(5.21)	(6.03)	(5.65)	(8.05)	(8.39)	(7.27)
Earnings	High Volume ($\overline{PR}_t$)	0.40	1.37	2.10	0.11	0.30	0.53
		(n/a)	(n/a)	(n/a)	(2.35)	(2.83)	(3.86)
	Low Volume ($\underline{PR}_t$)	0.10	-0.50	-1.17	0.11	0.17	-0.01
		(n/a)	(n/a)	(n/a)	(1.67)	(0.85)	(-0.03)
	Net Returns (NPR_t)	0.50	0.87	0.93	0.11	0.27	0.43
		(3.73)	(2.43)	(2.02)	(2.77)	(2.92)	(3.46)
		Panel C: Large Firms					
No event	High Volume ($\overline{PR}_t$)	0.12	0.39	0.74	0.05	0.16	0.28
		(n/a)	(n/a)	(n/a)	(2.34)	(2.74)	(3.43)
	Low Volume ($\underline{PR}_t$)	0.00	0.07	-0.27	0.07	0.22	0.21
		(n/a)	(n/a)	(n/a)	(4.08)	(3.78)	(2.63)
	Net Returns (NPR_t)	0.12	0.46	0.47	0.06	0.19	0.24
		(3.16)	(3.47)	(2.91)	(4.45)	(4.61)	(4.28)
Dividend	High Volume ($\overline{PR}_t$)	0.26	1.14	1.71	0.15	0.46	0.41
		(n/a)	(n/a)	(n/a)	(6.62)	(8.01)	(5.47)
	Low Volume ($\underline{PR}_t$)	-0.06	-0.55	-0.94	0.02	-0.06	0.05
		(n/a)	(n/a)	(n/a)	(0.72)	(-0.95)	(0.52)
	Net Returns (NPR_t)	0.20	0.59	0.77	0.10	0.26	0.28
		(3.71)	(4.09)	(3.95)	(6.03)	(5.95)	(4.69)
Earnings	High Volume ($\overline{PR}_t$)	0.27	1.34	2.12	0.12	0.35	0.38
		(n/a)	(n/a)	(n/a)	(3.56)	(4.48)	(3.93)
	Low Volume ($\underline{PR}_t$)	-0.04	-0.96	-2.04	0.09	-0.19	-0.22
		(n/a)	(n/a)	(n/a)	(1.26)	(-1.06)	(-0.88)
	Net Returns (NPR_t)	0.23	0.38	0.08	0.12	0.27	0.29
		(1.88)	(1.25)	(0.20)	(3.78)	(3.72)	(3.21)

Table 8
Empirical distribution and sample statistics for the twenty-day net returns of the zero investment portfolios using the daily CRSP sample.

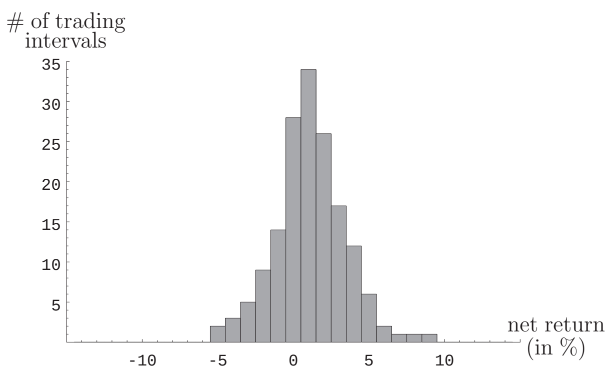
Empirical Distribution | Sample Statistics (in %)

Panel A: Small Firms



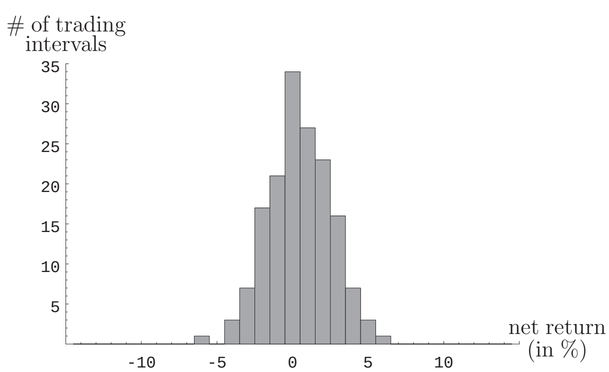
Minimum	-13.85
Maximum	12.56
Mean	0.94
25th percentile	-1.26
Median	0.92
75th percentile	2.90
Std. deviation	4.03
Skewness	-0.08

Panel B: Medium Firms



Minimum	-5.34
Maximum	8.80
Mean	1.07
25th percentile	-0.23
Median	0.98
75th percentile	2.45
Std. deviation	2.33
Skewness	0.18

Panel C: Large Firms



Minimum	-5.88
Maximum	6.23
Mean	0.50
25th percentile	-0.80
Median	0.43
75th percentile	1.77
Std. deviation	2.03
Skewness	-0.01

Table 9
Average net returns of the zero investment and the reference return strategies based on returns during the formation period, using the daily and weekly CRSP samples.

