Risk Market Journals
Journal of Risk & Control, 2019, 6(1), 1-17| January 1, 2019

Psychological Aspects of Stock Returns Accompanied by High Trading Volumes

Andrey Kudryavtsev[1]

Abstract

Present study explores the effect of the availability heuristic (representing people's tendency to determine the likelihood of an event according to the easiness of recalling similar instances, and, thus, to overweight current information, as opposed to processing all relevant information) on stock price dynamics following days of extremely high trading volumes. I hypothesize that if the sign of a stock's return on the day when it registers an extremely high trading volume corresponds to the sign of the same day's stock market index return, then because of the effect of the availability heuristic, investors may consider the underlying important news to have a greater subjective probability of leading to stock returns of the respective sign, amplifying the latter and creating overreaction, which results in subsequent price reversal. Defining high-volume days according to a number of alternative proxies, I document that, in line with my hypothesis, both positive and negative high-volume day stock returns accompanied by the same-sign contemporaneous daily market returns are followed by significant reversals on the next trading day and over five- and twenty-day intervals following the event, the magnitude of the reversals increasing over longer post-event windows, while high-volume day stock price changes taking place on the days when the market index moves in the opposite direction are followed by non-significant price drifts. The results remain robust after accounting for additional company-specific (size, beta, historical volatility) and event-specific (event-day stock's return) factors, and are stronger for low capitalization and high volatility stocks.

JEL Classification numbers: G11, G14, G19
Keywords: Availability Heuristic; Behavioral Finance; High Trading Volumes; Overreaction; Stock Price Reversals.

1 Introduction

The modern world becomes more and more information-based and information-driven. Information affects all spheres of human activity, and provides considerable advantages to people and organizations that possess it.

The role of information in financial markets is crucial. Stock market investors put a lot of effort trying to absorb any relevant item of information and to correctly incorporate it in the respective stocks' prices. In many cases, different investors possess different amounts of information and even interpret the same information differently. This kind of disagreement leads to different subjective valuations of the same stocks and gives rise to stock trading activity, continuously affecting stock trading volumes.

---

[1] The author is from The Economics and Management Department, The Max Stern Yezreel Valley Academic College, Emek Yezreel 19300, Israel, andreyk@yvc.ac.il.

Article Info: *Received*: September 14, 2018. *Revised:* October 20, 2018
Published online : January 1, 2019

A vast strand of literature concentrates exactly on this point. Previous studies demonstrate that trading volume may result from some form of heterogeneity among investors, including differences in information (e.g., Varian, 1989; Holthausen and Verrecchia, 1990; Kim and Verrecchia, 1991, 1994, 1997; Barron et al., 2005); differences in risk preferences (e.g., Beaver, 1968; Verrecchia, 1981); and differences in interpretation of company-specific news (e.g., Harris and Raviv, 1993; Kandel and Pearson, 1995; Bamber et al., 1997, 1999; Garfinkel and Sokobin, 2006; Hong and Stein, 2007; Bamber et al., 2011). Some of these studies (e.g., Verrecchia, 1981; Holthausen and Verrecchia, 1990; Kim and Verrrecchia, 1994, 1997; Barron et al., 2005) also argue that to the extent that the increase in abnormal trading volumes around company-specific events is explained by more information-based trading and/or different risk preferences, one should expect more complete price reaction, or in other words, less underreaction/more overreaction, and subsequently, a number of authors (e.g., Verrecchia, 1981; Diamond and Verrecchia, 1987; Israeli, 2015) conclude that higher abnormal trading volumes around company-specific events might be an indication that the news have been fully incorporated in stock price changes, leaving less space for post-event price drifts.

The present study follows this strand of literature, assuming that extremely high daily stock trading volumes serve an indication of important company-specific news arriving at the market. Having said that, I focus on another factor that may potentially affect both immediate stock price reactions to these important news and subsequent stock price dynamics. Namely, I consider the sign of the general stock market index return on the day when a stock's trading volume is extremely high (high-volume, or event day). A number of previous studies analyzing the effects of the availability heuristic[2] on financial markets (e.g., Lee et al., 2007; Kliger and Kudryavtsev, 2010; Kudryavtsev, 2018) document people's tendency to make judgments about the likelihood of events based on their recent experience or on the similarity of the events to current states. For example, Kudryavtsev (2018) detects that the same-sign contemporaneous market returns increase the availability of company-specific shocks represented by large daily stock price moves, leading to significant price reversals over up to twenty days following the initial shock. Following the same logic, I suggest that stock price increases (decreases) accompanied by extremely high stock trading volumes and taking place on the days when the stock market index rises (falls) may incorporate a component driven by the availability of the underlying news, which is increased by the same-sign contemporaneous market return. In other words, I predict that if the sign of a stock's return on the day when it registers an extremely high trading volume corresponds to the sign of the same day's stock market index return, then because of the effect of the availability heuristic, investors may consider the underlying important news to have a greater subjective probability of leading to stock returns of the respective sign, amplifying the latter and creating overreaction. Therefore, I hypothesize that high-volume day stock returns should be followed by significantly more pronounced reversals if the contemporaneous market return has the same sign.

I analyze daily price data for all the constituents of S&P 500 Index over the period from 1993 to 2017 and define events (high-volume days) according to two different proxies. For the total sample of events, depending on the event proxy and on the post-event time period, I find either non-significant or marginally significant reversals following both event-day stock price increases and decreases. On the other hand, after classifying the events according to the sign of S&P 500 return on the event day, I find supporting evidence for my research hypothesis. Namely, both positive and negative high-volume day stock returns accompanied by the same-sign contemporaneous daily S&P 500 returns are followed by significant reversals on the next trading day and over five- and twenty-day intervals following the event, the magnitude of the reversals increasing over longer post-event windows, while high-volume day stock price changes taking place on the days when S&P 500 index moves in the opposite direction are followed by non-significant price drifts. The results remain robust after accounting for additional company-specific (size, CAPM beta, historical volatility) and event-specific (event-day absolute stock return) factors, and are more pronounced for low capitalization and high volatility stocks.

The rest of the paper is structured as follows. Section 2 reviews the literature dealing with stock trading volumes and their connection to stock returns, as well as the literature on the availability heuristic and its economic applications. Section 3 defines my research hypothesis. Section 4 presents

[2] According to the availability heuristic (Tversky and Kahneman, 1973), people tend to determine the likelihood of uncertain events according to the ease of recalling similar instances.

the database and the research design. Section 5 describes the empirical tests and the results. Section 6 concludes and provides a brief discussion.