In each trading interval, stocks are classified according to size and return. The size groups are based on the firms' market capitalization decile at the close of the year prior to each formation date: 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 return classification is based on whether the stock's rate of return during the formation period of one day [week] in Panel A [Panel B] is among the top (high return) or bottom (low return) 10% of the 50 daily [10 weekly] returns in the whole trading interval. Every entry in the table shows the average net returns (NPR_t) of the strategies. For the zero investment portfolio formation strategy, NPR_t is as defined in equation (4). For the reference return portfolio formation strategy, NPR_t is as defined in equation (6). In both cases, ψ_{ij} should be replaced by ϕ_{ij} as defined in (7). Finally, for both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) trading days. The numbers in parentheses are t-statistics.

	Zero Investment			Reference Returns		
days after formation (t):	1	10	20	1	10	20
	Panel A: Daily CRSP sample					
Small firms	-0.09	-0.77	-0.98	-0.05	-0.43	-0.52
	(-0.98)	(-3.43)	(-3.22)	(-1.31)	(-4.80)	(-4.26)
Medium firms	0.09	-0.39	-0.64	0.05	-0.22	-0.33
	(1.49)	(-2.57)	(-3.38)	(2.74)	(-4.35)	(-4.74)
Large firms	0.15	-0.05	-0.24	0.07	-0.06	-0.07
	(2.48)	(-0.32)	(-1.08)	(4.55)	(-1.33)	(-1.23)
	Panel B: Weekly CRSP sample					
Small firms	-0.42	-1.17	-1.38	-0.22	-0.67	-0.80
	(-3.92)	(-3.91)	(-3.56)	(-6.43)	(-7.56)	(-6.75)
Medium firms	-0.16	-0.99	-0.98	-0.09	-0.46	-0.49
	(-2.76)	(-5.71)	(-4.20)	(-4.84)	(-8.83)	(-6.97)
Large firms	-0.12	-0.57	-0.28	-0.06	-0.24	-0.22
	(-1.89)	(-3.26)	(-1.10)	(-3.70)	(-5.47)	(-3.71)

Table 10
Average net returns of the zero investment and the reference return strategies based on absolute returns during the formation period, using the daily and weekly CRSP samples.

In each trading interval, stocks are classified according to size and absolute return. The size groups are based on the firms' market capitalization decile at the close of the year prior to each formation date: 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 absolute return classification is based on whether the stock's absolute rate of return during the formation period of one day [week] in Panel A [Panel B] is among the top (high absolute return) or bottom (low absolute return) 10% of the 50 daily [10 weekly] absolute returns in the whole trading interval. Every entry in the table shows the average net returns (NPR_t) of the strategies. For the zero investment portfolio formation strategy, NPR_t is as defined in equation (4). For the reference return portfolio formation strategy, NPR_t is as defined in equation (6). In both cases, ψ_{ij} should be replaced by γ_{ij} as defined in (10). Finally, for both portfolio formation strategies, we display the percentage returns (per dollar long) over three different horizons following the formation date: one ($t = 1$), ten ($t = 10$), and twenty ($t = 20$) trading days. The numbers in parentheses are t-statistics.

	Zero Investment			Reference Returns		
days after formation (t):	1	10	20	1	10	20
	Panel A: Daily CRSP sample					
Small firms	0.41	0.55	0.31	0.18	0.15	0.11
	(4.68)	(2.56)	(1.00)	(5.08)	(1.58)	(0.80)
Medium firms	0.17	0.11	0.01	0.08	0.05	0.02
	(3.60)	(0.89)	(0.05)	(4.16)	(1.05)	(0.24)
Large firms	0.12	0.03	0.16	0.04	-0.00	0.07
	(2.77)	(0.29)	(1.02)	(2.57)	(-0.07)	(1.21)
	Panel B: Weekly CRSP sample					
Small firms	0.05	0.18	0.25	0.04	0.07	0.04
	(0.60)	(0.80)	(0.84)	(1.29)	(0.84)	(0.34)
Medium firms	0.12	0.05	0.01	0.07	0.05	0.02
	(2.63)	(0.33)	(0.05)	(3.68)	(1.06)	(0.28)
Large firms	-0.00	-0.04	-0.11	0.01	-0.00	-0.02
	(-0.02)	(-0.35)	(-0.62)	(0.59)	(-0.10)	(-0.30)

Table 11
Cross sectional regression analysis on the daily TAQ sample.