2 Literature review

2.1. Stock trading volumes and their connection to stock returns

Prior studies suggest and discuss a number of factors that may explain and drive the trading activity. Karpoff (1986) shows that trading volume results from dispersion in prior expectations and idiosyncratic interpretations of information events. He also demonstrates that the increase in trading volume is positively correlated with the information “surprise”. Furthermore, Karpoff (1987) argues that if a "surprise" is followed by stock price revision in the direction corresponding to the quality of the "surprise", then the contemporaneous trading volume increases with the absolute value of the price change. In continuation of Karpoff's line of research, Kim and Verrecchia (1991) define a measure of market's information asymmetry as a ratio of volume to the absolute value of price change. In addition, they state that volume may increase either with the absolute value of stock returns, reflecting the average change in investors’ expectations, or following an increase in information asymmetry. Harris and Raviv (1993) and Kandel and Pearson (1995) assert that investors employ the same public information, but interpret it differently, a scenario which results in trading activity.

Investors may also trade for portfolio rebalancing reasons, the fact that gives rise to liquidity (or noise) trading, which is not based on information. A number of theoretical models predict that the volume of liquidity trading may be a function of past returns (e.g., DeLong et al., 1990; Hong and Stein, 1999; Hirshleifer et al., 1994, 2006). Chordia et al. (2007) conclude that liquidity trading is based on stock visibility (proxied by firm size, age, price and the book-to-market ratio), portfolio rebalancing needs, differences of opinion (proxied by forecast dispersion and firm leverage), and uncertainty about fundamental values.

Llorente et al. (2002) develop a model, in which investor's expectations of the future stock returns and exposure to the risk in equilibrium conditions are the drivers of the trading process. Baker and Stein (2004) suggest that high trading volume indicates the presence of irrational traders who push up prices (their model also involves short sale constraints). In Hong and Yu (2009), high volume indicates the presence of noise traders.

The concept of stock trading volume is closely related to the one of stock prices and returns. The early studies on volume-price relation establish that positive relations between the absolute value of daily price changes and daily volumes are present for both market indices and individual stocks (e.g., Ying, 1966; Westerfield, 1977; Rutledge, 1984; Karpoff, 1987; Schwert, 1989; Gallant et al., 1992). Additionally, Epps (1975, 1977) demonstrates that both in the stock and bond markets, the ratio of volume to absolute price change is larger for transactions when a security price rises than when it falls. Another group of studies point out at a positive relationship between absolute price changes and contemporaneous volume changes (e.g., Crouch, 1970; Epps and Epps, 1977; Harris, 1983).

More recent studies put more focus on different kinds of lag or inter-day relations between stock returns and trading volumes (e.g., Chen et al., 2001; Khan and Rizwan, 2001; Lee and Rui, 2002; Pisedtasalasai and Gunasekarage, 2007), and introduce additional relevant factors into their analysis. Ziebart (1990) states that the trading volume is positively correlated with the absolute changes in the mean analyst forecasts. Saatccioglu and Starks (1998) document that volume leads stock price changes in four out of the six emerging markets. Campbell et al. (1993) and Llorente et al. (2002) report the dynamic relation between volume and returns in the cross-section. Griffin et al. (2007) analyze the dynamic relation between market-wide trading activity and returns in 46 markets and detect a strong positive relationship between turnover and past returns. Statman et al. (2006) and Glaser and Weber (2009) obtain similar results.

Pathirawasam (2011) finds that stock returns are positively related to the contemporary changes in trading volumes. Moreover, he documents that past trading volume changes are negatively related to stock returns, and argues that this negative relationship may be caused by investor misspecification about future earnings or illiquidity of low volume stocks. Caginalpa and Desantisa (2011) point out that if the stock price is growing, but the trading volume is declining, then stock price growth is considered by technical analysts as unstable. Remorov (2014) constructs a model of stock price and volume behavior during market crashes and finds that trading volume is inversely proportional to the square of the stock price in the case of the sharp price declines, the result being empirically supported by price and volume data for major recent US stock bankruptcies and market crashes.

A vast strand of literature deals with trading volumes around company-specific events Previous research identifies three major sources of these abnormally high trading volumes, all stemming from some form of heterogeneity among investors: (i) differences in information (e.g., Varian, 1989; Holthausen and Verrecchia, 1990; Kim and Verrecchia, 1991, 1994, 1997; Barron et al., 2005); (ii) differing risk preferences (e.g., Beaver, 1968; Verrecchia, 1981); and (iii) differences in opinion, that is, differential interpretation of the company-specific news (e.g., Harris and Raviv, 1993; Kandel and Pearson, 1995; Bamber et al., 1997, 1999; Garfinkel and Sokobin, 2006; Hong and Stein, 2007; Bamber et al., 2011). Israeli (2015) analyzes trading volume reactions to earnings announcements and demonstrates that they provide information about future returns that cannot be deduced from the price reactions or the magnitudes of earnings surprises. He continues the line of literature (e.g., Verrecchia, 1981; Holthausen and Verrecchia, 1990; Kim and Verrrecchia, 1994, 1997; Barron et al., 2005), which argues that to the extent that the increase in abnormal trading volumes around company-specific events is explained by more information-based trading and/or different risk preferences, one should expect more complete price reaction and less underreaction. Consequently, in line with a number of previous studies (e.g., Verrecchia, 1981; Diamond and Verrecchia, 1987), Israeli (2015) concludes that higher abnormal trading volumes around earnings announcements might be an indication that the price changes have fully incorporated the earnings news, leaving less space for subsequent price drifts.

2.2. Availability heuristic: Psychological aspects and economic applications

The availability heuristic (Tversky and Kahneman, 1973) refers to the phenomenon of determining the likelihood of an event according to the ease of recalling similar instances. In other words, the availability heuristic may be described as a rule of thumb people use to estimate the probability of an outcome based on how easy that outcome is to imagine. As such, possibilities that are vividly described and emotionally charged will be perceived as being more likely than those that are harder to picture or difficult to understand. Tversky and Kahneman (1974) provide examples of ways in which availability may provide practical clues for assessing frequencies and probabilities. They argue that "recent occurrences are likely to be relatively more available than earlier experiences" (p. 1127), and thus conclude that people assess probabilities by overweighting current information as opposed to processing all relevant information.

A number of studies have discussed the influence of the availability heuristic on market investors. Shiller (1998) argues that investors' attention to investment categories (e.g., stocks versus bonds or real estate) may be affected by alternating waves of public attention or inattention. Similarly, Barber and Odean (2008) find that when choosing which stock to buy, investors tend to consider only those stocks that have recently caught their attention (stocks in the news, stocks experiencing high abnormal trading volume, stocks with extreme one-day returns). Daniel et al. (2002) conclude that investors and analysts are on average too credulous. That is, when examining an informative event or a value indicator, they do not adequately take into account the incentives of others to manipulate this signal. Credulity may be explained by limited attention and by the fact that the availability of a stimulus causes it to be weighed more heavily. Frieder (2003) finds that stock traders seek to buy following large positive earnings surprises and to sell following large negative earnings surprises. He explains this tendency by the availability heuristic, assuming that the salience of an earnings surprise increases its magnitude. Ganzach (2001) offers support for a model in which analysts base their judgments of risk and return for unfamiliar stocks upon a global attitude. If stocks are perceived as good, they are judged to have high return and low risk, whereas if they are perceived as bad, they are judged to be low in return and high in risk. Lee et al. (2007) discuss the "recency bias," or people's tendency to make judgments about the likelihood of events based on their recent experience. They find that analysts' forecasts of firms' long-term growth in earnings per share tend to be relatively optimistic when the economy is expanding and relatively pessimistic when the economy is contracting. This finding is consistent with the availability heuristic, indicating that forecasters overweigh the current state of the economy in making long-term growth predictions.

Kliger and Kudryavtsev (2010) find that positive stock price reactions to analyst recommendation upgrades are stronger when accompanied by positive stock market index returns, and negative stock price reactions to analyst recommendation downgrades are stronger when accompanied by negative stock market index returns. They designate this finding as the "outcome availability effect" and explain it by the higher availability of positive (negative) outcomes on days of market index rises (declines). Moreover, Kliger and Kudryavtsev (2010) document weaker (stronger) reactions to recommendation upgrades (downgrades) on days of substantial stock market moves. They designate this finding as the "risk availability effect" and explain it by the greater availability of risky outcomes on such "highly volatile" days. Kudryavtsev (2018) detects that large daily stock price moves accompanied by the same-sign contemporaneous market returns are followed by significant price reversals over up to twenty days following the event. He attributes this finding to the availability heuristic, suggesting that if the direction of a company-specific shock, resulting in a large stock price move, corresponds to the sign of the market index return on the day when the shock happens, then investors may consider the latter to have a greater subjective probability of leading to stock returns of the respective sign, which increases the magnitude of the shock, creating an overreaction and resulting in subsequent price reversal.

3 Research hypothesis

The present study concentrates on the effect of the availability heuristic on stock price dynamics following significant company-specific news, proxied by the respective stock's trading volume.

As discussed in the previous Section, a number of studies (e.g., Karpoff, 1987; Baker and Stein, 2004; Hong and Yu, 2009) connect stock trading volumes to the significance of the new relevant incoming information. Following this strand of literature and assuming that extremely high daily stock trading volumes serve an indication of important company-specific news arriving to the market, I suggest that if the sign of a stock's return on the day when it registers an extremely high trading volume corresponds to the sign of the same day's stock market index return, then because of the effect of the availability heuristic, investors may consider the underlying important news to have a greater subjective probability of leading to stock returns of the respective sign, amplifying the latter and creating an overreaction. In other words, I hypothesize that stock price increases (decreases) accompanied by extremely high stock trading volumes and taking place on the days when the stock market index rises (falls) may incorporate a component driven by the availability of the underlying news, which is increased by the same-sign contemporaneous market return. This hypothesis is consistent with the findings by Lee et al. (2007) and Kliger and Kudryavtsev (2010) with respect to people's tendency to make judgments about the likelihood of events based on their recent experience or on the similarity of the events to current states, and continues the line of reasoning by Kudryavtsev (2018), who documents that the same-sign contemporaneous market returns increase the availability of company-specific shocks represented by large stock price moves. Yet, unlike the latter study, I suggest that because of the availability heuristic, even "regular" stock price changes may incorporate overreaction to news.

Since stock price overreaction to news results in subsequent reversals, this study's main hypothesis may be formulated as follows:

<u>Hypothesis</u>: *Stock price reversals following days of positive (negative) negative stock returns accompanied by extremely high stock trading volumes should be significantly more pronounced if on the respective days, the general stock market index rises (falls).*

4 Data description and research design

In my empirical analysis, I employ the adjusted daily price and volume data for all the constituents of S&P 500 Index, which is also used as a proxy for the general stock market index, over the period from 1993 to 2017. The data is retrieved from the Center for Research in Security Prices (CRSP). For each day characterized by extremely high trading volume in a given stock ("high-volume day", as defined in the sequel), I match the underlying firm's market capitalization, as recorded on a quarterly basis at http://ycharts.com/, for the closest preceding date.

I employ two alternative volume proxies and define day *t* as a high-volume day for stock *i* if:

Proxy A: Stock *i*'s trading volume on day *t* (VOL_{it}) was at least three times higher than the stock's average trading volume over 250 trading days preceding day *t* ($AvVol_{it}$), that is: $VOL_{it} \geq 3AvVol_{it}$.

Proxy B: Stock *i*'s trading volume on day *t* was at least five times higher than the stock's average trading volume over 250 trading days preceding day *t*, that is: $VOL_{it} \geq 5AvVol_{it}$.

Proxy A allows to substantially increase the working sample, while proxy B concentrates on the most salient trading days in the respective stocks[3].

I include high-volume days in my working sample, provided (i) there were historical trading data for at least 250 trading days before, and 20 days after the event (high-volume day); (ii) market capitalization information was available for the respective stocks; and (iii) the absolute value of the stock price change on the high-volume day did not exceed 50%. The intersection of these filtering rules yielded a working sample of the following sizes for the two definition proxies:

- For Proxy A: 12,468 high-volume days, including 5,801 days with positive stock returns, 56 days with zero stock returns and 6,611 days with negative stock returns.
- For Proxy B: 5,243 high-volume days, including 2,383 days with positive stock returns, 26 days with zero stock returns and 2,834 days with negative stock returns.

Table 1 comprises some basic descriptive statistics of stock returns on high-volume days.

In order to measure the stock price dynamics after the high-volume days, I calculate abnormal stock returns (ARs) using the Market Model with alpha and beta estimated for the respective stock over 250 trading days preceding day *t*[4]. That is, for each event *i*, for the period of 250 trading days preceding the event, I regress the respective stock's returns on the contemporaneous market (S&P 500 Index) returns in the following way:

$$SR_{ik} = \alpha_i + \beta_i MR_{ik} + \varepsilon_{ik} \quad , k = t - 250, \dots, t - 1 \tag{1}$$

where: SR_{ik} is the stock return on day *k* (*k* runs from *t*-250 to *t*-1) preceding event *i*; and MR_{ik} is the market return on day *k* preceding event *i*, and then use the regression estimates $\widehat{\propto_i}$ and $\widehat{\beta_i}$ in order to calculate abnormal stock returns for 20 trading days following the event *i*, as follows:

$$AR_{il} = SR_{il} - [\widehat{\propto_i} + \widehat{\beta_i} MR_{il}] \quad , l = t + 1, \dots, t + 20 \tag{2}$$

where: AR_{il} is the abnormal stock return on day *l* (*l* runs from *t*+1 to *t*+20) following event *i*.

In order to analyze the availability effect on stock returns following high-volume days, in the next Section, I analyze abnormal stock returns during 20 trading days following the events, conditioned on the sign of the general stock market return corresponding to the event day.

5 Results description

5.1. Stock returns following high-volume days: Total sample

First of all, I employ the high-volume days and analyze the respective stocks' subsequent returns. Table 2 depicts average ARs and cumulative ARs (CARs), as well as their statistical significance, for the period of up to 20 trading days following high-volume days accompanied by stock price increases and decreases, defined according to the two above-mentioned proxies. Day 1 refers to the first trading day after the high-volume day[5].