Using the daily TAQ sample described in section 6.4, we run four cross-sectional regressions per trading interval, $i = 1, \ldots, 113$, for each size group. The first two regressions use the one-day stock returns after the formation date (R_{ij1}) as the dependent variable, whereas the latter two use the three-day returns (R_{ij3}). The independent variables used in these regressions are the formation period return (R_{ij0}), indicator variables determining whether a stock j is a high ($\psi_{ij} = H$) or low ($\psi_{ij} = L$) volume stock in a trading interval i, and the rank Ψ_{ij} (centered around zero) of that volume when compared to the 49 daily volumes of the reference period:

$$\begin{aligned}
R_{ij1} &= a_{i1} + b_{i1} R_{ij0} + c_{i1} \mathbf{1}_{\{\psi_{ij}=L\}} + d_{i1} \mathbf{1}_{\{\psi_{ij}=H\}} + \varepsilon_{ij1}; \\
R_{ij1} &= a_{i1} + b_{i1} R_{ij0} + e_{i1} (\Psi_{ij} - 25.5) + \epsilon_{ij1}; \\
R_{ij3} &= a_{i3} + b_{i3} R_{ij0} + c_{i3} \mathbf{1}_{\{\psi_{ij}=L\}} + d_{i3} \mathbf{1}_{\{\psi_{ij}=H\}} + \varepsilon_{ij3}; \\
R_{ij3} &= a_{i3} + b_{i3} R_{ij0} + e_{i3} (\Psi_{ij} - 25.5) + \epsilon_{ij3}.
\end{aligned}$$

Each regression is run cross-sectionally over M_i securities indexed by j. Finally, the estimated coefficients are averaged over the 113 trading intervals, $a_t \equiv \frac{1}{113}\sum_{i=1}^{113} a_{it}, t = 1, 3$, and similarly for $b_t, \ldots, e_t$. The numbers in parentheses are t-statistics.

Dependent variable	Averaged coefficients a_t	b_t	c_t	d_t	e_t
	Panel A: Small Firms				
R_{ij1}	-0.04949	0.00953	-0.19841	0.20196	
	(-1.07)	(0.74)	(-4.45)	(2.79)	
R_{ij1}	-0.04434	0.01012			0.00753
	(-1.00)	(0.79)			(6.62)
R_{ij3}	0.03730	-0.02215	-0.24656	0.37212	
	(0.38)	(-1.32)	(-3.16)	(3.68)	
R_{ij3}	0.05692	-0.02121			0.01493
	(0.61)	(-1.29)			(7.49)
	Panel B: Medium Firms				
R_{ij1}	-0.02147	0.03776	-0.11526	0.07568	
	(-0.47)	(3.95)	(-3.80)	(2.18)	
R_{ij1}	-0.02200	0.03665			0.00414
	(-0.50)	(3.89)			(6.22)
R_{ij3}	0.03604	-0.02099	-0.28587	0.24385	
	(0.38)	(-1.19)	(-5.85)	(4.00)	
R_{ij3}	0.03591	-0.02321			0.01055
	(0.38)	(-1.32)			(8.74)
	Panel C: Large Firms				
R_{ij1}	-0.01709	0.00353	-0.05999	0.08097	
	(-0.36)	(0.36)	(-2.61)	(2.82)	
R_{ij1}	-0.01443	0.00384			0.00240
	(-0.30)	(0.39)			(4.17)
R_{ij3}	0.02042	-0.05866	-0.10251	0.11179	
	(0.22)	(-3.89)	(-2.62)	(2.40)	
R_{ij3}	0.02111	-0.05911			0.00394
	(0.22)	(-3.93)			(3.60)

Table 12
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 6.4, we repeat the zero investment strategy using limit orders. In each trading interval, stocks are classified according to size and trading volume in the exact same way this was done in Table 2. In Panel A, we condition only on formation period volume to form the portfolios (as in Table 2). 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 4). For the first column ("limit orders"), the zero investment portofolios 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 the following day. The positions are cancelled at the end of twenty days using similar limit orders which, when still outstanding, turn into market orders two days later. The second and third column are shown for comparison purposes. 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 twenty-day net returns (NPR_{20}) of the zero investment strategy as defined in equation (4). Each number in the table represents a percentage return per dollar long. The numbers in parentheses are t-statistics.

Size Group (g)	Net Returns (NPR_{20}) Limit orders	 Market orders at midpoint	 Market orders at bid/ask
Panel A: No conditioning on return			
Small Firms	0.33 (1.56)	1.39 (7.26)	-3.08 (-15.37)
Medium Firms	0.26 (2.13)	0.88 (7.70)	-1.35 (-11.51)
Large Firms	-0.22 (-1.82)	0.32 (2.82)	-0.87 (-7.44)
Panel B: Conditioning on normal return			
Small Firms	0.89 (2.53)	1.43 (4.19)	-2.83 (-8.22)
Medium Firms	0.73 (3.99)	1.12 (6.81)	-1.02 (-6.13)
Large Firms	-0.06 (0.33)	0.41 (2.44)	-0.78 (-4.50)