The results for the total sample indicate that high-volume days, in general, are followed by either non-significant or marginally significant short-term price reversals, whose magnitude slightly

---

[3] I employ a number of additional volume proxies. The results for all of them (available upon request from the author) are qualitatively similar to those reported in Section 5.

[4] Alternatively, I calculate ARs using Market Adjusted Returns (MAR) – return differences from the market index, and the Fama-French three-factor plus momentum model. The results (available upon request from the author) remain qualitatively similar to those reported in Section 5.

[5] The post-event time windows are defined similarly to Kudryavtsev (2018).

increases for longer post-event time windows. The price reversals are slightly more pronounced after negative-return high-volume days, and for volume proxy B referring to the most extreme volume days, suggesting that the latter may bring with them some element of price overreaction to underlying news.

5.2. Availability effect on stock returns following high-volume days

In this Subsection, I perform the first general test of my research hypothesis, suggesting that if the direction of a stock's return on the day when the stock's trading volume is especially high corresponds to the sign of contemporaneous stock market return, then the magnitude of the stock's price reaction to the underlying news may be amplified via the mechanism of availability, creating overreaction and resulting in post-event price reversals. Similarly to Kudryavtsev (2018), who finds that large positive (negative) daily stock price moves accompanied by positive (negative) market returns are followed by significant price reversals, I divide the total sample of events by the sign of market index return corresponding to the event day.

Table 3 reports average ARs following high-volume days, by the sign of event-day market return (MR_t), as well as the respective AR differences and their statistical significance, for both volume proxies. The results corroborate the study's research hypothesis with respect to the effect of event-day market returns on post-event ARs. For both proxies, stock price increases (decreases) taking place on high-volume days are followed by significant price reversals if the on event day the stock market index rises (falls). The magnitude of these price reversals increases for longer post-event periods, so that for the post-event window 1 to 20, average ARs following event-day price increases accompanied by positive MR_t, reach -0.59% and -0.71%, according to proxies A and B, respectively, while average ARs following event-day price decreases accompanied by negative MR_t, are even more pronounced and equal 0.72% and 0.83%, according to proxies A and B, respectively, all the ARs being highly statistically significant. On the other hand, stock price increases (decreases) registered on the high-volume days when the stock market index falls (rises) result in non-significant stock price drifts over all the post-event windows. AR differences for the post-event windows between the two MR_t conditions are highly significant and also become more pronounced as the windows are expanded. According to the two volume proxies, for the Days 1 to 20, AR differences between $MR_t > 0$ and $MR_t < 0$ conditions equal -0.83% and -0.91%, following stock price increases on high-volume days, and even more impressive -0.91% and -0.97%, following stock price decreases on high-volume days. Finally, it should be once again noted that the availability effect on stock returns following high-volume days is more pronounced when the more extreme volume proxy B is employed.

5.3. Availability effect on the post-event stock returns within different stock groups

Having documented the availability effect on stock returns following high-volume days, I now verify if the magnitude of the effect may differ for different groups of stocks. The motivation for this analysis arises from the previous literature dealing with the effects of various behavioral biases on investors' decisions. A number of studies in this field (e.g., Baker and Wurgler, 2006; Kliger and Kudryavtsev, 2010; Kudryavtsev, 2018) conclude that stocks that are attractive to optimists and speculators and at the same time unattractive to arbitrageurs - younger stocks, small stocks, unprofitable stocks, non-dividend paying stocks, high volatility stocks, extreme growth stocks, and distressed stocks - are especially likely to be disproportionately sensitive to psychological biases.

Following these findings, I first divide my working sample in subsamples according to the firm size. For each of the two volume proxies and separately for stock price increases and decreases on high-volume days accompanied by positive and negative market returns, I split the samples of events into three roughly equal parts by the firms' market capitalization (high, medium and low) reported for the end of the quarter preceding each high-volume day. Table 4 exhibits for both proxies average post-event ARs, by the sign of MR_t, as well as the respective AR differences and their statistical significance, for high and low market capitalization firms. Consistently with Baker and Wurgler (2006) and Kudryavtsev (2018), the availability effect on stock price reversals following high-volume days accompanied by both price increases and decreases is stronger for low capitalization stocks. This result is twofold: (i) for small stocks, the magnitude of post-event price reversals in cases when the sign of the high-volume day's stock return corresponds to the sign of the contemporaneous market return is larger (e.g., according to proxies A and B, respectively, for post-event window 1 to 20, average ARs following event-day price increases accompanied by positive MR_t equal -0.37% and -0.45% for high capitalization stocks, and -0.78% and -0.96% for low capitalization stocks, while average ARs following event-day price decreases accompanied by negative MR_t equal 0.51% and 0.58% for high capitalization stocks, and 0.94% and 1.05% for low capitalization stocks); and (ii) for small stocks, AR differences for the post-event period between the two MR_t conditions are greater (e.g., according to proxies A and B, respectively, for post-event window 1 to 20, following event-day price increases, average AR differences between the $MR_t > 0$ and $MR_t < 0$ conditions are -0.56% and -0.62% for high capitalization stocks, and -1.06% and -1.22% for low capitalization stocks, while following event-day price decreases, average AR differences between the $MR_t > 0$ and $MR_t < 0$ conditions are -0.64% and -0.68% for high capitalization stocks, and -1.18% and -1.25% for low capitalization stocks)[6].

Furthermore, I classify my sample according to the stocks' historical volatility. For each of the two volume proxies and separately for stock price increases and decreases on high-volume days accompanied by positive and negative market returns, I split the samples of events into three roughly equal parts by the standard deviation of stock returns over 250 trading days preceding the event (high, medium and low volatility stocks)[7]. Table 5 presents for both proxies average post-event ARs, by the sign of MR_t, as well as the respective AR differences and their statistical significance, for high and low volatility stocks. Once again, in line with previous literature, the magnitude of the availability effect on stock price reversals following high-volume days is stronger pronounced for more volatile stocks, and namely: (i) for high volatility stocks, the magnitude of post-event price reversals in cases when the sign of the high-volume day's stock return corresponds to the sign of the contemporaneous market return is larger (e.g., according to proxies A and B, respectively, for post-event window 1 to 20, average ARs following event-day price increases accompanied by positive MR_t equal -0.77% and -0.92% for high volatility stocks, and -0.39% and -0.48% for low volatility stocks, while average ARs following event-day price decreases accompanied by negative MR_t equal 0.89% and 1.03% for high volatility stocks, and 0.53% and 0.60% for low volatility stocks); and (ii) for high volatility stocks, AR differences for the post-event period between the two MR_t conditions are greater (e.g., according to proxies A and B, respectively, for post-event window 1 to 20, following event-day price increases, average AR differences between the $MR_t > 0$ and $MR_t < 0$ conditions are -1.03% and -1.16% for high volatility stocks, and -0.59% and -0.65% for low volatility stocks, while following event-day price decreases, average AR differences between the $MR_t > 0$ and $MR_t < 0$ conditions are -1.11% and -1.22% for high volatility stocks, and -0.68% and -0.71% for low volatility stocks)[8].

Thus, one may suggest that high-volume days' stock returns of low market capitalization and more volatile stocks are more affected by the availability heuristic, possibly due to the reduced amount of information on these stocks and their higher risk levels. As a result, the post-event price reversals for these stocks are more pronounced[9].

---

6 The results for medium capitalization stocks for both event-day price increases and decreases, for all the post-event windows and according to both volume proxies, indicate that these stocks are less influenced by the effect of availability than low capitalization stocks, and more influenced by the effect of availability than high capitalization stocks. The detailed results are available upon request from the author. Overall, the results demonstrate that the availability effect on stock returns following high-volume days decreases with market capitalization.

7 The sample partition approach by both market capitalization and historical stock volatility is similar to the one employed by Kliger and Kudryavtsev (2010) and Kudryavtsev (2018).

8 The results for medium volatility stocks for both event-day price increases and decreases, for all the post-event windows and according to both volume proxies, indicate that these stocks are less influenced by the effect of availability than high volatility stocks, and more influenced by the effect of availability than low volatility stocks. The detailed results are available upon request from the author. Overall, the results demonstrate that the availability effect on stock returns following high-volume days increases with historical stock volatility.

9 I have also performed the analysis of post-event ARs for three subsamples partitioned by the CAPM stock beta calculated over Days -250 to -1. In line with Baker and Wurgler (2006) and Kliger and Kudryavtsev (2010), I have documented that the availability effect on stock returns following high-volume days increases with stock beta. The detailed results are available upon request from the author.

5.4. Multifactor analysis

Finally, I test if the availability effect on stock returns following high-volume days remains significant after controlling for other potentially influential factors. In order to do that, I run the following regressions, separately for high-volume day price increases and decreases, for the windows 1, 1 to 5 and 1 to 20 following the events, and according to both volume proxies:

$$AR/CAR_{il} = \gamma_0 + \gamma_1 MR\_dum_i + \gamma_2 MCap_i + \gamma_3 Beta_i + \gamma_4 SR\_Volat_i + \gamma_5 |SR|_i + \varepsilon_{il} \quad (3)$$

where: AR/CAR_{il} is the abnormal/cumulative abnormal stock return following event i for post-event window l (Days 1, 1 to 5, or 1 to 20); MR_dum_i is the dummy variable, taking the value 1 if the market return on the day of the event i is positive, and 0 otherwise; $MCap_i$ is the natural logarithm of the firm's market capitalization corresponding to event i, normalized in the cross-section; $Beta_i$ is the estimated CAPM beta for event i, calculated over 250 days preceding the event and normalized in the cross-section; SR_Volat_i is the standard deviation of stock returns over 250 days preceding event i, normalized in the cross-section; and $|SR|_i$ is the absolute stock return representing on the day of event i.

Table 6 reports the regression coefficients for all the post-event windows and volume proxies, indicating that:

- Regression coefficients of MR_dum are negative and highly significant for all the post-event windows, which means that negative post-event price reversals following high-volume day price increases are stronger if the contemporaneous market return is positive, and positive post-event price reversals following high-volume day price decreases are stronger if the contemporaneous market return is negative. That is, the availability effect on stock returns following high-volume days remains significant even after controlling for additional factors affecting post-event ARs.
- According to the signs of the coefficients of $MCap$, for low capitalization firms, post-event ARs following high-volume day price increases (decreases) are significantly lower (higher). That is, for small stocks, high-volume days are significantly more likely to be followed by stock price reversals.
- Regression coefficients of $Beta$ following high-volume day price increases (decreases) are negative (positive), yet, either non-significant or marginally significant, suggesting that stock price reversals following high-volume days tend to be stronger for high-beta stocks, yet, controlling for other company-specific and event-specific factors, the significance of the difference is questionable.
- Regression coefficients of SR_Volat following high-volume price increases (decreases) are significantly negative (positive), indicating that stock price reversals following high-volume days are significantly stronger for more volatile stocks.
- The coefficients of $|SR|$ are non-significant, demonstrating that the dynamics of post-event stock price changes does not depend on the event-day stock returns.

6 Concluding remarks

In the present study, I analyzed an additional aspect of the availability heuristic in financial decision making. Namely, I explored its effect on high-volume day stock returns. I suggested that if the sign of a stock's return on the day when it registers an extremely high trading volume corresponds to the sign of the same day's stock market index return, then because of the effect of the availability heuristic, investors may consider the underlying important news to have a greater subjective probability of leading to stock returns of the respective sign, amplifying the latter and creating overreaction. Therefore, since stock price overreaction to news is recognized to result in subsequent price reversals, I hypothesized that high-volume day stock returns should be followed by significantly more pronounced reversals if the contemporaneous market return has the same sign.

The results of the empirical analysis corroborated my research hypothesis. Analyzing a large sample of high-volume days and defining the latter according to a number of alternative proxies, I documented that both positive and negative high-volume day stock returns accompanied by the same-sign contemporaneous daily market returns are followed by significant reversals on the next trading day and over five- and twenty-day intervals following the event, the magnitude of the reversals increasing over longer post-event windows, while high-volume day stock price changes taking place on the days when the market index moves in the opposite direction are followed by non-significant price drifts.

Furthermore, I established that the effect of availability on stock returns following high-volume days was of higher magnitude for low capitalization firms and stocks with higher volatility of historical returns, suggesting that high-volume day stock returns of low market capitalization and more volatile stocks are more affected (or even, driven) by the availability heuristic, possibly due to the reduced amount of information on these stocks and their higher risk levels. Moreover, this availability effect remained significant after accounting for additional company-specific (size, CAPM beta, historical volatility) and event-specific (stock's return on the event day) factors. The results were robust to different volume definition proxies, and to different methods of adjusting returns, such as market-adjusted returns, market-model excess returns, and Fama-French three-factor model excess returns.

To summarize, at least in a perfect stock market with no commissions, the strategy based on investing in stocks after high-volume day price decreases accompanied by negative market returns and selling them short after high-volume day price increases accompanied by positive market returns looks promising, especially for small and volatile stocks. This may be an interesting result for both financial theoreticians in their eternal discussion about stock market efficiency, and practitioners in search of potentially profitable investment strategies. Potential directions for further research may include expanding the analysis to other stock exchanges, and comparing the magnitude of the effect during bull and bear market periods.

References

Baker, M., and J. Stein, 2004, Market Liquidity as a Sentiment Indicator, Journal of Financial Markets, 7(3), 271-299.

Baker, M., and J. Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, Journal of Finance, 61(4), 1645-1680.

Bamber, L.S., O.E. Barron, and T.L. Stober, 1997, Trading Volume and Different Aspects of Disagreement Coincident with Earnings Announcements, The Accounting Review, 72(4), 575-597.

Bamber, L.S., O.E. Barron, and T.L. Stober, 1999, Differential Interpretations and Trading Volume, The Journal of Financial and Quantitative Analysis, 34(3), 369-386.

Bamber, L.S., O.E. Barron, and D.E. Stevens, 2011, Trading Volume around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research, Contemporary Accounting Research, 28(2), 431-471.

Barber, B.M., and T. Odean, 2008, All that Glitters: The Effect of Attention and News on the Buying behavior of Individual and Institutional Investors, Review of Financial Studies, 21(2), 785-818.

Barron, O.E., Harris, D.G., and M. Stanford, 2005, Evidence That Investors Trade on Private Event-Period Information around Earnings Announcements, The Accounting Review, 80(2), 403-421.

Beaver, W.H., 1968, The Information Content of Annual Earnings Announcements, Empirical Research in Accounting: Selected Studies, Supplement to Journal of Accounting Research, 6, 67–92.

Caginalpa, G., and M. Desantisa, 2011, Stock Price Dynamics: Nonlinear Trend, Volume, Volatility, Resistance and Money Supply, Quantitative Finance, 11(6), 849-861.

Campbell, J.Y., S.J. Grossman, and J. Wang, 1993, Trading Volume and Serial Correlation in Stock Returns, The Quarterly Journal of Economics, 108(4), 905–939.

Chen, G., M. Firth, and O.M. Rui, 2001, The Dynamic Relation between Stock Returns, Trading Volume and Volatility, The Financial Review, 36(2), 153-174.

Chordia, T., S.W. Huh, and A. Subrahmanyam, 2007, The Cross-Section of Expected Trading Activity, Review of Financial Studies, 30(2), 709-740.

Crouch, R.L., 1970, A Nonlinear Test of the Random-Walk Hypothesis, American Economic Review, 60(1), 199-202.

Daniel, K., D. Hirshleifer, and S. H. Teoh, 2002, Investor Psychology in Capital Markets: Evidence and Policy Implications, Journal of Monetary Economics, 49(1), 139-209.

De Long, B., A. Shleifer, L. Summers, and R. Waldmann, 1990, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, Journal of Finance, 45(2), 379-386.

Diamond, D., and R.E. Verrecchia, 1987, Constraints on Short-Selling and Asset Price Adjustment to Private Information, Journal of Financial Economics, 18(2), 277-311.

Epps, T.W., 1975, Security Price Changes and Transaction Volumes: Theory and Evidence, American Economic Review, 65(4), 586–597.

Epps, T.W., 1977, Security Price Changes and Transaction Volumes: Some Additional Evidence, Journal of Financial and Quantitative Analysis, 12(1), 141–146.

Frieder, L., 2003, Evidence on Behavioral Biases in Trading Activity, Working Paper, UCLA, The Anderson School.

Gallant, R., P. Rossi, and G. Tauchen, 1992, Stock Prices and Volume, Review of Financial Studies, 5(2), 199-242.

Ganzach, Y., 2001, Judging Risk and Return of Financial Assets, Organizational Behavior and Human Decision Processes, 83(2), 353-370.

Garfinkel, J.A., and J. Sokobin, 2006, Volume, Opinion Divergence, and Returns: A Study of Post-Earnings Announcement Drift, Journal of Accounting Research, 44(1), 85-112.

Glaser, M., and M. Weber, 2009, Which Past Returns Affect Trading Volume? Journal of Financial Markets, 12(1), 1-31.

Griffin, M., F. Nardari, and R.M. Stulz, 2007, Do Investors Trade More When Stocks Have Performed Well? Evidence from 46 Countries, Review of Financial Studies, 20(3), 905–951.

Harris, L., 1983, The Joint Distribution of Speculative Prices and of Daily Trading Volume, Working Paper, University of Southern CA.

Harris, M., and A. Raviv, 1993, Differences of Opinion Make a Horse Race, Review of Financial Studies, 6(3), 473-506.

Hirshleifer, D., A. Subrahmanyam, and S. Titman, 1994, Security Analysis and Trading Patterns When Some Investors Receive Information before Others, Journal of Finance, 49 (5), 1665-698.

Hirshleifer, D., A. Subrahmanyam, and S. Titman, 2006, Feedback and the Success of Irrational Investors, Journal of Financial Economics, 81(2), 311-338.

Holthausen, R.W., and R.E. Verrecchia, 1990, The Effect of Informedness and Consensus on Price and Volume Behavior, The Accounting Review, 65(1), 191-208.

Hong, H., and J.C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, Journal of Finance, 54(6), 2143-2184.

Hong, H., and J.C. Stein, 2007, Disagreement and the Stock Market, Journal of Economic Perspectives, 21(2), 109-128.

Hong, H., and J. Yu, 2009, Gone Fishin': Seasonality in Trading Activity and Asset Prices, Journal of Financial Markets, 12(4), 672-702.

Israeli, D., 2015, Trading Volume Reactions to Earnings Announcements and Future Stock Returns, Working Paper, Interdisciplinary Center Herzliya.

Kandel, E., and N. Pearson, 1995, Differential Interpretation of Public Signals and Trade in Speculative Markets, Journal of Political Economy, 103(4), 831-872.

Karpoff, J.M., 1986, A Theory of Trading Volume, Journal of Finance, 41(5), 1069-1087.

Karpoff, J.M., 1987, The Relation between Price Changes and Trading Volume: A Survey, Journal of Financial and Quantitative Analysis, 22(1), 109-126.

Khan, S.U., and F. Rizwan, 2008, Trading Volume and Stock Returns: Evidence from Pakistan's Stock Market, International Review of Business Research Papers, 4(2), 151-162.

Kim, O., and R.E. Verrecchia, 1991, Market Reaction to Anticipated Announcements, Journal of Financial Economics, 30(2), 273-309.

Kim, O., and R.E. Verrecchia, 1994, Market Liquidity and Volume around Earnings Announcements, Journal of Accounting and Economics, 17(1), 41–67.

Kim, O., and R.E. Verrecchia, 1997, Pre-Announcement and Event-Period Private Information, Journal of Accounting and Economics, 24(3), 395-419.

Kliger, D, and A. Kudryavtsev, 2010, The Availability Heuristic and Investors' Reaction to Company-Specific Events, Journal of Behavioral Finance, 11(1), 50-65.

Kudryavtsev, A., 2018, The Availability Heuristic and Reversals Following Large Stock Price Changes, Journal of Behavioral Finance, 19(2), 159-176.

Lee, B, J. O'Brien, and K. Sivaramakrishnan, 2007, An Analysis of Financial Analysts' Optimism in Long-term Growth Forecasts, Journal of Behavioral Finance, 9(3), 171-184.

Lee, S.B., and O.M. Rui, 2002, The Dynamic Relationship between Stock Return and Trading Volume: Domestic and Cross-Country Evidence, Journal of Banking and Finance, 26(1), 51-78.

Llorente, G., R. Michaely, G. Saar, and J. Wang, 2002, Dynamic Volume-Return Relation of Individual Stocks, Review of Financial Studies, 15(4), 1005-1047.

Pathirawasam, C., 2011, The Relationship between Trading Volume and Stock Returns, Journal of Competitiveness, 3(3), 41-49.

Pisedtasalasai, A., and Gunasekarage, 2007, Causal and Dynamic Relationships among Stock Returns, Return Volatility and Trading Volume: Evidence from Emerging Markets in South-East Asia, Asia-Pacific Financial Markets, 14(4), 277-297.

Remorov, R., 2014, Stock Price and Trading Volume during Market Crashes, International Journal of Marketing Studies, 6(1), 21-30.

Rutledge, D.J.S., 1984, Trading Volume and Price Variability: New Evidence on the Price Effects of Speculation, In Peck A. E. (ed.), Selected Writings on Futures Markets: Research Directions in Commodity Markets, 237-251, Chicago: Chicago Board of Trade.

Saatccioglu, K., and L.T. Starks, 1998, The Stock Price–Volume Relationship in Emerging Stock Markets: The Case of Latin America, International Journal of Forecasting, 14(2), 215–225.

Schwert, W., 1989, Why Does Stock Market Volatility Change Over Time? Journal of Finance, 44(5), 1115-1155.

Shiller, R.J., 1998, Human Behavior and the Efficiency of the Financial System, NBER Working Paper.

Statman, M., S. Thorley, and K. Vorkink, 2006, Investor Overconfidence and Trading Volume, Review of Financial Studies, 19(4), 1531-1565.

Tversky, A., and D. Kahneman, 1973, Availability: A Heuristic for Judging Frequency and Probability, Cognitive Psychology, 4, 207-232.

Tversky, A., and D. Kahneman, 1974, Judgment under Uncertainty: Heuristics and Biases, Science, 185, 1124-1131.

Varian, H.R., 1989, Differences of Opinion in Financial Markets, In Financial Risk: Theory, Evidence and Implications: Proceedings of the 11th Annual Economic Policy Conference of the Federal Reserve Bank of St. Louis, 3–37.

Verrecchia, R.E., 1981, On the Relationship between Volume Reaction and Consensus of Investors: Implications for Interpreting Tests of Information Content, Journal of Accounting Research, 19(1), 271-283.

Westerfield, R., 1977, The Distribution of Common Stock Price Changes: An Application of Transactions Time and Subordinated Stochastic Models, Journal of Financial and Quantitative Analysis, 12(5), 743-765.

Ying, C.C., 1966, Stock Market Prices and Volumes of Sales, Econometrica, 34(3), 676-686.

Ziebart, D.A., 1990, The Association between Consensus of Beliefs and Trading Activity Surrounding Earnings Announcements, The Accounting Review, 65(2), 477-488.

Appendix (Tables)

Table 1: Descriptive statistics of stock returns on high-volume days

Statistics of stock returns	Proxy A (12,468 events)	Proxy B (5,243 events)
Mean, %	-0.32	-0.35
Median, %	-0.18	-0.20
Standard Deviation, %	1.46	1.57
Minimum, %	-48.87	-48.87
Maximum, %	41.28	41.28
Percent of positive	46.53	45.45

Table 2: Abnormal stock returns following high-volume days accompanied by positive and negative stock returns: Total sample

Panel A: High-volume days accompanied by positive stock returns		
Days relative to event	Average AR/CAR following high-volume days, % (2-tailed p-values)	
	Proxy A (5,801 events)	Proxy B (2,383 events)
1	-0.03 (34.18%)	-0.05 (27.55%)
2	-0.01 (72.84%)	-0.02 (49.67%)
1 to 5	-0.11 (27.46%)	-0.17 (21.40%)
1 to 20	-0.23 (18.62%)	-0.33 (13.78%)
Panel B: High-volume days accompanied by negative stock returns		
Days relative to event	Average AR/CAR following high-volume days, % (2-tailed p-values)	
	Proxy A (6,611 events)	Proxy B (2,834 events)
1	0.06 (19.74%)	0.08 (17.62%)
2	0.01 (93.65%)	0.01 (84.01%)
1 to 5	0.20 (18.21%)	0.27 (14.82%)
1 to 20	0.35 (12.03%)	*0.44 (9.13%)

Asterisks denote 2-tailed p-values: *p<0.10

Table 3: Abnormal stock returns following high-volume days accompanied by positive and negative stock returns, by the sign of MRt

Panel A: High-volume days accompanied by positive stock returns						
Days relative to event	Average AR/CAR following high-volume days, % (2-tailed p-values)					
	Proxy A (5,801 events)			Proxy B (2,383 events)		
	MRt>0 (3,356 events)	*MRt*<0 (2,445 events)	Difference	*MRt*>0 (1,425 events)	*MRt*<0 (958 events)	Difference
1	**-0.18 (2.01%)	0.16 (12.45%)	***-0.34 (0.94%)	**-0.20 (1.58%)	0.15 (15.47%)	***-0.35 (0.81%)
2	*-0.09 (9.34%)	0.08 (13.91%)	*-0.17 (8.12%)	*-0.10 (8.97%)	0.08 (12.65%)	*-0.18 (8.01%)
1 to 5	**-0.37 (1.54%)	0.22 (14.02%)	***-0.59 (0.23%)	***-0.43 (0.91%)	0.19 (17.85%)	***-0.61 (0.17%)
1 to 20	***-0.59 (0.17%)	0.24 (12.36%)	***-0.83 (0.02%)	***-0.71 (0.05%)	0.20 (14.39%)	***-0.91 (0.00%)
Panel B: High-volume days accompanied by negative stock returns						
Days relative to event	Average AR/CAR following high-volume days, % (2-tailed p-values)					
	Proxy A (6,611 events)			Proxy B (2,834 events)		
	MRt>0 (2,644 events)	*MRt*<0 (3,967 events)	Difference	*MRt*>0 (1,150 events)	*MRt*<0 (1,684 events)	Difference
1	-0.14 (14.28%)	**0.24 (1.63%)	***-0.38 (0.74%)	-0.13 (16.30%)	**0.27 (1.31%)	***-0.40 (0.51%)
2	-0.06 (19.87%)	*0.08 (9.36%)	*-0.14 (8.97%)	-0.06 (20.31%)	*0.09 (9.12%)	*-0.15 (8.75%)
1 to 5	-0.19 (13.71%)	**0.48 (1.09%)	***-0.67 (0.17%)	-0.15 (21.07%)	***0.57 (0.82%)	***-0.72 (0.11%)
1 to 20	-0.18 (16.39%)	***0.72 (0.08%)	***-0.91 (0.00%)	-0.14 (18.37%)	***0.83 (0.02%)	***-0.97 (0.00%)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 4: Abnormal stock returns following high-volume days accompanied by positive and negative stock returns, by the sign of MRt, for high and low market capitalization firms

Panel A: High-volume days accompanied by positive stock returns						
Days relative to event	Average AR/CAR following high-volume days for high/low market capitalization firms, %					
	Proxy A			Proxy B		
	MRt>0 (1,118/1,119 events)	*MRt*<0 (815/815 events)	Difference	*MRt*>0 (475/475 events)	*MRt*<0 (319/320 events)	Difference
1	-0.05/**-0.32	0.12/*0.19	*-0.17/**-0.51	-0.06/**-0.35	0.11/0.18	*-0.17/**-0.53
2	-0.04/*-0.14	0.07/0.09	-0.11/*-0.23	-0.04/*-0.16	0.06/0.09	-0.10/*-0.25
1 to 5	*-0.24/***-0.49	0.18/*0.25	**-0.42/***-0.74	*-0.26/***-0.55	0.15/0.22	**-0.41/***-0.77
1 to 20	**-0.37/***-0.78	0.19/*0.28	**-0.56/***-1.06	**-0.45/***-0.96	0.17/*0.26	**-0.62/***-1.22
Panel B: High-volume days accompanied by negative stock returns						
Days relative to event	Average AR/CAR following high-volume days for high/low market capitalization firms, %					
	Proxy A			Proxy B		
	MRt>0 (881/882 events)	*MRt*<0 (1,322/1,323 events)	Difference	*MRt*>0 (383/384 events)	*MRt*<0 (561/562 events)	Difference
1	-0.10/-0.17	*0.16/**0.31	*-0.26/**-0.48	-0.09/-0.18	*0.17/**0.36	*-0.26/**-0.54
2	-0.04/-0.09	0.04/*0.13	-0.08/*-0.22	-0.03/-0.10	0.04/*0.15	-0.07/*-0.25
1 to 5	-0.12/-0.25	*0.35/***0.63	**-0.47/***-0.88	-0.09/-0.21	*0.42/***0.74	**-0.51/***-0.95
1 to 20	-0.13/*-0.24	**0.51/***0.94	**-0.64/***-1.18	-0.10/-0.20	**0.58/***1.05	**-0.68/***-1.25

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 5: Abnormal stock returns following high-volume days accompanied by positive and negative stock returns, by the sign of MRt, for high and low volatility stocks

Panel A: High-volume days accompanied by positive stock returns						
Days relative to event	Average AR/CAR following high-volume days for high/low volatility stocks, %					
	Proxy A			Proxy B		
	MRt>0 (1,118/1,119 events)	*MRt*<0 (815/815 events)	Difference	*MRt*>0 (475/475 events)	*MRt*<0 (319/320 events)	Difference
1	**-0.31/-0.07	0.17/0.13	**-0.48/*-0.20	**-0.33/-0.08	0.16/0.12	**-0.49/*-0.20
2	*-0.13/-0.06	0.08/0.07	*-0.21/-0.13	*-0.14/-0.06	0.09/0.07	*-0.23/-0.13
1 to 5	**-0.48/*-0.25	0.23/0.19	***-0.71/**-0.44	**-0.55/*-0.28	0.21/0.16	***-0.76/**-0.44
1 to 20	***-0.77/**-0.39	*0.26/0.20	***-1.03/**-0.59	***-0.92/**-0.48	0.24/0.17	***-1.16/**-0.65
Panel B: High-volume days accompanied by negative stock returns						
Days relative to event	Average AR/CAR following high-volume days for high/low volatility stocks, %					
	Proxy A			Proxy B		
	MRt>0 (881/882 events)	*MRt*<0 (1,322/1,323 events)	Difference	*MRt*>0 (383/384 events)	*MRt*<0 (561/562 events)	Difference
1	-0.16/-0.10	**0.29/*0.17	**-0.45/*-0.27	-0.15/-0.10	**0.33/*0.19	**-0.48/*-0.29
2	-0.08/-0.05	*0.12/0.06	*-0.20/-0.11	-0.07/-0.05	*0.14/0.06	*-0.21/-0.11
1 to 5	-0.23/-0.13	**0.61/*0.36	***-0.84/**-0.49	-0.20/-0.10	**0.72/*0.41	***-0.92/**-0.51
1 to 20	-0.22/-0.15	***0.89/**0.53	***-1.11/**-0.68	-0.19/-0.11	***1.03/**0.60	***-1.22/**-0.71

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 6: Multifactor regression analysis of ARs following high-volume days accompanied by positive and negative stock returns

Panel A: High-volume days accompanied by positive stock returns						
Explanatory variables	Coefficient estimates, % (2-tailed p-values)					
	Post-event Day 1		Post-event Days 1 to 5		Post-event Days 1 to 20	
	Proxy A	Proxy B	Proxy A	Proxy B	Proxy A	Proxy B
Intercept	***0.17 (0.65%)	***0.16 (0.89%)	***0.24 (0.21%)	***0.21 (0.42%)	***0.25 (0.19%)	***0.22 (0.27%)
MR_dum	**-0.35 (1.34%)	**-0.36 (1.28%)	***-0.60 (0.08%)	***-0.63 (0.05%)	***-0.85 (0.00%)	***-0.92 (0.00%)
MCap	**0.23 (2.06%)	**0.24 (1.25%)	***0.29 (0.54%)	***0.30 (0.47%)	***0.34 (0.21%)	***0.34 (0.23%)
Beta	*-0.09 (8.65%)	*-0.08 (9.36%)	*-0.10 (8.12%)	*-0.10 (8.28%)	*-0.08 (9.36%)	*-0.09 (9.00%)
SR_Volat	*-0.18 (6.11%)	*-0.19 (6.02%)	*-0.20 (5.24%)	**-0.22 (4.85%)	**-0.24 (4.12%)	**-0.25 (4.03%)
|SR|	-0.03 (36.28%)	-0.02 (41.27%)	-0.01 (56.71%)	-0.01 (51.46%)	-0.04 (27.55%)	-0.03 (36.42%)
Panel B: High-volume days accompanied by negative stock returns						
Explanatory variables	Coefficient estimates, % (2-tailed p-values)					
	Post-event Day 1		Post-event Days 1 to 5		Post-event Days 1 to 20	
	Proxy A	Proxy B	Proxy A	Proxy B	Proxy A	Proxy B
Intercept	***0.25 (0.18%)	***0.28 (0.06%)	***0.47 (0.00%)	***0.56 (0.00%)	***-0.70 (0.00%)	***-0.81 (0.00%)
MR_dum	**-0.40 (1.18%)	***-0.43 (0.95%)	***-0.68 (0.08%)	***-0.74 (0.02%)	***-0.93 (0.00%)	***-0.98 (0.00%)
MCap	**-0.21 (4.25%)	**-0.20 (4.67%)	**-0.24 (3.20%)	**-0.23 (3.69%)	***-0.31 (0.47%)	***-0.30 (0.61%)
Beta	0.07 (10.98%)	*0.08 (9.91%)	*0.10 (8.09%)	*0.09 (8.88%)	*0.13 (6.35%)	*0.12 (6.92%)
SR_Volat	*0.19 (5.34%)	*0.19 (5.45%)	**0.21 (4.77%)	**0.22 (4.15%)	**0.25 (3.51%)	**0.26 (3.19%)
|SR|	0.02 (65.94%)	0.03 (52.68%)	0.03 (47.11%)	0.04 (39.28%)	0.05 (30.12%)	0.04 (35.46%)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01